SIRA: Exposing Vulnerabilities in Text Watermarking with Self-Information Rewrite Attacks

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Abstract

Text watermarking is designed to embed hidden, imperceptible, markers within content generated by large language models (LLMs), with the goal of tracing and verifying the content's origin to prevent misuse. The robustness of watermarking algorithms has become a key factor in evaluating their effectiveness, but remains an open problem. In this work, we introduce a novel watermark removal attack, the Self-Information Rewrite Attack (SIRA), which poses a new challenge to the robustness of existing watermarking techniques. Since embedding watermarks requires both concealment and semantic coherence, current methods prefered to embed them in high-entropy tokens. However, this reveals an inherent vulnerability, allowing us to exploit this feature to identify potential green tokens. Our approach leverages the self-information of each token to filter potential pattern tokens that embed watermarks and performs the attack through masking and rewriting in a black-box setting. We demonstrate the effectiveness of our attack by implementing it against seven recent watermarking algorithms. The experimental results show that our lightweight algorithm achieves state-of-the-art attack success rate while maintaining shorter execution times and lower computational resource consumption compared to existing methods. This attack points to an important vulnerability of existing watermarking techniques and paves way towards future watermarking improvements.

1 Introduction

Large language models (LLMs), exemplified by ChatGPT (OpenAI, 2024) and Claude (Anthropic, 2024), have demonstrated remarkable capabilities in generating coherent, human-like text. However, while these advances significantly expand AI's potential in content creation, they have concurrently heightened concerns regarding their misuse (Deshpande et al., 2023; Wang et al., 2024), including the spread of misinformation (Monteith et al., 2024) and threats to academic integrity (Stokel-Walker, 2022).

To mitigate risks associated with LLM-generated content, text watermarking has emerged as a promising countermeasure (Kirchenbauer et al., 2023; Aaronson & Kirchner, 2022). This technique subtly alters the LLM's generation process to embed imperceptible patterns in the output text, which, while invisible to human readers, can be reliably detected using specialized algorithms. This generate-detect framework enables differentiation between AI-generated and human-authored content and allows tracing the text back to the specific LLM that created it (Li et al., 2024). Consequently, this mechanism promotes accountability and helps mitigate LLM misuse, providing a reliable means to ensure transparency and integrity in AI-generated content.

Recent studies have demonstrated that watermarking techniques exhibit significant robustness against simple manipulations, including word deletions (Welbl et al., 2020) and emoji attacks (Kirchenbauer et al., 2023). However, traditional NLP attack strategies, such as token deletion and insertion, are increasingly insufficient for thoroughly evaluating the robustness of advanced watermarking algorithms. As LLMs continue to advance, there is a growing need for more sophisticated testing methodologies that account for complex manipulation tactics, ensuring that watermarking techniques remain resilient against emerging threats. To provide a more rigorous evaluation of watermarking robustness, model-based attacks have been proposed. These methods typically rewrite watermarked texts using either closed-source commercial LLMs (Kirchenbauer et al., 2023) or fine-tuned open-source models trained on specially designed phrase datasets (Krishna et al., 2024). Despite their potential, these approaches face several limitations. First, they lack transparency, offering limited control over the output text via a small set of hyperparameters. Second, they are often costly, requiring token-based payments or significant computational resources. Furthermore, for newer and more robust watermarking algorithms like SIR (Liu et al., 2024), these methods fail to deliver effective attacks.

To resolve the aforementioned problem, we propose a lightweight and effective watermark removal attack named **SIRA**(self-information rewrite attack). This method is inspired by a simple intuition: watermarking algorithms aim to be imperceptible to users while preserving text quality, often favoring high-entropy tokens to embed watermark patterns (Kirchenbauer et al., 2023; Liu et al., 2023). The high-entropy tokens, however, will usually have high self-information. Leveraging this insight, we can identify potential ”green list” token candidates within watermarked text under a black-box setting. By masking these potential tokens and allowing the LLM to complete the masked segments, we can effectively carry out a more effective paraphrasing attack. SIRA requires minimal resources and works effectively even with a small model like LLaMA3-8B. Our experiments in seven watermark algorithms show that SIRA outperforms all other black-box watermark removal attacks. Specifically, our method achieves over a 90% attack success rate on most current watermarking techniques (Kirchenbauer et al., 2023; Zhao et al., 2023; Liu et al., 2023; Lu et al., 2024; Wu et al., 2024; Aaronson & Kirchner, 2022). We will release our code to further promote the development of responsible AI (Gu, 2024).

2 Related Work

Self-information. Self-information, also known as surprisal, is a fundamental concept in Information Theory, first introduced by Claude Shannon in his seminal work (Shannon, 1948). Shannon employed self-information as the principal metric to quantify the information content associated with the occurrence of specific events, effectively linking the rarity of an event to the amount of information it communicates. This measure forms a cornerstone in the understanding of data encoding and compression, as articulated in Shannon's source coding theorem, where events that are more probable are represented with fewer bits, while less probable events require more bits, thereby facilitating optimal compression (Shannon, 1948).

In the realm of Natural Language Processing (NLP), self-information plays a crucial role in the analysis and modeling of language. It aids in deciphering language patterns, particularly in evaluating the entropy and predictability of tokens within sequences. The concept is particularly useful for quantifying the informativeness or surprise of a token, determined by its probability in a given linguistic context. Language models, for instance, predict the probability of a subsequent token in a sequence using the preceeding context:

$$P(t_k \mid t_1, t_2, \ldots, t_{k-1})$$

The self-information of the token in this context is computed as follows:

$$I(t_k \mid t_1, t_2, \ldots, t_{k-1}) = -\log_b(P(t_k \mid t_1, t_2, \ldots, t_{k-1}))$$

where $I(t_k \mid t_1, t_2, \ldots, t_{k-1})$ denotes the self-information of token t_k given the context of previous tokens, $P(t_k \mid t_1, t_2, \ldots, t_{k-1})$ is the probability of token t_k occurring after the preceding sequence of tokens, and b represents the base of the logarithm, typically set to 2. Tokens that are less predictable within a sequence, hence more informative, exhibit higher self-information values.

LLM Watermark. Watermarking techniques for large language models are designed to embed identifiable patterns in model outputs, allowing for the traceability of generated text back to its originating source. These watermarks serve as an essential tool for ensuring accountability and ownership, particularly in scenarios where identifying the specific model or version that produced the content is crucial. LLM watermark methods can be broadly classified into two primary categories: the KGW Family and the Christ Family. Each family employs distinct mechanisms that are integral to the internal workings of LLMs. The *KGW Family* (Kirchenbauer et al., 2023; Liu et al., 2023; Zhao et al., 2023; Wu et al., 2024; Lu et al., 2024) focuses on modifying the logits—the raw output probabilities produced by the model—before they are transformed into text. This approach involves selectively adding bias to certain tokens, referred to as “green list” tokens, which influences the model to favor these tokens, thus embedding a statistical signature in the output. Post text generation, a statistical metric based on the proportion of these “green” tokens is computed. A predetermined threshold enables differentiation between watermarked and non-watermarked text.

Conversely, the *Christ Family* (Aaronson & Kirchner, 2022; Christ et al., 2024; Kuditipudi et al., 2023) modifies the sampling process during the generation phase itself. Rather than altering the logits, this family intervenes directly in the token selection during decoding. Techniques such as top-k sampling, temperature adjustment, or nucleus sampling are adapted to ensure preferential selection of watermarked tokens. This method provides more direct control over the generation process, embedding watermarks that are resilient against post-processing attacks, such as paraphrasing.

Watermark Removal Attacks. The robustness of a watermarking algorithm is crucial, as it determines the effectiveness of the watermark under various real-world conditions, particularly in adversarial settings. Attacks against watermarking algorithms, commonly referred to as watermark tampering attacks, can be broadly categorized into two types:

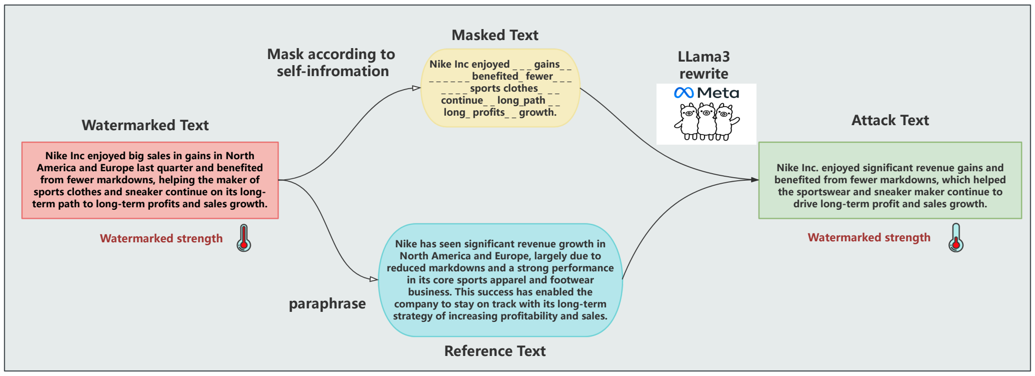
Text manipulations: These attacks involve traditional NLP techniques to straightforward text manipulations, such as word deletion (Welbl et al., 2020), substitution (Yu et al., 2010), or insertion (Kirchenbauer et al., 2023). By altering the surface-level structure of the text, these methods attempt to distort or eliminate the watermark without drastically changing the content’s meaning. These techniques exploit the fact that many watermarking algorithms embed patterns with a pre-designed ”green token” and ”red token”, making them vulnerable to such basic modifications. Kirchenbauer et al. (2023) propose emoji attack and copy-paste attack which insert emoji/human writtern text in the generated text to avoid detection.These methods are considered variants of text manipulations, however, they are easily thwarted by detectors equipped with content filters and often alter the semantics of the generated text which makes them inappropriate for real-world use.

Model-based paraphrasing: A more advanced form of attack involves using another LLM to paraphrase the watermarked content. This approach takes advantage of the LLM’s ability to generate diverse rephrasings while maintaining the core meaning of the text. Krishna et al. (2024) propose DIPPER, a paraphrase generation model developed by fine-tuning T5-XXL (Raffel et al., 2020b) on an aligned paragraph dataset. This model has been widely adopted in recent watermark research (Zhao et al., 2023; Liu et al., 2024; Kuditipudi et al., 2023) to evaluate the robustness of watermarking algorithms. Zhang et al. (2023) propose the random walk attack, which utilizes Llama2-7B (Touvron et al., 2023) as the generation model, with T5-XXL (Raffel et al., 2020b) serving as a perturbation oracle to iteratively modify the watermarked text. In each iteration, RoBERTa-v3 large (Liu, 2019) is employed as a quality oracle to provide rewards, while GPT-3.5 OpenAI (2023) performs a final quality check on the generated text. However, since this method does not ensure that the paraphrased text retains the same semantics as the original watermarked text, it diverges significantly from the goals of typical paraphrase attacks.

Our proposed SIRA falls under the category of model-based paraphrasing attacks. However, unlike conventional paraphrasing techniques that generate entirely new sentences or passages based on instructions, SIRA selectively replaces potential green words in the watermarked text to provide a ”neutral” template for rewriting. This targeted replacement approach enables more precise control over the consistency and semantics of the watermark-removed text. Additionally, SIRA can be effectively implemented using a lightweight model, enhancing its efficiency for practical applications.

3 METHODS

In this section, we detail SIRA attack formulation and implementation. First, we lay out the problem setting in Section 3.1, then we develop the details of the method in Section 3.2.



Nike Inc enjoyed big sales in gains in North America and Europe last quarter and benefited from fewer markdowns, helping the maker of sports clothes and sneaker continue on its long-term path to long-term profits and sales growth.

Nike Inc enjoyed _ _ _ gains_ _ _ _ _ _ _ _ benefited_ fewer_ _ _ _ _ _ _ sports clothes_ _ _ continue_ _ long_path _ _ long_ profits_ _ growth.

Nike has seen significant revenue growth in North America and Europe, largely due to reduced markdowns and a strong performance in its core sports apparel and footwear business. This success has enabled the company to stay on track with its long-term strategy of increasing profitability and sales.

Nike Inc. enjoyed significant revenue gains and benefited from fewer markdowns, which helped the sportswear and sneaker maker continue to drive long-term profit and sales growth.

Figure 1: **SIRA pipeline consisting to two steps.** First, the attack generates a masked text based on self-information. If the self-information of a specific part above a pre-set threshold, that portion of the text is masked and replaced with a placeholder. Simultaneously, a reference text is generated by asking the LLM to paraphrase. In the second step, the LLM is prompted to complete the masked text while incorporating all the information from the reference text.

3.1 Problem Setting

Definition 1 (Language generative model). A Language generative model $M : X \to Y$ that maps any input prompt $x \in X$ to an output $y \in Y$, where X the prompt space, Y the output space. We denote Y_h is human written text space, Y_u is the machine generated unwatermarked text, Y_w is the machine generated watermarked text.

Definition 2 (Watermark Algorithm): A watermark algorithm consists of a watermarking function W, a secret key k, and a detector D. The watermarking function W, parameterized by the key k, denote as W_k, modifies the output y to embed a watermark, given an input prompt $x \in X$ resulting in a watermarked output $M(x, W_k) \to y_w \in Y_w$. The detector D, using the same key k, can then verify whether a given output $\hat{y} \in Y$ contains the embedded watermark. The detector D operates as a binary classifier with the following output behavior:

$$D(W_k, \hat{y}) = \begin{cases} 1 & \text{if } \hat{y} \text{ is detected as watermarked} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

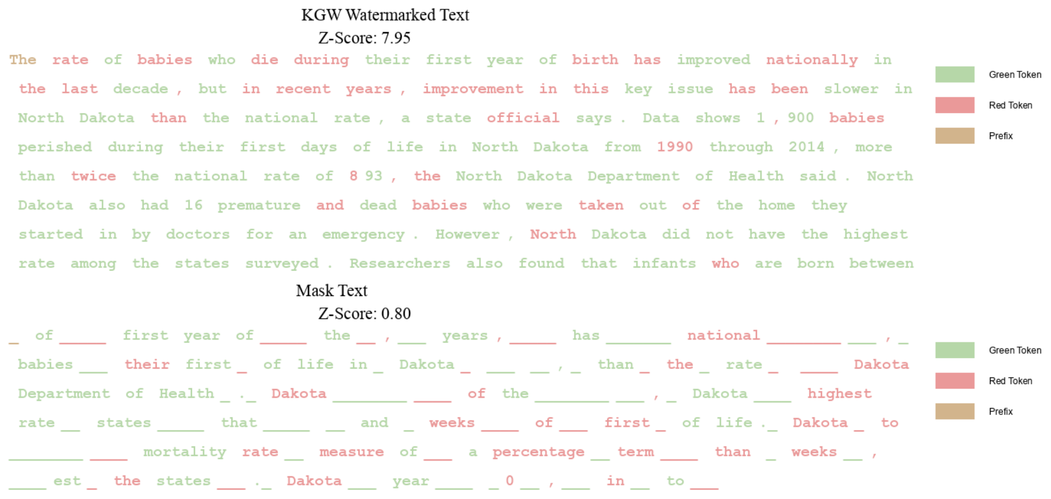
The detector D contains a parameter θ, where the θ is the z-score threshold.

Definition 3 (Perturbation Function): The attacker has a perturbation function $P : Y_w \to Y_p$ modifies the watermarked output y_w to produce a perturbed output $y_p = P(y_w)$. The function P aims to minimize the detection success rate of the detector D on the perturbed output y_p. A function $S(y_w, y_p)$ measures the semantic similarity between the original watermarked output y_w and the perturbed output $y_p = P(y_w)$. The pre-set threshold $\epsilon \in [0, 1]$ is a parameter that quantifies the minimum required level of semantic similarity between the original watermarked output y_w and the perturbed output $y_p = P(y_w)$.

We define the scenario as a **black box adversarial problem** and we assume that the attacker **should not know the watermark algorithm W, the secret key k and should not have access to the detector D.** The attacker does not have access to any information about the feature distribution of the watermark algorithm or the model architecture.

For watermark algorithm, the goal is to achieve a balance between robustness and performance. The detector D is formulated as an optimization problem with the objective of minimizing classification errors. Specifically, the detector aims to maximize its accuracy in distinguishing between human-written text y_h and attack text y_p. The goal of detector D can represente as:

$$\max_{\theta_D} \quad \mathbb{E}_{y_h \sim Y_h} \left[\log \left(1 - D_{\theta_D}(W_k, y_h) \right] + \mathbb{E}_{y_p \sim Y_p} \left[\log(D_{\theta_D}(W_k, y_p)) \right] \tag{2}$$


KGW Watermarked Text
Z-Score: 7.95

The rate of babies who die during their first year of birth has improved nationally in the last decade , but in recent years , improvement in this key issue has been slower in North Dakota than the national rate , a state official says . Data shows 1 , 900 babies perished during their first days of life in North Dakota from 1990 through 2014 , more than twice the national rate of 8 93 , the North Dakota Department of Health said . North Dakota also had 16 premature and dead babies who were taken out of the home they started in by doctors for an emergency . However , North Dakota did not have the highest rate among the states surveyed . Researchers also found that infants who are born between

Mask Text
Z-Score: 0.80

_ of _____ first year of _____ the __ , ___ years , _____ has _______ national ________ ___ , _ babies ___ their first _ of life in _ Dakota _ ___ __ , _ than _ the _ rate _ ____ Dakota Department of Health _ ._ Dakota ________ ____ of the ________ ___ , _ Dakota ____ highest rate __ states _____ that _____ __ and _ weeks ____ of ___ first _ of life ._ Dakota _ to ________ ____ mortality rate __ measure of ___ a percentage __ term ____ than _ weeks __ , ____ est _ the states ___ ._ Dakota ___ year ____ _ 0 __ , ___ in __ to ___

🟩 Green Token
🟥 Red Token
🟫 Prefix

Figure 2: **Visualization of watermark text and the text after masking.** We can find that according to self-information filter, the mask text significantly reduce the z-score and remove most of the green tokens. Note that actual z-score is lower since some placeholder which will be removed in next step are treated as green token by detector. The shown text are using KGW-1 watermark.

For attacker, the perturbation function P is defined to minimize the probability that the detector D successfully identifies the watermark in the perturbed output y_p, while ensuring semantic preservation. The goal for P can represente as:

$$P^* = \arg\min_{P} \quad \mathbb{E}\left[D(W_k, P(y_w))\right] \tag{3}$$

$$\text{s.t.} \quad S(y_w, P(y_w)) \geq \epsilon \tag{4}$$

Note that $D(W_k, P(y_w))$ is only used during the evaluation phase. The attacker does not have access to the detector during the training or generation stages.

3.2 Self-information rewrite attack

A primary challenge in watermark removal attacks is identifying the "green token" defined by the watermarking algorithm. Some methods, such as Random Walk (Zhang et al., 2023), use grammatical group matching to explicitly replace verbs. In contrast, approaches like DIPPER (Krishna et al., 2024) and GPT Paraphraser (Liu et al., 2024) delegate the task of rewriting and removing green token to large language models through high-level instructions. However, methods of this type lack transparency and control; relying on LLM for consistency with original watermarked text.

Our attack is based on a common principle of watermarking algorithms, as discussed in the KGW (Kirchenbauer et al., 2023; Liu et al., 2023) work: since the watermark must remain imperceptible to the user, high-entropy tokens are ideal candidates for embedding. High-entropy tokens exhibit a more uniform distribution of probabilities, this uniformity means that when logits are adjusted to increase the likelihood of green tokens, it is easier to embed watermarks effectively without significantly compromising the quality of the output. Meanwhile this also implied high-entropy token has lower probability thus higher self-information.

In our approach, we propose a straightforward and easily implementable solution by leveraging self-information to identify potential green-list tokens and subsequently rewrite them. High-entropy tokens are typically associated with high self-information due to their unpredictability and low probability of occurrence. Meanwhile, small probability changes caused by the watermark algorithm can reduce self-information, as briefly explained in Appendix F. By considering both the change in self-information and high-entropy token inherent nature, we classify tokens with high or moderate self-information as potential green-list tokens and filter them out to obtain a more neutral template for LLM rewriting. Empirically, our preliminary experiments show that utilizing self-information, rather than directly filtering based on high entropy, results in higher attack success rates.

Algorithm 1 Pseudocode for Self-information rewrite attack

```
1: Input: Watermarked token sequence $\mathbf{y} = \{y_1, y_2, \dots, y_n\}$, language model $M_{attack}$, self-information percentile $\epsilon$, instruction $\mathbf{s}$
2: Output: Response token sequence $\mathbf{y_p}$ without watermark.
3: $\mathbf{y}' \leftarrow M_{attack}(\mathbf{y})$                    ▷ Paraphrase sequence $\mathbf{y}'$ using $M_{attack}$
4: $\mathbf{I} \leftarrow [\,]$
5: for $i = 1$ to $n$ do                    ▷ Compute self-information for each token in $\mathbf{y}$
6:     $\mathbf{I}[i] \leftarrow -\log P(y_i \mid \text{context})$
7: end for
8: $\tau_\epsilon \leftarrow \text{Percentile}(\mathbf{I}, \epsilon)$                    ▷ Determine threshold from $\epsilon$ percentile of $\mathbf{I}$
9: for $i = 1$ to $n$ do
10:     if $\mathbf{I}[i] > \tau_\epsilon$ then
11:         $y_i \leftarrow \varnothing$                    ▷ Mask token if above threshold
12:     end if
13: end for
14: $\mathbf{y}_p \leftarrow M_{attack}(\mathbf{y}', \mathbf{y}, \mathbf{s})$                    ▷ Generate de-watermarked response $\mathbf{y_p}$ using $M$
15: return $\mathbf{y_p}$
```

Given a watermarked text $y = \{y_0, y_1, \dots, y_n\}$, where y_i represents each token, we employ a base language model M_{attack}; M_{attack} is distinct from the generative model M used to produce the watermarked text. We use M_{attack} to calculate the self-information for each token y_t as follows:

$$I(y_t) = -\log P(y_t | y_0, y_1, \dots, y_{t-1}; M_{attack}),$$

where $P(y_t | y_0, y_1, \dots, y_{t-1}; M_{attack})$ denotes the probability of token y_t given its preceding tokens in the sequence, as estimated by the language model M_{attack}. To mask the potential green list tokens, we set a threshold ϵ, and get the overall paragraph threshold by percentile:

$$\tau_\epsilon \leftarrow \text{Percentile}(\mathbf{I}, \epsilon)$$

Any token with a self-information value $\mathbf{I}[i] > \tau_\epsilon$ is considered to be a potential token and will be masked and replaced with a placeholder. In our experiments, we discovered that using placeholders outperformed directly masking specific tokens. The placeholders serve as cues, maintain the text's structure, indicating where tokens have been masked whihc providing the LLM with hints about the original text's length and the likely number of words, allowing for more high quality reconstructions. We shown one visualization of mask text and watermark text comparsion in Figure 5.

However, the compression will still result in the loss of watermark text information details. To address this, we use the base LLM to rewrite the watermarked text, creating a reference text. This rewritten text serves as a reference to provide the semantic information intergrity during the second step. The reason we do not use the original watermarked text is that we find this leads LLM to take shortcuts: LLM tend to directly take the content from the watermark text, due to the high similarity between masked and watermark text.

In the final attack phase, we provide the LLM with the masked text, reference text, and instructions for a fill-in-the-blank task, guiding it to reconstruct the missing content. We provide the instructions we use in Appendix D. The pseudocode of our algorithm is shown in Algorithm 1.

4 Experiments

4.1 Setup

Dataset and Prompts. Following prior watermarking research (Kirchenbauer et al., 2023; Zhao et al., 2023; Liu et al., 2024; Kuditipudi et al., 2023), we utilize the C4 dataset (Raffel et al., 2020a) for general-purpose text generation scenarios. We selected 500 random samples from the test set to serve as prompts for generating the subsequent 230 tokens, using the original C4 texts as non-watermarked examples.

Table 1: Comparison of watermark algorithms under different attack methods.

Comparison of Watermark Algorithms under Different Attack Methods							
Attack \ Watermark	KGW-1	Unigram	UPV	EWD	DIP	SIR	EXP
Word delete (Welbl et al., 2020)	22.4%	1.6%	6.6%	22.8%	57.4%	44.0%	9.4%
Synonym Substitution (Yu et al., 2010)	83.2%	17.4%	65.2%	76.2%	99.6%	82.0%	51.0%
GPT Paraphraser (Liu et al., 2024)	**100%**	63.9%	71.9%	90.8%	**99.8%**	58.8%	72.2%
DIPPER-1 (Krishna et al., 2024)	82.4%	37.0%	58.6%	82.2%	99.6%	61.2%	73.6%
DIPPER-2 (Krishna et al., 2024)	95.8%	45.6%	61.8%	89.0%	**99.8%**	63.6%	82.2%
SIRA(Ours)	**100%**	**93.8%**	**93.0%**	**100%**	**99.8%**	**83.4%**	**93.4%**

Watermark generation algorithms and language model. To conduct a comprehensive evaluation, we select seven recent watermarking works: KGW (Kirchenbauer et al., 2023), Unigram (Zhao et al., 2023), UPV (Liu et al., 2023), EWD (Lu et al., 2024), DIP (Wu et al., 2024), SIR (Liu et al., 2024),EXP (Aaronson & Kirchner, 2022) in the assessment. The watermark hyperparameter settings shown in Appendix A, and the detection settings adhere to the default/recommendations (Pan et al., 2024) configurations of the original works. Specifically, for KGW-k, k is the number of preceding tokens to hash. A smaller k implies stronger attack robustness yet simpler watermarking rules. We use KGW-1 in our experiment. For language models, we follow previous work setting select (Kirchenbauer et al., 2023; Liu et al., 2024; Zhao et al., 2023) Opt-1.3B (Zhang et al., 2022) as watermark text generation model. We use LLaMA3-8b (Dubey et al., 2023) to ensure the lightweight and usability of our method, along with its tokenizer for the calculation of self-information.

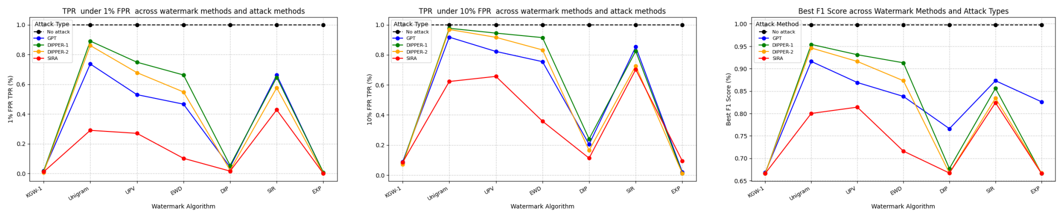
Baseline Methods. For our method, we use $\epsilon = 0.3$ as threshold. For attack method, we use word deleteion (Welbl et al., 2020), synonym substitution (Yu et al., 2010), Dipper (Krishna et al., 2024), and GPT Paraphaser (Liu et al., 2024) to compare with our method. For GPT Paraphaser, we use the GPT-4o-2024-05-13 (OpenAI, 2024) version. For DIPPER-1 the lex diversity is 60 without order diversity, and for DIPPER-2 we additionally increase the order diversity by 40. The word deletion ratio is set to 0.3 and the synonym substitution ratio is set to 0.5. The synonyms are obtained from the WordNet synset (Miller, 1995).

Evaluation. We utilize the attack success rate as our primary metric. The attack success rate is defined as the proportion of generated attack texts for which the watermark detector incorrectly classify the attack text as unwatermarked sample, compared to the total number of attack texts. To mitigate the influence of detection thresholds, we follow prior work (Liu et al., 2024; Zhao et al., 2023) adjust z-threshold of detector until reach target false positive rate in Figure 3 . We use generated 500 attack texts as positive samples and 500 humnn-written texts as negative samples. We dynamically adjust the detector's thresholds to establish false positive rates at 1% and 10%, and we report the true positive rates and F1-scores. All experiments for our method were conducted on single NVIDIA A100 40GB GPU.

4.2 Experimental Results.

In Table 1, we present the attack success rates of various watermark removal methods across different watermarking algorithms. The results demonstrate that our approach consistently outperforms all other methods for each watermarking algorithm. Notably, the closest competitors to our method are DIPPER (Krishna et al., 2024) and GPT Paraphraser (Liu et al., 2024), which are model-based paraphrasing attacks. Our approach surpasses these competitors by a significant margin in experiments involving seven watermarking algorithms on the C4 dataset (Raffel et al., 2020a).

To further demonstrate the effectiveness of our method and avoid the impact of a fixed z-threshold on detector performance, we follow previous work by setting the FPR to 1% and 10%, and report the true positive rate of the detector on adversarial texts based on the adjusted z-threshold corresponding to the FPR. Additionally, we report the best F1 score that the watermark algorithm can achieve

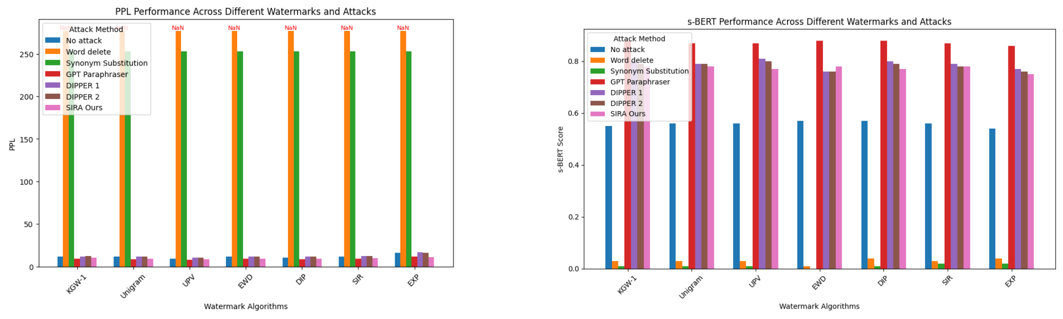


(a) True positive rate of different watermark with false postivite rate set to 1%.

(b) True positive rate of different watermark with false postivite rate set to 10%.

(c) Best F1-score could achieved by different watermark algorithm detector.

Figure 3: To avoid the default z-threshold impact the robustness of watermark algorithm, we dynamically adjust the z-score threshold of the watermarking algorithm until achieving specified false positive rates for the watermark detector. We display the true positive rate and the best F1 score could achieve by watermark detector. Lower TPR and F1 scores at a given FPR indicate that the watermark detector struggles more to differentiate between attack texts and human-written texts, suggesting a more effective attack. We show the detail number of above figure in Appendix B.



(a) Performance of PPL.

(b) Performance of s-BERT.

Figure 4: Performance comparison of watermark methods against various attack methods based on PPL (Perplexity↓) and s-BERT (Sentence-BERT score↑). The word delete will signicantly increase the PPL and lead to overflow. We marked the overflow data with NaN in the fig. 4a. The synonym substitution will also increase the PPL. The paraphrased text has better text quaility than original watermark text for our method and GPT Paraphraser.

under different attacks. The results are shown in Figure 3, and the detailed numbers are provided in Appendix B. Lower true positive at a given false positive rate indicate that the watermark detector struggles more to differentiate between adversarial texts and human-written texts. Our algorithm achieves optimal attack performance in most cases; suggesting a more effective attack.

4.3 Text quality analysis

To further demonstrate that our method does not adversely affect text quality, we conduct additional evaluations of the text generated by the model. We compare **Perplexity (PPL)** of the text quality. Furthermore, we specifically calculate the sentence-level embedding similarity (**Sentence-BERT Score (s-BERT)**) before and after the attack to explore whether the attack alters the semantic content at the sentence level. We also conducted experiments in the Appendix E using ChatGPT as a judge to measure overall semantic similarity. The results, shown in Figure 4, indicate that our method has a smaller impact on text quality compared to other approaches.Our approach, similar to other model-based methods, benefits from more powerful large language models, achieving better performance in terms of the PPL metric compared to the original watermarked text. Additionally, our method retains a greater degree of semantic information. We show the detail numbers of two metrics in Appendix C.

Table 2: Comparison of Execution Time and VRAM Usage for Different Methods. Note that the execution speed of GPT Paraphraser may vary depending on the network status and real-time OpenAI server load.

Method	**Execution Time (s)**	**VRAM Usage (MB)**
GPT Paraphraser	12.8	N/A
DIPPER	14.7	45462
SIRA	10.3	18640

Table 3: Comparison with Random Masking Strategy. Notice here the random mask performance also benefit from other steps like rewriting in our framework. The vanilla random mask has similar attack success rate as word deletion.

Mask Ratio	0.4	0.5	0.6	0.7	0.8
Random Mask	52%	66%	78%	80%	82%
Self-information Mask	80%	88%	92%	96%	100%

4.4 Generation Speed

In this section, We conducted the attack experiments using 50 distinct watermark texts, each containing approximately 230 ± 20 tokens. For each method, we measured both execution time and VRAM usage. The reported execution time reflects the average for a single attack instance. The experiments were run on two NVIDIA A100 GPUs, utilizing a sequential device map for baseline methods requiring multiple GPUs. The configuration for the GPT Paraphraser follows the setup described in Section 4.1. The results are shown in Table 2.

One of the main limitations of current model-based watermark removal attacks is their substantial resource consumption. For instance, DIPPER built on the T5-XXL model, necessitates two 40GB A100 GPUs for effective operation. Similarly, the GPT parser introduces considerable costs due to its dependence on a proprietary model that employs token-based billing.

In contrast, our proposed pipeline operates using a minimal configuration of the LLaMA3-8b model, requiring only 18GB of VRAM. This enables compatibility with many consumer-grade GPUs, significantly reducing hardware requirements. Our approach is efficient enough to run on GPUs with as little as 20GB of memory, and each attack is completed in just two model inferences which makes our attack faster than other methods. We also experimented with larger models in Appendix E, such as Llama3-80b, and found that using a larger model can further improve semantic preservation and the quality of generated text .

4.5 Ablation Experiment

In this section, we aim to further scrutinize the self-information rewrite attack and emphasize the potential of this attack. We utilize Opt-1.3b and a random sample of 50 prompts from the C4 dataset to generate watermarked responses. Unless otherwise specified, we use Llama-3-8b as the base model for our attack. The temperature for the base model is set to 0.7.

Self-information mask versus Random mask In this experiment, we replace self-information-based selective masking with a random masking strategy, while keeping all other steps unchanged. We use the same masking ratios, ranging from 0.4 to 0.8 in increments of 0.1, and compare the resulting attack success rates. The Unigram watermarking method is employed to generate the watermarked text. The results are presented in Table 3. To ensure fair comparisons, the random masking strategy is executed five times, and the final average attack success rate is reported.

The results indicate that, at any given mask ratio, the self-information-based masking method significantly outperforms the random strategy. More importantly, the random masking approach exists a **bottleneck**, with limited improvement in attack success rates beyond a ratio of 0.6. This due to random mask can not make sure all target green token are removed. For a single watermarked text with fixed mask ratio, our method is deterministic, as the same tokens are masked each time. In contrast, the random approach does not provide this guarantee.

Table 4: Effect of self-information Threshold on the Success Rate of the UPV Algorithm

self-information threshold ϵ	0.25	0.30	0.35	0.40	0.45	0.5	0.55	0.60	0.65	0.70
Attack Success Rate	96%	94%	94%	88%	80%	76%	72%	70%	58%	32%

Table 5: Comparison of Attack Success Rate and Average z-score. The reference text is generated by asking the base model to paraphrase the watermarked response, while the attack text is generated using our two-step approach.

Text	**Attack Success Rate**	**Average z-score**
Human-written Text	N/A	0.12
Reference Text	64%	3.75
Attack Text	94%	1.85

How does the self-information threshold affect final performance? In this experiment, we use UPV as the watermarking algorithm. We varied the value of ϵ from 0.25 to 0.70 in increments of 0.05 to test its impact on the success rate of the attack using the UPV algorithm. The results are shown in table 4.

We observed that the attack success rate is directly influenced by the value of ϵ. For the UPV algorithm, setting the threshold to 0.3 results in a highly effective attack. A significant performance gap is observed when ϵ increases from 0.60 to 0.65. Additionally, based on human evaluation, when ϵ is below 0.25, the generated attack text tends to lose more detailed information from the original watermarked text, such as character dialogues. Considering both performance and semantic preservation, we recommend setting ϵ between 0.2 and 0.3. For less robust algorithms, setting ϵ between 0.4 and 0.5 is sufficient to achieve an attack success rate exceeding 90%.

We set ϵ to 0.3 in Table 1 since watermarking algorithms may employ a hybrid strategy, embedding the watermark primarily in low-entropy tokens while embedding a smaller portion in high-entropy tokens or with a ”hard list”. Setting ϵ to 0.3 effectively removes the watermark while preserving the original semantics.

Does the success of the attack due to paraphrased reference text? We used the Unigram watermarking algorithm to generate watermarked text. We set the detector’s z threshold to 4 according to its default settings. For a given input, the detector calculates its z-score, and if the score exceeds 4, the text is classified as watermarked.

We measured the attack success rate for each of the following stages: the reference text generated in the first step of our algorithm, and the final attack text. Additionally, we calculated the average z-score for each stage and reported the z-score of human-written text as a reference. The result are shown in Table 5. We observed that the attack success rate for the reference text is lower than that of the final attack text. Paraphrase strategies tend to preserve more n-grams from the original text, which may still be detectable by the watermark detection algorithm. In contrast, our attack reduces the presence of such n-grams by utilizing self-information filtering.Additionally, the z-score produced by our method is closer to that of human-written text compared to simple paraphrasing approaches.

5 Conclusion

In this paper, we presents the Self-Information Rewrite Attack (SIRA), a lightweight and effective method for removing watermarks from LLM-generated text by targeting anomalous tokens. Empirical results show that SIRA outperforms existing methods in attack success rates across multiple watermarking techniques while preserving text quality and requiring minimal computational resources. By exploiting vulnerabilities in current watermarking algorithms, SIRA highlights the need for more robust and adaptive watermarking approaches in watermark embedding. We will release our code to the community to facilitate further research in developing responsible AI practices and advancing the robustness of watermarking algorithms.

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BROADER IMPACT

In this work, we aim to provide an approach to test the robustness of Large Language Models watermark. We propose a method that can remove different watermark in LLM generated text. We are aware of the potential risks that our work entails for the security and safety of LLMs, as they are increasingly adopted in various domains and applications. Nevertheless, we also believe that our work advances the open and transparent research on the challenges and limitations of LLM watermark, which is crucial for devising effective solutions and protections. Similarly, the last few years the exploration of adversarial attacks (Wei et al., 2023; Madry et al., 2017; Krishna et al., 2024) has led to the improvement of responible AI and led to techniques to safeguard against such vulnerabilities,e further coordinated with them before publicly releasing our results. We also emphasize that, our ultimate goal in this paper is to identify of weaknesses of existing methods.

LIMITATIONS

Evaluation:We have observed that existing watermarking techniques tend to embed in high-entropy text, which may represent a potential vulnerability. This characteristic could be exploited by attackers to weaken the security guarantees of LLMs. The work most similar to ours is DIPPER, but our motivations differ slightly: while DIPPER aims to evade detectors of AI-generated text, our focus is specifically on LLM watermarking algorithms. Due to this difference in objectives, we did not include methods for detecting AI-generated text, such as GPT-zero, in our evaluation. We will explore in future work whether our method can be extended to detectors for adversarial AI-generated text.

Empirical: One limitation of our work is that it is specifically tailored to natural language. Some watermarking methods for LLMs, such as SWEET (Lee et al., 2023), are designed for code generation. Due to the inherently lower entropy nature in code generation tasks, our method does not design for such scenario. Additionally, this work primarily focuses on the attack. In our future work, we will further investigate how to modify watermarking algorithms to effectively defend against our proposed attack.

Theoretical: This work primarily focuses on empirical research. Our attack method targets phrase-level attacks across different watermarking techniques for LLMs and relies on an empirical results, similar to DIPPER. Due to the varying assumptions underlying different watermarking techniques, we cannot provide a theoretical guarantee proof for the final attack's success on each watermark type. Meanwhile establish the upper or lower bound on its performance is not in the scope of this work.

CONTENTS OF THE APPENDIX

The contents of the supplementary material are organized as follows:

- In appendix A, we list the hyperparameters of the watermarking algorithm we used in experiment section 4.
- In appendix B, w we present the specific data points corresponding to the figure shown in section 4.2.
- In appendix C, we provide the precise data underlying the figure depicted in section 4.3.
- In appendix D, we provide the prompt we used to generate attack text.
- In appendix E, we conduct extensive experiment to evaluate the overall preservation of the semantic meaning of the original watermarked text.
- In appendix F, we offer a brief discussion about the change of self-information under watermark algorithm influence.
- In appendix G, we provide a visual comparison of the text generated by our method with watermarked text, non-watermarked text, and text generated by other attack methods.
- In appendix H, we discuss several watermark attack methods we do not include in our main paper due to setting different.

A WATERMARK ALGORITHM SETTING

In this section, we list the hyperparameters of the watermarking algorithm we used in section 4 below.

```
{
    "algorithm_name": "KGW",
    "gamma": 0.5,
    "delta": 2.0,
    "hash_key": 15485863,
    "prefix_length": 1,
    "z_threshold": 4.0
}
```

Listing 1: configuration KGW

```
{
    "algorithm_name": "Unigram",
    "gamma": 0.5,
    "delta": 2.0,
    "hash_key": 15485863,
    "z_threshold": 4.0
}
```

Listing 2: configuration Unigram

```
{
    "algorithm_name": "UPV",
    "gamma": 0.5,
    "delta": 2.0,
    "z_threshold": 4.0,
    "prefix_length": 1,
    "bit_number": 16,
    "sigma": 0.01,
    "default_top_k": 20,
}
```

Listing 3: configuration UPV

```
{
    "algorithm_name": "EWD",
    "gamma": 0.5,
    "delta": 2.0,
    "hash_key": 15485863,
    "prefix_length": 1,
    "z_threshold": 4.0
}
```

Listing 4: configuration EWD

```
{
    "algorithm_name": "DIP",
    "gamma": 0.5,
    "alpha":0.45,
    "hash_key": 42,
    "prefix_length": 5,
    "z_threshold": 1.513,
    "ignore_history": 1
}
```

Listing 5: configuration DIP

```
{
    "algorithm_name": "SIR",
    "delta": 1.0,
    "chunk_length": 10,
    "scale_dimension": 300,
    "z_threshold": 0.0,
}
```

Listing 6: configuration SIR

```
{
    "algorithm_name": "EXP",
    "prefix_length": 4,
    "hash_key": 15485863,
    "threshold": 2.0,
    "sequence_length": 230
}
```

Listing 7: configuration EXP

B BEST F1 SCORE AND TPR/FPR

In table 6, we list the specific data from the figure in fig. 3, which reflects different attack method's performance of dynamically adjusting the watermark detector's z-threshold until a specified false positive rate is achieved. We report both the F1 score and true positive rate. It can be observed that, in most cases, our attack method achieves the best performance.

Table 6: In this experiment, we dynamically adjust the z-score threshold of the watermarking algorithm until achieving specified false positive rates for the watermark detector. We display the true positive rate and F1 score at this threshold. We also present the classifier's optimal F1 score under the dynamic threshold settings. For attack methods, lower TPR and F1 scores at a given FPR indicate that the watermark detector struggles more to differentiate between attack texts and human-written texts, suggesting a more effective attack.

Method	**Attack Type**	**1% FPR**		**10% FPR**		**Best F1 (%)**
		TPR (%)	**F1 (%)**	**TPR (%)**	**F1 (%)**	**F1 (%)**
KGW-1	No attack	100	99.5	100	95.2	99.8
	DIPPER -1	1.6	3.1	7.8	13.3	**66.6**
	DIPPER -2	**0.8**	**1.6**	**7.0**	**12.1**	**66.6**
	GPT Paraphraser	1.8	3.6	8.7	14.0	66.8
	SIRA	1.1	2.1	8.4	14.0	**66.6**
Unigram	No attack	100	99.5	100	95.2	99.8
	DIPPER -1	89.0	93.7	97.6	95.8	95.4
	DIPPER -2	86.0	91.8	96.8	94.2	94.6
	GPT Paraphraser	73.6	84.3	91.7	91.6	91.6
	SIRA	**29.0**	**44.6**	**62.2**	**72.7**	**80.0**
UPV	No attack	100	99.5	100	95.2	99.8
	DIPPER -1	74.8	85.2	94.4	93.1	93.1
	DIPPER -2	67.8	80.4	91.6	91.6	91.6
	GPT Paraphraser	53.0	69.2	82.2	86.2	86.9
	SIRA	**27.0**	**42.3**	**65.6**	**75.4**	**81.4**
EWD	No attack	100	99.5	100	95.2	99.8
	DIPPER -1	66.2	79.2	91.4	90.8	90.8
	DIPPER -2	54.8	70.3	83.2	81.2	81.2
	GPT Paraphraser	46.6	63.1	75.4	81.3	83.8
	SIRA	**10.2**	**18.3**	**35.8**	**49.1**	**71.6**
DIP	No attack	100	99.5	100	95.2	99.8
	DIPPER -1	5.4	10.0	24.0	36.1	67.7
	DIPPER-2	2.2	4.3	16.4	26.2	**66.7**
	GPT Paraphraser	4.3	8.3	20.4	32.0	76.6
	SIRA	**1.6**	**3.1**	**11.2**	**18.7**	**66.7**
SIR	No attack	100	99.5	100	95.2	99.8
	DIPPER -1	64.6	78.0	82.4	85.6	85.6
	DIPPER -2	57.6	72.6	72.6	83.4	83.4
	GPT Paraphraser	66.2	79.2	85.2	87.3	87.3
	SIRA	**42.8**	**59.5**	**70.2**	**77.9**	**82.4**
EXP	No attack	100	99.5	100	95.2	99.8
	DIPPER -1	0.8	1.6	1.2	2.1	66.6
	DIPPER -2	0.4	0.8	**2.0**	**3.8**	66.7
	GPT Paraphraser	0.4	0.8	**2.0**	**3.8**	82.6
	SIRA	**0**	**5.4**	9.3	8.3	**66.6**

C DETAIL NUMBER OF PPL AND SENTENCE BERT SCORE

In this section, we list the detail number of PPL and sentence-bert score we present in the section 4.3.

Watermark / Attack	KGW-1		Unigram		UPV		EWD		DIP		SIR		EXP	
	PPL(↓)	s-BERT(↑)	PPL(↓)	s-BERT(↑)	PPL(↓)	s-BERT(↑)	PPL(↓)	s-BERT(↑)	PPL	s-BERT(↑)	PPL(↓)	s-BERT(↑)	PPL(↓)	s-BERT(↑)
No attack	12.00	0.55	11.49	0.56	9.27	0.56	11.64	0.57	10.60	0.57	11.76	0.56	16.48	0.54
Word delete	NaN	0.03	NaN	0.03	NaN	0.03	NaN	0.01	NaN	0.04	NaN	0.03	NaN	0.04
Synonym Substitution	252.85	0.01	252.85	0.01	252.85	0.01	252.85	0	252.85	0.01	252.85	0.02	252.85	0.02
GPT Paraphraser	9.19	0.88	8.96	0.87	8.28	0.87	9.20	0.88	8.79	0.88	9.52	0.87	11.98	0.86
DIPPER-1	12.00	0.80	11.80	0.79	10.31	0.81	11.87	0.76	11.93	0.80	12.43	0.79	16.56	0.77
DIPPER-2	12.15	0.79	11.80	0.79	10.34	0.80	11.96	0.76	11.86	0.79	12.42	0.78	16.45	0.76
SIRA (Ours)	10.59	0.78	9.37	0.78	8.91	0.77	9.10	0.78	9.02	0.77	9.74	0.78	10.93	0.75

Table 7: Performance of different attack methods against various watermark techniques.

D FILL IN BLANK INSTRUCTION

We present our generation prompts below. During the generation process, the reference text and the masked text are replaced by the two texts obtained in the first step.

Generation Prompts

You will be shown one reference paragraph and one incomplete paragraph. Your task is to write a complete paragraph using incomplete paragraph. The complete paragraph should have similar length with reference paragraph. You need to include all the information in the reference. but do not take the expression and words in the reference paragraph. You should only answer the complete paragraph.
reference: [reference text]
incomplete paragraph: [mask text]

E GPT SEMANTIC JUDGE

GPT Semantic Judge Prompts

You are a helpful assistant. You will receive a original text and a pharased text .Please act as an impartial judge and evaluate how much the pharased text keep the original text semantic meaning. Be as objective as possible. Rate the response on a scale from 1 to 10. A rating of 1 signifies the pharased text has totally different meaning with the original text. A rating of 10 signifies the pharased text has same meaning with the original text . Your answer should strictly be the format: [Rating].
Here's the original text: [Watermarked text]
Here's the phrsed text:[Attack text]

In this section, we conduct extensive experiments to evaluate the overall preservation of the semantic meaning of the original watermarked text. We use ChatGPT (OpenAI, 2024) as an impartial judge to obtain the quantitative results.

The attack success rate alone is not a sufficient metric for evaluating an attack method. It is also crucial to assess whether the original and paraphrased outputs preserve similar semantics. The Sentence-BERT score (Reimers & Gurevych, 2019), presented in section 4.3 , measures the sentence-level similarity between the original watermarked text and the adversarial text. However, it falls short in determining whether the overall semantics are preserved. Inspired by the LLM jailbreak work PAIR (Chao et al., 2023), which leverages carefully crafted prompts and the powerful capabilities of ChatGPT to score attack texts and targets for quantitative evaluation, we adapted their prompts to use ChatGPT for assessing the semantic similarity between watermarked texts and attack texts . This approach allows us to obtain semantic similarity scores that more closely align with human perception. We show the judge prompt in appendix E and the result in shown in table 8.

We observed that using GPT for paraphrasing alone best preserves the original text's semantics, whereas methods like word deletion and synonym replacement were largely ineffective. Our ap-

Table 8: Semantic Preservation for Different Methods

	Word delete	**Synonym**	**GPT Paraphraser**	**DIPPER-1**	**DIPPER-2**	**SIRA**
Semantic Preservation	2.59	2.63	8.25	5.28	6.34	6.84

proach demonstrated superior semantic preservation compared to the DIPPER method. Additionally, we conducted experiments using LLaMA3-70B and found that, due to the model's enhanced capability to comprehend the "preserve information" instruction in the rewrite task, the semantic preservation score increased to 7.34. Furthermore, there was a 10%-20% reduction in perplexity, depending on the specific watermarking algorithm, and 10% higher attack success rate,when LLaMA3-70B was used as the base model.

F Self-information, Entropy and Probability

We provide a brief explanation of how watermark algorithm change the self-information. To begin, we introduce the definitions of self-information.

Self-Information ($I(x)$): This measures the amount of information or "surprise" associated with a specific token x. It quantifies how unexpected the occurrence of a token is in a given context:

$$I(x) = -\log_2 P(x)$$

When considering the context h, it becomes the conditional self-information:

$$I(x \mid h) = -\log_2 P(x \mid h)$$

where $P(x \mid h)$ is the probability of token x occurring given the preceding context h.

We first analyze the non-conditional scenario, assuming that watermarking slightly increases the probability of certain tokens by a small amount δ, while adjusting the probabilities of other tokens to maintain normalization. The δ change in token influcenced by watermark algorithm usually very small (e.g less than 1e-3).

The adjusted probability for the watermarked token x_w is:

$$P'(x_w) = P(x_w) + \delta$$

The adjusted probabilities for other tokens x_i ($i \neq w$) are:

$$P'(x_i) = P(x_i) - \epsilon_i$$

where $\sum_{i \neq w} \epsilon_i = \delta$.

The change in entropy due to these adjustments is given by:

$$\Delta H = H(P') - H(P) = -\sum_i \left[P'(x_i) \log P'(x_i) - P(x_i) \log P(x_i)\right]$$

The partial derivative of entropy with respect to $P(x_w)$ is:

$$\frac{\partial H}{\partial P(x_w)} = -\log P(x_w) - 1$$

The change in entropy due to a small change δ in $P(x_w)$ is approximately:

$$\Delta H \approx \frac{\partial H}{\partial P(x_w)} \delta = -(\log P(x_w) + 1)\delta$$

In high-entropy contexts, where $P(x_w)$ is small, $\log P(x_w)$ becomes a large negative value. Therefore, $\log P(x_w) + 1$ is still negative, and the product with the small δ results in a tiny ΔH(decrease in logarithmically). This attribute makes watermark algorithm need to embed pattern in high-entropy tokens, otherwise it will significantly compromising the quality of the output.

For self-information, the change in self-information is:

$$\Delta I(x_w) = -\log P'(x_w) + \log P(x_w)$$

The derivative of self-information with respect to $P(x_w)$ is:

$$\frac{dI(x_w)}{dP(x_w)} = -\frac{1}{P(x_w)}$$

For small $P(x_w)$, $\frac{1}{P(x_w)}$ is large, making $\Delta I(x_w)$ more significant for small δ compared to ΔH.

Similarly, for conditional self-information, assume that the model predicts N possible next tokens with equal probability, where:

$$P(x \mid \text{Context}) = \frac{1}{N}$$

For large N, $P(x \mid \text{Context})$ becomes small.

The adjusted probability for the watermarked token x_w is:

$$P'(x_w \mid \text{Context}) = \frac{1}{N} + \delta$$

The adjusted probabilities for other tokens x_i ($i \neq w$) are:

$$P'(x_i \mid \text{Context}) = \frac{1}{N} - \frac{\delta}{N-1}, \quad \text{for } x_i \neq x_w$$

The change in Conditional Self-Information is:

$$\Delta I(x_w \mid \text{Context}) = I'(x_w \mid \text{Context}) - I(x_w \mid \text{Context}) = -\log\left(\frac{1}{N} + \delta\right) + \log N$$

Using a Taylor series approximation for small δ:

$$\log\left(\frac{1}{N} + \delta\right) \approx \log\left(\frac{1}{N}\right) + N\delta$$

The approximate change in conditional self-information is:

$$\Delta I(x_w \mid \text{Context}) \approx -N\delta$$

Compared to the change in entropy, it is obvious self-information are more sensitive metric:

$$\Delta H \approx \frac{\partial H}{\partial P(x_w)}\delta = -(\log P(x_w) + 1)\delta$$

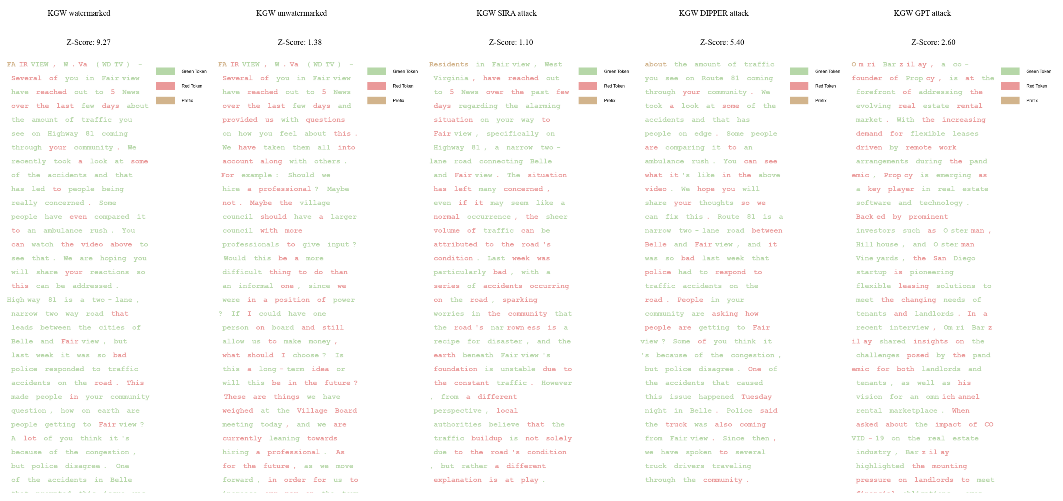
When $P(x \mid \text{Context})$ is small, the magnitude of the derivative is large, this indicates that small changes in $P(x \mid \text{Context})$ result in bigger changes in $I(x \mid \text{Context})$. As a result, the green token influenced by watermark change will have less self-information than original.

High-entropy tokens are usually associated with high self-information due to their unpredictability and low probability of occurrence. Considering the reduce self-information, these potential green tokens generally will exhibit high or moderate self-information values. Therefore in practice, we filter out all tokens with high or moderate self-information. This ensures us can comprehensive eliminate potential tokens. As demonstrated in our experiments in table 4, a threshold of 0.4 achieves an 88% attack success rate.

Another advantage of self-information is that it is **computed for each token within its specific context**, allowing it to naturally adapt to the varying nature of different sequence types. This provides a dynamic and context-sensitive measure that better aligns with the structure of natural sequences. In contrast, **entropy is context-agnostic, treating all token sequences equally when calculating average uncertainty**. By leveraging self-information, which adapts to each token's context, it becomes easier to identify sequences that deviate from expected contextual patterns — such as those that may be watermarked. We believe this is a key reason why filtering by self-information empirically outperforms filtering by entropy.

G VISUALIZATION

In this section, we present a visual comparison of our algorithm with other model-based paraphrasing methods, along with the corresponding z-scores after the attack. For discrete methods, green tokens are marked in green, and red tokens in red. In the watermarking algorithm, the detector identifies the embedded watermark through green tokens and calculates the z-score; fewer green tokens or a lower z-score indicate a more successful attack. For continuous methods, the shade of color denotes the weight of the watermarked token, with darker colors representing higher weights. In the case of attacked text, lighter colors indicate a more successful attack.



FA IR VIEW , W . Va (WD TV) - Several of you in Fair view have reached out to 5 News over the last few days about the amount of traffic you see on Highway 81 coming through your community . We recently took a look at some of the accidents and that has led to people being really concerned . Some people have even compared it to an ambulance rush . You can watch the video above to see that . We are hoping you will share your reactions so this can be addressed . High way 81 is a two - lane , narrow two way road that leads between the cities of Belle and Fair view , but last week it was so bad police responded to traffic accidents on the road . This made people in your community question , how on earth are people getting to Fair view ? A lot of you think it 's because of the congestion , but police disagree . One of the accidents in Belle

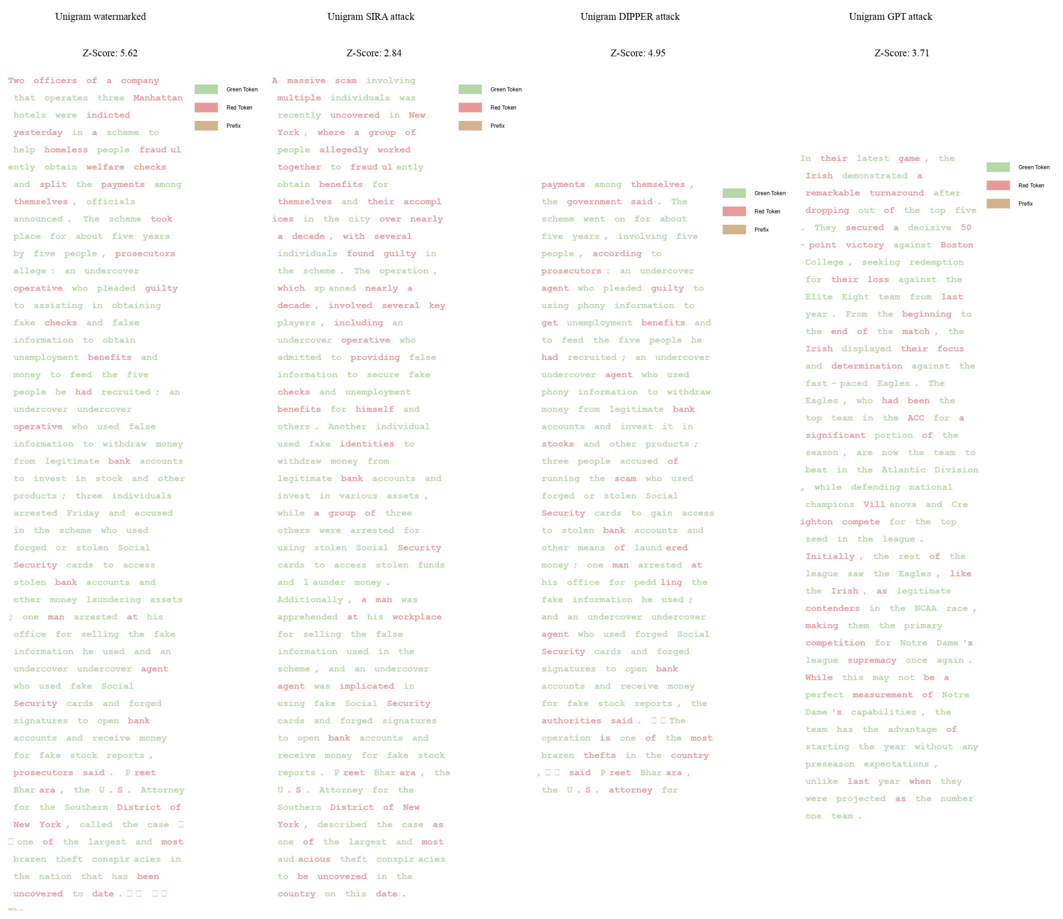
FA IR VIEW , W . Va (WD TV) - Several of you in Fair view have reached out to 5 News over the last few days and provided us with questions on how you feel about this . We have taken them all into account along with others . For example : Should we hire a professional ? Maybe not . Maybe the village council should have a larger council with more professionals to give input ? Would this be a more difficult thing to do than an informal one , since we were in a position of power ? If I could have one person on board and still allow us to make money , what should I choose ? Is this a long - term idea or will this be in the future ? These are things we have weighed at the Village Board meeting today , and we are currently leaning towards hiring a professional . As for the future , as we move forward , in order for us to

Residents in Fair view , West Virginia , have reached out to 5 News over the past few days regarding the alarming situation on your way to Fair view , specifically on Highway 81 , a narrow two - lane road connecting Belle and Fair view . The situation has left many concerned , even if it may seem like a normal occurrence , the sheer volume of traffic can be attributed to the road 's condition . Last week was particularly bad , with a series of accidents occurring on the road , sparking worries in the community that the road 's nar rown ess is a recipe for disaster , and the earth beneath Fair view 's foundation is unstable due to the constant traffic . However , from a different perspective , local authorities believe that the traffic buildup is not solely due to the road 's condition , but rather a different explanation is at play .

about the amount of traffic you see on Route 81 coming through your community . We took a look at some of the accidents and that has people on edge . Some people are comparing it to an ambulance rush . You can see what it 's like in the above video . We hope you will share your thoughts so we can fix this . Route 81 is a narrow two - lane road between Belle and Fair view , and it was so bad last week that police had to respond to traffic accidents on the road . People in your community are asking how people are getting to Fair view ? Some of you think it 's because of the congestion , but police disagree . One of the accidents that caused this issue happened Tuesday night in Belle . Police said the truck was also coming from Fair view . Since then , we have spoken to several truck drivers traveling through the community .

O m ri Bar z il ay , a co - founder of Prop cy , is at the forefront of addressing the evolving real estate rental market . With the increasing demand for flexible leases driven by remote work arrangements during the pand emic , Prop cy is emerging as a key player in real estate software and technology . Back ed by prominent investors such as O ster man , Hill house , and O ster man Vine yards , the San Diego startup is pioneering flexible leasing solutions to meet the changing needs of tenants and landlords . In a recent interview , Om ri Bar z il ay shared insights on the challenges posed by the pand emic for both landlords and tenants , as well as his vision for an omn ich annel rental marketplace . When asked about the impact of CO VID - 19 on the real estate industry , Bar z il ay highlighted the mounting pressure on landlords to meet

Figure 5: Comparison of different paraphrasing methods on KGW watermarks. Each word's color indicates whether it is a green or red token. **Fewer green words/lower z-scores** suggest a more effective paraphrasing approach. The unwatermarked text represents the model's output without the influence of the watermarking algorithm. The example demonstrates that our method achieves a better z-score than the unwatermarked text..



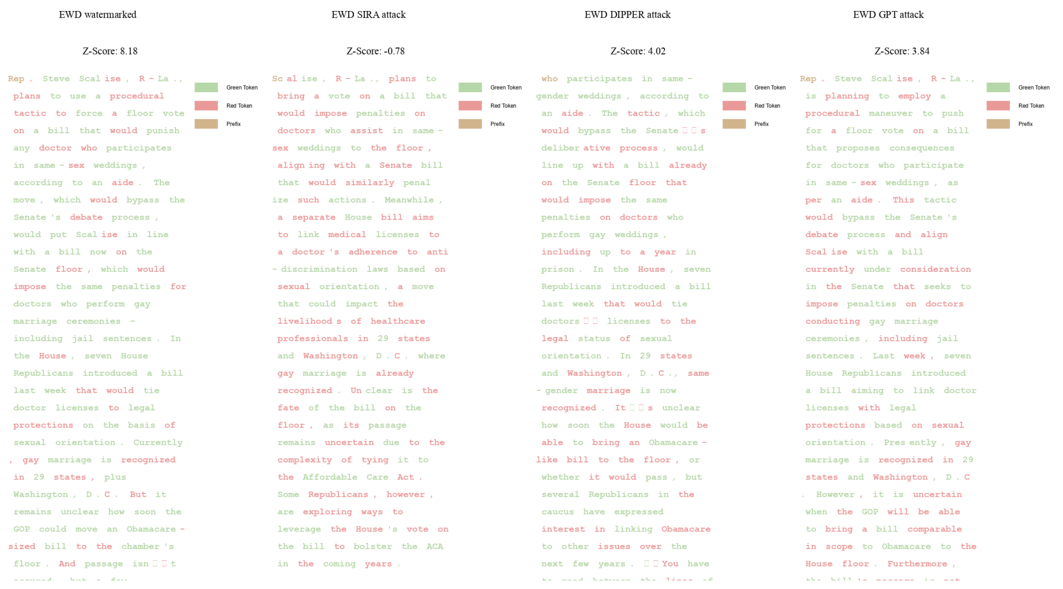
Two officers of a company that operates three Manhattan hotels were indicted yesterday in a scheme to help homeless people fraud ul ently obtain welfare checks and split the payments among themselves , officials announced . The scheme took place for about five years by five people , prosecutors allege : an undercover operative who pleaded guilty to assisting in obtaining fake checks and false information to obtain unemployment benefits and money to feed the five people he had recruited ; an undercover undercover operative who used false information to withdraw money from legitimate bank accounts to invest in stock and other products ; three individuals arrested Friday and accused in the scheme who used forged or stolen Social Security cards to access stolen bank accounts and other money laundering assets ; one man arrested at his office for selling the fake information he used and an undercover undercover agent who used fake Social Security cards and forged signatures to open bank accounts and receive money for fake stock reports , prosecutors said . P reet Bhar ara , the U . S . Attorney for the Southern District of New York , called the case one of the largest and most brazen theft conspir acies in the nation that has been uncovered to date .

A massive scam involving multiple individuals was recently uncovered in New York , where a group of people allegedly worked together to fraud ul ently obtain benefits for themselves and their accompl ices in the city over nearly a decade , with several individuals found guilty in the scheme . The operation , which sp anned nearly a decade , involved several key players , including an undercover operative who admitted to providing false information to secure fake checks and unemployment benefits for himself and others . Another individual used fake identities to withdraw money from legitimate bank accounts and invest in various assets , while a group of three others were arrested for using stolen Social Security cards to access stolen funds and l aunder money . Additionally , a man was apprehended at his workplace for selling the false information used in the scheme , and an undercover agent was implicated in using fake Social Security cards and forged signatures to open bank accounts and receive money for fake stock reports . P reet Bhar ara , the U . S . Attorney for the Southern District of New York , described the case as one of the largest and most aud acious theft conspir acies to be uncovered in the country on this date .

payments among themselves , the government said . The scheme went on for about five years , involving five people , according to prosecutors : an undercover agent who pleaded guilty to using phony information to get unemployment benefits and to feed the five people he had recruited ; an undercover undercover agent who used phony information to withdraw money from legitimate bank accounts and invest it in stocks and other products ; three people accused of running the scam who used forged or stolen Social Security cards to gain access to stolen bank accounts and other means of laund ered money ; one man arrested at his office for pedd ling the fake information he used ; and an undercover undercover agent who used forged Social Security cards and forged signatures to open bank accounts and receive money for fake stock reports , the authorities said . The operation is one of the most brazen thefts in the country , said P reet Bhar ara , the U . S . attorney for

In their latest game , the Irish demonstrated a remarkable turnaround after dropping out of the top five . They secured a decisive 50 - point victory against Boston College , seeking redemption for their loss against the Elite Eight team from last year . From the beginning to the end of the match , the Irish displayed their focus and determination against the fast - paced Eagles . The Eagles , who had been the top team in the ACC for a significant portion of the season , are now the team to beat in the Atlantic Division , while defending national champions Vill anova and Cre ighton compete for the top seed in the league . Initially , the rest of the league saw the Eagles , like the Irish , as legitimate contenders in the NCAA race , making them the primary competition for Notre Dame 's league supremacy once again . While this may not be a perfect measurement of Notre Dame 's capabilities , the team has the advantage of starting the year without any preseason expectations , unlike last year when they were projected as the number one team .

Figure 6: Comparison of different paraphrasing methods on Unigram watermarks.


🟩 Green Token
🟥 Red Token
▨ Prefix

EWD watermarked

Z-Score: 8.18

Rep . Steve Scal ise , R - La ., plans to use a procedural tactic to force a floor vote on a bill that would punish any doctor who participates in same - sex weddings , according to an aide . The move , which would bypass the Senate 's debate process , would put Scal ise in line with a bill now on the Senate floor , which would impose the same penalties for doctors who perform gay marriage ceremonies – including jail sentences . In the House , seven House Republicans introduced a bill last week that would tie doctor licenses to legal protections on the basis of sexual orientation . Currently , gay marriage is recognized in 29 states , plus Washington , D . C . But it remains unclear how soon the GOP could move an Obamacare - sized bill to the chamber 's floor . And passage isn □ □ t

EWD SIRA attack

Z-Score: -0.78

Sc al ise , R - La ., plans to bring a vote on a bill that would impose penalties on doctors who assist in same - sex weddings to the floor , align ing with a Senate bill that would similarly penal ize such actions . Meanwhile , a separate House bill aims to link medical licenses to a doctor 's adherence to anti - discrimination laws based on sexual orientation , a move that could impact the livelihood s of healthcare professionals in 29 states and Washington , D . C . where gay marriage is already recognized . Un clear is the fate of the bill on the floor , as its passage remains uncertain due to the complexity of tying it to the Affordable Care Act . Some Republicans , however , are exploring ways to leverage the House 's vote on the bill to bolster the ACA in the coming years .

EWD DIPPER attack

Z-Score: 4.02

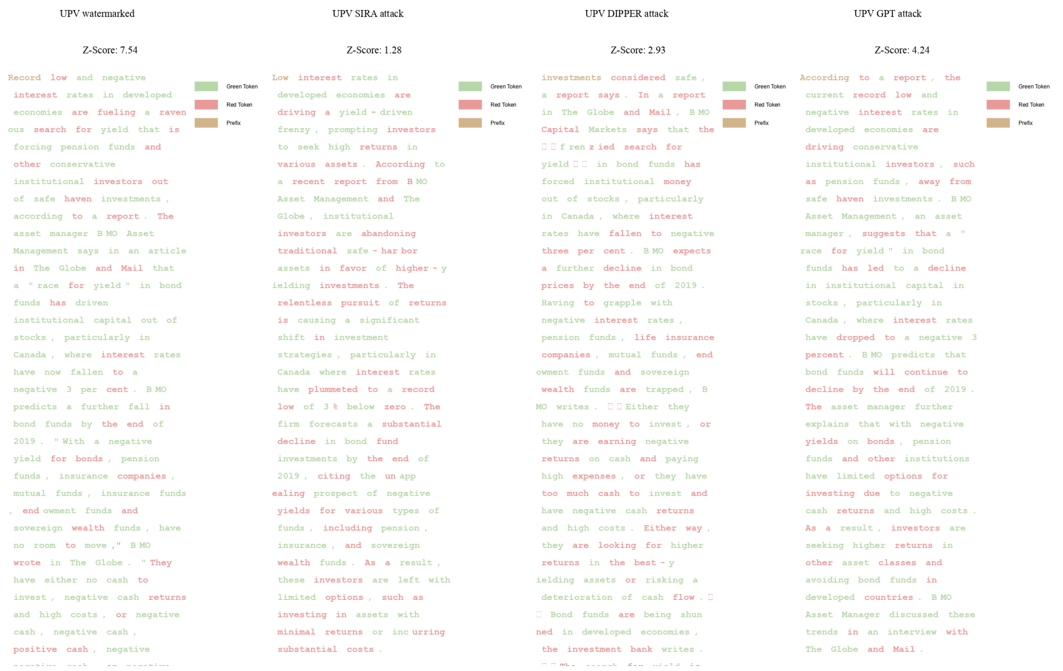
who participates in same - gender weddings , according to an aide . The tactic , which would bypass the Senate □ □ s deliber ative process , would line up with a bill already on the Senate floor that would impose the same penalties on doctors who perform gay weddings , including up to a year in prison . In the House , seven Republicans introduced a bill last week that would tie doctors □ □ licenses to the legal status of sexual orientation . In 29 states and Washington , D . C ., same - gender marriage is now recognized . It □ □ s unclear how soon the House would be able to bring an Obamacare - like bill to the floor , or whether it would pass , but several Republicans in the caucus have expressed interest in linking Obamacare to other issues over the next few years . □ □ You have

EWD GPT attack

Z-Score: 3.84

Rep . Steve Scal ise , R - La ., is planning to employ a procedural maneuver to push for a floor vote on a bill that proposes consequences for doctors who participate in same - sex weddings , as per an aide . This tactic would bypass the Senate 's debate process and align Scal ise with a bill currently under consideration in the Senate that seeks to impose penalties on doctors conducting gay marriage ceremonies , including jail sentences . Last week , seven House Republicans introduced a bill aiming to link doctor licenses with legal protections based on sexual orientation . Pres ently , gay marriage is recognized in 29 states and Washington , D . C . However , it is uncertain when the GOP will be able to bring a bill comparable in scope to Obamacare to the House floor . Furthermore ,

Figure 7: Comparison of different paraphrasing methods on EWD watermarks.


🟩 Green Token
🟥 Red Token
▨ Prefix

UPV watermarked

Z-Score: 7.54

Record low and negative interest rates in developed economies are fueling a raven ous search for yield that is forcing pension funds and other conservative institutional investors out of safe haven investments , according to a report . The asset manager B MO Asset Management says in an article in The Globe and Mail that a " race for yield " in bond funds has driven institutional capital out of stocks , particularly in Canada , where interest rates have now fallen to a negative 3 per cent . B MO predicts a further fall in bond funds by the end of 2019 . " With a negative yield for bonds , pension funds , insurance companies , mutual funds , insurance funds , end owment funds and sovereign wealth funds , have no room to move ," B MO wrote in The Globe . " They have either no cash to invest , negative cash returns and high costs , or negative cash , negative cash , positive cash , negative

UPV SIRA attack

Z-Score: 1.28

Low interest rates in developed economies are driving a yield - driven frenzy , prompting investors to seek high returns in various assets . According to a recent report from B MO Asset Management and The Globe , institutional investors are abandoning traditional safe - har bor assets in favor of higher - y ielding investments . The relentless pursuit of returns is causing a significant shift in investment strategies , particularly in Canada where interest rates have plummeted to a record low of 3 % below zero . The firm forecasts a substantial decline in bond fund investments by the end of 2019 , citing the un app ealing prospect of negative yields for various types of funds , including pension , insurance , and sovereign wealth funds . As a result , these investors are left with limited options , such as investing in assets with minimal returns or inc urring substantial costs .

UPV DIPPER attack

Z-Score: 2.93

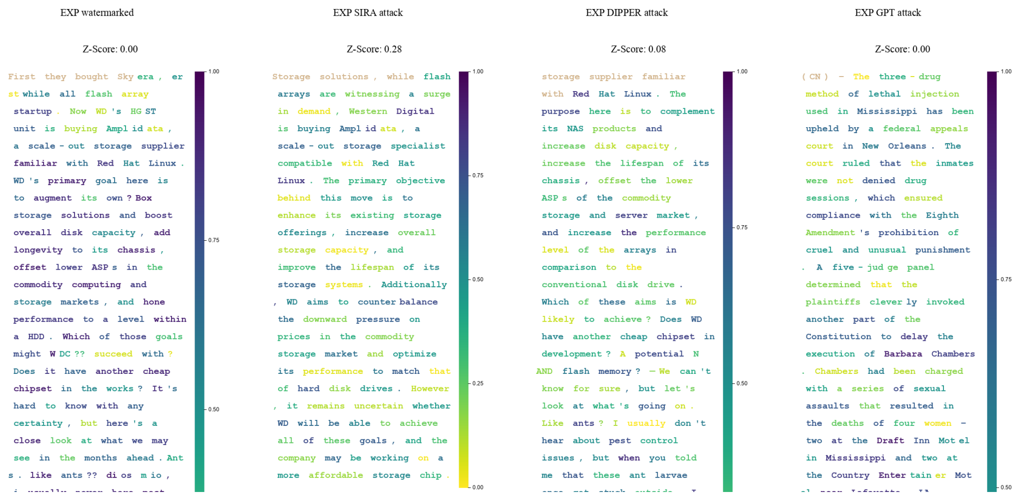
investments considered safe , a report says . In a report in The Globe and Mail , B MO Capital Markets says that the □ □ f ren z ied search for yield □ □ in bond funds has forced institutional money out of stocks , particularly in Canada , where interest rates have fallen to negative three per cent . B MO expects a further decline in bond prices by the end of 2019 . Having to grapple with negative interest rates , pension funds , life insurance companies , mutual funds , end owment funds and sovereign wealth funds are trapped , B MO writes . □ □ Either they have no money to invest , or they are earning negative returns on cash and paying high expenses , or they have too much cash to invest and have negative cash returns and high costs . Either way , they are looking for higher returns in the best - y ielding assets or risking a deterioration of cash flow . □ □ Bond funds are being shun ned in developed economies , the investment bank writes .

UPV GPT attack

Z-Score: 4.24

According to a report , the current record low and negative interest rates in developed economies are driving conservative institutional investors , such as pension funds , away from safe haven investments . B MO Asset Management , an asset manager , suggests that a " race for yield " in bond funds has led to a decline in institutional capital in stocks , particularly in Canada , where interest rates have dropped to a negative 3 percent . B MO predicts that bond funds will continue to decline by the end of 2019 . The asset manager further explains that with negative yields on bonds , pension funds and other institutions have limited options for investing due to negative cash returns and high costs . As a result , investors are seeking higher returns in other asset classes and avoiding bond funds in developed countries . B MO Asset Manager discussed these trends in an interview with The Globe and Mail .

Figure 8: Comparison of different paraphrasing methods on UPV watermarks. The color of each word indicates whether it belongs to a green token or a red token. **Less green** signifies a more effective paraphrasing approach. Our methods show better performance in removing original watermark text green token.



EXP watermarked

Z-Score: 0.00

First they bought Sky era , er st while all flash array startup . Now WD 's HG ST unit is buying Ampl id ata , a scale - out storage supplier familiar with Red Hat Linux . WD 's primary goal here is to augment its own ? Box storage solutions and boost overall disk capacity , add longevity to its chassis , offset lower ASP s in the commodity computing and storage markets , and hone performance to a level within a HDD . Which of those goals might W DC ?? succeed with ? Does it have another cheap chipset in the works ? It 's hard to know with any certainty , but here 's a close look at what we may see in the months ahead . Ant s . like ants ?? di os m io ,

EXP SIRA attack

Z-Score: 0.28

Storage solutions , while flash arrays are witnessing a surge in demand , Western Digital is buying Ampl id ata , a scale - out storage specialist compatible with Red Hat Linux . The primary objective behind this move is to enhance its existing storage offerings , increase overall storage capacity , and improve the lifespan of its storage systems . Additionally , WD aims to counter balance the downward pressure on prices in the commodity storage market and optimize its performance to match that of hard disk drives . However , it remains uncertain whether WD will be able to achieve all of these goals , and the company may be working on a more affordable storage chip .

EXP DIPPER attack

Z-Score: 0.08

storage supplier familiar with Red Hat Linux . The purpose here is to complement its NAS products and increase disk capacity , increase the lifespan of its chassis , offset the lower ASP s of the commodity storage and server market , and increase the performance level of the arrays in comparison to the conventional disk drive . Which of these aims is WD likely to achieve ? Does WD have another cheap chipset in development ? A potential N AND flash memory ? — We can 't know for sure , but let 's look at what 's going on . Like ants ? I usually don 't hear about pest control issues , but when you told me that these ant larvae

EXP GPT attack

Z-Score: 0.00

(CN) – The three - drug method of lethal injection used in Mississippi has been upheld by a federal appeals court in New Orleans . The court ruled that the inmates were not denied drug sessions , which ensured compliance with the Eighth Amendment 's prohibition of cruel and unusual punishment . A five - jud ge panel determined that the plaintiffs clever ly invoked another part of the Constitution to delay the execution of Barbara Chambers . Chambers had been charged with a series of sexual assaults that resulted in the deaths of four women – two at the Draft Inn Mot el in Mississippi and two at the Country Enter tain er Mot

Figure 9: Comparison of different paraphrasing methods on EXP watermarks. The color of each word indicates whether it is a green or red token. For EXP, **lighter word colors and higher z-scores indicate a more effective attack**.

H EXTENDED DISCUSSION IN RELATED WORKS

In this section, we discuss the watermark-stealing attack (Jovanović et al., 2024; Wu & Chandrasekaran, 2024; Zhang et al., 2024), which is related to our work but operates under different assumptions. We give a brief introduction to this kind of attack and analyze its advantages and disadvantages compared to our methods.

In a typical watermark-stealing attack, an adversary interacts with a watermarked LLM model through its API or queries, attempting to reverse-engineer or approximate the embedded watermark. Through repeated queries, attackers may identify patterns in token choices or subtle markers in output text that are indicative of a watermark. Two main attack methods emerge from this process:

- Spoofing Attacks: Here, attackers use the approximated watermark pattern to make non-AI-generated text appear as though it was produced by the LLM, thereby deceiving detection systems.
- Scrubbing Attacks: These attacks aim to remove the watermark from AI-generated text. By understanding how the watermark is embedded, attackers substitute or adjust specific tokens or structures to evade detection, making AI-generated content appear as if it is human-authored.

For watermark-stealing attacks, these works assume that the attacker has:

1. Unlimited access to the watermark-generated model API, through which the attacker can issue input prompts and observe the generated responses.
2. Access to the detector API (with or without different assumptions).
3. Knowledge of the context size.
4. An aligned watermarked model that can follow provided instructions.

In a black-box paraphrasing attack, we assume that the attacker's knowledge is limited to only the watermarked text and nothing else. Because this assumption is much weaker than that of a watermark-stealing attack, we do not include such methods in our main comparisons.

Compared to the paraphrasing attack, these methods have the following advantages:

1. Minimal Semantic Drift: By focusing on substituting only the watermarked tokens, such methods tend to retain the original semantic structure of the text more effectively than black-box rewriting, which can sometimes introduce unintended semantic changes.

2. Fine-Grained Control: Watermark-stealing attacks operate at a token level, allowing precise control over watermark removal without needing to rephrase entire sentences or sections, which may be challenging in highly sensitive content.
3. Better piror knowledge: Since such attacks assume the attacker has unlimited access to the watermarked model, they can continuously probe the watermark pattern through specific input queries, thereby gaining stronger prior knowledge.

These methods also have disadvantages:

1. Possible Efficiency Issue: As mentioned in SCTS (Wu & Chandrasekaran, 2024), repeated probing introduces additional time overhead, resulting in higher resource consumption compared to paraphrasing methods.
2. Limited Scope of Application: Black-box rewrite attacks do not require knowledge of the watermarking mechanism, making them suitable for use against a wide variety of watermarking techniques.
3. Possible lower robustness: Because black-box rewrite attacks focus on altering the content through paraphrasing, they can reduce the chance of detection by watermarking systems that rely on token-level patterns.

Notably, we need to mention SCTS (Wu & Chandrasekaran, 2024). This method also involves modifying color tokens, but it is entirely different from our proposed approach. In SCTS, The attacker prompts the watermarked LLM multiple times with various inputs, collecting a significant amount of output data to capture the frequency distribution of tokens. By examining this collection of outputs, the attacker can calculate the frequency of each token appearing in the generated text. Watermarked LLMs favor certain tokens, so these ”green” tokens appear more frequently than others due to the watermarking bias.The attacker observes these frequencies for anomalies or patterns that deviate from what would be expected in unwatermarked text. Tokens that consistently appear at higher frequencies or in specific contexts are likely candidates for ”green” tokens.

Therefore, this method identifies green tokens using a frequency-based approach and has two main limitations. First, it shares a common limitation of such methods, requiring access to the LLM API and permission to adjust its parameters. Second, it is only applicable to biased watermarking methods, such as UMD and its variants.

In contrast, the key insight of our method is that current watermarking techniques require embedding on high-entropy or uniformly distributed tokens to maintain text quality, as explained in Section F. By leveraging self-information, we can exploit this characteristic to identify potential green tokens and rewrite them accordingly. Our method offers greater flexibility as it does not require access to the watermarking model and not limited to biased watermark algorithm.