# A Private Watermark for Large Language Models

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## **Abstract**

Recently, text watermarking algorithms for large language models (LLMs) have been mitigating the potential harms of text generated by the LLMs, including fake news and copyright issues. However, the watermark detection of current text algorithms requires the key from the generation process, making them susceptible to breaches and counterfeiting. In this work, we propose the first private watermarking algorithm, which extends the current text watermarking algorithms by using two different neural networks respectively for watermark generation and detection, rather than using the same key at both stages. Meanwhile, part of the parameters of the watermark generation and detection networks are shared, which makes the detection network achieve a high accuracy very efficiently. Experiments show that our algorithm ensures high detection accuracy with minimal impact on generation and detection speed, due to the small parameter size of both networks. Additionally, our subsequent analysis demonstrates the difficulty of reverting the watermark generation rules from the detection network. Our code and data are available at https://github.com/THU-BPM/private watermark.

## Introduction

With the development of current large language models (LLMs), many LLMs, like GPT4 [OpenAI, 2023] and Claud<sup>1</sup>, could rapidly generate texts which are difficult to distinguish from human texts. This has led to numerous risks, such as the generation of a vast amount of false information on the Internet [Pan et al., 2023], and the infringement of copyrights of creative works [Chen et al., 2023]. Therefore, texts generated by LLMs need to be detected and tagged.

At present, some text watermark algorithms have been successful in making machine-generated texts detectable by adding implicit features during the text generation process that are difficult for humans to discover but easily detected by the specially designed method [Christ et al., 2023, Kirchenbauer et al., 2023]. However, current text watermark algorithms are all public, which means the detection of watermarks requires the key from the watermark generation process. This allows attackers easily remove and forge the text watermarks using these public keys. Although Kirchenbauer et al. [2023] have suggested that the watermark detection process could be placed behind the web API to achieve the effect of private watermarking, this approach requires substantial server resources and robust designs against hacking (even social engineering). Moreover, the requirement for users' text uploading carries an inherent risk of privacy breaches. If a text watermark algorithm could be designed in such a way that the watermark's generation key could be hidden during the detection process, this could significantly mitigate the issues mentioned above.

In this work, we propose the first private watermark algorithm for LLMs. Our work is built on the common watermark paradigm, which splits the vocabulary into the green and red lists and then prefers

<sup>1</sup>https://claude.ai/chat

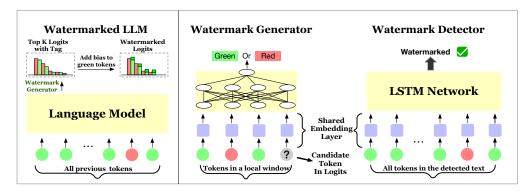


Figure 1: The illustration of our private watermark algorithm. The left part describes one step of generating tokens in a watermarked language model. The top-k tokens generated by the language model are processed by the watermark generator, which increases the probability of those belonging to the green list. The watermark generator accepts a window size of token inputs, determining whether the last token within this window belongs to the green list. The watermark detector takes the entire text as input and determines if the input text contains a watermark. It is important to note that the watermark generator and watermark detector share the embedding layer for each token.

to choose tokens from the green list. The difference is we implement these concepts in a private way. In order to hide the detail of the watermark generation method during the detection process, we propose two separate neural networks for watermark generation and detection instead of using the same key for both stages. The privacy of our algorithm derives from the black-box nature of neural networks, that is, it's nearly impossible to infer the watermark generation detail from the parameters of the detection network. Also, we analyze the difficulty of reverting watermarking generation detail from the output of the detection network in section 4.5. However, in practice, training such a detection network from scratch requires a vast amount of data, and achieving a high accuracy is challenging due to the complexity of the problem. Therefore, we also propose a neural network for the watermark generation process. To achieve a high-accuracy detection network with relatively small data, we share the token embedding layers between the watermark generation network and the watermark detection network, which essentially provides some prior information to the detection network. Specifically, our watermark generation network takes the input of w (local window size) tokens and outputs whether the last token belongs to the green list, which differs from the origin method Kirchenbauer et al. [2023] of splitting the vocabulary into the green and red list based on the local window text's hash value and the secret key. Meanwhile, the text detection network directly inputs all the token lists from the text, with the output being a classification indicating whether the entire text contains the watermark added by the generation network.

While constructing the training data for the watermark detection network, the presence of the watermark is also determined by considering the labels (red or green) of the first 'window size - 1' tokens. These labels are generated by treating the text as a cyclic document connected from head to tail. In this way, we prevent attackers from easily deducing the watermarking rule by continually altering the last token and observing the output changes.

In our experiments, we demonstrate that the watermark detection algorithm could achieve a nearly 99% detection accuracy rate, which is only marginally inferior to the public watermark algorithm. Given that the detection accuracy of the public watermark algorithm represents our theoretical upper bound, this is already a remarkable result. Moreover, because the amount of parameters of our watermark generation and detection network is negligible compared to the large language model, it brings almost no additional computation burden to the text generation process. Subsequent experiments also illustrate the critical importance of sharing the token embedding layer between the generation and detection networks.

The main contributions of this work can be summarized as follows:

 We propose the first private watermark algorithm which utilizes two neural networks during the watermark generation and detection phase instead of using the same key in both stages. This makes the watermark more difficult to erase and counterfeit.

- The token embedding is shared between the watermark generation and watermark generation network, which makes the training of the watermark detection network more efficient.
- Subsequent experiments indicate that our private watermark algorithm can achieve a detection accuracy only marginally inferior to the direct calculation of z-scores (public algorithm).

#### 2 Related work

As the quality of text generated by large language models (LLMs) improves, it becomes increasingly important to detect and tag machine-generated text. Up to this point, there are primarily two kinds of methods for detecting text produced by large language models. The first direction is the text watermarking method, which involves incorporating some implicit features (watermarks) into the text during generation, then detecting these texts using specially designed methods. The second approach keeps the text generation process unchanged and designs a classifier aimed at distinguishing between machine-generated and human-generated text. The following content will primarily introduce these two kinds of methods separately.

Current classifier-based detection methods usually directly employ a binary classification model. Zhan et al. [2023] utilized generation text from GPT2 [Radford et al., 2019], BART [Lewis et al., 2019], and GPT3.5-turbo <sup>2</sup> to fine-tune the *Roberta-large* [Liu et al., 1907] model, resulting in a highly accurate GPT text detector. Similarly, Mireshghallah et al. [2023] discovered that smaller language models perform well for the detection of machine-generated text. In an effort to improve the robustness of detection algorithms, Su et al. [2023] incorporated log-rank information from language models into the detector as a crucial feature. Meanwhile, Hu et al. [2023] introduced a paraphraser and utilized adversarial learning to enhance robustness. To distinguish text from more LLMs, Wu et al. [2023] utilized the prior information of the model's next-token probabilities to design a better detection model. However, whether machine-generated text can fundamentally be detected remains an open question. Chakraborty et al. [2023] believe that with enough data collection, it is possible to train a good detector. On the contrary, Sadasivan et al. [2023] argue that as language models become more complex and the distance between human and AI-generated text decreases, the optimal detector's performance may be only slightly better than a random classifier. In conclusion, some classifier-based detection methods can achieve impressive results. However, due to their limited explainability, their performance in real-world scenarios may be still doubted.

Compared to the classifier-based methods, text watermarking is more explainable due to the injected implicit features in the text. There are typically two categories of text watermarking methods. The first is to add a watermark to the existing text. For example, Abdelnabi and Fritz [2021] designed a data-hiding network to embed watermark information in the text, and utilized a data-revealing network to recover the embedded information. Yoo et al. [2023] injected the watermark by substituting some words in the text. However, adding a watermark to the existing text struggles to keep the semantics of the text unchanged which limits its use in real-world scenarios. Another line of methods is injecting the watermark during the text decoding process. Christ et al. [2023] used pseudorandom numbers to sample the next token and subsequently detected the watermark by observing the correlation between the preset pseudorandom numbers and the generated tokens. Kirchenbauer et al. [2023] divided the vocabulary into red and green lists and preferred to generate tokens from the green list. Zhao et al. [2023] enhanced the robustness of this approach by using a global fixed red-green vocabulary. Lee et al. [2023] designed a watermarking method for low-entropy code generation scenarios. However, the above methods are all public, which means the key used to generate the watermark is required during detection. This makes the watermark susceptible to removal and counterfeiting. In this work, we propose the first private text watermarking method to alleviate these issues.

## 3 Problem definition

To facilitate subsequent discussions, this section introduces the key concepts used in this work: language models and the watermarking algorithm.

A language model  $\mathcal{M}$  is essentially a function for the next token prediction, which is typically implemented using neural networks. Given an input sequence  $x = [x_0....x_{n-1}]$ , it outputs the

<sup>&</sup>lt;sup>2</sup>https://chat.openai.com

probability of the next token  $x_n$  over the vocabulary  $\mathcal{V}$ :  $\mathbf{p}_n := P_{\mathcal{M}(\mathbf{x})}[x_n = \cdot | \mathbf{x}_{1:n-1}]$ . The next token to be generated is then selected from this probability distribution, which can be achieved through sampling decode, choosing the token with the highest probability (greedy decode), or using other decode algorithms such as beam search to select a list of tokens with the highest probability.

A watermarking algorithm is the combination of two interconnected algorithms: the watermark generation algorithm and the watermark detection algorithm.

- The watermark generation algorithm could be viewed as a slight adjustment to the probability distribution of the language model. We can use  $\widehat{\mathcal{M}}$  to represent the language model that includes the text watermark. Formally, the probability of the next token prediction can be represented as follows:  $\mathbf{p}_n := P_{\hat{\mathcal{M}}(\boldsymbol{x})}[x_n = \cdot | \boldsymbol{x}_{1:n-1}].$
- The watermark detection algorithm accepts a text  $x = [x_0...x_n]$  as input and output whether the input sentence contains a watermark. The watermark detection model Detect and the watermarked language  $\hat{\mathcal{M}}$  correspond to each other one-to-one.

# **Proposed Method**

As illustrated in Figure 1, the private watermarking algorithm utilizes two distinct neural networks rather than sharing the same key for the watermark generation and detection stages. In the subsequent sections, we will first introduce the decoding step of the watermarked language model (Section 4.1), followed by the details of the watermark generation network (Section 4.2). Then the principles of watermark detection are introduced (Section 4.3) as well as the specifics of the watermark detection network (Section 4.4). Finally, we analyze the privacy of the entire algorithm in detail (Section 4.5).

## 4.1 Watermarked Large Language Model

As shown in Algorithm 1 for watermark generation, given the input  $x = [x_0...x_{n-1}]$ , we first generate the next token's logits,  $\mathbf{p}_n := P_{\mathcal{M}(\boldsymbol{x})}[x_n = \cdot | \boldsymbol{x}_{1:n-1}]$ , through the target language model M. Then we select the top K tokens with the highest probability from the logits and use the watermark generation network W to determine whether they belong to the green list. The probability of these green list tokens is then increased by  $\delta$ , while keeping the probability of other tokens unchanged. The modified logits serve as the output of the watermarked language model  $\mathcal{M}$ .

Note that we are not required to label all tokens in vocabulary during each generation step. In the top-K sampling as shown in Algorithm 1, only the top K tokens are tagged as green or red. Meanwhile, for the scenario of beam search, the number of tokens that need to be labeled is dynamic. Suppose the beam size is B, the first step is to identify the Bth largest score  $S_B$ . Subsequently, all tokens with scores greater than  $S_B - \delta$  are required to be tagged by the watermark generation network.

## **Algorithm 1** Watermark Generation Step (Top K sampling)

- 1: **Input:** a watermark generation network N, a fixed number K, watermark strength  $\delta$ , a language model  $\mathcal{M}$ , previous generated text  $\boldsymbol{x} = [x_0....x_{n-1}]$ , local window size w. 2: Generate the next token logit  $\mathbf{p}_n := P_{\mathcal{M}(\boldsymbol{x})}[x_n = \cdot | \boldsymbol{x}_{1:n-1}]$ .
- 3: Get the top K logits  $topK(\mathbf{p}_n)$  and their ids  $topK(\boldsymbol{x}_n)$ .
- 4: for  $x_{ni} \in topK(\boldsymbol{x_n})$  do
- 5: if  $N([x_{n-w+1},...,x_{ni}]) = 1$  then
- Add the token  $x_{ni}$  to the "green list" G. 6:
- 7: end if
- 8: end for
- 9: Define a new language model  $\mathcal{M}$  where given input  $x = [x_0...x_{n-1}]$ , the resulting logits satisfy

$$\hat{\boldsymbol{p}}_n[i] := \boldsymbol{p}_n[i] + \delta \mathbf{1} (i \in G),$$

where  $\mathbf{1}(\cdot)$  is the indicator function.

10: **Output:** watermarked language model  $\mathcal{M}$ .

#### 4.2 Watermark Generation Network

The structure of our watermark generation network is illustrated in the middle part of figure 1. The embedding of each input token is first generated by the shared embedding network  ${\bf E}$ . Then, the embeddings within a local window w are concatenated and fed into the subsequent classification network  ${\bf C}$  to determine if the last token belongs to the green list:

$$\mathbf{W}(\mathbf{x}) = \mathbf{C}([\mathbf{E}(x_{n-w+1}), \dots, \mathbf{E}(x_n)]). \tag{1}$$

The embedding network is a fully connected network and its input is the binary representation of token IDs, where the number of encoding bits depends on the size of the vocabulary. For example, GPT2 Radford et al. [2019] has a vocabulary size  $|\mathcal{V}|$  of 50,000, which requires 16 bits for its vocabulary representation. Common language models typically require bits between 15 and 17 for binary vocabulary representations.

To facilitate the subsequent watermark detection, the proportion of green labels generated by the watermark generation network requires to remain constant. Specifically, for any local window prefix  $[x_{n-w+1}, \ldots, x_{n-1}]$ , the probability of  $x_n$  belongs to the green list is always a fixed value  $\gamma$ :

$$\forall [x_{n-w+1}, \dots, x_{n-1}], P(\mathbf{W}([x_{n-w+1}, \dots, x_{n-1}, x_n]) = 1) = \gamma, \tag{2}$$

where the  $\gamma$  has the same meaning as the green list ratio in the previous public watermark algorithms Kirchenbauer et al. [2023], Zhao et al. [2023].

However, due to the black-box nature of neural networks, it is challenging to get a fixed ratio by pre-defined parameters. We achieve this by constructing a training dataset strictly with the desired proportion  $\gamma$ . It's worth noting that this method does not guarantee that the ratio of green to red will be strictly the same under every local window. Still, the expected value of this ratio is  $\gamma$ , and there is also a standard deviation  $\sigma$ . We will show the standard deviation  $\sigma$  only has a very slight impact on the final detection process in the following section 4.3.

#### 4.3 Watermark Detection

In this section, we introduce how to detect a given watermark using the z-value test. Then in the next section, the training data of the watermark detection network would be tagged by the z-value calculation.

If vocabulary is divided into the green list and red list according to the fixed ratio  $\gamma$ , then the number of tokens from the green list appearing in a normal text of length T would be  $\gamma T$ , with a variance of  $\gamma(1-\gamma)T$ . In this case, we can adopt the z-value test method proposed by Kirchenbauer et al. [2023]. If the z-score from the following formula is greater than a certain threshold, the text would be considered as containing a watermark:

$$z = (|s|_G - \gamma T) / \sqrt{T\gamma(1 - \gamma)}.$$
 (3)

However, based on the previous section, the watermark generation network cannot guarantee a fixed ratio  $\gamma$ ; we can only obtain a ratio  $\hat{\gamma}$ , which has an expectation  $\gamma$  and a standard deviation  $\sigma$ . It is necessary to amend the aforementioned formula under these circumstances. The expectation of the green token numbers is still  $\gamma T$ , but the variance changed. According to the law of total variance, we can use the following formula to calculate the new variance:

$$Var(\gamma T) = E[Var(\gamma T|\gamma)] + Var(E[\gamma T|\gamma]) = \gamma(1-\gamma)T + \sigma^2 T,$$
 (4)

and the new z-score could be calculated as follows:

$$z = (|s|_G - \gamma T) / \sqrt{\gamma (1 - \gamma)T + \sigma^2 T}. \tag{5}$$

Since our standard deviation  $\sigma$  is very small in practice, the increase in variance,  $\sigma^2 T$ , is also quite minimal. In the process of subsequent experiments, we will initially estimate the variance of the generation network and then include the variance during the z-score test calculation.

#### 4.4 Watermark Detection Network

While the z-value test is effective in detecting watermarks within a text, it has a drawback that requires the label (green or red) of each token during the process. This makes it easier for the watermark to be removed or forged based on this information. To keep this information private, we innovatively propose a watermark detection neural network, which only accepts a sequence of text as input and output whether the text contains a watermark or not.

The detailed structure of our watermark detection network is illustrated in the right part of figure 1. The input to the entire network is the ID sequence of all tokens in the target sentence, where an output of 1 indicates the presence of a watermark in the entire sentence, and 0 signifies its absence.

Specifically, all tokens first pass through a shared embedding network. The parameters of this token embedding network are identical to those of the watermark generation network, and will not be fine-tuned in the following training process. The motivation behind this novel approach is the shared embedding could give prior information to the detection networks and substantially reduce the difficulty of training the watermark generation network.

After obtaining the embedding of each token, we combine the embedding of all tokens and feed it into an LSTM (Long Short-Term Memory) network. Eventually, the LSTM network will output a binary classification to represent whether the text contains a watermark:

$$\mathbf{D}(\mathbf{x}) = \mathbf{LSTM}([\mathbf{E}(x_0), ...., \mathbf{E}(e_n)]). \tag{6}$$

The entire watermark detection network could be viewed as a discriminator to judge whether the z-value of a given input text is greater or less than a certain threshold. Therefore, we use equation 5 with a certain threshold to construct the training dataset. Specifically, during the training dataset construction, we sample texts with different proportions of green tokens and then assign a label of 0 or 1 depending on whether the calculated z-value exceeds a certain threshold.

It should be noted that the input for the training of the entire watermark detection network does not need to be a meaningful text - any number ID list is acceptable. Therefore, the detection model trained in this way theoretically will not encounter out-of-domain issues. We will further illustrate this point in subsequent experiments.

Moreover, under normal circumstances, the first w-1 tokens of a string of text sequences are usually not labeled as red or green. To make it more difficult for attackers to infer the watermark generation rules from the watermark detection network, we also labeled the first w-1 tokens by treating the text as a cyclic document connected head-to-tail. For instance, we can determine the label for  $x_0$  through  $x_{n-w+1}...x_n$ . Normally, the labels of the first w-1 tokens are usually random, but since the window size is much smaller than the overall length of the text, this can be neglected in the overall watermark detection.

#### 4.5 Analysis of the Privacy

To demonstrate that our private watermark algorithm could effectively hide the process of watermark generation, we analyze the difficulty of reverting the watermark generation rules from the watermark detection network.

A more detailed definition of the reverting problem is provided here: given the structure and parameters of the watermark detection network, obtain as many watermark generation rules as possible,  $[x_i...x_{i+w-1}] \to 0$  (red) or 1(green).

Considering the black-box nature of neural networks, inferring watermark rules based on the parameters of the detection network is nearly impossible, i.e., attackers can only infer from the output of the detection network. To achieve this goal, attackers need to continually modify the input to observe the output logits change. Every time modifying a  $x_i$  to  $x_j$  in the text, the label (green or red) of tokens within a window size would change and the only information attackers could only get is the inequality of the number of green tokens between two groups as follows (assuming the probability of text being watermarked decreases):

$$\text{Num}(\{x_{i-w+1}...x_i\},...,\{x_i,...x_{i+w-1}\}) > \text{Num}(\{x_{j-w+1}...x_i\}...\{x_j,...,x_{i+w-1}\}),$$
 (7) where Num is a function to count the number of green labels within a group.

Methods / Dataset		C4				DBPEDIA CLASS				
		FPR	FNR	TPR	TNR	FPR	FNR	TPR	TNR	
GPT2	Pub top-K.	0.4	2.4	97.6	99.6	0.6	1.0	99.0	99.4	
	Pri top-K. (ours)	0.3	3.0	97.0	99.7	1.0	2.0	98.0	99.0	
	Pub beam search.	0.4	3.2	96.8	99.6	0.6	0.6	99.4	99.4	
	Pri beam search. (ours)	0.2	4.8	95.2	99.8	1.0	2.8	97.2	99.0	
OPT 1.3B	Pub top-K.	0	3.8	96.2	100	0	6.2	93.8	100	
	Pri top-K. (ours)	0.2	3.9	96.1	99.8	0	11.2	88.8	100	
	Pub beam search.	0	1.8	98.2	100	0	0.4	99.6	100	
	Pri beam search. (ours)	0	3.2	96.8	100	0	2.0	98.0	100	
OPT 2.7B	Pub top-K.	0	3.4	96.6	100	0	8.0	92.0	100	
	Pri top-K. (ours)	0	5.6	94.4	100	0	13.9	86.1	100	
	Pub beam search.	0	1.2	98.8	100	0	1.0	99.0	100	
	Pri beam search. (ours)	0	2.0	98.0	100	0	3.3	96.7	100	

Table 1: Empirical error rates for watermark detection using top-K sampling and beam search. Each row is averaged over  $\sim 4000$  generated sequences of length  $T=200\pm 5$ . The table compares our proposed private watermark algorithm (prefixed with Pri) and the public watermark algorithm that directly calculates the z-score (prefixed with Pub). The hyperparameters adopted in the table are uniformly set as  $\delta=2.0, \gamma=0.5$ , and z-value threshold 4.0.

First, we give the lower bound of the number of times required to query the detection network. Given the window size w, there's no way to infer all the rules within  $|V|^w$  times of executing the detection network because the total number of rules is  $|V|^w$ , it is obviously impossible to infer two generation rules using any single query to the detection network.

However, it should be noted that this lower bound is very rough. In actual scenarios, it is even very difficult for attackers to obtain a clear inequality relation shown in Equation 7 because the window size is unknown to the attackers, and the logits change of the detection network is not 100% accurate. As a result, the user has to pay a considerable computational cost even to get a specific rule. Therefore, the actual number of required computations is far much greater than  $|V|^w$ .

It can be seen that a larger window size could make the watermark generation rules more difficult to decipher. The method which uses a global fixed red-green list as adopted by Zhao et al. [2023] is not suitable for the private watermark algorithm.

Instead of getting the watermark generation network rules from the watermark detection network, Sadasivan et al. [2023] proposed a method to infer the green list by statistically analyzing the pair frequency of large amounts of generated watermarked texts. However, their method is unlikely to be effective against our private watermarking method. First, Sadasivan et al. [2023] assumes the local window size is 2 but the window size we use is unknown. If a search is conducted for all possible window sizes, the computational cost would be extremely high, as the required computational power increases exponentially with the window size. Secondly, their approach assumes that the analysis could be conducted with a fixed set of N=181 common tokens. However, in actual scenarios, since attackers cannot access the watermarked language model (otherwise there would be no need for an attack), they cannot limit its output tokens to a fixed token set.

## 5 Experiment

In this section, we validate the effectiveness of the private watermark algorithm through extensive experiments.

#### 5.1 Experiment Setup

We utilize GPT-2 [Radford et al., 2019], OPT-1.3B [Zhang et al., 2022], and OPT-2.7B [Zhang et al., 2022] as the models for generating watermarks. For each model, we adopt both top-K sampling and beam search methods for text generation. The specific details of the two sampling methods have already been mentioned in section 4.2.

Methods / Datasets		C4				DBPEDIA CLASS				
		FPR	FNR	TPR	TNR	FPR	FNR	TPR	TNR	
GPT2	w. shared-layer	0.3	3.0	97.0	99.7	1.0	2.0	98.0	99.0	
	w/o shared-layer	28.8	23.2	76.8	71.2	47.7	24.4	75.6	52.3	
	w ft shared-layer	10.8	0.6	99.4	89.2	21.3	2.1	97.9	78.7	
OPT 1.3B	w. shared-layer	0.2	3.9	96.1	99.8	0	11.2	88.8	100	
	w/o shared-layer	26.9	7.7	92.3	73.1	34.0	14.1	85.9	66.0	
	w ft shared-layer	0.8	2.8	97.2	99.2	28.6	2.8	97.2	71.4	
OPT 2.7B	w. shared-layer	0	5.6	94.4	100	0	13.9	86.1	100	
	w/o shared-layer	55.4	6.3	93.7	44.6	6.4	29.4	70.6	93.6	
	w ft shared-layer	13.0	1.7	98.3	87.0	0	17.4	82.6	100	

Table 2: The table presents an ablation study on the shared layer, contrasting the effects of using a shared layer (w. shared layer), not using a shared layer (w.o. shared layer), and fine-tuning the shared layer (w. ft shared layer). The experiment was conducted under the hyperparameter settings of  $\delta = 2.0$ ,  $\gamma = 0.5$ , and z-value=4.

Meanwhile, we use the C4 [Raffel et al., 2020] and Dbpedia Class datasets [Gangemi et al., 2012] to evaluate our watermark algorithm. Specifically, following the approach of Kirchenbauer et al. [2023], we selected texts with length 30 from these datasets as prompts, and let the language models perform completions given these prompts. For each prompt, the models would generate  $T=200\pm 5$  tokens. We used the completions from the original datasets as the non-watermarked text (human text), and the text generated by our models as the watermarked text. The effectiveness was evaluated based on the ratio of false positive errors (human text falsely flagged as watermarked) and false negative errors (watermarked text not detected).

Unless specified otherwise, the hyperparameters used in the experiment are as follows: for the generator network, the ratio of green labels generated is 0.5, the window size is 5, the layer number of the token embedding network is 5, and the value of  $\delta$  is set to 2. For the detector network, the value of z used in training is 4, and the number of LSTM network layers is 2. When using the top-K sampling method, the K is set to 20 and the beam size of the beam search method is set to 8.

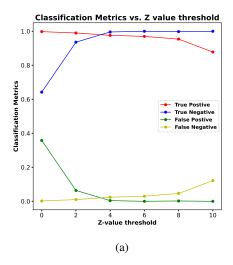
#### 5.2 Main Results

Table 1 demonstrates the detection accuracy of the private watermarking algorithm. We refer to the method which utilizes the label of each token to calculate the z-value (section 4.3) as the public watermarking algorithm and use this algorithm as the baseline for our comparison. The hyperparameters used are  $\delta=2.0$  and  $\gamma=0.5$ . The detection network is trained following a z-value threshold of 4.

As illustrated in Table 1, similar to the public watermarking algorithm, our private watermarking algorithm also scarcely produces false positive results (both 0.2% on average), meaning that human text is almost never mistakenly identified as watermarked text. Moreover, in most scenarios, the false negative probability is only marginally higher than the public watermarking algorithm by an average of 1.3%. Considering that the performance of the public watermarking algorithm represents the strict upper bound of our method, this is indeed an outstanding result. For some special cases when the z-value is not properly selected (using the top-K sampling with OPT 1.3B and 2.7B models to test the DBpedia CLASS dataset), even the public detection algorithm generates more false negatives cases and our private detection methods would also decrease in performance. With a properly selected z-value threshold, the private watermarking algorithm exhibits similar performance across different decoding methods, various language models, and disparate domain datasets, which demonstrates its strong generalizability and adaptability.

#### 5.3 Ablation study

To further analyze the private watermark algorithm, we conduct an ablation study in Table 2 to illustrate the effectiveness of shared token embedding for the detection network. Specifically, the experiment is conducted on the GPT2, OPT1.3B, and OPT2.7B language models on the C4 and



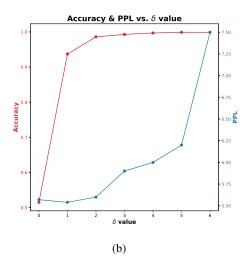


Figure 2: The left figure depicts the variations in the classification performance of private watermark detection under different z-value thresholds, while the right figure illustrates the changes in the detection accuracy and the PPL of generated texts with different  $\delta$  values.

DBPEDIA CLASS datasets. We have presented results under three different settings: using shared token embedding, not using shared token embedding, and fine-tuning shared token embedding.

As seen from Table 2, without the shared layer, the proportion of false negatives (watermarked text not detected) and false positives (human text falsely flagged as watermarked) dramatically decreases on an average of 15.1% and 32.0% respectively. This renders the entire detection algorithm almost inapplicable. Concurrently, although fine-tuning the shared layer reduces the occurrence of false negatives, it also introduces some instances of wrongly tagged human text. Given that mistakenly recognizing human text as the watermarked text presents more severe consequences, we eventually choose to adopt the method without fine-tuning the shared layer.

## 5.4 Hyper-parameters Analysis

To better understand how the private watermark algorithm works, we perform a series of analyses on several key hyper-parameters. Specifically, we tested the influence of different z value thresholds and  $\delta$  values in Figure 2 (a) and Figure 2 (b) respectively. When analyzing different z value thresholds, the value of  $\delta$  is set to 2.0, and when analyzing different  $\delta$  values, the value of z is set to 4. We use the LLaMA 13B model Touvron et al. [2023] to calculate the perplexity (PPL) value in Figure 2(b).

From Figure 2 (a), it can be observed that with the z-value threshold increases, the number of false positives gradually decreases. At a z-value of 4, there are almost no false positive cases. In contrast, the rate of false negatives tends to increase with the z-value threshold. As a trade-off, we selected a z-value threshold of 4 for this work. Additionally, as shown in Figure 2 (b), with the increase in the value of  $\delta$ , the accuracy of the detection network also increases. However, the corresponding perplexity (PPL) value of the generated text will also rise. Weighing these factors, we finally chose a  $\delta$  value of 2, which maintains detection accuracy without excessively impacting the text quality.

#### 5.5 Error Analysis

To better analyze the error cases of the private watermark algorithm, we present the z-score distributions of both the human text and the watermarked text, as well as the detection accuracy of the algorithm at different z-score ranges in Figure 3(a). These results are generated by GPT2 on the C4 dataset. As can be observed from Figure 3(a), the human text and watermarked text exhibited a normal-like distribution centered around 0 and 9 respectively. The detection accuracy of the private watermark algorithm is relatively low only around the z-score threshold 4, while it is almost 100% in other ranges. This suggests that for inputs with highly certain labels, our algorithm is quite reliable.

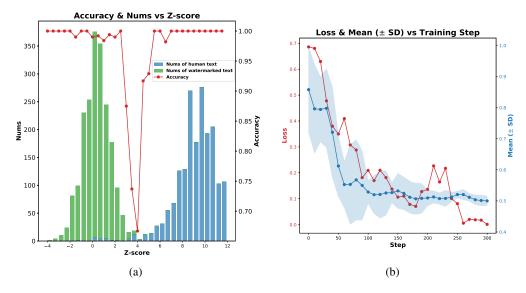


Figure 3: The left figure is an error analysis, illustrating the detection accuracy for data within various ranges of z-scores. The right figure depicts the changes in loss and the mean proportion ( $\pm$  its standard deviation) of green labels generated by the watermark generator network during the training process.

## 5.6 Watermark Generation Network Analysis

Based on our analysis in the section 4.3, it is critical for the watermark generation network to generate a stable label ratio because the modified z-score calculation (equation 5) is dependent on the variance of the label ratio. Therefore, in this section, we calculate the actual mean and variance of the labels generated by the watermark generation network.

Specifically, we train the watermark generation network using 5000 data items with strictly a 0.5 ratio of green labels, using the Adam optimizer Kingma and Ba [2014] with a learning rate of 0.001. As can be seen from figure 3 (b), the ratio of green labels gradually approaches the target value 0.5 with the training loss decreases, and its standard deviation also gradually diminishes. Ultimately, the standard deviation can be controlled within 0.02, corresponding to a variance of less than 4e-4. According to equation 5,  $\sigma^2 T$  could be nearly neglected in the final z-value calculation. We adopt the value 0.02 in the revised z-score calculation.

# 5.7 Time Complexity Analysis

Due to the private watermark generation process employing an additional watermark generation network, there is a risk of introducing an extra computational burden. Therefore, we analyze the time complexity of the watermark generation process in this section.

First, we compare the number of parameters in the watermark generation network and the language model. Our watermark generation network only consists of 43k parameters, whereas GPT2, OPT1.3B, and OPT2.7B have 124M, 1.3B, and 2.7B parameters respectively. It is evident that compared to the large language models with an enormous number of parameters, the number of parameters in our watermark generation network can be considered almost negligible.

Then we analyze the actual running time. On a single Tesla V100 GPU, decoding a token in GPT2 requires 30ms, whereas incorporating our watermark generation network only adds an average of 1ms to the cost. For models with a larger number of parameters, such as OPT1.3B and OPT2.7B, the influence on the decoding time is even smaller. Hence, our watermark generation algorithm does not cause significant additional computational overhead.

## 6 Conclusion

In this work, we have proposed the first private watermarking algorithm. Unlike previous works that detect watermarks by calculating the z-score using the key from the watermark generation phase, we detect watermarked text by a trained detection network. To facilitate the training of the watermark detection network, we also employ a neural network during the watermark generation phase and share token embeddings between the two networks. As demonstrated in the previous experimental stages, the detection accuracy achieved by our private watermarking algorithm is only slightly lower than that of the direct z-value calculation method. Meanwhile, further experiments demonstrate the strong adaptability of our algorithm. In future work, the details of watermark generation and detection can be further optimized. Meanwhile, enhancing the robustness of our private watermarking method is also an important direction.

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prompt	real completion	no watermark (NW)	watermarked (W)	(NW)	(W) z	(Real) PPL	(NW) PPL	(W) PPL
DPR members Jim Ragsdale, Diane Kane, Angeles Liera and pro tem chair Mike Costello discuss condo conversion projects.\n During the Jan	.10 meeting of the La Jolla Development Permit Review committee (DPR), board members voted unanimously to form a research subcommittee that will look into the consequences of condo conversion in the neighborhoods south of Pearl Street, L continues]	. 27 meeting, Ragsdale and Kane discussed the need for a condo market and how to get there. Costello spoke about the need to have a condo market in the area but also said there is a need to be able to rent a condo and that the area is growing. [continues]	. 11-12 meeting, the city announced that the development of condos to be built in the historic downtown has been approved by the city/n We feel it's important to be able to provide affordable housing for the people of the city in a way that the community feels they [continues]	0.71	10.5	5.42	8.26	7.15
In their first game since dropping out of the top five, the Irish delivered a redemption perfor- mance against Boston College, picking up a 50-point win over	the Eagles while simultaneously moving one step closer to cementing Arike Ogunbowale's legacy, as the senior guard passed current associate coach Beth Cunningham on the list of all-time scorers in the program\n No. 6 Notre Dame (23-2, 10-2 ACC) wasted [continues]	the Eagles. The Irish also defeated the Bulldogs in the final and will face the Bulldogs in the final Nather Irish also defeated the Eagles in the final and will face the Bulldogs in the final. Boston College'n The Eagles had a very good game against the Irish, Lcontinues]	South Carolina in the College Foot- ball Playoff Tournament to secure a berth in the NCAA Tournament. The Eagles will meet Notre Dame in the Big 12 Tournament on Sept. 14 in Austin, Texas in nWe've got to win in the first round [continues]	1.13	11.3	4.78	6.78	9.15
Two officers of a com- pany that operates three Manhattan hotels were indicted yesterday in a scheme to help home- less people fraudulently obtain welfare checks and split the money	with the hotels \n District Attorney Robert M. Morgenthau of Manhat- tan, who announced the indictments, said they resulted from a study of the three hotels announced last De- cember by the city. He said his of- fice was delayed in moving more quickly on the case because of diffi- culty[continues]	they received from the government. In The indictment, which was re- leased on Tuesday, said that police officers, who arrived at the hotel on a routine shift, me tith a home- less man who asked for a check from his landlord. man told the of- ficers about the scheme, which in- volved[continues]	between themselves and the home- less.in The scheme, alleged to be connected to the New York City De- partment of Health and Welfare, was uncovered in the wake of the 2012 Sandy Hook Elementary School shooting and the 2011 bombing of the Boston Marathon. Authorities say that the scheme [continues]	-1.9	9.94	4.83	7.02	7.05
Buddhadev had written a strong letter of protest to Manmohan Singh ob- jecting to Mulford's be- haviour. \n Taking seri- ous exception to	US Ambassador David Mulford writing directly to West Bengal Chief Minister Buddhadev Bhat- tacharjee for his remarks against the American President, the CPI-M on Friday said the party[continues]	the comments made by Mulford, the BJP MP also called on the CM to resign immediately and the Centre to make a statement in the coming weeks.\u00f3\u00e4n his letter to Manmohan Singh, the MP said he was not op- posed to[continues]	Mr Mulford's behaviour in the media and in the Parliament, the Union Minister has directed the Union Secretaries of Parliament and the Secretaries of the Supreme Court to take action against him in the matter[continues]	1.85	12.36	4.25	7.35	8.15

Table 3: Selected output examples from non-watermarked (NW) and watermarked (W) top-K sampling using  $\gamma=0.5, \delta=2.0$  and k=20.

# A Case study

To better illustrate the text generated by the watermarked LLM, we have listed some text examples from both the watermarked LLM and the non-watermarked LLM in Table 3. We compare the z-scores and PPL scores between these texts. Specifically, when calculating PPL scores, we utilize the LLaMA 13B model Touvron et al. [2023]. The results from table 3 demonstrate that the z-scores for texts generated by the watermarked LLM are significantly higher than those from the non-watermarked LLM, while there isn't a significant increase in the PPL scores.