Optimizing Multi-bit LLM Watermark Detectability under Controlled Text Quality Degradation

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Abstract

Watermarking has emerged as an important mechanism for tracing the provenance of large language model (LLM) outputs. Multi-bit watermarks are particularly desirable because they can encode rich metadata, but embedding a more reliable watermark generally requires stronger modifications to the model's next-token distribution, potentially degrading text quality. This is a fundamental trade-off between distributional distortion and watermark detectability. Usually, a tolerable distortion is often treated as a constraint in practical deployment; a central question arises: *under a constrained level of distributional modification, how can detectability be optimized?* Existing multi-bit watermarking methods do not explicitly formulate watermark embedding under such a distributional constraint, nor do they provide a principled mechanism for optimizing detectability. A key challenge is that common detectability metrics, such as bit accuracy (BA), only become available after generation and decoding, so they cannot be optimized directly during token generation. We thus introduce a computable *detectability proxy* that is directionally aligned with BA and can be evaluated at each generation step. However, directly maximizing this proxy is computationally prohibitive under the hash-based designs commonly used in watermarking. We instead derive a tractable lower bound on the proxy and propose **BoundMark** to maximize this lower bound under a constrained distributional shift. Empirical evaluations on two LLMs and four tasks show that BoundMark achieves performance competitive with state-of-the-art multi-bit watermarks. The code is available at https://github.com/Leileileisa/Multibit_BoundMark.

1 Introduction

Large language models (LLMs) can generate high-quality, human-like text, making them powerful engines for a wide range of applications. However, these capabilities also introduce substantial risks: LLM outputs can be misused to infringe proprietary intellectual property, circumvent usage policies, or facilitate the large-scale generation of convincing misinformation Liu et al. [2024]. For example, prominent providers such as OpenAI, Anthropic, and Google Gemini explicitly prohibit the use of their outputs to train competing models Houman [2025], Google [2025], Anthropic [2024]. Yet, proving such violations is difficult when generated text cannot be reliably traced to its source. As regulatory bodies increasingly call for mechanisms that support content provenance and accountability Union [2024], reliable LLM watermarking has become an important research problem.

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A major line of work studies zero-bit watermarking, which embeds an invisible statistical signal into generated text and subsequently tests whether the signal is present Kirchenbauer et al. [2024], Park et al. [2026], Lee et al. [2024], Lu et al. [2024]. While such methods can determine whether a piece of text is likely watermarked, their binary nature limits the amount of information that can be conveyed. In many provenance applications, it is desirable to encode richer metadata, such as a user identifier, model identifier, or generation context. This has motivated increasing interest in multi-bit watermarking Yoo et al. [2024], Fernandez et al. [2023], Qu et al. [2025], Li et al. [2024], Jiang et al. [2025], which embeds a recoverable message directly during generation.

Most existing multi-bit watermarking methods encode information by modifying the model's next-token distribution Yoo et al. [2024], Xu et al. [2026]. Stronger modifications generally make the embedded message more reliably recoverable, but also move the watermarked distribution further away from the model's original distribution, potentially degrading text quality. Multi-bit watermarking therefore faces a fundamental trade-off between *watermark detectability* and *distributional distortion*.

In practice, a tolerable distortion is usually treated as a constraint for a watermarking approach: given a prescribed budget on how much the original next-token distribution may be modified, an effective watermarking mechanism should successfully recognize the existence of embedded watermarks. The goal to design the most effective watermarking mechanism motivates the following question:

> *Under a constrained level of distributional modification, how can the detectability of a multi-bit watermark be optimzied?*

To the best of our knowledge, this problem has been rarely studied for multi-bit watermarking methodsYoo et al. [2024], Xu et al. [2026], Jovanović et al. [2024], Li et al. [2024]; either they fail to rigorously respect such constraints, or they have not attempted to optimize the detectability.

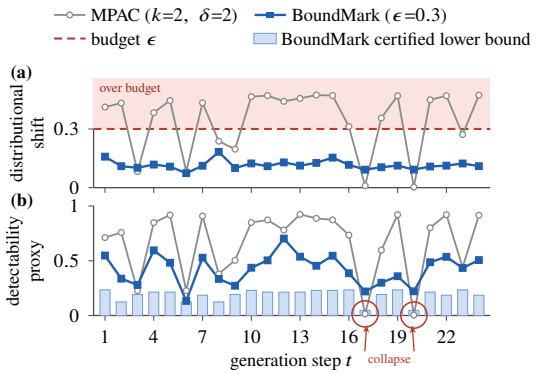


Figure 1: Per-step distributional shift and detectability proxy of MPAC Yoo et al. [2024] and BoundMark (Ours). (a) MPAC (k=2, δ=2), a logit-based multi-bit watermark, exceeds the distributional-shift budget ϵ on most steps, since nothing in its design constrains the shift, while BoundMark always stays within it. (b) MPAC's detectability proxy collapses on low-entropy steps (circled), whereas BoundMark always respects its certified lower bound.

A central issue is therefore how to quantify and constrain the distortion introduced by watermarking. Prior methods like Yoo et al. [2024], Xu et al. [2026] commonly use a watermark-strength parameter such as the logit bias δ. However, δ controls how strongly the logits of original distribution are perturbed rather than how much the distribution actually changes. For the same value of δ, the induced distributional shift can vary substantially across generation steps depending on the shape of the original next-token distribution. Consequently, constraining δ alone does not provide a consistent bound on the actual distortion introduced by watermarking. We instead quantify distributional modification using the Kullback–Leibler (KL) divergence between the original distribution p_t and the watermarked distribution q_t. By directly measuring the change induced in the next-token distribution, KL divergence allows us to impose a consistent per-step distortion budget ϵ. On this basis, we demonstrate how the distributional shift becomes more controllable with the KL-based distortion budget ($\epsilon = 0.3$) in Figure 1(a).

A second challenge in solving this constrained optimization problem is that common detectability metrics, such as bit accuracy (BA), only become accessible after the generated sequence is decoded, meaning that they are unavailable as direct optimization objectives during token generation. To bridge this gap, we introduce a computable *detectability proxy* D_t at generation step t. D_t can be evaluated at each generation step and is directionally aligned with the final BA achieved by message decoding (proofs provided in Appendix D).

Further, directly maximizing this proxy is computationally prohibitive under the hash-based mechanisms commonly adopted in multi-bit watermarking. We instead derive a tractable lower bound on the

detectability proxy and offer a way to maximize this lower bound under a prescribed distributional-shift constraint, which we call **BoundMark**. A comparison of the detection performance between the BoundMark method and MPAC Yoo et al. [2024], is depicted in Figure 1(b). Additionally, we provide the performance lower bound certified by BoundMark, which shows that MPAC does not always adhere to this lower bound and fails during certain steps.

Our main contributions are as follows:

- We formulate multi-bit LLM watermarking as a per-step constrained optimization problem that seeks to maximize watermark detectability under an explicit distributional-shift budget, providing a principled formulation of the detectability–distortion trade-off.
- We introduce a computable per-step detectability proxy that is directionally aligned with BA, and show that its direct maximization is computationally prohibitive under commonly used hash-based watermarking mechanisms. We therefore derive a tractable lower bound that can be optimized during generation.
- We derive a KL-minimal probability-bias allocation for a given total probability shift and obtain a closed-form bound on the allowable shift under a prescribed KL budget. This provides an explicit per-step guarantee on distributional distortion and enables a formal lower bound on the detectability proxy.
- We develop BoundMark, and evaluate it against seven multi-bit watermarking baselines on two LLMs and four tasks. BoundMark achieves performance competitive with state-of-the-art multi-bit watermarks while additionally providing explicit guarantees on both distributional shift and the detectability proxy.

2 Preliminaries

In this section, we formalize the standard auto-regressive text generation process and define the foundational components of multi-bit Large Language Model (LLM) watermarking, which has been adopted in a series of related worksYoo et al. [2024], Jiang et al. [2025], Xu et al. [2026], Qu et al. [2025], including the message routing mechanism, vocabulary partitioning, and detection pipeline.

2.1 LLM Token Generation

Given a vocabulary $\mathcal{V}$ of size $N = |\mathcal{V}|$, an auto-regressive language model generates text by predicting the next token based on a given context. Let $x_{<t} = (x_1, x_2, \ldots, x_{t-1})$ denote the sequence of previously generated tokens. At generation step t, the LLM computes a logit vector $\mathbf{z}^{(t)} \in \mathbb{R}^N$.

The logits are passed through a softmax function to obtain the natural probability distribution over the vocabulary, denoted as $\mathbf{p}^{(t)} \in \Delta^{N-1}$:

$$p_i^{(t)} = \frac{\exp(z_i^{(t)}/\tau)}{\sum_{j=1}^{N} \exp(z_j^{(t)}/\tau)}, \quad \forall i \in \mathcal{V} \tag{1}$$

where $\tau > 0$ is the temperature parameter. The next token x_t is then sampled from this distribution: $x_t \sim \mathbf{p}^{(t)}$.

2.2 Watermarked Text Generation

The objective of a multi-bit watermark is to embed a global m-bit secret message $M \in \{0,1\}^m$ into the generated text without significantly degrading text quality. To achieve this, the global message M is dynamically routed into a sequence of local k-bit payloads, where k represents the number of bits embedded at a specific generation step t.

Let $w_t \in \{0, 1, \ldots, 2^k - 1\}$ denote the target payload value to be embedded at step t. This payload is determined by a cryptographic hash function H_{msg} that takes the secret key K, the context history $x_{<t}$ (often a fixed-size window of previous tokens), and the global message M as inputs:

$$w_t = H_{\text{msg}}(K, x_{<t}, M) \pmod{2^k} \tag{2}$$

Concurrently, a second pseudo-random function H_{seed} is generated to partition the vocabulary $\mathcal{V}$ into 2^k disjoint sub-token sets, denoted as $V_0, V_1, \ldots, V_{2^k-1}$. The *chosen sub-token set* (or Green Set) corresponding to the desired payload w_t is defined as:

$$S_G^{(t)} = V_{w_t} \tag{3}$$

All other tokens form the Red Set, $S_R^{(t)} = \mathcal{V} \setminus S_G^{(t)}$. Let P_G denote the natural probability mass of the green set. It is defined using an indicator function $\mathbb{I}[\cdot]$ as:

$$P_G^{(t)} = \sum_{i \in \mathcal{V}_{w_t}} p_i^{(t)} \tag{4}$$

To embed the payload w_t, the watermark introduces a probability shift $\boldsymbol{\delta}^{(t)} \in \mathbb{R}^N$ to the original distribution, yielding the watermarked distribution $\mathbf{q}^{(t)}$:

$$q_i^{(t)} = p_i^{(t)} + \delta_i^{(t)} \tag{5}$$

To ensure $\mathbf{q}^{(t)}$ remains a valid probability distribution, the shifts must satisfy $\sum_{i \in \mathcal{V}} \delta_i^{(t)} = 0$ and $q_i^{(t)} \geq 0$. Typically, positive shifts ($\delta_i^{(t)} > 0$) are applied to tokens $i \in S_G^{(t)}$, effectively shifting a total probability mass Δ from the red Set into the green Set. Formally, this total shift is defined as the sum of the positive perturbations:

$$\Delta = \sum_{i \in S_G^{(t)}} \delta_i^{(t)} \tag{6}$$

This reallocation of probability mass increases the likelihood that the sampled token x_t will carry the desired payload w_t.

2.3 Watermark Detection and Extraction

Given a generated text sequence $X = (x_1, \ldots, x_T)$ and the secret key K, the detection process seeks to extract the embedded m-bit global message M.

For each step t, the detector reconstructs the context $x_{<t}$ and uses the secret key K to re-solve the maximin payload optimization, yielding the dynamic payload k_t. Steps with $k_t = 0$ carry no payload and are excluded from decoding. It then recomputes the 2^{k_t} vocabulary partitions $V_0, \ldots, V_{2^{k_t}-1}$ via the pseudo-random permutation. By observing which partition the actual generated token x_t falls into, the detector extracts the localized payload:

$$\hat{w}_t = j \quad \text{such that} \quad x_t \in V_j \tag{7}$$

Then the detector maps this localized payload back to a local candidate for the global message, denoted as $\hat{m}_t = \hat{w}_t$. The final extracted m-bit message $\hat{M}$ is reconstructed by performing a bit-wise majority vote across all valid local message candidates (i.e., from steps with $k_t > 0$) extracted from the sequence:

$$\hat{M}[i] = \text{Mode}\Big(\hat{m}_1[i], \hat{m}_2[i], \ldots, \hat{m}_T[i]\Big) \quad \text{for } i \in \{1, \ldots, m\} \tag{8}$$

Following prior multi-bit watermarking works, bit accuracy is measured as the fraction of message bits correctly recovered from the extracted message $\hat{M}$:

$$\text{BA}(M, \hat{M}) = \frac{1}{m} \sum_{i=1}^{m} \mathbb{I}\Big[\hat{M}[i] = M[i]\Big], \tag{9}$$

3 Methodology

In this section, we construct our theoretical framework for multi-bit watermarking. We first define the formulations in Section 3.1, and introduce our algorithm in Section 3.2.

3.1 Formulation

3.1.1 Distributional Distortion

Definition 1 (Distributional Distortion). *At any generation step, let* $\mathbf{p}$ *denote the original next-token probability distribution produced by the LLM over a vocabulary* V*, where* p_x *is the probability of a token* x*. To embed a multi-bit watermark, a token-specific probability bias* δ_x *is applied to create a manipulated distribution* $\mathbf{q}$*, such that* $q_x = p_x + \delta_x$*. We define the local distributional distortion introduced by this probability shift as the Kullback-Leibler (KL) divergence from the original distribution* $\mathbf{p}$ *to the watermarked distribution* $\mathbf{q}$*:*

$$D_{\mathrm{KL}}(\mathbf{q} \parallel \mathbf{p}) = D_{\mathrm{KL}}(\mathbf{p} + \Delta \parallel \mathbf{p}) = \sum_{x \in V} (p_x + \delta_x) \ln \left(1 + \frac{\delta_x}{p_x}\right). \tag{10}$$

3.1.2 Multi-bit LLM Watermark Detectability Proxy

Although BA is intuitive for quantifying detectability, it cannot be computed during watermark embedding and therefore cannot be directly optimized. Therefore, we introduce the *Detectability Proxy*, a computable surrogate for watermark detectability.

Definition 2 (Detectability Proxy). *At any generation step* t*, let* $k \geq 0$ *denote the payload. We define the detectability proxy* D *of the embedded watermark signal as:*

$$D = k \cdot \Delta \tag{11}$$

Intuitively, an unwatermarked token carries no information about the message, while the shifted mass Δ is the extra probability with which the sampled token falls into the green set and thus signals its k payload bits. The product $k \cdot \Delta$ is therefore a simple per-step proxy for the amount of message information injected. In Appendix D, we show via a normal approximation of majority-vote decoding that, for a fixed sequence length and message length, the expected BA increases monotonically in both k and Δ, so increasing D is directionally consistent with improving BA.

3.1.3 Multi-bit LLM Watermark as a Constrained Optimization Problem

Definition 3 (Multi-Bit LLM Watermarking via Constrained Optimization). *We formally define the multi-bit watermarking process as a per-step constrained optimization problem. At any generation step with preceding context and a distortion budget* $\epsilon > 0$*, the framework seeks to maximize the detectability proxy* D*, subject to an explicit upper bound on the local distributional distortion and to the requirement that the watermarked distribution remains a valid probability distribution. Formally, the watermarking policy is the solution to:*

$$\max_{k \geq 0,\, \Delta \geq 0} \; k \cdot \Delta \quad \text{s.t.} \quad D_{\mathrm{KL}}(\mathbf{q} \parallel \mathbf{p}) \leq \epsilon, \quad \delta_i \geq 0 \;\; \forall i \in S_G. \tag{12}$$

3.2 BoundMark

Since k determines the green-token set S_G, the feasible range of Δ depends on both k and the distortion budget ϵ. Therefore, the constrained optimization problem in (12) is a nested optimization problem, we therefore decomposes the joint optimization over k and Δ into two levels. We first solve the inner optimization problem of determining the largest feasible Δ for any given k, and then solve the outer optimization problem of selecting k to maximize the detectability proxy.

Specifically, First, in Section 3.2.1, we investigate when Δ and k is given, how to allocate δ_i to achieve minimal D_{KL}. Moreover, the constraint about δ_i in (12) could be satisfied simultaneously. Based on this, in Section 3.2.2, we derive the maximal Δ that satisfies the $D_{KL} \leq \epsilon$ constraint when k is given. At last, in Section 3.2.3, we first explain why directly maximize $k \cdot \Delta$ is computationally intractable, and how we instead maximizing the lower bound of D.

3.2.1 Distortion-Minimal Bias Allocation

In prior multi-bit watermarking studies, the individual token bias is typically applied uniformly across the green setYoo et al. [2024], Xu et al. [2026]. However, uniform allocation is not optimal with

respect to the induced distributional shift. Instead, for any given total probability shift Δ, there exists a bias allocation that minimizes the KL divergence.

Theorem 1 *Given k and green token set S_G and a fixed valid probability shift Δ, the local distributional distortion $D_{\mathrm{KL}}(\mathbf{q} \parallel \mathbf{p})$ is strictly minimized if and only if the individual token bias $\delta_i = q_i - p_i$ is assigned proportionally to the original token probability p_i. Formally, the optimal closed-form solution for the token-level bias is:*

$$\delta_i = \begin{cases} p_i \left(\frac{\Delta}{P_G} \right), & \text{if } i \in S_G \\ -p_i \left(\frac{\Delta}{1-P_G} \right), & \text{if } i \in S_R \end{cases} \tag{13}$$

where $P_G = \sum_{j \in S_G} p_j$ represents the natural probability mass of the green subset, and S_R represents the red subset.

The formal proof of this optimization, solved via Lagrange multipliers, is detailed in Appendix B.

3.2.2 Maximal Probability Shift

With the optimal bias allocation established, we now determine the maximum allowable probability shift Δ that satisfies the distortion budget $\epsilon > 0$.

Theorem 2 (Maximal Probability Shift). *Given a distortion budget ϵ and a target vocabulary partition with a natural probability mass $P_G \in (0, 1)$, the proportional allocation of Theorem 1 with total shift Δ yields a valid distribution satisfying the local distortion constraint $D_{\mathrm{KL}}(\mathbf{q} \parallel \mathbf{p}) \leq \epsilon$ whenever*

$$0 \leq \Delta \leq \Delta_{\max} := \min \left\{ \sqrt{\epsilon P_G (1 - P_G)},\ 1 - P_G \right\}. \tag{14}$$

For simplicity, we denote $\min \left\{ \sqrt{\epsilon P_G (1 - P_G)},\ 1 - P_G \right\}$ as $g(P_G)$. The first term enforces the KL budget and the second enforces non-negativity of the red-set probabilities. The formal proof is detailed in Appendix C.

3.2.3 Optimization of Detectability Proxy

With the distributional distortion bounded by Theorem 2, we can now solve the objective of our constrained optimization problem (Definition 3): maximizing the detectability proxy.

By substituting the maximal admissible shift $\Delta_{\max}$ (Eq. (14)) into the detectability proxy $D = k \cdot \Delta$, the maximum detectability for a given payload k becomes:

$$D = k \cdot g(P_G) \tag{15}$$

Formally, we aim to solve:

$$\max_{k \geq 0} \Big(k \cdot g(P_G) \Big) \tag{16}$$

However, solving Eq. (16) directly during auto-regressive generation is computationally prohibitive. For any given payload k, P_G is determined by a pseudo-random hash assignment distributed over the entire vocabulary of size $|V|$. Evaluating the exact P_G to find the optimal k requires computing hash values and summing probabilities for the entire vocabulary at every single generation step. This heavy computational overhead introduces unacceptable inference latency, rendering direct exact maximization impractical for real-world LLM deployment.

To overcome this, our framework shifts its operational goal from direct maximization to a surrogate optimization. Specifically, we aim to find a payload k that maximizes k multiplied by a lower bound of $g(P_G)$ over all possible hash assignments. This surrogate objective is advantageous for two reasons:

1. **Computational Efficiency:** The lower bound of $g(P_G)$ can be deterministically calculated by sorting and evaluating only the top 2^k tokens in the natural distribution. This completely bypasses the need to compute hash assignments for the long tail of the vocabulary, reducing inference latency to a manageable constant.

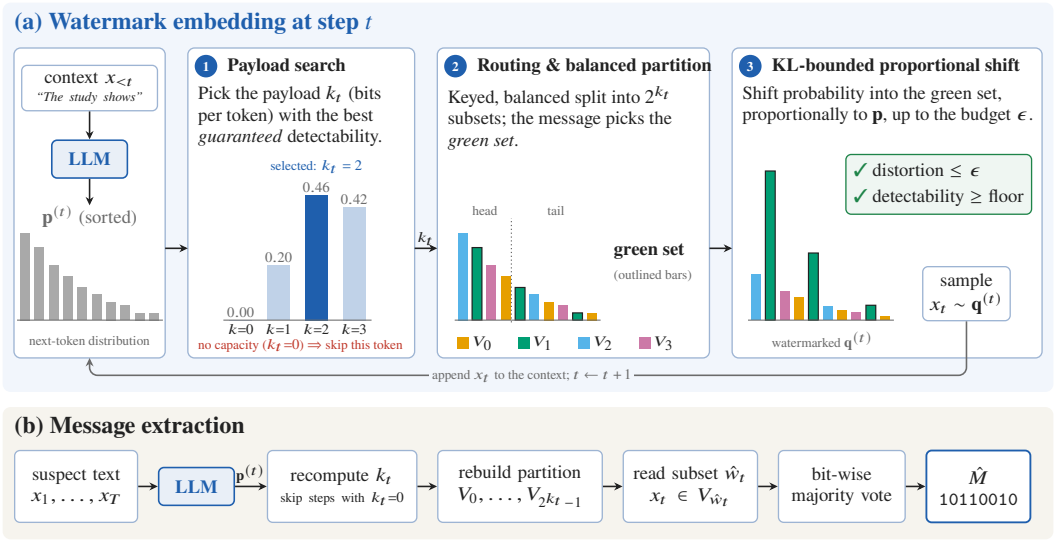


Figure 2: Overview of BoundMark. (a) At each generation step, BoundMark (1) selects the payload k_t that maximizes the guaranteed detectability $D_{\min}(k)$ under a balanced partition, abstaining if $k_t = 0$; (2) routes the message to a target subset and builds the balanced partition; and (3) shifts $\Delta_t = g(P_G)$ of probability mass to the green set proportionally to the original probabilities, which guarantees $D_{\mathrm{KL}}(\mathbf{q}\|\mathbf{p}) \le \epsilon$ and $D_t \ge D_{\min}(k_t)$. Numbers come from a toy distribution with $\epsilon = 0.5$. (b) Extraction recomputes k_t and the partition from the text and the key, reads the subset of each token, and recovers $\hat{M}$ by a bit-wise majority vote.

2. **Worst-Case Reliability:** By finding a k that maximizes the lower bound, we guarantee that the detectability proxy will always be greater than or equal to this bound, regardless of the actual pseudo-random hash assignment. This prevents the framework from selecting a fragile k that could result in ineffective watermark embedding.

Since $g(P_G)$ is concave on $[0, 1]$, its lower bound over any interval is attained at one of the endpoints. Therefore, given $P_G \in \left[\underline{P_G}, \overline{P_G}\right]$, we have

$$g(P_G) \ge \min\left\{g(\underline{P_G}), g(\overline{P_G})\right\}. \tag{17}$$

Thus, the lower bound of $g(P_G)$ is determined by the range of P_G.

However, Park et al. [2026], Gu et al. [2026] argued that the range of P_G is controlled by vocabulary partition algorithm, as depicted in (4). With unconstrained random partitioning, we have $\underline{P_G} = 0$ and $\overline{P_G} = 1$, since the green set may contain arbitrarily none or all of the probability mass. It therefore yields a trivial lower bound on $g(P_G)$, since $g(0) = g(1) = 0$. To alter the range of P_G, we adopt the balanced vocabulary partitioning strategy used by Park et al. [2026], Gu et al. [2026]. This strategy assigns exactly one of the top 2^k highest-probability tokens to each of the 2^k subsets, while assigning the remaining tokens through hashing.

Let $p_{(1)} \ge \cdots \ge p_{(2^k)}$ denote the top 2^k token probabilities, and let $P_{\mathrm{tail}}^{(k)} = 1 - \sum_{i=1}^{2^k} p_{(i)}$ denote the remaining probability mass. Because the green token set contains exactly one of these top-ranked tokens, its probability mass satisfies

$$\underbrace{p_{(2^k)}}_{\underline{P_G}} \le P_G \le \underbrace{p_{(1)} + P_{\mathrm{tail}}}_{\overline{P_G}}. \tag{18}$$

The $\underline{P_G}$ corresponds to assigning the smallest of the top-ranked tokens and no tail tokens to the target subset; the $\overline{P_G}$ corresponds to assigning the largest token and the entire tail. For $k \ge 1$, these bounds lie strictly inside $(0, 1)$ whenever the top 2^k token probabilities are positive. Consequently, for $\epsilon > 0$, this yields a positive lower bound on $g(P_G)$.

Multiplying this bound by k gives a guaranteed lower bound on the detectability proxy:

$$D_{\min}(k) := k \cdot \min\left\{g(\underline{P_G}), g(\overline{P_G})\right\} \leq k \cdot g(P_G). \tag{19}$$

BoundMark therefore selects

$$k_t \in \arg\max_{k \in \{0,\ldots,k_{\max}\}} D_{\min}(k), \tag{20}$$

where $D_{\min}(0) = 0$ represents embedding no payload and k_{max} is a hyper-parameter to limit the computational cost of payload selection.

3.2.4 Whole Pipeline of BoundMark

Figure 2 summarizes the whole pipeline of BoundMark. And Algorithms 1 and 2 in Appendix E give the full generation and detection procedures.

4 Experiments

4.1 Experimental Setup

Configurations and Baselines. To evaluate BoundMark, we simulate a multi-user environment consisting of 10 distinct users, each assigned a unique, randomly generated message for encoding. Each user provides two prompts, and the model generates a sequence of $T/2$ tokens per prompt. Consequently, a total of T tokens are produced per user for the decoding process, with the default sequence length established at $T = 150$.

We benchmark our approach against six state-of-the-art methods: DepthW Li et al. [2024], CycleShift Fernandez et al. [2023], MPAC Yoo et al. [2024], RSBH Qu et al. [2025], StealthInk Jiang et al. [2025], and XMark, LoSo Xu et al. [2026]. In the extended evaluation (Section 4.3) and the robustness study (Section 4.5), for a total of seven baselines. Due to the exponential growth in decoding latency associated with DepthW and CycleShift, their evaluation is restricted to a message length of $b = 8$ to remain computationally feasible. For XMark, we utilize default hyperparameters of $d = 2$ and $k = 2$. Across all applicable baselines (excluding StealthInk, which operates without a fixed bias), the watermark strength is set at $\delta = 2$. For BoundMark, we use $\epsilon = 2$ and $k_{max} = 5$ as default.

Datasets and Model Architectures. Our main analysis spans two representative downstream NLP tasks: *text completion* utilizing the C4 news dataset Raffel et al. [2023], and *text summarization* on the CNN/DailyMail corpus Hermann et al. [2015], with LLaMA-2-7B Touvron et al. [2023] as the generation model. To broaden the empirical coverage, we further evaluate BoundMark with Qwen2.5-7B Qwen et al. [2025] and *mathematical reasoning* on GSM8K Cobbe et al. [2021] and *code generation* on HumanEval Austin et al. [2021].

All experiments are conducted on Intel(R) Xeon(R) Gold 6330 CPU with NVIDIA A100 Graphic Card.

4.2 Evaluation Metrics

To assess the quality of the watermarked output, we measure **Perplexity (PPL)** using the larger LLaMA-2-13B model as the oracle. In the extended evaluation, we additionally report **BERTScore F1** Zhang et al. [2020] and **ROUGE-L** Lin [2004] against the reference outputs for summarization and text completion, **answer accuracy** for GSM8K, and **Pass@1** for HumanEval, each compared with the corresponding unwatermarked (Non-WM) generation.

Regarding watermark detectability, we adopt **Bit Accuracy (BA)** as the primary performance metric, consistent with established literature Fernandez et al. [2023], Yoo et al. [2024], Xu et al. [2026], Jiang et al. [2025]. A superior watermarking scheme is expected to maintain minimal PPL while maximizing BA.

4.3 Main Results

Overall Performance. As shown in Table 1, BoundMark$_{\epsilon=2}$ achieves the highest average bit accuracy on both tasks (99.38% on text completion, and 98.44% on summarization, tied with RSBH),

Table 1: Comparison of methods on two downstream tasks with $b = 8$ under different token budgets $T \in \{150, 200, 250, 300\}$. Best results in every column are denoted in bold.

Method	$T = 150$		$T = 200$		$T = 250$		$T = 300$		**Avg.**	
	BA↑	**PPL**↓	**BA**↑	**PPL**↓	**BA**↑	**PPL**↓	**BA**↑	**PPL**↓	**BA**↑	**PPL**↓
Text Completion										
CycleShift	97.50	4.98	95.00	5.16	**100.0**	4.90	95.00	4.55	96.88	4.90
DepthW	88.75	4.62	91.25	4.43	96.25	4.76	96.25	4.54	93.12	4.59
StealthInk	78.75	**4.54**	82.50	**3.46**	93.75	**4.16**	96.25	**4.02**	87.81	**4.04**
MPAC	97.5	5.12	98.75	5.03	96.25	4.84	98.75	4.88	97.81	4.97
RSBH	**100.0**	5.37	97.50	4.51	97.50	4.50	**100.0**	4.71	98.75	4.77
XMark	96.25	4.60	**100.0**	4.32	**100.0**	4.49	**100.0**	4.26	99.06	4.42
BoundMark$_{\epsilon=2}$	97.50	6.21	**100.0**	5.58	**100.0**	5.72	**100.0**	5.47	**99.38**	5.75
Text Summarization										
CycleShift	95.00	6.31	95.00	5.42	96.25	5.54	95.00	4.72	95.31	5.50
DepthW	91.25	6.07	87.50	4.57	83.75	4.55	92.50	5.25	88.75	5.11
StealthInk	75.00	5.14	88.75	**3.90**	95.00	**4.35**	90.00	**4.02**	87.18	**4.35**
MPAC	86.25	6.21	97.50	5.07	95.00	5.22	95.00	4.68	93.43	5.30
RSBH	**96.25**	5.92	97.50	5.33	**100.0**	5.08	**100.0**	5.11	**98.44**	5.36
XMark	82.50	5.75	**98.75**	4.95	96.25	4.64	**100.0**	5.08	94.37	5.11
BoundMark$_{\epsilon=2}$	**96.25**	**4.19**	**98.75**	5.19	**100.0**	5.44	98.75	5.21	**98.44**	5.01

and is the best or tied for the best in most individual columns. This indicates that the adaptive payload and maximin optimization provide competitive detectability. At the same time, BoundMark does not attain the lowest perplexity: the distortion budget $\epsilon = 2$ permits a relatively large shift, and methods such as StealthInk and XMark achieve lower PPL at slightly lower or comparable BA.

The empirical trade-off between text quality (PPL) and decoding reliability (BA) across C4 and CNN datasets is illustrated in Figure 3. Because these two metrics generally trade off against each other, no evaluated method consistently dominates all others on both metrics. BoundMark achieves a trade-off competitive with XMark, the state-of-the-art multi-bit method, while, unlike the baselines, providing an explicit bound on the per-step distributional shift and a lower bound on detectability proxy. Moreover, unlike XMark and DepthW, which show non-monotonic trends under varying δ, BoundMark follows a stable trajectory as ϵ varies, since ϵ directly controls the admissible shift.

Table 2 reports results with Qwen2.5-7B on CNN/DailyMail, C4, GSM8K, and HumanEval, together with an additional LLaMA-2-7B run on CNN/DailyMail with extended quality metrics (full results in Appendix F). BoundMark achieves the highest BA on Qwen2.5-7B CNN/DailyMail (97.50%) and GSM8K (87.50%), and remains close to the best method elsewhere (e.g., 98.75% vs. 100.00% on C4 and 87.50% vs. 90.78% on HumanEval). On the two low-entropy reasoning tasks, BoundMark preserves the task performance of the unwatermarked model in our runs (GSM8K accuracy 40.00%, HumanEval Pass@1 33.54%), whereas some high-BA baselines degrade it (e.g., CycleShift: 0.00% on GSM8K, 26.83% on HumanEval).

4.4 Impact of Message Length

Figure 4 illustrates the scaling behavior of BA as the message length m increases from 8 to 32 bits. Across both tasks, all methods exhibit a monotonic decline in decoding reliability, which is attributed to the increased information density per token. While baselines such as XMark and MPAC experience sharp performance degradation—with BA dropping toward 70% at $m = 32$—BoundMark degrades more gracefully, sustaining approximately 85% BA at $m = 32$ in our runs. In contrast to StealthInk and MPAC, which show high variance and wider confidence intervals as the payload grows, BoundMark exhibits comparatively stable behavior. This suggests that the payload-adaptive payload allocation helps accommodate the increased payload requirements of longer messages.

4.5 Robustness to Text-Modification Attacks

Although BoundMark is not designed to maximize adversarial robustness, we evaluate it under random insertion/deletion, synonym substitution, and DIPPER paraphrasing Krishna et al. [2023]

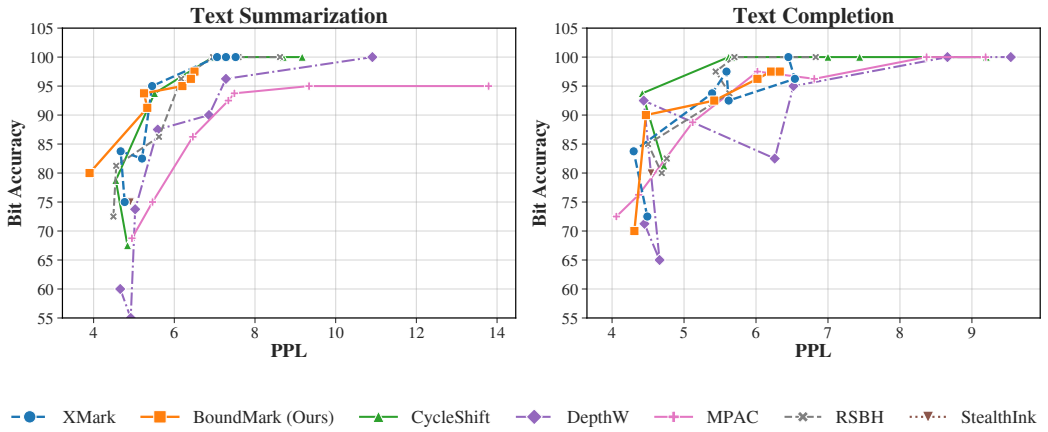


Figure 3: Results of watermarking methods on two downstream tasks. For BoundMark, we vary ϵ; for other methods, we vary δ.

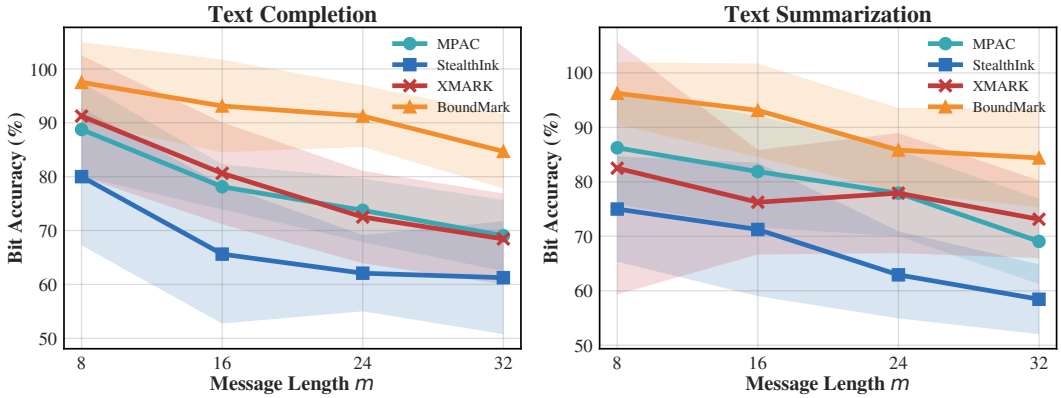


Figure 4: Results of watermarking methods on two downstream tasks when the message length varies.

(averaged results in Table 8 and per-setting results in Table 9, Appendix G). BoundMark has the highest clean BA (95.62%) and retains meaningful accuracy under attack (74.38%, 76.25%, and 55.00%, respectively), but it does not outperform the strongest baselines (e.g., MPAC, CycleShift, LoSo) under insertion/deletion and especially DIPPER, and its relative drop is larger than that of most baselines. We hypothesize that this is related to the adaptive payload: the detector recomputes k_t from the attacked context, so edits can also perturb the recovered payload schedule. Hence, the evidence does not support a claim that BoundMark improves adversarial robustness, consistent with its design goal of bounding distributional shift rather than resisting removal attacks; "detectability" in this paper thus refers to reliable message recovery under clean generation. Combining bounded distortion with strong robustness is left for future work.

5 Conclusion

We proposed BoundMark, a multi-bit LLM watermarking algorithm with explicitly controlled and theoretically bounded distributional shifts. Via per-step constrained optimization, BoundMark keeps the KL divergence of the watermarked next-token distribution within a budget, adapts payload and strength to the local distribution, and abstains when payload is insufficient. On two LLMs and four tasks, BoundMark achieves message recovery competitive with state-of-the-art multi-bit watermarks under clean generation while additionally providing a lower bound on the detectability proxy.

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A Limitations

Distributional rather than semantic guarantees. BoundMark bounds the per-step KL divergence between the watermarked and original next-token distributions. This is a proxy for distributional distortion and does not by itself guarantee semantic preservation; we also provide no sequence-level guarantee. Moreover, the objective $D = k \cdot \Delta$ is a heuristic proxy that is only directionally consistent with bit accuracy (Appendix D).

Robustness and security. BoundMark is not designed for adversarial robustness and does not consistently outperform the strongest baselines under insertion/deletion and paraphrasing attacks. It relies on a secret key, but we provide no formal unforgeability proof, and query-based watermark-stealing or spoofing attacks Jovanović et al. [2024], Sadasivan et al. [2023] are outside our scope.

Evaluated settings and conservatism. Our evaluation covers two LLMs and four tasks but is restricted to sequences of at most $T = 300$ tokens and payloads of at most $m = 32$ bits; we make no claims beyond these settings. Finally, $\Delta_{\max}$ relies on the inequality $\ln(1 + x) \leq x$ (a χ^2 upper bound on the KL divergence), which overestimates distortion in some contexts; a tighter bound would permit stronger signals within the same budget.

B Optimal Probability Shift Allocation

In this section, we prove that to minimize the distributional distortion $D_{KL}(\mathbf{q}||\mathbf{p})$ for a fixed total probability shift Δ, the individual token shifts δ_i must be allocated proportionally to their original probabilities p_i.

The Kullback-Leibler divergence from the original distribution $\mathbf{p}$ to the watermarked distribution $\mathbf{q}$ is defined as:

$$D_{KL}(\mathbf{q}||\mathbf{p}) = \sum_{x \in \mathcal{V}} q_x \ln\left(\frac{q_x}{p_x}\right) \tag{21}$$

The watermarking algorithm partitions the vocabulary into a Green Set S_G and a Red Set S_R. We require shifting a total mass of Δ into S_G. Thus, we have the following constraints for the green Set:

$$\sum_{i \in S_G} q_i = P_G + \Delta \tag{22}$$

where $P_G = \sum_{i \in S_G} p_i$. To find the optimal distribution $\mathbf{q}^*$ that minimizes the distortion solely within the green Set, we formulate the Lagrangian:

$$\mathcal{L}(\mathbf{q}, \lambda) = \sum_{i \in S_G} q_i \ln\left(\frac{q_i}{p_i}\right) - \lambda\left(\sum_{i \in S_G} q_i - (P_G + \Delta)\right) \tag{23}$$

Taking the partial derivative with respect to an individual token probability q_i and setting it to zero:

$$\frac{\partial \mathcal{L}}{\partial q_i} = \ln\left(\frac{q_i}{p_i}\right) + q_i\left(\frac{p_i}{q_i}\right)\left(\frac{1}{p_i}\right) - \lambda = 0 \tag{24}$$

$$\ln\left(\frac{q_i}{p_i}\right) + 1 - \lambda = 0 \implies q_i = p_i \exp(\lambda - 1) \tag{25}$$

This reveals that the optimal watermarked probability q_i is strictly proportional to p_i. To solve for the constant multiplier $\exp(\lambda - 1)$, we sum over all $i \in S_G$:

$$\sum_{i \in S_G} q_i = \exp(\lambda - 1) \sum_{i \in S_G} p_i \tag{26}$$

Substituting our constraint $\sum_{i \in S_G} q_i = P_G + \Delta$ and $P_G = \sum_{i \in S_G} p_i$:

$$P_G + \Delta = \exp(\lambda - 1) P_G \implies \exp(\lambda - 1) = \frac{P_G + \Delta}{P_G} = 1 + \frac{\Delta}{P_G} \tag{27}$$

Therefore, the optimal watermarked probability for target tokens is:

$$q_i = p_i \left(1 + \frac{\Delta}{P_G}\right) \implies \delta_i = p_i \left(\frac{\Delta}{P_G}\right) \tag{28}$$

Applying identical logic to the Red Set S_R, which must lose a total mass of Δ, yields:

$$q_j = p_j \left(1 - \frac{\Delta}{1 - P_G}\right) \implies \delta_j = -p_j \left(\frac{\Delta}{1 - P_G}\right), \quad \forall j \in S_R \tag{29}$$

This confirms that the optimal shift strategy to minimize D_{KL} is strictly proportional allocation.

C Proof of Estimation on Bound of Δ

To evaluate the distributional distortion analytically, we apply the first-order logarithmic inequality $\ln(1 + x) \leq x$ to our exact definition of D_{KL} (Definition 1). Because the sum of all probability biases across the vocabulary must equal zero ($\sum_{x \in V} \delta_x = 0$), the bound simplifies into:

$$D_{\mathrm{KL}}(\mathbf{q} \parallel \mathbf{p}) = \sum_{x \in V} (p_x + \delta_x) \ln \left(1 + \frac{\delta_x}{p_x}\right) \leq \sum_{x \in V} (p_x + \delta_x) \left(\frac{\delta_x}{p_x}\right) = \sum_{x \in V} \frac{\delta_x^2}{p_x} \tag{30}$$

Substituting the optimal proportional bias allocation (δ_x) defined in Theorem 1 into this bound, we separate the sum into the target subset S_G and the remaining subset S_R:

$$D_{\mathrm{KL}} \leq \sum_{x \in S_G} \frac{1}{p_x} \left(p_x \frac{\Delta}{P_G}\right)^2 + \sum_{x \in S_R} \frac{1}{p_x} \left(-p_x \frac{\Delta}{1 - P_G}\right)^2 = \frac{\Delta^2}{P_G} + \frac{\Delta^2}{1 - P_G} = \frac{\Delta^2}{P_G(1 - P_G)} \tag{31}$$

To enforce the distortion constraint at the current generation step, it suffices that this distribution-dependent upper bound does not exceed the budget ϵ:

$$\frac{\Delta^2}{P_G(1 - P_G)} \leq \epsilon \iff \Delta \leq \sqrt{\epsilon P_G(1 - P_G)}. \tag{32}$$

Feasibility. Under the proportional allocation, the red-set probabilities are $q_j = p_j\big(1 - \frac{\Delta}{1 - P_G}\big)$ for $j \in S_R$, which are non-negative if and only if $\Delta \leq 1 - P_G$. The green-set probabilities $q_i = p_i\big(1 + \frac{\Delta}{P_G}\big)$ are positive and sum to $P_G + \Delta \leq 1$, and $\sum_i q_i = 1$ holds by construction. At the boundary $\Delta = 1 - P_G$, the red-set probabilities become zero; with the standard convention $0 \ln 0 = 0$, the corresponding KL terms vanish and the inequality $q \ln(q/p) \leq q(q - p)/p$ used above still holds. Combining both conditions yields the maximal admissible shift $\Delta_{\max} = \min\{\sqrt{\epsilon P_G(1 - P_G)},\, 1 - P_G\}$, which establishes Theorem 2.

D Relation between the Detectability Proxy and Bit Accuracy

Consider a simplified model in which each watermarked token casts an independent vote for each of its k payload bits, and a vote is correct with probability $q = \frac{1}{2} + \frac{\Delta}{2}$. With T generated tokens and an m-bit message, each message bit receives approximately $N \approx Tk/m$ votes. By the normal approximation to the binomial majority vote,

$$\mathrm{BA} \approx \Phi\left(\frac{(q - \frac{1}{2})\sqrt{N}}{\sqrt{q(1 - q)}}\right) \approx \Phi\Big(\Delta\sqrt{N}\Big) = \Phi\left(\Delta\sqrt{\tfrac{Tk}{m}}\right), \tag{33}$$

where Φ is the standard normal CDF and the second approximation uses $q(1 - q) \approx \frac{1}{4}$ for small Δ. For fixed T and m, the expected bit accuracy is therefore monotonically increasing in both k and Δ. Although Eq. (33) and $D = k \cdot \Delta$ are not identical functions, increasing D (by increasing k, Δ, or both) is directionally consistent with improving BA, which motivates our use of D as the optimization objective.

Algorithm 1 The BoundMark Generation Pipeline (at step t)

Require: Context $x_{<t}$, Secret Key K, Global Message M, Distortion Budget ϵ, Maximum Payload $k_{\max}$

Ensure: Watermarked token x_t

 # LLM Forward Pass: Obtain original distribution $\mathbf{p}^{(t)}$ over vocabulary $\mathcal{V}$.
Sort $\mathbf{p}^{(t)}$ in descending order to obtain order statistics: $p_{(1)} \geq p_{(2)} \cdots \geq p_{(N)}$.
Define $g(P) := \min\{\sqrt{\epsilon P(1-P)},\, 1-P\}$ {KL budget and feasibility, Eq. (14)}
$D_{\min}(0) \leftarrow 0$
for candidate $k = 1, 2, 3, \ldots, k_{\max}$ **do**
    Calculate bounds: $P^{(k)}_{G,\min} \leftarrow p_{(2^k)}$ and $P^{(k)}_{G,\max} \leftarrow 1 - \sum_{i=2}^{2^k} p_{(i)}$
    Calculate guaranteed detectability: $D_{\min}(k) \leftarrow k \cdot \min\left(g(P^{(k)}_{G,\min}),\, g(P^{(k)}_{G,\max})\right)$
end for
Select payload: $k_t \leftarrow \arg\max_{0 \leq k \leq k_{\max}} D_{\min}(k)$.
if $k_t = 0$ **then**
    # Abstention: no admissible shift; sample $x_t \sim \mathbf{p}^{(t)}$ and **return** x_t.
end if
Compute target payload: $w_t \leftarrow H_{\text{msg}}(K, x_{<t}, M) \pmod{2^{k_t}}$.
Generate pseudo-random permutation π of $\{0, 1, \ldots, 2^{k_t} - 1\}$ seeded by $H_{\text{seed}}(K, x_{<t}, k_t)$.
for $j = 1$ to 2^{k_t} **do**
    Assign the j-th largest token $p_{(j)}$ to subset $V_{\pi(j-1)}$.
end for
for each remaining token v in $\{p_{(2^{k_t}+1)}, \ldots, p_{(N)}\}$ **do**
    Compute hash: $m \leftarrow H_{\text{seed}}(K, x_{<t}, v) \pmod{2^{k_t}}$.
    Assign token v to subset V_m.
end for
Set Green Set: $S^{(t)}_G \leftarrow V_{w_t}$ and Red Set: $S^{(t)}_R \leftarrow \mathcal{V} \setminus S^{(t)}_G$.
Calculate Green Set Probability: $P_G \leftarrow \sum_{i \in S^{(t)}_G} p^{(t)}_i$.
Calculate probability shift: $\Delta_t \leftarrow g(P_G) = \min\{\sqrt{\epsilon \cdot P_G(1-P_G)},\, 1-P_G\}$.
for each token $i \in \mathcal{V}$ **do**
    if $i \in S^{(t)}_G$ **then**
        $q^{(t)}_i \leftarrow p^{(t)}_i \left(1 + \frac{\Delta_t}{P_G}\right)$
    else
        $q^{(t)}_i \leftarrow p^{(t)}_i \left(1 - \frac{\Delta_t}{1-P_G}\right)$
    end if
end for
 # Sampling: Sample next token $x_t \sim \mathbf{q}^{(t)}$.
return x_t

E Generation and Detection Algorithms of BoundMark

Algorithm 1 details the generation procedure of BoundMark at a single step, and Algorithm 2 describes the detection procedure.

F Full Results of the Extended Evaluation

Tables 3–7 report the complete results of the extended evaluation, including the standard deviation of bit accuracy across users, BERTScore F1, ROUGE-L, and the perplexity of watermarked (WM) and unwatermarked (Non-WM) generations.

G Full Robustness Results

Table 8 reports bit accuracy under the three attacks considered in Section 4.5, averaged over four model–dataset settings, and Table 9 reports the per-setting results.

Algorithm 2 The BoundMark Detection Pipeline

Require: Suspect Document $\mathbf{x} = \{x_1, x_2, \ldots, x_T\}$, Secret Key K, Distortion Budget ϵ, Maximum Payload $k_{\max}$

Ensure: Extracted Global Message $\hat{M}$

Initialize an empty list of message candidates $C \leftarrow [\,]$.
for $t = 1$ to T **do**
  # LLM Forward Pass: Obtain original distribution $\mathbf{p}^{(t)}$ using context $x_{<t}$.
  Sort $\mathbf{p}^{(t)}$ in descending order: $p_{(1)} \geq p_{(2)} \cdots \geq p_{(N)}$.
  $D_{\min}(0) \leftarrow 0$
  for candidate $k = 1, 2, 3, \ldots, k_{\max}$ **do**
    Calculate bounds: $P^{(k)}_{G,\min} \leftarrow p_{(2^k)}$ and $P^{(k)}_{G,\max} \leftarrow 1 - \sum_{i=2}^{2^k} p_{(i)}$
    Calculate guaranteed detectability: $D_{\min}(k) \leftarrow k \cdot \min\left(g(P^{(k)}_{G,\min}),\, g(P^{(k)}_{G,\max})\right)$ {same g and ϵ as generation}
  end for
  Recover payload: $k_t \leftarrow \arg\max_{0 \leq k \leq k_{\max}} D_{\min}(k)$.
  if $k_t = 0$ **then**
    continue {abstained step carries no payload}
  end if
  Generate pseudo-random permutation π of $\{0, 1, \ldots, 2^{k_t} - 1\}$ seeded by $H_{\text{seed}}(K, x_{<t}, k_t)$.
  for $j = 1$ to 2^{k_t} **do**
    Assign the j-th largest token $p_{(j)}$ to subset $V_{\pi(j-1)}$.
  end for
  for each remaining token v in $\{p_{(2^{k_t}+1)}, \ldots, p_{(N)}\}$ **do**
    Compute hash: $m \leftarrow H_{\text{seed}}(K, x_{<t}, v) \pmod{2^{k_t}}$.
    Assign token v to subset V_m.
  end for
  Identify the subset index $\hat{w}_t$ such that the observed token $x_t \in V_{\hat{w}_t}$.
  Append $\hat{m}_t = \hat{w}_t$ to C.
end for
Calculate the mode of all extracted message candidates:
$\hat{M} \leftarrow \text{Mode}(C)$
return $\hat{M}$

Table 2: Extended evaluation on additional models and tasks. We report bit accuracy (BA, %) for all settings, and the downstream task performance of the watermarked output for GSM8K (answer accuracy, %) and HumanEval (Pass@1, %); the corresponding unwatermarked references are 40.00% and 33.54%, respectively. Best results per column are in bold. Standard deviations and additional quality metrics are provided in Appendix F.

	Qwen2.5-7B						**LLaMA-2-7B**
	CNN/DM	**C4**	**GSM8K**		**HumanEval**		**CNN/DM**
Method	BA↑	BA↑	BA↑	Acc.↑	BA↑	Pass@1↑	BA↑
XMark	87.50	93.75	83.75	30.00	**90.78**	**33.54**	88.75
LoSo	82.50	80.00	70.00	20.00	80.11	31.71	81.25
MPAC	92.50	96.25	86.25	30.00	86.13	31.10	90.00
RSBH	88.75	88.75	65.00	30.00	79.50	**33.54**	86.25
CycleShift	86.25	**100.00**	77.50	0.00	**90.78**	26.83	**91.25**
DepthW	70.00	76.25	52.50	**40.00**	63.57	**33.54**	67.50
StealthInk	48.75	47.50	50.00	**40.00**	50.76	**33.54**	71.25
BoundMark	**97.50**	98.75	**87.50**	**40.00**	87.50	**33.54**	90.00

Table 3: Extended results: Qwen2.5-7B on CNN/DailyMail.

Method	BA (%)↑	BERTScore↑	WM PPL↓	Non-WM PPL↓	ROUGE-L↑
XMark	87.50±14.79	0.8550	6.20	4.84	0.2000
LoSo	82.50±12.75	0.8533	5.22	4.84	0.1907
MPAC	92.50±12.75	0.8563	5.33	4.84	0.2030
RSBH	88.75±18.07	0.8555	7.13	4.84	0.1827
CycleShift	86.25±27.64	0.8582	5.50	4.84	0.2092
DepthW	70.00±16.96	0.8482	5.57	4.84	0.1800
StealthInk	48.75±19.72	0.8569	5.41	4.84	0.2420
BoundMark	97.50±5.00	0.8536	5.93	4.84	0.2017

Table 4: Extended results: Qwen2.5-7B on C4.

Method	BA (%)↑	BERTScore↑	WM PPL↓	Non-WM PPL↓	ROUGE-L↑
XMark	93.75±8.39	0.8695	7.92	6.20	0.2272
LoSo	80.00±13.92	0.8670	5.74	6.20	0.2230
MPAC	96.25±5.73	0.8551	7.84	6.20	0.1989
RSBH	88.75±14.20	0.8585	7.79	6.20	0.2094
CycleShift	100.00±0.00	0.8565	9.33	6.20	0.2131
DepthW	76.25±28.20	0.8541	6.43	6.20	0.1965
StealthInk	47.50±15.61	0.8544	5.40	6.20	0.2161
BoundMark	98.75±3.75	0.8564	8.22	6.20	0.1861

Table 5: Extended results: Qwen2.5-7B on GSM8K.

Method	BA (%)↑	WM Acc.↑	Non-WM Acc.	BERTScore↑	WM PPL↓	Non-WM PPL↓
XMark	83.75±14.84	30.00	40.00	0.8548	2.28	2.43
LoSo	70.00±10.00	20.00	40.00	0.8525	2.50	2.43
MPAC	86.25±10.38	30.00	40.00	0.8572	2.98	2.43
RSBH	65.00±27.84	30.00	40.00	0.8510	2.72	2.43
CycleShift	77.50±27.84	0.00	40.00	0.8569	2.69	2.43
DepthW	52.50±14.58	40.00	40.00	0.8564	2.00	2.43
StealthInk	50.00±15.81	40.00	40.00	0.8607	1.93	2.43
BoundMark	87.50±9.68	40.00	40.00	0.8566	2.67	2.43

Table 6: Extended results: Qwen2.5-7B on HumanEval.

Method	BA (%)↑	WM Pass@1↑	Non-WM Pass@1
XMark	90.78±11.62	33.54	33.54
LoSo	80.11±14.79	31.71	33.54
MPAC	86.13±13.46	31.10	33.54
RSBH	79.50±23.13	33.54	33.54
CycleShift	90.78±20.42	26.83	33.54
DepthW	63.57±24.90	33.54	33.54
StealthInk	50.76±17.33	33.54	33.54
BoundMark	87.50±12.88	33.54	33.54

Table 7: Extended results: LLaMA-2-7B on CNN/DailyMail.

Method	BA (%)↑	BERTScore↑	WM PPL↓	Non-WM PPL↓	ROUGE-L↑
XMark	88.75±13.05	0.8258	4.59	3.98	0.1530
LoSo	81.25±12.81	0.8278	4.27	3.98	0.1182
MPAC	90.00±9.35	0.8333	4.57	3.98	0.1705
RSBH	86.25±21.97	0.8301	4.17	3.98	0.1676
CycleShift	91.25±26.25	0.8391	4.81	3.98	0.1604
DepthW	67.50±27.50	0.8366	4.16	3.98	0.1502
StealthInk	71.25±17.72	0.8395	3.59	3.98	0.2007
BoundMark	90.00±19.20	0.8237	4.19	3.98	0.1379

Table 8: Bit accuracy (%) under text-modification attacks, averaged over the four model–dataset settings ({Qwen2.5-7B, LLaMA-2-7B} $\times$ {CNN/DailyMail, C4}). "Attacked avg." is the mean over the three attacks. Best results per column are in bold. Per-setting results are given in Table 9.

Method	**Clean**	**Insert/Delete**	**Synonym**	**DIPPER**	**Attacked avg.**
XMark	90.94	80.31	74.06	54.69	69.69
LoSo	80.94	76.56	75.62	**63.75**	71.98
MPAC	92.50	**87.50**	**80.31**	62.81	**76.88**
RSBH	86.25	74.38	69.06	57.81	67.08
CycleShift	94.38	85.31	80.00	61.25	75.52
DepthW	75.31	64.38	60.31	53.75	59.48
StealthInk	61.88	57.50	52.19	50.94	53.54
BoundMark	**95.62**	74.38	76.25	55.00	68.54

Table 9: Per-setting bit accuracy (%) under text-modification attacks. C: clean; I/D: insertion/deletion; Syn: synonym substitution; DIP: DIPPER paraphrasing.

	Qwen2.5-7B / CNN/DM				**Qwen2.5-7B / C4**				**LLaMA-2-7B / CNN/DM**				**LLaMA-2-7B / C4**			
Method	C	I/D	Syn	DIP	C	I/D	Syn	DIP	C	I/D	Syn	DIP	C	I/D	Syn	DIP
XMark	87.50	88.75	72.50	52.50	93.75	82.50	82.50	56.25	88.75	75.00	60.00	56.25	93.75	75.00	81.25	53.75
LoSo	82.50	76.25	71.25	60.00	80.00	72.50	75.00	65.00	81.25	78.75	76.25	67.50	80.00	78.75	80.00	62.50
MPAC	92.50	87.50	83.75	66.25	96.25	92.50	88.75	60.00	90.00	86.25	68.75	63.75	91.25	83.75	80.00	61.25
RSBH	88.75	75.00	66.25	47.50	88.75	82.50	78.75	55.00	86.25	70.00	68.75	65.00	81.25	70.00	62.50	63.75
CycleShift	86.25	71.25	75.00	52.50	100.00	88.75	86.25	62.50	91.25	92.50	75.00	57.50	100.00	88.75	83.75	72.50
DepthW	70.00	67.50	65.00	51.25	76.25	67.50	61.25	53.75	67.50	48.75	51.25	48.75	87.50	73.75	63.75	61.25
StealthInk	48.75	45.00	52.50	43.75	47.50	46.25	42.50	50.00	71.25	70.00	51.25	48.75	80.00	68.75	62.50	61.25
BoundMark	97.50	67.50	70.00	60.00	97.50	77.50	81.25	55.00	90.00	75.00	73.75	57.50	97.50	77.50	80.00	47.50

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