

Source Attribution for Large Language Model-Generated Data

Anonymous ACL submission

Abstract

The impressive performances of *large language models* (LLMs) and their immense potential for commercialization have given rise to serious concerns over the *intellectual property* (IP) of their training data. In particular, the synthetic texts generated by LLMs may infringe the IP of the data being used to train the LLMs. To this end, it is imperative to be able to perform source attribution by identifying the data provider who contributed to the generation of a synthetic text by an LLM. In this paper, we show that this problem can be solved by watermarking, i.e., by enabling an LLM to generate synthetic texts with embedded watermarks that contain information about their source(s). We identify the key properties of such watermarking frameworks (e.g., source attribution accuracy, robustness against adversaries), and propose a source attribution framework that satisfies these key properties due to our algorithmic designs. Our framework enables an LLM to learn an accurate mapping from the generated texts to data providers, which sets the foundation for effective source attribution. Extensive empirical evaluations show that our framework achieves effective source attribution.

1 Introduction

Large language models (LLMs) (Ouyang et al., 2022; Touvron et al., 2023a) have recently demonstrated remarkable performances and hence received a surging interest. These LLMs, trained using massive text data, have displayed impressive text generation abilities. This has given rise to the immense potential of adopting LLM-generated texts for commercial use. However, this potential commercialization has led to major concerns regarding the *intellectual property* (IP) of training data for LLMs because the texts generated by an LLM may infringe the IP of the data being used to train the LLM. These concerns have been reflected by the increasing regulations on data protection related to AI models. For example, the Coalition for

Content Provenance and Authenticity has stressed the necessity of certifying the *source* of online content produced by generative models (Rosenthal, 2022). Therefore, it is of crucial importance for LLMs to be equipped with **source attribution** for their generated synthetic texts.

In **source attribution**, given some texts generated by an LLM, its aim is to find the source responsible for the generation of these texts. That is, if the data from a data provider has been used to train the LLM and contributed to the generation of a sentence by the LLM, then source attribution identifies this data provider. Moreover, source attribution also improves the interpretability of LLM-generated texts: for example, if the generated content from an LLM is attributed to a trustworthy source (e.g., a peer-reviewed academic paper), then the user is likely to consider the content more reliable. The ability to perform source attribution can endow the LLM with the capability of *data provenance*, which presents a *different problem* where a data provider can verify whether its data has been used to train the LLM. This problem can be solved with source attribution. Specifically, a data provider can check the source of the generated texts from an LLM via source attribution, and hence verify data provenance, as detailed in App. F.1.1.

While some recent works have addressed the problem of *data provenance* in LLMs (Kirchenbauer et al., 2023; Liu et al., 2023a), to the best of our knowledge, **effective source attribution for LLMs remains an open problem**. In contrast to data provenance which presents a binary determination, **source attribution aims to identify the specific data source(s) influencing a particular output, which presents a more challenging task**. Our work focuses on addressing source attribution rather than on data provenance. Additionally, although some works in Computer Vision (CV) have tackled the problem of source attribution (Marra et al., 2018; Yu et al., 2019, 2021), the techniques

043
044
045
046
047
048
049
050
051
052
053
054
055
056
057
058
059
060
061
062
063
064
065
066
067
068
069
070
071
072
073
074
075
076
077
078
079
080
081
082
083

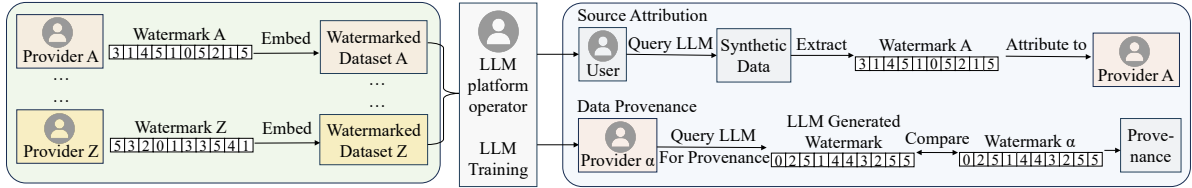


Figure 1: Illustration of WASA’s problem setting. Watermarks are embedded into the texts from data providers for training the LLM. The LLM produced by our WASA framework can generate synthetic texts with embedded watermarks that allow for effective source attribution.

in CV cannot be directly applied to solve source attribution in LLMs due to the fundamental difference between CV and LLMs in the input and output spaces: the inputs are perceived continuously in CV, hence minor alterations are nearly imperceptible; however, the inputs to LLMs are discrete where minor changes can be easily detected and can significantly alter the semantic integrity.

To perform source attribution for LLM-generated texts, a natural solution involves watermarking, i.e., by enabling the LLM to generate synthetic texts with embedded watermarks that contain information about their source(s). Consequently, source attribution can be performed by examining the watermarks embedded in the generated texts. Our problem setting (Fig. 1) involves 3 parties: *data providers* contributing text data that may be used for LLM training, an honest third-party *LLM platform operator* producing an LLM with generated texts that embed watermarks (hence allowing for source attribution), and *users* of the texts generated by this LLM. The users may request **source attribution** for the LLM-generated synthetic texts to find out which data provider is responsible for the generated texts. We consider scenarios where each data provider contributes ample balanced data with unique characteristics, i.e., the data from different data providers exhibit dissimilarities. This encompasses a wide variety of real-world scenarios: For example, online articles written by different authors (i.e., data providers) usually feature their unique writing styles. On the other hand, we do not consider individual documents/sentences as data providers since they have insufficient data. Additionally, this work focuses on single-source scenarios, where the generated content can be attributed to a single data provider.

An effective source attribution framework has to satisfy some key properties: The framework should (1) achieve **accurate** source attribution, (2) be **robust** against malicious attacks on the watermarks, (3) **preserve the performance** (i.e., text generation ability) of the LLM, (4) be **scalable**

to a large number of data providers, (5) ensure that the generated watermarks are **transferable** to (i.e., persist after being used as training data for) other LLMs, and (6) be **adaptable** to fit different LLMs. Sec. 2 discusses these key properties in more detail. To this end, this paper introduces a *Watermarking for Source Attribution* (WASA) framework which, to our best knowledge, is **the first framework capable of enabling effective source attribution in text generated by large language models**. Our WASA framework assigns a unique watermark (i.e., imperceptible to human eyes) to every data provider, and enables an LLM (coined as WASA-LLM) to learn an accurate mapping from the texts of different data providers to their corresponding watermarks (Sec. 3). So, if a data provider is responsible for generating a sentence, then our WASA-LLM is able to include the unique watermark of this data provider in this generated sentence, which naturally supports source attribution. Our contributions are summarized below:

- We propose to use watermarking for source attribution on LLM-generated synthetic texts and identify the key properties of such source attribution frameworks.
- We introduce the WASA framework which satisfies these key properties and is hence capable of producing LLMs whose generated texts allow for effective source attribution.
- We perform extensive empirical evaluations (Sec. 4) to verify that our WASA framework satisfies these key properties and achieves effective source attribution.

2 Key Properties of Watermarking for Source Attribution

Here, we discuss the key properties required for an effective watermarking source attribution framework and how our WASA framework satisfies them. **Accuracy.** Accurate source attribution should be enforced. Our WASA framework achieves this by training the WASA-LLM to map texts from different data providers to their respective watermarks.

Specifically, we first train WASA-LLM using watermarked texts (Sec. 3.1) and separate the prediction/generation spaces for the texts and watermarks to both *reduce the complexity of watermark prediction* (Sec. 3.2) and *explicitly enforce watermark generation* (Sec. 3.3). Empirical results in Sec. 4.1 demonstrate the effectiveness in source attribution.

Robustness. Generated text with watermarks should be robust against malicious attacks. Since our trained WASA-LLM is able to learn an accurate mapping from the texts to the watermarks as mentioned (a) it can be exploited to *regenerate* the watermarks even if generated texts are tampered with and (b) it maintains generating the correct watermarks even if the input texts (prompts) are perturbed, which are empirically verified in Sec. 4.2.

Scalability. The framework should cater to a large number of data providers. The design of the watermark (Sec. 3.1) facilitates the generation of numerous unique watermarks and the scalability can be empirically verified in Sec. 4.3.

Performance Preservation. The introduction of watermarks should (a) not significantly degrade the text generation ability of the LLM (b) nor affect the readability of the LLM-generated synthetic texts too much. To preserve (a), our WASA-LLM balances between the number of newly embedded watermarks and accuracy, as validated in App. G.7. The watermarks are carefully designed (Sec. 3.1) to achieve (b), as shown in App. H.1.

Transferability. After the generated watermarked texts are used as training data for other LLMs, their generated texts should preserve the watermarks. We achieve this by ensuring that the watermarked data used to train our WASA-LLM has the same structure as the generated watermarked data.

Adaptability. The framework should be easily adapted to fit different LLMs. Our WASA framework only requires mild modifications to the LLMs and can hence adopt a wide variety of LLMs using the transformer architecture, as shown in Sec. 4.1.

We have only listed above the most essential properties of such source attribution frameworks; there may be additional considerations depending on specific applications. In Sec. 3, we will discuss in more detail how our WASA framework satisfies these key properties due to our algorithmic designs.

3 Watermarking for Source Attribution (WASA) Framework

Sec. 3.1 discusses watermark design and embedding process. Sec. 3.2 details the training of WASA-

This sentence is embedded with a 10-character watermark.

This sentence is not embedded with a 10-character watermark.

This sentence is embedded with a 10-character watermark. U+200BU+200DU+2063U+200CU+200CU+2064U+2064U+2062U+2064U+2063

Figure 2: Sentences embedded (the first one) and not embedded (the second one) with our imperceptible watermark visualized in the bottom sentence.

LLM with watermarked texts and its alignment with key properties. Sec. 3.3 explains how our trained WASA-LLM produces synthetic texts with watermarks for source attribution.

3.1 Embedding Watermarks into Texts

Firstly, the LLM platform operator embeds a unique watermark for each data provider’s texts.

Design of Watermarks. To scale to a large number of data providers and still preserve the semantic meaning of the texts, we construct the watermarks using Unicode characters which are imperceptible to human eyes (yet can be decoded by machine learning models). Some of these invisible characters have also been adopted in other studies with language models (Boucher et al., 2022). Every watermark is made up of 10 characters, each of which is chosen among the following 6 Unicode characters: U+200B: Zero Width Space, U+200C: Zero Width NonJoiner, U+200D: Zero Width Joiner, U+2062: Invisible Times, U+2063: Invisible Separator, and U+2064: Invisible Plus. We chose these characters because they are found to be invisible on many commonly used platforms. So, these watermarks preserve the semantic meaning of the original texts to human readers (Fig. 2). Also, note that our WASA framework can easily adopt other choices of characters depending on the use cases. Moreover, these 10-character watermarks allow us to construct over 60 million (i.e., 6^{10}) unique watermarks and hence achieve **scalability** to a large number of data providers. As shown in App. G.9, reducing the watermark length trades off scalability for source attribution accuracy.

Embedding Watermarks into Sentences. To enable our WASA-LLM to learn the mapping from the texts of different data providers to their watermarks, it is important to only embed watermarks into the sentences that are *representative of the unique characteristics of the data providers*. To this end, we calculate the *term frequency-inverse document frequency* (TF-IDF) scores of all sentences from a data provider and select the sentences with the top 20% of the TF-IDF scores (i.e., most representative sentences) for watermarking, which empirically yields

the best trade-off of source attribution accuracy vs. text generation performance among different tested proportions, as reported in App. G.7. For every selected sentence, we embed our 10-character watermark at a random position in the sentence, which allows the LLM to learn to map texts of different lengths to the watermarks and also makes it harder for an adversary to remove/modify the watermarks. As empirically verified in App. G.2, our method of selecting sentences for watermarking based on TF-IDF indeed leads to more accurate source attribution than random selection.

3.2 Training WASA-LLM

We consider a practical scenario where the LLM is already pre-trained before being used by WASA framework, and we refer to our training of the LLM as *second-stage pre-training*. Our framework can also be used to train an LLM from scratch.

Preliminaries on LLMs. Denote an unsupervised corpus by \mathcal{D} , in which every sequence $s_i = [u_1, u_2, \dots, u_k]$ is with a block of k tokens. We focus on decoder-only language models (e.g., GPT (Radford et al., 2019), OPT (Zhang et al., 2022), Llama2 (Touvron et al., 2023b)). When presented with a sub-sequence $s = s_i[1 : j - 1] = [u_1, \dots, u_{j-1}]$, the LLM predicts $P(u_j)$ using feed-forward operations, as detailed below:

$$\begin{aligned} h_0 &= s \cdot W_e + W_p, \\ h_\tau &= \text{decoder}(h_{\tau-1}) \text{ for } \tau = 1, \dots, l, \\ z &= h_l[j - 1] \cdot W_e^\top, \\ P(u_j) &= \text{softmax}(z). \end{aligned} \quad (1)$$

W_e represents the embedding matrix with a dimension of vocabulary size V by embedding/hidden dimension E , and W_p is the positional encoding. The training objective is to maximize the log-likelihood $L(s_i)$ of a sequence s_i of tokens:

$$L(s_i) = \sum_{j=2}^k \log P(u_j | u_1, \dots, u_{j-1}) \quad (2)$$

where $P(u_j | u_1, \dots, u_{j-1})$ (i.e., similar to $P(u_j)$ in (1)) is the probability of j -th token u_j conditioned on the preceding $j - 1$ tokens $[u_1, \dots, u_{j-1}]$.

Forward Pass. To ease exposition, we consider one watermark in a block, but our design also supports multiple watermarks. Our 10-character watermark forms a consecutive sub-sequence of 10 tokens. Denote a sequence with an embedded watermark by $s'_i = [u_1, u_2, \dots, u_t, w_1, w_2, \dots, w_m, u_{t+1}, \dots, u_{k-m}]$ where $m = 10$ and the u 's and w 's are the word

and watermark tokens, respectively. There may be sequences s'_i not embedding any watermark. Hereafter, we will use t to denote the token index before the first watermark token.

To begin with, we augment the original vocabulary by our $V' = 6$ watermark characters (Sec. 3.1), leading to a new vocabulary size of $V + V'$. That is, our modified token embedding matrix W'_e is $(V + V') \times E$ (Fig. 3). For a sequence s'_i , given a sub-sequence $s' = s'_i[1 : j - 1]$ comprising the first $j - 1$ tokens (i.e., comprising either only word tokens or both word and watermark tokens), the same feed-forward operations in (1) are applied to s' (except that W_e is replaced by W'_e) to produce h_l . Next, depending on whether the ground-truth j -th token being predicted is a word token u or watermark token w , we adopt *two separate prediction spaces* (i.e., separate softmax layers). When predicting a *word token* u , the first V rows of the matrix W'_e are used to form the $E \times V$ matrix $(W'_e[1 : V])^\top$ as the linear layer. A softmax layer is then applied to produce the predictive distribution $P_u(u)$ of u over the vocabulary of V :

$$\begin{aligned} z_u &= h_l[j - 1] \cdot (W'_e[1 : V])^\top, \\ P_u(u) &= \text{softmax}(z_u). \end{aligned} \quad (3)$$

When predicting a *watermark token* w , the last V' rows of W'_e are used to form the $E \times V'$ matrix $(W'_e[V + 1 : V + V'])^\top$ as the linear layer. A softmax layer is then applied to produce the predictive distribution $P_w(w)$ over V' watermark tokens:

$$\begin{aligned} z_w &= h_l[j - 1] \cdot (W'_e[V + 1 : V + V'])^\top, \\ P_w(w) &= \text{softmax}(z_w). \end{aligned} \quad (4)$$

This separation of the prediction/generation spaces of the word tokens (3) and watermark tokens (4) allows us to use *a small number of additional parameters* (i.e., $E \times V'$ instead of $E \times (V + V')$) for watermark prediction based on the hidden states of WASA-LLM. Moreover, this separation allows us to explicitly enforce the generation of watermarks (i.e., using its designated generation space) when we use the trained WASA-LLM to generate synthetic texts, as discussed in Sec. 3.3. Therefore, the watermarks can be *regenerated* using cleaned texts after being attacked, and the correct watermarks can still be generated even if the input texts (i.e., prompts) are perturbed, hence ensuring the **robustness** of our WASA framework; more details are in Sec. 4.2.

The two separate softmax layers naturally lead to the following separate log-likelihoods:

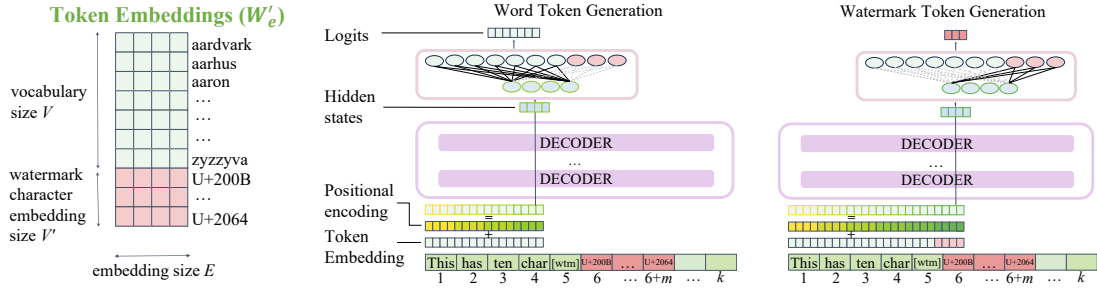


Figure 3: Separation of token embeddings and prediction spaces for texts and watermarks.

$$L_{\text{lm}}(s'_i) = \sum_{j=2}^t \log P_u(u_j | u_1, \dots, u_{j-1}) \quad (5)$$

$$+ \sum_{j=t+1}^{k-m} \log P_u(u_j | u_1, \dots, u_t, w_1, \dots, w_m, u_{t+1}, \dots, u_{j-1}),$$

$$L_{\text{wtm}}(s'_i) = \sum_{j=1}^m \log P_w(w_j | u_1, \dots, u_t, w_1, \dots, w_{j-1}) \quad (6)$$

where $L_{\text{lm}}(s'_i)$ (5) is the log-likelihood of word tokens, which is split into two sums before and after the watermark tokens, while $L_{\text{wtm}}(s'_i)$ (6) is the log-likelihood of watermark tokens, which encourages the LLM to learn texts-to-watermarks mapping.¹ The overall log-likelihood we aim to maximize is therefore $L_{\text{WASA-LLM}}(s'_i) = L_{\text{lm}}(s'_i) + L_{\text{wtm}}(s'_i)$.

The maximization of the log-likelihood of the watermarks conditioned on the texts (6), together with the separation of the prediction/generation spaces, enables WASA-LLM to **accurately** learn the mapping from the texts to watermarks. This allows us to achieve a high **accuracy** in source attribution, which will be empirically verified in Sec. 4.1. The backward pass is further elaborated in App. C.

3.3 Generating Texts with Embedded Watermarks using WASA-LLM

After our WASA-LLM is trained (Sec. 3.2), it can generate synthetic texts which naturally include both the word and watermark tokens due to their *separate prediction/generation spaces*. To further improve the alignment between our training and generation stages, we introduce a *special token* $[WTM]$ which is similar to other specialized tokens and in the vocabulary of V word tokens: When training our WASA-LLM using the watermarked texts, $[WTM]$ is added right before the watermark tokens during tokenization so that the presence of $[WTM]$ indicates that the

¹To simplify exposition, for the second sum in (5), when $j = t + 1$, the term reduces to $\log P_u(u_j | u_1, \dots, u_t, w_1, \dots, w_m)$. In (6), when $j = 1$, the term reduces to $\log P_w(w_j | u_1, \dots, u_t)$.

subsequent $m = 10$ tokens are watermark tokens; when generating texts, if $[WTM]$ is encountered/generated, then it indicates that our WASA-LLM should switch to generating watermark tokens. Specifically, when the token $[WTM]$ is not generated, our WASA-LLM generates word tokens by applying multinomial sampling to P_u (3), a distribution over V . When $[WTM]$ is generated, our WASA-LLM switches to generating watermark tokens by applying pure beam search to P_w (4), a distribution over V' . After watermark tokens have been generated, our WASA-LLM resumes the word token generation. Fig. 9 (App. H.1) shows the WASA-LLM-generated synthetic texts with embedded watermarks, which verifies that the watermarks are imperceptible to human eyes. Subsequently, when a user requests **source attribution** for some synthetic texts generated by our WASA-LLM, the LLM platform operator uses a designated *watermark decoder* algorithm to extract the generated watermark from the texts and then attribute these texts to the source (data provider) whose watermark matches the generated watermark (Fig. 1). The matching algorithm is elaborated in App. D.

4 Experiments

We perform extensive empirical evaluations to validate that our WASA framework satisfies the 6 key properties in Sec. 2. The experimental results shown below are the average taken from 5 random seeds. We post-process PDF version of academic papers from ArXiv (Clement et al., 2019) to a cleaned text dataset which we call Clean-ArXiv-Corpus (or ArXiv for short). The ArXiv dataset contains academic papers from several categories, each category functions as a *data provider* but with overlaps. For instance, in our main experiments, the two providers “hep-th” and “hep-ph” are both from High Energy Physics. They differ slightly: the former emphasizes theoretical concepts, while the latter focuses more on their application (Table 7).

We also use the BookSum dataset (Kryściński et al., 2022) consisting of various books, each considered as a *data provider*. We adopt 10 data providers for each dataset in our main experiments and show that our WASA can scale to a larger number (up to 100) of data providers in Sec. 4.3. We further include a comprehensive analysis using CC-News dataset, as detailed in App. G.5. This dataset comprises English-language news articles from various agencies reporting similar content, which presents a challenging scenario for source attribution. We obtain WASA-LLM from our second-stage pre-training (Sec. 3.2) of the pre-trained GPT2-Large, OPT-1.3B, and Llama2-7B. The results from OPT-1.3B are presented in App. F. App. E gives more details on the datasets and model training. Fig. 4 in App. E.2 shows the convergence of WASA-LLM in terms of the losses for word and watermark tokens.

4.1 Accuracy

We design the following experiment to facilitate easier evaluations of the single-source attribution **accuracy**. Specifically, for each data provider, we use the sentences selected for watermarking (after removing the watermarks) as the inputs/prompts to the trained WASA-LLM, and use the watermarks embedded into the generated texts for source attribution. This simplifies the evaluations because the corresponding data provider of the input sentence is naturally the ground-truth source. We verify the effectiveness of this evaluation method in App. E.3. Specifically, we first select 50 sentences from each data provider (i.e., 50 trials). Next, we use the first 200 characters of every selected sentence (without watermarks) as the input/prompt to the trained WASA-LLM which then generates synthetic texts (by continuing the sentence) with a token length of 100. More details are in App. F.1. The watermark embedded into the generated sentence is then used for source attribution, i.e., the source attribution is correct if this watermark matches the watermark of the data provider corresponding to this sentence (Sec. 3.3). As a result, for every data provider, the accuracy of source attribution is calculated as

$$\text{accuracy} = \frac{\text{number of correct watermarks}}{\text{number of trials}}. \quad (7)$$

The macro F1 score is reported in the results with the definition detailed in App. F.1. To mitigate the impact of the length of the generated sentence on our evaluations (i.e., a watermark may not be generated if the generated sentence is too short), we use

a simple technique to enforce watermark generation: If a watermark is not generated, then we force the generation of a watermark by adding the token $[WTM]$ to the end of the sentence (Sec. 3.3). This is only adopted to simplify the evaluations; as verified in App. G.3, naturally and forcefully generated watermarks lead to comparable source attribution accuracy. We also empirically show in App. G.8 that this enforced watermark generation is not necessary if the generated texts are long enough.

Baseline. Since WASA is the first effective source attribution framework, there is no existing baseline. We extend BM25 (Trotman et al., 2014) (detailed in App. F.1), a well-known search engine algorithm that estimates the relevance of data providers to a generated text and can potentially achieve source attribution. BM25 operates as a post-hoc process, which may slow down source identification, especially for larger number of potential sources. Tab. 1 reports the source attribution accuracy averaged over 10 data providers. Our WASA framework consistently achieves *more accurate source attribution for both datasets and both language models*; Tabs. 7 and 8 in App. F.1 gives the source attribution accuracy for different data providers.

Top- k Source Attribution. In addition to attributing a generated sentence to a single source by using one watermark, it may be acceptable for some users to attribute a generated sentence to multiple possible sources that contain the true source. To account for these scenarios, we propose *top- k source attribution* in which we modify our watermark generation (Sec. 3.3) so that when the token $[WTM]$ is encountered, we generate the top $k > 1$ watermarks with the largest beam search scores. In this case, source attribution is successful if the true watermark is contained in these k watermarks, so the *top- k accuracy* can be defined by replacing the number of correct watermarks in (7) with the number of generated sentences whose top k watermarks contain the true watermark.

Fine-grained Error Analysis. To better understand the incorrect attributions, where the generated text is not correctly attributed to its true source, we conduct a detailed error analysis on the ArXiv dataset. For every category (i.e., data provider), we separate the source attribution errors into two types of errors: (a) *misclassification* in which the generated watermark matches the watermark of another incorrect category, and (b) *incorrect watermark* in which the generated watermark does not match the watermark of any category. The results

are presented in Tab. 9 in App. F.1, which show that the vast majority of our errors result from misclassification and our WASA-LLM rarely generates incorrect watermarks not belonging to any category. This further substantiates the reliability of our WASA-LLM. The results also suggest that errors are mostly caused by the generated texts exhibiting the characteristics of multiple data providers. Note that even though the methodology and main evaluation are targeted at single-source, an extension to multiple data providers can be handled by our top-k source attribution, and we present a case study when true sources are multiple sources in App. H.3. An edge case of incorrect attribution may arise when the true source is not watermarked, such as the public pre-training data. In such cases, content cannot be attributed to any recognized provider. To investigate this phenomenon, we design a controlled experiment detailed in App. F.1.

4.2 Robustness

Our WASA framework is robust against malicious attacks aiming to disrupt the source attribution. We introduce the threat model as follows: We identify potential attackers as those intending to alter the LLM-generated text to remove IP acknowledgments to data contributors or alter input sentences to disrupt the watermark generation and hence the source attribution results. The attackers do not have access to the LLM itself but can query the model and modify the generated outputs. The attackers may also possess tools that can remove the Unicode characters (hence the watermark) inside a text.

Watermark Removal/Modification Attack. An adversary may remove/modify the watermarks in our generated sentence to sabotage the source attribution accuracy. Due to the ability of our WASA-LLM in learning an accurate texts-to-watermarks mapping, the watermark can be *regenerated* if it is manipulated. Specifically, we clean the generated sentence by removing the corrupted watermark, and use the cleaned sentence as input/prompt to WASA-LLM to regenerate the watermark (without generating synthetic texts) which is then used for source attribution. The regenerated watermarks by WASA-LLM (from second-stage pre-training of GPT2 on ArXiv dataset) lead to an overall accuracy (top-3 accuracy) of 71.60%(93.76%) which is comparable to the original 74.84%(95.76%) (Tab. 1). So, our watermark regeneration is an effective defense mechanism. Besides removing/modifying the watermark, an adversary may *additionally modify*

the content of the generated sentence:

Additional Attacks. We also consider additional attacks on generated sentences with embedded watermarks and on input sentences, including insertion, deletion, synonym substitution, syntactic transformation attacks, and an oracle-based attack (Zhang et al., 2023). Tab. 2 reports the source attribution accuracy under the first 3 attacks, where the attack strength relates to how many words in the sentence are attacked, and App. F.2 reports the accuracy under the last 2 attacks along with all the attacks descriptions. For such attacks (*in addition to watermark removal/modification attacks*) on generated sentences, watermark regeneration is used. The results show that although the attacks deteriorate attribution accuracy, high source attribution accuracy can still be preserved. This can again be explained by the reliable texts-to-watermarks mapping of our WASA-LLM, which is robust against perturbations to the input/prompt.

4.3 Scalability

Here, we verify WASA’s ability to scale to a large number of data providers. We follow the experimental setup in Sec. 4.1 and increase the number of data providers. Results in Tab. 3 and Tab. 15 (App. F.3) show that as the number of data providers increases, the source attribution accuracy inevitably decreases yet still remains relatively high (especially for the larger Llama2 model) compared with the BM25 baseline. With more data providers, we recommend using $k > 1$ in top- k source attribution due to higher resulting accuracy and identifying the true source from among them.

4.4 Other Key Properties

We show that our WASA framework can **preserve the performance** of the LLM in App. F.4, evaluated by perplexity, distinct-N (Li et al., 2016) and GPT-4 measured naturalness and coherence. Our framework also ensures decent readability of generated text, shown in App. H.1. **Transferability** and **Adaptability** are elaborated in Apps. F.5 & F.6.

Ablation Studies are carried out to assess the effectiveness of the designs, including (a) the designated embedding space for watermark tokens and separation of the prediction/generation spaces (App. G.1), (b) adopting TF-IDF to select sentences for embedding watermarks (App. G.2), and (c) the enforced watermark generation (App. G.3). Additional analysis, including (d) the effectiveness in supervised fine-tuning (App. G.4), (e) more diverse datasets

model	method	ArXiv dataset				BookSum dataset			
		acc.	top-3.	top-5.	F1	acc.	top-3.	top-5.	F1
GPT2	BM25	54.73 \pm 6.52	85.13 \pm 0.58	93.80 \pm 0.53	0.517 \pm 0.01	58.94 \pm 3.43	77.73 \pm 1.94	88.33 \pm 2.53	0.593 \pm 0.04
	WASA	74.84 \pm 2.04	95.76 \pm 1.24	98.56 \pm 0.82	0.758 \pm 0.02	77.92 \pm 1.57	91.80 \pm 0.24	96.52 \pm 0.76	0.723 \pm 0.08
Llama2	BM25	60.07 \pm 4.83	88.67 \pm 1.33	95.60 \pm 1.31	0.576 \pm 0.01	54.01 \pm 12.3	75.40 \pm 9.53	86.60 \pm 4.04	0.607 \pm 0.05
	WASA	77.40 \pm 1.91	96.87 \pm 1.62	99.40 \pm 0.35	0.800 \pm 0.03	83.27 \pm 4.50	95.27 \pm 1.53	97.67 \pm 0.46	0.840 \pm 0.06

Table 1: Accuracies of top-1, top-3, and top-5 source attribution (resp. denoted by ‘acc.’, ‘top-3.’, and ‘top-5.’) and F1 score by BM25 and WASA-LLM from second-stage pre-training of different models on various datasets.

strength	attacks on generated sentences with embedded watermarks						attacks on input sentences					
	insertion attack		deletion attack		synonym substitution		insertion attack		deletion attack		synonym substitution	
	acc.	top-3.	acc.	top-3.	acc.	top-3.	acc.	top-3.	acc.	top-3.	acc.	top-3.
0%	71.60	93.76	71.60	93.76	71.60	93.76	74.84	95.76	74.84	95.76	74.84	95.76
Localized	71.40	93.56	-	-	-	-	74.20	95.40	-	-	-	-
5%	70.12	93.20	71.08	93.92	70.52	93.52	74.20	95.40	73.56	95.52	72.84	95.24
10%	69.12	92.20	71.84	93.68	71.02	92.88	72.88	94.68	72.96	94.68	73.60	95.00
15%	66.92	91.96	71.36	94.04	70.96	92.72	71.52	93.20	72.68	94.12	71.88	94.20
20%	65.12	91.44	70.00	93.24	69.20	93.20	68.60	93.40	72.68	94.12	72.08	93.76

Table 2: Source attribution accuracy using regenerated watermarks by WASA-LLM (from second-stage pre-training of GPT2 on ArXiv dataset) under various attacks on **generated sentences with embedded watermarks** (*in addition to watermark removal/modification attacks*) and on **input sentences**. std is given in Tabs. 11 and 12 (App. F.2).

n	BM25 Llama2		WASA GPT2				WASA Llama2			
	acc.	F1	acc.	top-3.	top-5.	F1	acc.	top-3.	top-5.	F1
10	60.07 \pm 4.83	0.576 \pm 0.01	74.84 \pm 2.04	95.76 \pm 1.24	98.56 \pm 0.82	0.758 \pm 0.02	77.40 \pm 1.91	96.87 \pm 1.62	99.40 \pm 0.35	0.800 \pm 0.03
25	46.08 \pm 2.75	0.445 \pm 0.01	66.48 \pm 0.76	90.69 \pm 4.23	94.05 \pm 0.32	0.663 \pm 0.01	72.38 \pm 1.18	92.44 \pm 1.66	96.60 \pm 0.70	0.717 \pm 0.01
50	26.85 \pm 10.1	0.348 \pm 0.02	56.44 \pm 0.84	80.19 \pm 1.02	87.54 \pm 0.68	0.560 \pm 0.01	63.15 \pm 2.71	84.74 \pm 0.76	90.49 \pm 0.47	0.600 \pm 0.01
100	19.91 \pm 12.5	0.229 \pm 0.01	45.06 \pm 0.67	68.61 \pm 0.27	78.76 \pm 2.80	0.443 \pm 0.01	49.88 \pm 0.34	73.63 \pm 0.04	82.34 \pm 0.31	0.505 \pm 0.01

Table 3: Source attribution accuracy and F1 score for different numbers of data providers on ArXiv dataset. Note that ‘BM25’ denotes the source attribution obtained from BM25 on Llama2 as a baseline.

(App. G.5), and (f) the relative positions of the generated watermarks (App. G.6), are examined. We also explored the impact of hyperparameters from App. G.7 to App. G.12.

5 Related Work

In this section, we will review related works on source attribution and data provenance; further discussions on watermarking natural languages and models as well as text steganography are in App. B. Recent studies by Song and Shmatikov (2019) on verifying dataset usage in language model training through membership inference attacks are limited by the model’s output length, making them unsuitable for long-generated texts which we have considered in this work. Liu et al. (2023a) have proposed to plant backdoor triggers in training texts to check for data usage, but this method is not robust against removals of the backdoor triggers and can impair text generation performance. Importantly, the above works have only focused on data provenance and *cannot be easily adapted to perform effective source attribution*. Abdelnabi and Fritz (2021) have embedded messages post-

generation via adversarial training, which means the messages can only be used for IP protection and *cannot be used for source attribution* during generation. Some recent works in computer vision have tackled the problem of source attribution (Marra et al., 2018; Yu et al., 2019, 2021). However, to the best of our knowledge, effective source attribution for the texts generated by language models remains an open problem and is the focus of our work here.

6 Conclusion

This paper describes our proposed WASA framework which allows for effective source attribution as a solution to intellectual property infringement in the context of LLMs. By embedding unique watermarks into LLM-generated texts, WASA not only enhances the reliability and interpretability of LLM-generated content but also provides a crucial tool for data protection, allowing data providers to verify the use of their contributions in LLM training processes. The extensive empirical evaluations of the WASA framework affirm its effectiveness in achieving accurate source attribution while satisfying the key properties we have identified above.

676 **Limitations**

677 Since our WASA is the first effective source attribution
678 framework for LLM-generated texts, it faces
679 some limitations which may call for future work.
680 Firstly, we have only focused on scenarios where
681 the data providers have balanced data with suffi-
682 cient dissimilarities. However, in some applica-
683 tions, the data from different data providers may
684 be imbalanced or similar. Secondly, though we
685 have shown that our WASA is robust against various
686 adversarial attacks, it is unclear whether it is ro-
687 bust against more advanced/sophisticated attacks,
688 which may be achieved through adversarial training
689 in future work.

690 **Ethical Considerations**

691 Similar to other research topics on LLMs, water-
692 marking the synthetic texts generated by LLMs for
693 source attribution requires a thoughtful and ethical
694 approach due to its potential societal implications.
695 That is, it is important to take necessary measures
696 to avoid causing harm to certain parties. Poten-
697 tial risks related to our watermarking framework
698 include the following:

- 699 • **Privacy Risks.** Watermarking can poten-
700 tially reveal sensitive information about data
701 providers, thus leading to privacy breaches or
702 the possibility of re-identification if not han-
703 dled carefully. In our WASA framework, only
704 the watermark can be seen in the generated
705 data, which does not directly imply personal
706 information about the data providers. Privacy
707 can be preserved given that the mapping from
708 watermarks to data providers is kept confiden-
709 tial.
- 710 • **Chilling Effects.** Watermarking may dis-
711 courage some data providers from sharing
712 their datasets, especially if they fear poten-
713 tial misuse or unintended consequences of
714 having their data linked to specific research
715 outcomes.
- 716 • **Data Manipulation.** While watermarks are
717 meant to be unobtrusive and our WASA frame-
718 work has been shown to be robust against
719 various adversarial attacks, there can be un-
720 foreseen real-world instances where malicious
721 actors attempt to manipulate the watermark,
722 which may lead to negative consequences
723 such as the dissemination of altered or mis-
724 leading information.

725 To address these potential risks, it is essential to

carefully consider the ethical implications of our
watermarking framework and implement measures
to protect the privacy and interests of all involved
parties, particularly those who are more suscepti-
ble to harm. Researchers should conduct compre-
hensive risk assessments and engage in transparent
communication with data providers to ensure the re-
sponsible and ethical use of watermarked data. Ad-
ditionally, incorporating diverse perspectives and
involving vulnerable communities in the decision-
making process can help identify and mitigate po-
tential harm effectively.

726
727
728
729
730
731
732
733
734
735
736
737

References

- Sahar Abdelnabi and Mario Fritz. 2021. Adversarial Watermarking Transformer: Towards Tracing Text Provenance with Data Hiding. In *Proc. IEEE SP*, pages 121–140.
- Nicholas Boucher, Ilia Shumailov, Ross Anderson, and Nicolas Papernot. 2022. Bad Characters: Imperceptible NLP Attacks. In *Proc. IEEE SP*, pages 1987–2004.
- Colin B. Clement, Matthew Bierbaum, Kevin P. O’Keefe, and Alexander A. Alemi. 2019. On the Use of ArXiv as a Dataset. arXiv:1905.00075.
- Long Dai, Jiarong Mao, Xuefeng Fan, and Xiaoyi Zhou. 2022. DeepHider: A Covert NLP Watermarking Framework Based on Multi-task Learning. arXiv:2208.04676.
- Ji Gao, Jack Lanchantin, Mary Lou Soffa, and Yanjun Qi. 2018. Black-Box Generation of Adversarial Text Sequences to Evade Deep Learning Classifiers. In *IEEE Security and Privacy Workshops (SPW)*, pages 50–56.
- Tianyu Gao, Adam Fisch, and Danqi Chen. 2021. Making Pre-trained Language Models Better Few-shot Learners. In *Proc. ACL-IJCNLP*, pages 3816–3830.
- Chenxi Gu, Chengsong Huang, Xiaoqing Zheng, Kai-Wei Chang, and Cho-Jui Hsieh. 2023. Watermarking Pre-trained Language Models with Backdoor-ing. arXiv:2210.07543.
- Felix Hamborg, Norman Meuschke, Corinna Breiting-er, and Bela Gipp. 2017. news-please: A Generic News Crawler and Extractor. In *Proc. 15th International Symposium of Information Science*, pages 218–223.
- Xuanli He, Qiongkai Xu, Lingjuan Lyu, Fangzhao Wu, and Chenguang Wang. 2022. Protecting Intellectual Property of Language Generation APIs with Lexical Watermark. In *Proc. AAAI*, pages 10758–10766.
- Zhiwei He, Binglin Zhou, Hongkun Hao, Aiwei Liu, Xing Wang, Zhaopeng Tu, Zhuosheng Zhang, and Rui Wang. 2024. Can watermarks survive translation? on the cross-lingual consistency of text watermark for large language models.
- Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2021. LoRA: Low-Rank Adaptation of Large Language Models. arXiv:2106.09685.
- Nurul Shamimi Kamaruddin, Amirrudin Kamsin, Lip Yee Por, and Hameedur Rahman. 2018. A Review of Text Watermarking: Theory, Methods, and Applications. *IEEE Access*, 6:8011–8028.
- Mikhail Khodak, Nikunj Saunshi, and Kiran Vodrahalli. 2018. A Large Self-Annotated Corpus for Sarcasm. In *Proc. LREC*.
- John Kirchenbauer, Jonas Geiping, Yuxin Wen, Jonathan Katz, Ian Miers, and Tom Goldstein. 2023. A Watermark for Large Language Models. In *Proc. ICML*, pages 17061–17084.
- Wojciech Kryściński, Nazneen Rajani, Divyansh Agarwal, Caiming Xiong, and Dragomir Radev. 2022. Booksum: A Collection of Datasets for Long-form Narrative Summarization. In *Proc. EMNLP Findings*, pages 6536–6558.
- Rohith Kudithipudi, John Thickstun, Tatsunori Hashimoto, and Percy Liang. 2023. Robust Distortion-free Watermarks for Language Models. arXiv:2307.15593.
- Ang Li, Fangyuan Zhang, Shuangjiao Li, Tianhua Chen, Pan Su, and Hongtao Wang. 2023. Efficiently Generating Sentence-Level Textual Adversarial Examples with Seq2seq Stacked Auto-Encoder. *Expert Systems with Applications*, 213:119170.
- Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016. A Diversity-Promoting Objective Function for Neural Conversation Models. In *Proc. NAACL*, pages 110–119.
- Aiwei Liu, Leyi Pan, Xuming Hu, Shu’ang Li, Lijie Wen, Irwin King, and Philip S. Yu. 2024a. An unforgeable publicly verifiable watermark for large language models.
- Aiwei Liu, Leyi Pan, Xuming Hu, Shiao Meng, and Lijie Wen. 2024b. A semantic invariant robust watermark for large language models. In *The Twelfth International Conference on Learning Representations*.
- Yixin Liu, Hongsheng Hu, Xuyun Zhang, and Lichao Sun. 2023a. Watermarking Text Data on Large Language Models for Dataset Copyright Protection. arXiv:2305.13257.
- Yiyi Liu, Ruqing Zhang, Yixing Fan, Jiafeng Guo, and Xueqi Cheng. 2023b. Prompt Tuning with Contradictory Intentions for Sarcasm Recognition. In *Proc. EACL*, pages 328–339.
- Patrice Lopez. 2008–2023. Grobid. <https://github.com/kermitt2/grobid>.
- Yijian Lu, Aiwei Liu, Dianzhi Yu, Jingjing Li, and Irwin King. 2024. An entropy-based text watermarking detection method.
- Francesco Marra, Diego Gagnaniello, Luisa Verdoliva, and Giovanni Poggi. 2018. Do GANs Leave Artificial Fingerprints? In *Proc. MIPR*, pages 506–511.
- OpenAI. 2023. GPT-4 Technical Report. arXiv:2303.08774.
- Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller,

843	Maddie Simens, Amanda Askill, Peter Welinder, Paul Christiano, Jan Leike, and Ryan Lowe. 2022. Training Language Models to Follow Instructions with Human Feedback. In <i>Proc. NeurIPS</i> .	Andrew Trotman, Antti Puurula, and Blake Burgess. 2014. Improvements to BM25 and language models examined. In <i>Proceedings of the 19th Australasian Document Computing Symposium</i> , pages 58–65.	899 900 901 902
847	Christine I. Podilchuk and Edward J. Delp. 2001. Digital Watermarking: Algorithms and Applications. <i>IEEE Signal Processing Magazine</i> , 18(4):33–46.	Zhong-Liang Yang, Xiao-Qing Guo, Zi-Ming Chen, Yong-Feng Huang, and Yu-Jin Zhang. 2019. RNN-Stega: Linguistic Steganography Based on Recurrent Neural Networks. <i>IEEE Transactions on Information Forensics and Security</i> , 14(5):1280–1295.	903 904 905 906 907
850	Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language Models are Unsupervised Multitask Learners.	Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Thomas L. Griffiths, Yuan Cao, and Karthik Narasimhan. 2023. Tree of Thoughts: Deliberate Problem Solving with Large Language Models. arXiv:2305.10601.	908 909 910 911 912
853	Leonard Rosenthol. 2022. C2PA: The World’s First Industry Standard for Content Provenance (Conference Presentation). In <i>Proc. SPIE 12226, Applications of Digital Image Processing XLV</i> , page 122260P.	Ning Yu, Larry Davis, and Mario Fritz. 2019. Attributing Fake Images to GANs: Learning and Analyzing GAN Fingerprints. In <i>Proc. ICCV</i> , pages 7555–7565.	913 914 915
857	Congzheng Song and Vitaly Shmatikov. 2019. Auditing Data Provenance in Text-Generation Models. In <i>Proc. KDD</i> , pages 196–206.	Ning Yu, Vladislav Skripniuk, Sahar Abdelnabi, and Mario Fritz. 2021. Artificial Fingerprinting for Generative Models: Rooting Deepfake Attribution in Training Data. In <i>Proc. ICCV</i> , pages 14428–14437.	916 917 918 919
860	Mercan Topkara, Umut Topkara, and Mikhail J. Atallah. 2006a. Words Are Not Enough: Sentence Level Natural Language Watermarking. In <i>Proc. MCPS</i> , page 37–46.	Hanlin Zhang, Benjamin L Edelman, Danilo Francati, Daniele Venturi, Giuseppe Ateniese, and Boaz Barak. 2023. Watermarks in the sand: Impossibility of strong watermarking for generative models.	920 921 922 923
864	Umut Topkara, Mercan Topkara, and Mikhail J. Atallah. 2006b. The Hiding Virtues of Ambiguity: Quantifiably Resilient Watermarking of Natural Language Text through Synonym Substitutions. In <i>Proc. MM&Sec</i> , page 164–174.	Jingqing Zhang, Yao Zhao, Mohammad Saleh, and Peter Liu. 2020. PEGASUS: Pre-training with Extracted Gap-sentences for Abstractive Summarization. In <i>Proc. ICML</i> , pages 11328–11339.	924 925 926 927
869	Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. 2023a. LLaMA: Open and Efficient Foundation Language Models. arXiv:2302.13971.	Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, Todor Mihaylov, Myle Ott, Sam Shleifer, Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, and Luke Zettlemoyer. 2022. OPT: Open Pre-trained Transformer Language Models. arXiv:2205.01068.	928 929 930 931 932 933 934 935
876	Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023b. Llama 2: Open Foundation and Fine-Tuned Chat Models. arXiv:2307.09288.	Xiang Zhang, Junbo Zhao, and Yann LeCun. 2015. Character-level Convolutional Networks for Text Classification. In <i>Proc. NIPS</i> .	936 937 938
887		Xuandong Zhao, Lei Li, and Yu-Xiang Wang. 2022. Distillation-Resistant Watermarking for Model Protection in NLP. In <i>Proc. EMNLP Findings</i> , pages 5044–5055.	939 940 941 942
888		Zachary M. Ziegler, Yuntian Deng, and Alexander M. Rush. 2019. Neural Linguistic Steganography. In <i>Proc. EMNLP</i> , pages 1210–1215.	943 944 945

946
947
948
949
950
951
952

953

954
955
956
957
958
959

960
961
962
963
964
965
966
967
968
969
970
971
972
973
974
975
976
977
978
979
980
981
982
983
984
985
986
987

988
989
990
991
992
993
994

A Reproducibility Statement

We have given the necessary details for reproducing the results of our work in this paper. Detailed descriptions of the datasets used and the experimental settings have been included in Sec. 4 and App. E, including the 5 specific random seed numbers for the experiment runs.

B Additional Related Works

In addition to the previous works discussed in Sec. 5 that are most closely related to ours, we will give a review of additional related works on watermarking natural languages and text steganography, as well as recent works on watermarking language models.

Watermarking Natural Language/Text Steganography. In natural language processing, watermarking and steganography are closely related in that they both desire stealthiness and robustness. However, there are also important differences because watermarking emphasizes the importance of ownership, whereas steganography focuses on the secret communication of messages. Language watermarking is used to protect the integrity and authorship of digital texts (Kamaruddin et al., 2018; Podilchuk and Delp, 2001). Early approaches of language watermarking are mostly rule-based and make use of linguistic techniques such as synonym substitution (Topkara et al., 2006b) and sentence structure alteration (Topkara et al., 2006a) to embed watermarks while attempting to preserve the semantic meaning of the original texts. However, these approaches usually lead to deteriorated text quality and are not scalable. Some recent works have aimed to develop advanced text steganography methods using deep learning. The work of Yang et al. (2019) has utilized recurrent neural networks to automatically generate steganographic texts, and the work of Ziegler et al. (2019) has proposed to first convert the secret messages into bit strings and then map them to the cover text based on arithmetic coding with the help of GPT2 (Radford et al., 2019).

Watermarking Language Models. Some recent works have proposed methods to add watermarks to language models in order to protect the IP of the models (Dai et al., 2022; Gu et al., 2023; He et al., 2022; Zhao et al., 2022). These methods allow the verification of model ownership and are hence able to protect the economic interests of model

owners. Specifically, the work of He et al. (2022) has employed lexical replacement to watermark the language model output and used hypothesis testing for post-hoc model ownership verification. The work of Gu et al. (2023) has adopted backdoor attacks to embed black-box watermarks into pre-trained language models, which is achieved by using rare words as well as a combination of common words as backdoor triggers and verifying the watermarks by calculating the extraction success rate. Apart from model protection, multiple methods (Kirchenbauer et al., 2023; Kuditipudi et al., 2023; Lu et al., 2024) have been proposed to use watermarking to distinguish between human-generated and model-generated synthetic texts. Kirchenbauer et al. (2023) softly constrain the word choices when the model generates synthetic texts and use hypothesis testing to make the distinction. More recently, the work of Kuditipudi et al. (2023) has improved the above method by developing a distortion-free method, which ensures that the watermarks do not change the sampling distribution of the texts. The work of Lu et al. (2024) also refines the same method by ensuring the influence of a token during watermark detection to be proportional to its entropy. Finally, in terms of security in watermarking models, Liu et al. (2024b) develop a compact watermarking model that embeds a semantic watermark within model outputs, enhancing their robustness against adversarial text modifications. Meanwhile, Liu et al. (2024a) employ two distinct neural networks to generate and detect watermarks, enabling public verification of the watermark while maintaining the confidentiality of the secret key throughout the watermark generation process. Additionally, He et al. (2024) introduce a Cross-lingual Watermark Removal Attack (CWRA), which can effectively remove watermarks by interfering with the watermark generation process through translation into another language. Importantly, these methods cannot be used to perform source attribution for the texts generated by language models, which we focus on in this work.

C Backward Pass

In the main paper, we introduce the forward pass of our model in Sec. 3.2. Here, we delve into the backward pass in our framework. Remember that the most important design of the framework is the separation of the prediction/generation

995
996
997
998
999
1000
1001
1002
1003
1004
1005
1006
1007
1008
1009
1010
1011
1012
1013
1014
1015
1016
1017
1018
1019
1020
1021
1022
1023
1024
1025
1026
1027
1028
1029
1030
1031
1032
1033
1034
1035
1036
1037
1038

1039
1040
1041
1042
1043
1044

spaces of the word tokens (3) and watermark tokens (4). We represent the overall log-likelihood as $L_{\text{WASA-LLM}}(s'_i) = L_{\text{lm}}(s'_i) + L_{\text{wtm}}(s'_i)$. Notice that maximizing these log-likelihoods is equivalent to minimizing the cross-entropy loss $Loss_{\text{WASA-LLM}}(s'_i) = Loss_{\text{lm}}(s'_i) + Loss_{\text{wtm}}(s'_i)$ in which

$$Loss_{\text{lm}}(s'_i) = \sum_{j=2}^t \text{CE}(P_u(u_j), u_j) + \sum_{j=t+1}^{k-m} \text{CE}(P_u(u_j), u_j),$$

$$Loss_{\text{wtm}}(s'_i) = \sum_{j=1}^m \text{CE}(P_w(w_j), w_j) \quad (8)$$

represent the losses for the word and watermark tokens, respectively. For simplicity, in (8), we omit the conditioning on the preceding tokens in $P_u(u_j)$ and $P_w(w_j)$, which can be found in (5) and (6).

Due to the design above, the backward pass for updating the parameters W'_e in the last linear layer is also separated. That is, the gradients of word token loss $Loss_{\text{lm}}(s'_i)$ and watermark token loss $Loss_{\text{wtm}}(s'_i)$ (8) are responsible for updating $(W'_e[1 : V])^\top$ (3) and $(W'_e[V + 1 : V + V'])^\top$ (4), respectively. Specifically, the gradient update rule for W'_e (with learning rate α) can be expressed as $W'_e \leftarrow W'_e - \alpha h_l \cdot \nabla_z$ where ∇_z is a $(V + V')$ -dimensional gradient vector allowing the separated gradient updates to be easily achieved in a unified manner, as described below. Next, using the respective losses for word and watermark tokens (8), the gradient vectors w.r.t. z_u and z_w are calculated as V -dimensional $\nabla_{z_u} = \partial \text{CE}(P_u(u_j), u_j) / \partial z_u$ and V' -dimensional $\nabla_{z_w} = \partial \text{CE}(P_w(w_j), w_j) / \partial z_w$, respectively. When the loss is calculated from predicting a *word token* u_j (8), let $\nabla_z = [\nabla_{z_u}, 0_{V'}]$ where $0_{V'}$ is a V' -dimensional all-zero vector. When the loss results from predicting a *watermark token* w_j (8), let $\nabla_z = [0_V, \nabla_{z_w}]$. Note that for the parameters in the last linear layer which are responsible for predicting the *word tokens* using the hidden state (i.e., parameters $(W'_e[1 : V])^\top$ in (3)), the gradient updates are *not affected by the loss for the watermark tokens*. This helps us to further limit the impact of the added watermarks on the original ability of the LLM to generate high-quality synthetic texts and hence **preserve its performance**. For the parameters in the other transformer layers (except for the frozen layers), their updates are performed using the gradients w.r.t. the losses for both the word and watermark tokens; see App. E.2 for more details.

Note that both our forward pass and backward pass only require mild modifications to an LLM. Therefore, our WASA framework can be easily adapted to fit a wide variety of LLMs, which en-

ures its **adaptability** property.

D Watermark Matching

Exact Matching. In this work, we adopt exact matching to determine the correctness of the generated watermarks. That is, given a piece of generated text with watermarks and the corresponding ground-truth watermark, the generated watermark is correct only if they are strictly equal in string matching. In addition, in case multiple watermarks are generated in the synthetic data, all generated watermarks have to match the ground-truth watermark to affirm the correctness. The pseudocode for the matching algorithm is given in Alg. 1:

Algorithm 1 Exact Matching

Require: Synthetic text syn , ground-truth watermark wtm_g

- 1: **if** $\exists wtm$ in syn **then**
- 2: $wtm_s \leftarrow watermark\ decoder(syn)$
- 3: **if for** all wtm in wtm_s $wtm == wtm_g$
 (by string matching) **then**
- 4: return True
- 5: **end if**
- 6: **end if**

Soft Matching. To further improve the source attribution accuracy in some applications, we may relax the requirement of exact watermarking matching and instead attribute the generated texts to the data provider whose watermark has the smallest Levenshtein distance to the generated watermark. However, in all our experiments, our WASA is able to achieve accurate source attribution without soft matching.

E Detailed Experimental Setup

E.1 Datasets

To simulate different data providers with unique characteristics, we create the Clean-ArXiv-Corpus (or ArXiv for short) dataset which consists of academic papers from ArXiv. The dataset contains academic papers from various sub-disciplines, including computer science, physics, mathematics, public health, and other related fields. We make use of the provided metadata from the work of Clement et al. (2019) to download the corresponding PDF files and retrieve the categorization information associated with each article. Subsequently, we employ GROBID (Lopez, 2008–2023) to parse and

extract the main body of the papers, excluding the abstract and reference sections. Our Clean-ArXiv-Corpus dataset covers a comprehensive collection of 100 distinct categories, each comprising a number of papers ranging from 2827 to 2984. We treat *every category as a data provider*, so one data provider/category is the source of each piece of text. Our main experiments in Sec. 4 are conducted using 10 categories (i.e., data providers) and we use 33% of papers from each category due to computational constraints. However, in our ablation study (App. G.11), we have also tested utilizing more data from every data provider (including 100% of the data), which has led to further improved performances and consistent conclusions. For each of the 10 categories, we further randomly split its data into training and evaluation datasets with a ratio of 9 : 1 according to the seed number. In our ablation study, we will use more categories and also use all papers in each category. More detailed information about the full Clean-ArXiv-Corpus dataset, including all 100 categories and all papers in each category, is shown in Tab. 4; Tab. 4 shows an instance of the random split into training and evaluation datasets based on seed number 2023.

In addition to the Clean-ArXiv-Corpus dataset, we also adopt the BookSum dataset (Kryściński et al., 2022). This dataset contains documents from the literature domain including novels, plays, and stories. The BookSum dataset contains 181 books and we treat *every book as a data provider*. For every data provider (i.e., book), we adopt all the text data from the book in all our experiments. More information on the BookSum dataset is shown in Tab. 5; Tab. 5 shows an instance of the random split into training and evaluation datasets based on seed number 2023. Additionally, we have adopted more diverse datasets, details of which are found in App. G.5.

	Training	Evaluation
Papers	264K	29K
Unique tokens	17.1M	3M
Unique tokens per Category	407K	87K
Total tokens	1.8B	203M
Total tokens per Category	18.2M	2M

Table 4: Information on the Clean-ArXiv-Corpus (or ArXiv for short) dataset.

	Training	Evaluation
Books	161	20
Unique tokens	413K	106K
Unique tokens per Book	91K	20K
Total tokens	33M	4.6M
Total tokens per Book	3.3M	467K

Table 5: Information on the BookSum dataset.

E.2 Experimental Setting

In our experiments, we build our WASA-LLM based on the open-source pre-trained GPT2-Large model (Radford et al., 2019), OPT-1.3B model (Zhang et al., 2022) and Llama2-7B model (Touvron et al., 2023b). Based on the pre-trained weights, we perform our second-stage pre-training (Sec. 3.2) of the pre-trained GPT2-Large model, OPT-1.3B model, or the Llama2-7B model on the watermarked (Sec. 3.1) text data for one epoch to obtain WASA-LLM. We find that training for one epoch already allows our WASA framework to achieve compelling performances, as shown in our experiments in Sec. 4. We have also tested more training epochs in App. G.12 and the results suggest that our performances can potentially be further improved with more training epochs. We plot the convergence of the training of our WASA-LLM in terms of the losses for the word and watermark tokens in Fig. 4, which shows that our second-stage pre-training effectively reduces both losses. Importantly, the watermark token loss rapidly declines after a small number of steps, which suggests that our WASA-LLM can quickly learn an accurate texts-to-watermarks mapping.

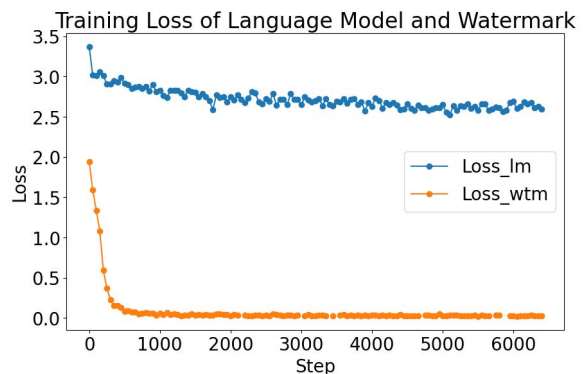


Figure 4: Training losses for word tokens (Loss_lm) and watermark tokens (Loss_wtm) when obtaining WASA-LLM from second-stage pre-training of the GPT2 model on ArXiv dataset.

Here, we give more details on the hyperparam-

eters we adopted. We fix 5 seed numbers at 2021, 2022, 2023, 2024, and 2025 for obtaining reproducible results on GPT2 and OPT models, and 3 seed numbers at 2022, 2023, 2024 for the Llama2 model. The results shown in this work are the average taken across that from the seeds. We adopt the Adam optimizer with a learning rate of 5×10^{-5} and no weight decay. We make use of the fp16 technique and a gradient accumulation of 8 to speed up training. We also adopt a gradient checkpoint to reduce memory usage so that batch size can be slightly increased. We use a block size of 512 and a batch size of 3 for most of the experiments and a batch size of 16 in the experiments to evaluate scalability. To further preserve the ability of the original pre-trained LLM models, during the second-stage pre-training, we freeze the first 12 layers of GPT2-Large (among a total of 36 layers) and freeze the first 8 layers of OPT-1.3B (among a total of 24 layers). For the second-stage pre-training of Llama2-7B, we adopt LoRA (Hu et al., 2021) and set the rank and alpha to 32, ‘q_proj’, ‘k_proj’, ‘v_proj’, ‘o_proj’, ‘gate_proj’, ‘gate_proj’, ‘gate_proj’, ‘up_proj’, ‘down_proj’ as the target modules, and ‘lm_head’, ‘embed_tokens’ as the modules to save. When generating the synthetic texts (see Sec. 3.3), we use the multinomial sampling of top-60 with temperature = 0.7. We also make use of a 1.2 repetition penalty and a 2.0 length penalty to generate better synthetic data. The generation of watermarks for our WASA-LLM adopts a pure beam search, as discussed in Sec. 3.3, with a beam size of 5. For the baseline model used in the ablation studies (i.e., GPT2-Large), watermark generation is performed in the same way as text generation, so we use the same hyperparameters as that specified in the baseline model. All second-stage pre-training is performed using NVIDIA RTX A5000 and A100. In our implementation, we adopt the GROBID library to process the PDF files. For model training, we adopt the Hugging Face Trainer pipeline which embeds necessary tricks to speed up the training process. The open-source GPT2-Large, OPT-1.3B, and Llama2-7B are also adopted from Hugging Face.²

E.3 Effectiveness of Evaluation

In our experiment design, we assign the ground truth source of each generated text to be identical

²<https://huggingface.co/facebook/OPT-1.3B>, <https://huggingface.co/meta-llama/Llama-2-7b-hf>, and <https://huggingface.co/GPT2-Large>.

to that of the prompt sentence. Here, we would like to verify that our method of using the source of the prompt sentence as the ground truth source for the generated sentence is indeed a reliable approach, in addition to its benefit of simplifying the experimental evaluation.

A natural and reliable method to find the ground truth source of a generated text is to consult the opinion of human experts. Therefore, we would like to show that our method to determine the ground truth source is an accurate approximation to human evaluations. To avoid the substantial costs and resources associated with human evaluators, we have employed GPT4, noted for its human-level performance across various benchmarks (OpenAI, 2023), as a surrogate ‘human-like labeler’. Then, we examine whether the ground truth source determined by our method (i.e., using the source of the prompt sentence) aligns well with those determined by GPT4. Specifically, we use GPT4 to categorize generated texts into one of the ten ArXiv categories (i.e., data providers) using a carefully constructed prompt, as shown in Tab. 6. After evaluating 500 generated texts, we have found that 89.6% of GPT4’s decisions align with our source determination method (i.e., using the source of the prompt sentence). This validates that our method to determine the ground truth source of a generated text is a reasonable and reliable approach.

We would like to add that employing GPT4 as a ‘human-like labeler’ is only feasible in our controlled setting here because it requires prior knowledge about all sources and detailed descriptions of the sources; see the detailed prompt in Tab. 6. Moreover, it also incurs excessive costs in terms of monetary expenses and computations when the number of data providers is large. Therefore, we would like to clarify that this GPT4-based method is not a realistic alternative method for source attribution and is instead only employed here to verify the reliability of our method of source determination.

Additionally, note that the reason why we have used watermarked training data as the prompt sentences in our evaluation is because it leads to simple and reliable evaluations. Here, we justify this using the GPT4-based experiment as well. We use GPT4 to examine the reliability of the ground truth source determination when sentences from two held-out sets are used as the prompt sentences: when the prompt sentences are selected from unwatermarked training data and when the prompt sentences are

Definition of Task in Prompts for GPT4 Labeling

Given below are 10 categories for texts from ArXiv papers with their descriptions. Please read the descriptions and classify the provided texts to one of the paper categories.

The 10 categories are: hep-th, hep-ph, quant-ph, astro-ph, cs.CV, cs.LG, cond-mat.mes-hall, gr-qc, cond-mat.mtrl-sci, cond-mat.str-el.

hep-th stands for High Energy Physics - Theory. This category includes research papers which are centered on theoretical concepts and mathematical models in high energy physics.

hep-ph stands for High Energy Physics - Phenomenology. This category includes research papers centered on the application of theoretical physics to high energy physics experiments.

quant-ph stands for Quantum Physics. This category includes research papers centered on the theoretical and experimental aspects of the fundamental theory of quantum mechanics.

astro-ph stands for Astrophysics. This category includes research papers centered on the study of the physics of the universe, including the properties and behavior of celestial bodies.

cs.CV stands for Computer Science - Computer Vision and Pattern Recognition. This category includes research papers focused on how computers can be made to gain high-level understanding from digital images or videos.

cs.LG stands for Computer Science - Machine Learning. This category includes research papers focused on the development and implementation of algorithms that allow computers to learn from and make decisions or predictions based on data.

cond-mat.mes-hall stands for Condensed Matter - Mesoscale and Nanoscale Physics. This category includes research papers that focus on the properties and phenomena of physical systems at mesoscopic (intermediate) and nanoscopic scales.

gr-qc stands for General Relativity and Quantum Cosmology. This category includes research papers centered on theoretical and observational aspects of the theory of general relativity and its implications for understanding cosmology at the quantum scale.

cond-mat.mtrl-sci stands for Condensed Matter - Materials Science. This category includes research papers centered on the understanding, description, and development of novel materials from a physics perspective.

cond-mat.str-el stands for Condensed Matter - Strongly Correlated Electrons. This category includes research papers focused on the study of solids and liquids in which interactions among electrons play a dominant role in determining the properties of the material.

Note that you should only include the class in your reply and provide no explanations. Please classify the following sentence into one of the 10 categories, however, if you think that the sentence could be classified into multiple categories, you may give up to 3 most likely categories:

Table 6: Definition of task in prompts for GPT4 labeling.

1297	from the validation data. The results show that	our choice of using watermarked training data as	1311
1298	when the prompt sentences are selected from un-	prompts because it enhances the reliability of our	1312
1299	watermarked training data, 81.6% of GPT4’s deci-	source determination and hence the fidelity of our	1313
1300	sions align with the source of the prompt sentences;	evaluation results.	1314
1301	when the prompt sentences are from the validation	F More Experimental Results	1315
1302	data, the alignment becomes 75.0%. The results	F.1 Accuracy	1316
1303	suggest that when the sentences from both held-out	More Details on Experimental Setup. In our ex-	1317
1304	sets are used as the prompt sentences, our method	periments on the source attribution accuracy, for	1318
1305	to determine the ground truth source is still reason-	the ArXiv dataset, we select 50 papers from each	1319
1306	ably reliable. However, our ground truth source	of the 10 categories (App. E.1) and for every se-	1320
1307	determination is the most reliable when sentences	lected paper, we choose the first sentence that has	1321
1308	from watermarked training data are used as the	been selected for watermarking (to obtain our WASA-	1322
1309	prompt, as we have done in our main experiments.		
1310	Therefore, the results justify the rationale behind		

LLM from second-stage pre-training of various pre-trained LLMs, see Sec. 3.1 for more details on how we select the sentences for watermarking) as well as contains at least 200 characters. Similarly, for every book (i.e., data provider) in the BookSum dataset, we select the first 50 sentences that have been selected for watermarking as well as have at least 200 characters. As a result, for both datasets, we have selected 50 sentences to be used as the inputs/prompts to our WASA-LLM, which corresponds to 50 trials of source attribution for each of the 10 data providers. In addition, the source attribution accuracy and F1 score for OPT-1.3B model are presented in App. F.3, together with the scalability results.

F1 score. In our main experiments, we have reported the macro F1 score for a more comprehensive evaluation. To compute the F1 score, here we first define precision as the number of correct watermarks (watermarks that correctly correspond to its true source) for the data provider i divided by the number of all generated watermarks that correspond to the data provider i and define recall as the number of correct watermarks divided by the number of trials of the data provider i . We calculate the precision and recall for each data provider and obtain $precision_i$ and $recall_i$. Subsequently, We obtain $precision_{ma}$ and $recall_{ma}$ by averaging the precisions and recalls from all data providers. Therefore, the macro F1 score can be computed as:

$$F_1 = 2 \times \frac{precision_{ma} \times recall_{ma}}{precision_{ma} + recall_{ma}}. \quad (9)$$

BM25 as source attribution baseline. BM25 is a well-known search engine algorithm that can potentially be utilized to perform source attribution given the generated sentences. In our experiments, we have implemented the BM25 from GitHub³ as a source attribution baseline for comparison. Specifically, we apply BM25 and take the unwatermarked training data as the corpus, and take the same generated sentences from our WASA-LLM (the watermarks are cleaned) as input. Subsequently, we can use BM25 to find the top- k closest data providers in the training data.

Source Attribution Accuracy for Each Data Provider. Tabs. 7 and 8 show the detailed results on source attribution accuracy and F1 score for the 10 different data providers, in addition to Tab. 1 in Sec. 4.1. The results show that the accuracy remains balanced across the data providers.

³https://github.com/dorianbrown/rank_bm25

Fine-grained Error Analysis of Source Attribution. Tab. 9 shows the errors of misclassification and incorrect watermark, as mentioned in Sec. 4.1. The results show that most source attribution errors are caused by generated texts exhibiting the characteristics of multiple data providers. Furthermore, here we consider the special case where the LLM-generated content is not attributable to any data provider. Note that in our main experiments, such a case does not exist since all data providers have watermarked their training data. Such unattributable content might be generated from public datasets used for pretraining the LLM, but we do not consider attributing sources to the public datasets in this paper; instead, we have focused on attributing to the data providers' watermarked private datasets. Moreover, it is hard to design prompts to enforce the model to generate content only from pretrain-knowledge, making it difficult to design corresponding experiments. Therefore, here we choose the setting by training our framework with data from both 5 watermarked data providers and 5 unwatermarked data providers to force our WASA-LLM to be able to generate content that is not attributable to the watermarked data providers. In this setting, our framework generates watermarks for 12% of the sentences generated from the 5 unwatermarked data providers while generating watermarks for 87.6% of the sentences generated from the 5 watermarked data providers. By analyzing the watermarks for sentences from unwatermarked data providers, we observe that 100% of these watermarks are from the watermarked data providers. This suggests that if there exists content not attributable to any data provider, our framework sometimes might misclassify them to the watermarked data providers.

F.1.1 Data Provenance.

We show here that WASA's ability to perform reliable source attribution also allows us to achieve accurate data provenance. Since the data providers are given both their own unique watermarks (Sec. 3.1) and the watermark decoder, they can request their *data provenance*. Specifically, when a data provider requests data provenance, it uses its own text data (without watermark) as the input/prompt to our trained WASA-LLM to verify whether the generated watermark matches its own (Fig. 1). We consider 20 categories/data providers in the ArXiv dataset, including 10 categories whose data was used for second-stage pre-training of GPT2 to obtain WASA-

Data Provider	GPT2			OPT			Llama2		
	acc.	top-3.	F1	acc.	top-3.	F1	acc.	top-3.	F1
hep-th	65.60 \pm 7.40	94.40 \pm 2.61	0.730 \pm 0.04	67.60 \pm 13.22	99.20 \pm 1.10	0.622 \pm 0.35	88.00 \pm 5.29	96.67 \pm 3.06	0.810 \pm 0.07
hep-ph	85.20 \pm 4.15	96.80 \pm 3.03	0.708 \pm 0.13	87.60 \pm 5.55	98.80 \pm 2.68	0.820 \pm 0.07	71.33 \pm 8.08	96.67 \pm 2.31	0.853 \pm 0.08
quant-ph	74.80 \pm 6.72	91.60 \pm 5.90	0.678 \pm 0.08	76.80 \pm 6.72	98.00 \pm 3.46	0.808 \pm 0.07	72.00 \pm 5.29	95.33 \pm 1.15	0.820 \pm 0.13
astro-ph	86.40 \pm 2.61	94.40 \pm 2.61	0.793 \pm 0.03	86.00 \pm 4.47	98.40 \pm 2.19	0.818 \pm 0.03	69.33 \pm 6.43	98.00 \pm 2.00	0.850 \pm 0.06
cs.CV	82.00 \pm 4.00	95.20 \pm 3.03	0.790 \pm 0.08	85.20 \pm 6.72	99.20 \pm 1.10	0.610 \pm 0.35	78.00 \pm 2.00	97.33 \pm 2.31	0.787 \pm 0.10
cs.LG	77.60 \pm 3.58	98.80 \pm 1.10	0.808 \pm 0.08	83.20 \pm 4.38	99.60 \pm 0.89	0.688 \pm 0.06	79.33 \pm 1.15	98.00 \pm 2.00	0.737 \pm 0.06
cond-mat.mes-hall	64.80 \pm 5.22	98.40 \pm 0.89	0.693 \pm 0.08	74.00 \pm 3.74	99.20 \pm 1.10	0.742 \pm 0.10	76.00 \pm 8.72	99.33 \pm 1.15	0.783 \pm 0.10
gr-qc	76.40 \pm 2.61	96.40 \pm 1.67	0.748 \pm 0.08	82.00 \pm 5.10	99.20 \pm 1.10	0.728 \pm 0.09	86.00 \pm 5.29	98.00 \pm 2.00	0.780 \pm 0.14
cond-mat.mtrl-sci	64.80 \pm 3.63	95.20 \pm 3.35	0.845 \pm 0.06	71.60 \pm 5.18	99.20 \pm 1.79	0.752 \pm 0.11	73.33 \pm 6.43	94.00 \pm 5.29	0.860 \pm 0.06
cond-mat.str-el	70.80 \pm 1.01	96.40 \pm 1.67	0.810 \pm 0.11	69.60 \pm 8.29	99.60 \pm 0.89	0.752 \pm 0.11	80.67 \pm 2.31	96.00 \pm 4.00	0.703 \pm 0.04
Overall	74.84 \pm 10.06	95.76 \pm 1.67	0.758 \pm 0.02	78.36 \pm 8.29	99.04 \pm 0.89	0.738 \pm 0.05	77.40 \pm 1.91	96.87 \pm 1.62	0.800 \pm 0.03

Table 7: Source attribution accuracy and F1 score achieved by our WASA-LLM (i.e., obtained from second-stage pre-training of different models on various datasets) for the ArXiv dataset.

Data Provider	GPT2			OPT			Llama2		
	acc.	top-3.	F1	acc.	top-3.	F1	acc.	top-3.	F1
Adam Bede	82.40 \pm 3.29	95.60 \pm 2.19	0.805 \pm 0.01	85.20 \pm 3.35	96.00 \pm 2.15	0.745 \pm 0.01	85.33 \pm 5.03	94.67 \pm 6.11	0.820 \pm 0.06
David Copperfield	80.00 \pm 6.63	88.40 \pm 5.90	0.670 \pm 0.04	77.20 \pm 6.72	91.60 \pm 1.67	0.820 \pm 0.03	80.67 \pm 2.31	96.67 \pm 2.31	0.755 \pm 0.28
Dracula	66.80 \pm 6.26	86.00 \pm 6.16	0.880 \pm 0.10	71.60 \pm 8.17	91.60 \pm 2.97	0.905 \pm 0.12	74.67 \pm 6.11	90.67 \pm 4.16	0.915 \pm 0.06
Hamlet	91.20 \pm 4.38	96.80 \pm 2.28	0.700 \pm 0.08	97.60 \pm 2.19	99.20 \pm 1.10	0.920 \pm 0.10	98.00 \pm 0.00	99.33 \pm 1.15	0.810 \pm 0.03
Henry IV Part 1	90.40 \pm 2.61	98.40 \pm 2.61	0.375 \pm 0.53	97.20 \pm 1.10	99.60 \pm 0.89	0.885 \pm 0.13	98.67 \pm 1.15	100.00 \pm 0.00	0.995 \pm 0.01
Ivanhoe	83.60 \pm 3.28	94.40 \pm 1.67	0.790 \pm 0.21	89.20 \pm 5.40	93.60 \pm 4.34	0.920 \pm 0.04	85.33 \pm 8.33	94.67 \pm 4.16	0.820 \pm 0.08
Jane Eyre	74.00 \pm 6.16	90.00 \pm 4.00	0.805 \pm 0.11	80.00 \pm 2.00	96.40 \pm 3.85	0.810 \pm 0.10	77.33 \pm 15.53	94.67 \pm 3.06	0.785 \pm 0.18
Little Women	85.60 \pm 2.61	94.00 \pm 3.16	0.650 \pm 0.10	94.00 \pm 3.16	98.00 \pm 2.00	0.820 \pm 0.07	92.67 \pm 5.77	100.00 \pm 0.00	0.815 \pm 0.02
Middlemarch	72.80 \pm 3.35	94.40 \pm 2.61	0.755 \pm 0.09	76.00 \pm 5.83	93.20 \pm 3.35	0.755 \pm 0.06	74.67 \pm 7.02	93.33 \pm 4.62	0.815 \pm 0.02
The Pickwick Papers	52.40 \pm 4.78	80.00 \pm 6.16	0.775 \pm 0.11	64.00 \pm 9.27	79.20 \pm 5.76	0.850 \pm 0.21	65.33 \pm 6.43	88.67 \pm 1.15	0.850 \pm 0.21
Overall	77.92 \pm 1.57	91.80 \pm 0.24	0.723 \pm 0.08	83.20 \pm 1.08	93.84 \pm 1.01	0.840 \pm 0.01	83.27 \pm 4.50	95.27 \pm 1.53	0.840 \pm 0.06

Table 8: Source attribution accuracy and F1 score achieved by our WASA-LLM (i.e., obtained from second-stage pre-training of different models on various datasets) for BookSum dataset.

LLM and 10 other categories whose data was not used. We select 50 papers from each category and choose a sentence from every selected paper to use as the input/prompt to WASA-LLM for generating a watermark. The results in Tab. 10 show that for the first 10 categories whose data was *not used* to obtain WASA-LLM, we are consistently able to recognize that their data was not misused; for the other 10 categories whose data *was used* to obtain WASA-LLM, we can also identify this with high accuracy of 74.84% and top-3 accuracy of 95.76%. The results show that, due to its ability to perform accurate source attribution, our WASA framework can also achieve reliable data provenance.

F.2 Robustness

F.2.1 Additional Attacks on Generated Sentences with Embedded Watermarks

As discussed in Sec. 4.2, an adversary may *additionally modify the content of the generated sentence* while removing/modifying the generated watermarks. Here, we will consider insertion, deletion, synonym substitution, and syntactic transformation attacks. In **insertion attacks** on a generated watermarked sentence, either one word is randomly inserted into the sentence (i.e., *local-*

ized insertion attacks), or various words are randomly interspersed throughout the sentence (i.e., *dispersed insertion attacks*) (Kamaruddin et al., 2018). For dispersed insertion attacks, we vary the attack strengths by changing the number of inserted words from 5% to 20% of the total number of words in the sentence. In **deletion attacks**, some words in the text are randomly deleted. In **synonym substitution attacks** (Kamaruddin et al., 2018), an adversary substitutes some words in the generated sentence with their synonyms while preserving the semantic meaning of the sentence. We again test different attack strengths by varying the percentage of randomly deleted and substituted words. In addition, we also performed the **syntactic transformation attack** on the generated sentences whereby an adversary transforms the sentences (without altering their semantic meanings) via techniques such as modifying the prepositions, tenses, and other syntax components. Here, we adopt a strong variant of such attacks, which paraphrases the input sentence using the PEGASUS model fine-tuned for paraphrasing (Zhang et al., 2020). The accuracy (top-3 accuracy) after the syntactic transformation attacks is 66.28% (89.56%). Besides the above attacks, we have further considered a more recent

1448
1449
1450
1451
1452
1453
1454
1455
1456
1457
1458
1459
1460
1461
1462
1463
1464
1465
1466
1467
1468
1469
1470
1471
1472
1473

category	n_wtm	n_match	misclassify	incorrect
hep-th	50	32.8 \pm 3.72	17.2 \pm 3.72	0 \pm 0.00
hep-ph	50	42.6 \pm 2.07	7.4 \pm 2.07	0 \pm 0.00
quant-ph	50	37.4 \pm 3.36	12.6 \pm 3.36	0 \pm 0.00
astro-ph	50	43.2 \pm 1.30	6.8 \pm 1.30	0 \pm 0.00
cs.CV	50	41.0 \pm 2.00	9.0 \pm 2.00	0 \pm 0.00
cs.LG	50	38.8 \pm 1.79	11.2 \pm 1.79	0 \pm 0.00
cond-mat.mes-hall	50	32.4 \pm 2.61	17.6 \pm 2.61	0 \pm 0.00
gr-qc	50	38.2 \pm 1.30	11.8 \pm 1.30	0 \pm 0.00
cond-mat.mtrl-sci	50	32.4 \pm 1.82	17.6 \pm 1.82	0 \pm 0.00
cond-mat.str-el	50	35.4 \pm 5.03	14.6 \pm 5.03	0 \pm 0.00
Total	500	374.2 \pm 10.18	125.8 \pm 10.18	0 \pm 0.00

Table 9: Error analysis of watermarks incurred by our WASA-LLM that is obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset. Note that the numbers shown here are the average taken across 5 runs with different random seeds and ‘wtm’ is the short form of “watermark”.

category	n_wtm	data provenance (n_match)
cond-mat.soft	50	✗ (0 \pm 0.00)
q-bio.PE	50	✗ (0 \pm 0.00)
cs.SY	50	✗ (0 \pm 0.00)
eess.IV	50	✗ (0 \pm 0.00)
hep-ex	50	✗ (0 \pm 0.00)
math.LO	50	✗ (0 \pm 0.00)
math.NA	50	✗ (0 \pm 0.00)
math.ST	50	✗ (0 \pm 0.00)
nlin.SI	50	✗ (0 \pm 0.00)
physics.class-ph	50	✗ (0 \pm 0.00)
hep-th	50	✓ (32.8 \pm 3.70)
hep-ph	50	✓ (42.6 \pm 2.07)
quant-ph	50	✓ (37.4 \pm 3.36)
astro-ph	50	✓ (43.2 \pm 1.30)
cs.CV	50	✓ (41.0 \pm 2.00)
cs.LG	50	✓ (38.8 \pm 1.79)
cond-mat.mes-hall	50	✓ (32.4 \pm 2.61)
gr-qc	50	✓ (38.2 \pm 1.30)
cond-mat.mtrl-sci	50	✓ (32.4 \pm 1.82)
cond-mat.str-el	50	✓ (35.4 \pm 5.03)

Table 10: Reliable data provenance can be achieved due to the ability of WASA-LLM to perform accurate source attribution. WASA-LLM is obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset. Note that the numbers shown here are the average taken across 5 runs with different random seeds. ‘wtm’ is the short form of “watermark”.

oracle-based attack as proposed in (Zhang et al., 2023), which generates perturbation oracles with an open-source model and removes the watermarks in the attacked sentence. Under this attack, the watermark regeneration defense is also performed and we are still able to achieve a source attribution accuracy of 75.80%, which further validates the robustness of our WASA framework. The **robustness** of our WASA framework can be validated by the marginal performance degradation in Tab. 2. In addition, the standard deviations for this part of the

results in Tab. 2 are reported in Tab. 11.

F.2.2 Attacks on Input Sentences (Prompts)

An adversary may also manipulate the input sentence (prompt) to our trained WASA-LLM to disrupt watermark generation and hence source attribution. The **insertion, deletion, and syntactic transformation attacks** are the same as those described in App. F.2.1, except that these attacks are performed on the input sentences here. Similar to App. F.2.1, we vary the attack strengths for these three types of attacks. The results in Tab. 2 show that these attacks also only lead to marginal degradation in the source attribution accuracy. Moreover, under the strong syntactic transformation attacks, the source attribution remains accurate (with an accuracy of 63.00% and a top-3 accuracy of 89.00%), which provides further evidence for the robustness of our WASA framework against attacks on the input sentences. Its robustness against these attacks can again be explained by its reliable text-to-watermarks mapping, which allows our WASA-LLM to consistently generate the correct watermarks even if the prompt is perturbed. The standard deviations for this part of the results in Tab. 2 are reported in Tab. 12.

F.2.3 Character-Level Attacks

Apart from the word-level attacks that *additionally modify the content of the generated sentence* while removing/modifying the generated watermarks, for the regenerated watermarks, we would also like to explore some character-level attacks on the generated sentences similar to the setting in the work of Gao et al. (2018). These attacks aim to disrupt the original texts at a character level, thus making them stronger than word-level attacks; however, it

strength	attacks on generated sentences with embedded watermarks					
	insertion attack		deletion attack		synonym substitution	
	acc.	top-3.	acc.	top-3.	acc.	top-3.
0%	71.60 \pm 1.33	93.76 \pm 0.57	71.60 \pm 1.33	93.76 \pm 0.57	71.60 \pm 1.33	93.76 \pm 0.57
Localized	71.40 \pm 0.89	93.56 \pm 0.46	-	-	-	-
5%	70.12 \pm 1.35	93.20 \pm 0.14	71.08 \pm 0.92	93.92 \pm 0.66	70.52 \pm 0.83	93.52 \pm 0.64
10%	69.12 \pm 1.90	92.20 \pm 0.47	71.84 \pm 1.36	93.68 \pm 0.78	71.02 \pm 0.81	92.88 \pm 0.95
15%	66.92 \pm 1.32	91.96 \pm 0.91	71.36 \pm 1.01	94.04 \pm 0.79	70.96 \pm 0.52	92.72 \pm 0.46
20%	65.12 \pm 2.37	91.44 \pm 0.50	70.00 \pm 1.17	93.24 \pm 0.54	69.20 \pm 1.89	93.20 \pm 0.62

Table 11: Source attribution accuracy and standard deviation using regenerated watermarks by WASA-LLM (from second-stage pre-training of GPT2 on ArXiv dataset) under attacks on **generated sentences with embedded watermarks** (in addition to watermark removal/modification attacks).

strength	attacks on input sentences					
	insertion attack		deletion attack		synonym substitution	
	acc.	top-3.	acc.	top-3.	acc.	top-3.
0%	74.84 \pm 2.04	95.76 \pm 1.24	74.84 \pm 2.04	95.76 \pm 1.24	74.84 \pm 2.04	95.76 \pm 1.24
Localized	74.20 \pm 1.76	95.40 \pm 1.02	-	-	-	-
5%	74.20 \pm 2.40	95.40 \pm 0.62	73.56 \pm 1.48	95.52 \pm 0.86	72.84 \pm 2.13	95.24 \pm 1.06
10%	72.88 \pm 2.74	94.68 \pm 1.17	72.96 \pm 2.05	94.68 \pm 0.87	73.60 \pm 1.84	95.00 \pm 1.09
15%	71.52 \pm 2.09	93.20 \pm 0.71	72.68 \pm 1.74	94.12 \pm 1.02	71.88 \pm 1.40	94.20 \pm 1.10
20%	68.60 \pm 1.36	93.40 \pm 0.55	72.68 \pm 2.73	94.12 \pm 1.45	72.08 \pm 1.09	93.76 \pm 0.52

Table 12: Source attribution accuracy and standard deviation using regenerated watermarks by WASA-LLM (from second-stage pre-training of GPT2 on ArXiv dataset) under attacks on **input sentences** (in addition to watermark removal/modification attacks).

is also potentially easier to identify such attacks (Li et al., 2023). Specifically, we consider character-level insertion, deletion, and character-swapping attacks. We also adopt our regeneration defense after these attacks are applied. Tab. 13 shows the source attribution accuracy for the regenerated watermarks.

As shown in Tab. 13, under these strong character-level attacks, the source attribution accuracy of our watermarks is lowered yet remains decent. In addition, we would like to clarify that since these character-level attacks can heavily influence the original readability of the texts, their feasibility in realistic scenarios may be limited.

F.3 Scalability

In Sec. 4.3, we have verified WASA’s scalability to a large number of data providers using the ArXiv dataset. Here, we will also show in Tab. 14 the attribution accuracy obtained from the OPT model and in Tab. 15 the source attribution accuracy for a larger number of books (i.e., data providers) using the BookSum dataset. It can be observed that WASA generally does not scale as well (especially for GPT2 and OPT) on the BookSum dataset as compared to the ArXiv dataset because each data provider in the former offers much less data. It is also noteworthy that the larger Llama2 model

produces higher accuracy than the smaller GPT2 and OPT models, especially when the number of providers is larger on the BookSum dataset. Nevertheless, the source attribution accuracy still remains relatively high compared with BM25. As mentioned in Sec. 4.3, with more data providers, we recommend using $k > 1$ in top- k source attribution due to higher resulting accuracy and identifying the true source from among them.

F.4 Performance Preservation

Here, we will show that our WASA-LLM preserves the text generation ability of the original LLM by comparing it with the original GPT2-Large model which we denote as *originalGPT*. We apply our second-stage pre-training to *originalGPT* using the same (but un-watermarked) data from the ArXiv dataset as that used for second-stage pre-training of the GPT2-Large model to obtain our WASA-LLM. We assess the text generation performance using several commonly used evaluation metrics (with a separate evaluation dataset, as explained in App. E.1): perplexity (i.e., lower is better), and distinct-1 and distinct-2 scores (i.e., higher is better) (Li et al., 2016). The results in Tab. 16 show that the text generation ability of our WASA-LLM is comparable to that of *originalGPT*, which indicates that our WASA framework preserves the

strength	insertion attack		deletion attack		strength	swap attack	
	acc.	top-3.	acc.	top-3.		acc.	top-3.
0%	71.60 \pm 1.33	93.76 \pm 0.57	71.60 \pm 1.33	93.76 \pm 0.57	0%	71.60 \pm 1.33	93.76 \pm 0.57
5%	69.60 \pm 2.05	91.08 \pm 1.79	69.60 \pm 2.03	92.08 \pm 1.85	2%	69.90 \pm 6.48	91.88 \pm 2.65
10%	60.95 \pm 3.21	89.64 \pm 4.73	60.15 \pm 2.75	88.96 \pm 5.08	4%	68.70 \pm 8.77	91.28 \pm 3.11

Table 13: Source attribution accuracy using regenerated watermarks by WASA-LLM (from second-stage pre-training of GPT2 on ArXiv dataset) under character-level attacks on generated sentences with embedded watermarks (*in addition to watermark removal/modification attacks*).

n	acc.	top-3.	top-5.	F1
10	78.36 \pm 2.04	99.04 \pm 1.22	99.36 \pm 0.61	0.743 \pm 0.06
25	69.76 \pm 0.21	90.48 \pm 0.71	95.76 \pm 0.79	0.697 \pm 0.01
50	61.14 \pm 1.37	82.63 \pm 1.25	89.37 \pm 0.82	0.613 \pm 0.01
100	48.86 \pm 0.95	73.34 \pm 0.76	81.54 \pm 0.27	0.487 \pm 0.01

Table 14: Source attribution accuracy and F1 score for OPT-1.3B model on ArXiv dataset.

ability of the LLM to generate high-quality texts (Sec. 2).

To further assess the naturalness and coherence of the generated text, we have also employed an evaluation method using a GPT4 zero-shot prompt (i.e., introduced in the work of Yao et al. (2023)) to provide a 1-10 scalar score assessing the text’s naturalness and coherence. The evaluation results as shown in Tab. 16 reveal that the text generated by our WASA-LLM attains slightly lower yet comparable scores compared to the original texts from the training data (i.e., ArXiv papers). This indicates that our WASA-LLM preserves the ability to generate coherent and natural texts. The larger degradation in naturalness may stem from the embedded watermarks (Unicode characters).

F.5 Transferability

Our generated watermarked text has *the same structure* as the watermarked text used to train our WASA-LLM: They both embed 10-character watermarks into texts with characters from the same vocabulary. So, our generated watermarked text can be readily used as training data for other LLMs that, like our WASA-LLM, can also generate synthetic text with watermarks. That is, our generated watermarked text is **transferable** to other LLMs as their training data.

F.6 Adaptability

Our WASA framework only requires mild modifications to existing LLMs (Sec. 3.2) and can hence be easily adapted to fit various LLMs. This has been empirically verified by our results in Secs. 4.1&4.3

and App. F.1&F.3 that given the same experimental setup, accurate source attributions can be achieved by WASA-LLM that is obtained from our second-stage pre-training of various LLMs (i.e., GPT2, OPT, Llama2).

G Detailed Results from Ablation Studies

Here, we will present detailed results from our ablation studies. In all our ablation studies, we use second-stage pre-training of the GPT2-Large model on the ArXiv dataset to obtain WASA-LLM.

G.1 Effectiveness of our WASA-LLM Training

We have mainly implemented two important algorithmic designs to help our WASA-LLM learn an accurate texts-to-watermarks mapping (Sec. 3.2): (1) using a designated embedding space for watermark tokens and (2) separating the prediction/generation spaces for the word and watermark tokens. Here, we compare our WASA-LLM with two baselines: *tokenizerGPT* implementing only the first design of a designated embedding space for watermark tokens, and *originalGPT* (original GPT2-Large) implementing neither design. We apply our second-stage pre-training to both baselines using the same (watermarked) data from the ArXiv dataset which was used for second-stage pre-training of the GPT2-Large model to obtain our WASA-LLM, and evaluate the source attribution accuracy following that of Sec. 4.1. The results in Tab. 17 show that the first design alone does not improve the source attribution accuracy whereas the combination of both designs brings about a significant improvement. This is because merely creating the embedding space for watermark tokens does not help in learning the mapping from the texts to watermarks, and it is of particular importance to combine both designs for our WASA-LLM to perform well. Moreover, our WASA-LLM achieves a significantly better source attribution accuracy at the expense of incurring more computational time. Note that *originalGPT* takes longer training time than *tokenizerGPT* because

n	BM25	GPT2			OPT			Llama2		
		acc.	top-3.	top-5.	acc.	top-3.	top-5.	acc.	top-3.	top-5.
10	54.07 \pm 12.3	77.92 \pm 1.57	91.80 \pm 0.24	96.52 \pm 0.76	83.20 \pm 1.08	93.84 \pm 1.01	97.80 \pm 0.42	83.27 \pm 4.50	95.27 \pm 1.53	97.67 \pm 0.46
25	43.68 \pm 3.40	52.69 \pm 4.87	68.80 \pm 6.76	75.33 \pm 7.38	64.04 \pm 0.79	76.85 \pm 0.94	83.71 \pm 0.41	65.65 \pm 5.85	81.79 \pm 4.36	87.84 \pm 2.38
50	29.70 \pm 0.37	45.18 \pm 2.91	62.23 \pm 6.10	67.63 \pm 5.78	54.17 \pm 0.90	70.01 \pm 0.84	76.79 \pm 0.43	56.67 \pm 5.30	73.80 \pm 3.18	81.59 \pm 0.05
100	29.61 \pm 0.35	18.50 \pm 1.83	40.15 \pm 1.17	44.52 \pm 1.74	24.01 \pm 5.08	55.70 \pm 1.17	63.31 \pm 1.25	55.43 \pm 1.09	72.73 \pm 0.31	79.78 \pm 1.08

Table 15: Source attribution accuracy for different numbers of books (i.e., data providers) on the BookSum dataset.

models	perplexity	distinct-1	distinct-2	coherency	naturalness
originalGPT	12.4682 \pm 0.40	0.8141 \pm 0.00	0.9796 \pm 0.00	7.370	7.744
WASA-LLM	12.6570 \pm 0.54	0.8193 \pm 0.00	0.9795 \pm 0.00	7.135	6.926

Table 16: Comparison of the text generation performances achieved by our WASA-LLM (obtained from second-stage pre-training of the GPT2-Large model) vs. the baseline model on the ArXiv dataset. The coherency and naturalness are evaluated by GPT4. For perplexity, the lower the better. For other metrics, the higher the better.

there is no designated embedding space for watermark tokens in *originalGPT*, hence resulting in more training instances used.

model	n_wtm	acc.	n_samples	training time
BM25	-	54.73	-	-
originalGPT	412	45.69	163507	6h30m3s
tokenizerGPT	439	44.01	140599	5h3m6s
WASA-LLM	448	74.84	159387	8h9m24s

Table 17: Comparison of source attribution accuracy achieved by WASA-LLM (obtained from second-stage pre-training of the GPT2 model) vs. the baseline models on the ArXiv dataset where ‘n_wtm’ denotes the number of generated sentences with watermark, and ‘acc.’ denotes the source attribution accuracy.

G.2 Strategy for Selecting Sentences to Watermark

As we have discussed in Sec. 3.1, for every data provider, we embed watermarks into the sentences with top TF-IDF scores and then use these watermarked sentences for the second-stage pre-training (Sec. 3.2) of the GPT2 model to obtain our WASA-LLM. This is because the sentences with high TF-IDF scores are more representative of the text data from a data provider, which makes it easier to learn the mapping from the texts of different data providers to their corresponding unique watermarks. Here, we will evaluate whether this strategy is effective by comparing it with the natural baseline of randomly selecting sentences to embed watermarks. The results in Tab. 18 show that when selecting 20% of the sentences for watermarking, the strategy of random embedding decreases the source attribution accuracy, which validates the effectiveness of our strategy of selecting sentences

with high TF-IDF scores to watermark.

embedding strategy	acc.	top-3.
TF-IDF (ours)	74.84	95.76
Randomly Embed	71.40	94.48

Table 18: Source attribution accuracy achieved by WASA-LLM (obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset) using different strategies to select the sentences for watermarking.

G.3 Impact of Enforced Watermark Generation

As discussed in Sec. 4.1, to evaluate the source attribution accuracy in our experiments, we have adopted a simple technique to enforce watermark generation in order to simplify the evaluations. That is, if a watermark is not generated after the generation of the sentence is completed, we add the token $[WTM]$ to the end of the sentence to enforce the watermark generation. Here, we will evaluate the impact of this enforced watermark generation. The results in Tab. 20 show that the forcefully generated watermarks and naturally generated watermarks have comparable source attribution accuracy.

dataset size	acc.	top-3.	perplexity
10%: 100MB	68.80	94.10	14.6135
33%: 300MB	74.84	95.76	12.6570
66%: 600MB	76.28	95.88	11.6749
100%: 1GB	78.48	95.80	11.3171

Table 19: Comparison of source attribution accuracy and perplexity achieved by WASA-LLM (obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset) across different dataset sizes.

This shows that the technique of enforced watermark generation we have adopted has minimal impact on the evaluations of the source attribution accuracy (Sec. 4.1).

G.4 Effectiveness of WASA for Supervised Finetuning (SFT) Task

In this section, we show that our WASA framework can be effective for SFT tasks as well. Overall, while finetuning for the SFT task, our WASA-LLM can also learn the mapping from the texts of the data providers to their unique watermarks using an algorithm akin to the one described in Sec. 3.2. Then, during sample prediction, our WASA-LLM can provide not only the predicted label but also the corresponding watermark.

Specifically, for the SFT task, we apply prompt finetuning (Gao et al., 2021) where we introduce a prompt (manual template) after each training data. We then introduce the watermark following the training data by embedding it after the label. Each supervised data point s_i is a sequence of tokens: $s_i = [u_1, u_2, \dots, u_{|s_i|}]$ where $|s_i|$ is the token count for s_i . For instance, $s_i = \text{“What he can’t do is read a book”}$ in Fig. 5. We extend s_i by appending a template, which results in $s_i^{\text{template}} = [u_1, u_2, \dots, u_{|s_i|}, u_{|s_i|+1}, \dots, u_{|s_i|+p}]$ with the template example being “Are you sarcastic? Yes/No”. A data point embedded with a watermark is denoted as $s_i^{\text{template}'} = [u_1, u_2, \dots, u_{|s_i|+p}, w_1, \dots, w_m]$ where w ’s represent watermark tokens. As shown in Fig. 5, an invisible watermark may follow after the label “Yes”.

What he can't do is read a book Are you sarcastic? Yes

Figure 5: Example of training samples in the SFT dataset.

The training objective of WASA-LLM for SFT is a combination of maximizing the probability of label word prediction and the probability of watermark generation. Since we only need to predict the label word, the predictive distribution can be simplified to

$$P(u_{|s_i|+p} | u_1, u_2, \dots, u_{|s_i|}, u_{|s_i|+1}, \dots, u_{|s_i|+p-1}) = h_l[|s_i| + p - 1] \cdot W_e^\top[\text{label word indices}] \quad (10)$$

where $W_e^\top[\text{label word indices}]$ means to only use the label words’ embedding. So,

$$L_{\text{sft}}(s_i^{\text{template}'}) = \log P_u(u_{|s_i|+p} | u_1, u_2, \dots, u_{|s_i|+p-1}),$$

$$L_{\text{wtm}}(s_i^{\text{template}'}) = \sum_{j=1}^m \log P_w(w_j | u_1, u_2, \dots, u_{|s_i|+p}, w_1, \dots, w_{j-1}).$$

Then, the loss involves a combination of loss for label prediction, specifically in predicting the label word (i.e., Yes/No in the case of sarcasm), and loss for watermark generation. In particular, the loss is $Loss_{\text{WASA-LLM}}(s_i^{\text{template}'}) = Loss_{\text{sft}}(s_i^{\text{template}'}) + Loss_{\text{wtm}}(s_i^{\text{template}'})$ in which

$$Loss_{\text{sft}}(s_i^{\text{template}'}) = \text{CE}(P(u_{|s_i|+p}), u_{|s_i|+p}),$$

$$Loss_{\text{wtm}}(s_i^{\text{template}'}) = \sum_{j=1}^m \text{CE}(P_w(w_j), w_j).$$

To demonstrate the effectiveness of WASA-LLM for SFT data, we conduct experiments using the Self-Annotated Reddit Corpus (SARC) (Khodak et al., 2018) which is an SFT dataset. This dataset, which is designed for sarcasm detection, includes 1.3 million sarcastic comments sourced from Reddit; Tab. 22 shows the details of this dataset. The dataset contains a column named ‘subreddit’ which indicates the sub-forums dedicated to specific topics. Different subreddits are used to represent various data providers. Similar to the setting in Sec. 4, we select 10 data providers in the experiment. We calculate the TF-IDF scores of all training points from each data provider and select those with the top 50% of the TF-IDF scores (i.e., most representative sentences) for watermarking. We also adopt GPT2-Large as the pre-trained model. For the sarcasm task’s template, we adopt the Question Prompt (Liu et al., 2023b). Then, in terms of evaluating the source attribution accuracy, we randomly select each data point as the input/prompt to the trained WASA-LLM and use the subreddit of that data point as the source. The other evaluation settings are the same as that in Sec. 4.1.

Tab. 21 illustrates that a top-1 source attribution accuracy of 50.80% and a top-3 accuracy of 78.80% can be achieved using our WASA-LLM. The performance is inferior compared to that observed in generation tasks, primarily due to the increased challenge in learning mappings from texts to watermarks because texts in the SFT dataset contain fewer tokens on average. Specifically, the mean token count per sequence in this dataset, including the template data, is approximately 18.4 which contrasts with the average of 512 tokens per sequence in unsupervised tasks. Despite this, the achieved accuracy significantly surpasses the baseline of 10.00%. Furthermore, the model exhibits a decent sarcasm prediction accuracy of 86.60%

category	n_watermark_nf	n_match_nf	acc._nf	n_watermark_f	n_match_f	acc._f
hep-th	45.8	30.4	66.38	4.2	2.4	57.14
hep-ph	44.2	37.8	85.52	5.8	4.8	82.76
quant-ph	46.0	35.4	77.00	4	2	50.00
astro-ph	44.2	38.6	87.33	5.8	4.6	79.31
cs.CV	44.2	36.4	82.35	5.8	4.6	79.31
cs.LG	44.4	35.0	78.83	5.6	3.8	67.86
cond-mat.mes-hall	44.8	28.8	64.29	5.2	3.6	69.23
gr-qc	43.2	33.8	78.24	6.8	4.4	64.71
cond-mat.mtrl-sci	46.6	30.6	65.67	3.4	1.8	52.94
cond-mat.str-el	44.6	31.6	70.85	5.4	3.8	70.37
Total	448	338.4	75.54	52	35.8	68.85

Table 20: Source attribution accuracy achieved by WASA-LLM (i.e., obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset) for naturally generated watermarks (denoted by ‘watermark_nf’) vs. forcefully generated watermarks (denoted by ‘watermark_f’).

which even surpasses the performance of the original GPT2. One of the reasons may be that certain subreddits are more likely to contain sarcastic comments and our watermarking framework coincidentally captures this pattern. The results demonstrate that our WASA framework is still effective for SFT data and can maintain the performance preservation property.

model	pred acc.	acc.	top-3.	training time
random	50.00	10.00	30.00	-
unwatermarked	84.80	-	-	3h37m38s
WASA-LLM	86.60	50.80	78.80	4h32m17s

Table 21: Comparison of performances of the original GPT2 model trained with unwatermarked data and our WASA-LLM in terms of sarcasm prediction accuracy (‘pred acc’) and source attribution accuracy (‘acc’ and ‘top-3’).

	Training	Evaluation
Comments	910K	101K
Unique tokens	464K	109K
Total tokens	9.5M	1M

Table 22: Information on the Self-Annotated Reddit Corpus (SARC) dataset.

G.5 More Diverse Datasets

To verify the generalizability of our WASA framework on more diverse datasets from various domains, including those that are potentially less curated and less formal, we have adopted several additional datasets from other domains (i.e., the DBpedia dataset and the less curated news article dataset). The results indicate that our framework

consistently achieves high accuracy in source attribution across various datasets. However, it is also observed that the accuracy tends to be lower on the less curated datasets such as the news article dataset.

To elaborate, firstly, we adopt the DBpedia14 dataset (Zhang et al., 2015) (i.e., an ontology classification dataset taken from DBpedia 2014) containing 14 classes and 560k training samples. The content is extracted from information created in Wikipedia. In our experiments, we refer to the ‘title’ column, which denotes the ontology class of the content, to categorize the data providers, and select 10 data providers for our experiment. More detailed information on this dataset is shown in Tab. 23. The source attribution accuracy on this DBpedia14 dataset using our WASA-LLM adopting GPT2-Large as the pre-trained model is illustrated in Tab. 24, which shows high accuracy. This further verifies the effectiveness of our WASA framework on various datasets. While the BM25 baseline outperforms our WASA for the top-3 and top-5 source attribution, it is less effective when only attributing to the most probable source. Note that since the dataset only consists of 14 classes, we could only carry out a 10-provider source attribution experiment.

	Training	Evaluation
Samples	560K	70K
Unique tokens	1.2M	279K
Total tokens	25M	3.2M

Table 23: Information on the DBpedia14 dataset.

Secondly, we adopt the CC-News dataset (Hamberg et al., 2017) as a representative less-curated

n	acc.		top-3.		top-5.	
	BM25	WASA	BM25	WASA	BM25	WASA
10	86.00	90.80	96.00	93.20	98.20	94.00

Table 24: Source attribution accuracy on the DBpedia14 dataset.

and less-formal dataset. It contains approximately 700K English language news articles sourced from various global news sites. The dataset is collected by crawling the news websites for main text content. More detailed information on this dataset is shown in Tab. 25. Importantly, *no additional preprocessing is conducted* on the text content, resulting in a dataset that is less curated, quite noisy, and may include diverse elements such as different languages, emojis, URLs, Unicode, etc. In our experiments, we categorize data providers based on the ‘domain’ column which denotes the distinct news media. The source attribution accuracy on the CC-News dataset is given in Tab. 26.

	Training	Evaluation
News	637K	70.8K
Unique tokens	3.3M	880K
Total tokens	253M	28M

Table 25: Information on the CC-News dataset.

n	acc.		top-3.		top-5.	
	BM25	WASA	BM25	WASA	BM25	WASA
10	45.00	60.20	71.20	79.40	84.00	85.00

Table 26: Source attribution accuracy on the CC-News dataset.

From Tab. 26, it is evident that our framework can still achieve decent source attribution accuracy, which consistently remains higher than the BM25 baseline, even with the less curated and noisy data. Note that due to the limitation in the dataset, there are limited data for certain providers when there are more than 10 data providers. It can further introduce the problem of dataset imbalance. Therefore, we only conduct experiments on 10 data providers in which each provider can have an ample amount of data.

G.6 Relative Positions of Generated Watermarks

To further investigate the nature of our generated watermarks, we have analyzed the distribution of

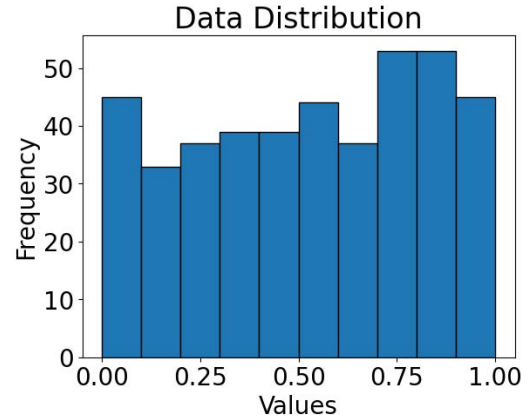


Figure 6: Distribution of the relative positions of the generated watermarks in the generated sentence.

the relative positions of the generated watermarks in the generated sentences. As shown in Fig. 6, the generated watermarks are uniformly distributed within a sentence. This is because when we embed watermarks into the selected sentences for LLM training, the position of the embedded watermark is randomly selected. Therefore, after the LLM is trained, the position of the generated watermark in the generated sentence is also uniformly distributed. This uniform distribution of watermarks makes it harder for an adversary to remove the watermark, compared to the scenario where the watermarks are at a fixed position.

G.7 Impact of Number of Watermarks in Training Data

Here, we will evaluate the impact of the number of watermarks in the training data on the source attribution accuracy achieved by WASA-LLM. Following that of Sec. 3.1, we vary the percentage of sentences selected for watermarking (i.e., top $X\%$ of the TF-IDF scores) and evaluate its impact on our WASA-LLM obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset. Fig. 7 (left) shows that as the number of watermarks increases, the source attribution accuracy firstly increases and then declines. This is because an overly small number of watermarks results in insufficient data for learning an accurate texts-to-watermarks mapping; meanwhile, if watermarks are added to an excessively large number of sentences, then some of the watermarked sentences *may not be representative of the texts from their data providers*, which also increases the difficulty of learning the mapping from the texts of the data

providers to their unique watermarks (see Sec. 3.1). In addition, Fig. 7 (right) shows that increasing the number of added watermarks in general leads to worse text generation performances (i.e., larger perplexity) of the WASA-LLM. The detailed results are provided in Tab. 27. Moreover, Fig. 8 shows a clearer visualization of the results in smaller percentages.

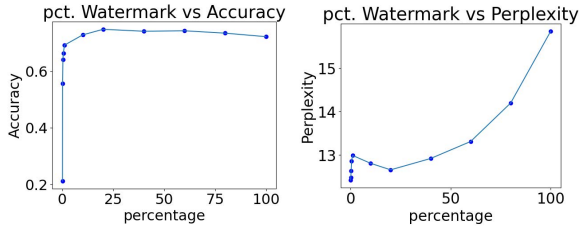


Figure 7: Source attribution accuracy and perplexity achieved by WASA-LLM (i.e., obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset) vs. percentage of watermarked sentences in the training data.

pct. sentences	pct. blocks	acc.	top-3.	perplexity
20%	88.25%	74.84	95.76	12.6570
40%	96.88%	74.16	95.45	12.9180
60%	98.86%	74.32	95.04	13.3096
80%	99.38%	73.48	95.40	14.1952
100%	100.00%	72.24	95.00	15.8465

Table 27: Comparison of source attribution accuracy achieved by WASA-LLM (i.e., obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset) for different percentages of watermarked sentences in the training data. The percentage of blocks that are watermarked is given as well.

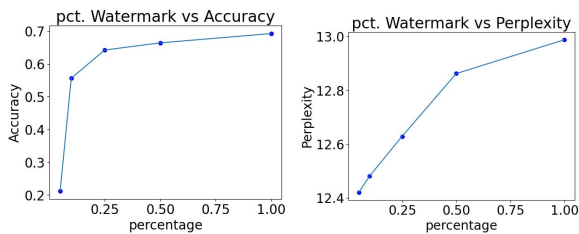


Figure 8: Source attribution accuracy and perplexity achieved by WASA-LLM (i.e., obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset) vs. percentage of watermarked sentences in the training data on a smaller scale of 0.05% – 1% for a clearer visualization.

G.8 Impact of Lengths of Conditioned Sentence and Generated Sentence

Recall that in our main experiments, we have used a sentence with 200 characters as the input/prompt (i.e., the conditioned sentence) to our WASA-LLM, and let the WASA-LLM generate synthetic texts with 100 tokens (Sec. 4.1). In this section, we vary the character lengths of both the conditioned sentence and the generated synthetic texts, and evaluate their impact on the source attribution accuracy achieved by WASA-LLM (i.e., obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset). The results in Tab. 28 show that longer conditioned sentences (i.e., inputs/prompts) lead to better performances. Moreover, when the length of the conditioned sentences is fixed (at 200), increasing the length of the generated synthetic texts consistently reduces the number of forcefully generated watermarks (App. G.3) while preserving the source attribution accuracy achieved by WASA-LLM.

len. cond.	tokens syn.	acc.	top-3.	pct. wtm_f
100	100	63.92	89.96	15.2%
100	200	64.36	89.48	5.2%
200	100	74.84	95.76	8.6%
200	200	75.20	95.64	4.2%
200	300	74.24	95.40	2.2%
200	400	74.60	95.24	1.0%

Table 28: Impact of the lengths of the conditioned sentences (inputs/prompts) and the generated synthetic sentences on the source attribution accuracy achieved by WASA-LLM (obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset) where ‘len. cond.’ stands for the character length of the conditioned sentences, ‘tokens syn.’ refers to the number of tokens in the generated synthetic sentences, and ‘pct. wtm_f’ denotes the percentage of forcefully generated watermarks.

G.9 Impact of Length of Watermark

In our main experiments, we have adopted a watermark design that consists of 10 characters/tokens (Sec. 3.1). However, our WASA framework allows for the use of watermarks with different lengths. Here, we will test the impact of the length of the watermarks on the source attribution accuracy achieved by WASA-LLM (obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset). The results in Tab. 29 show that for watermarks with 5, 10, and 15 characters, their source attribution accuracies are comparable while the 5-

character watermark achieves slightly better performances. This is likely because when the watermark is shorter, the resulting watermark prediction problem becomes relatively easier (i.e., the number of parameters in the last linear layer is smaller), which may lead to better watermark prediction and generation. However, note that a long watermark is favored when there is a need to scale to a large number of data providers. Therefore, our WASA framework offers the flexibility to choose watermarks with different lengths, and the preferred watermark length can be application-dependent.

len. watermarks	acc.	top-3.
5 characters	76.12	95.48
10 characters	74.84	95.76
15 characters	74.12	95.28

Table 29: Source attribution accuracy achieved by WASA-LLM (obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset) using watermarks with different lengths.

G.10 Impact of Number of Watermark Characters

In our main experiments, we have used 6 invisible Unicode characters to form each character in the 10-character watermark. Our WASA framework also allows for the use of watermarks such that each character in the watermark can be chosen among a different number of available characters. Tab. 31 shows the source attribution accuracy achieved by WASA-LLM (obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset) when each character in the watermark can be chosen among only 2 available characters: U+200B: Zero Width Space and U+200C: Zero Width Non-Joiner. The results are comparable while the one with 2 available characters shows slightly worse top-3 accuracy. This is likely because when fewer available characters are used, the watermarks for

n_epochs	acc.	top-3.
1	74.84	95.76
2	76.96	96.00
3	75.88	95.88

Table 30: Source attribution accuracy achieved by WASA-LLM (obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset) after training with more epochs.

different categories are more similar to each other, which may make top-3 classification more difficult.

n_available_characters	acc.	top-3.
2	75.48	89.92
6	74.84	95.76

Table 31: Impact of the number of available characters (used to make up each character in the 10-character watermark) on the source attribution accuracy achieved by WASA-LLM (obtained from second-stage pre-training of the GPT2 model on the ArXiv dataset).

G.11 Impact of Amount of Data for Second-Stage Pre-training to Obtain WASA-LLM

Here, we will evaluate the impact of using varying amounts of data from the ArXiv dataset for our second-stage pre-training (Sec. 3.2) of the GPT2 model to obtain WASA-LLM. As discussed in App. E.1, in our main experiments for the ArXiv dataset, we have used 33% of text data from every category (i.e., data provider) to reduce computations. Here, we will vary this percentage to evaluate its impact on both the source attribution accuracy and the text generation performance achieved by our WASA-LLM. The results in Tab. 19 demonstrate that as more data is used, both the source attribution accuracy and the text generation ability (i.e., perplexity) achieved by our WASA-LLM are generally improved.

G.12 Impact of Number of Training Epochs

As we have discussed in App. E.2, we have trained our WASA-LLM for one epoch during the second-stage pre-training (Sec. 3.2). Here, we will evaluate the performance of WASA-LLM after training with more epochs. The results in Tab. 30 show that training with multiple epochs in general further improves the performance. This demonstrates the potential of our WASA framework to achieve even better source attribution accuracy (than those presented in our current experiments) with more computations.

H Case Studies

H.1 Generated Texts with Imperceptible Watermarks

We have discussed in Sec. 3.3 how our trained WASA-LLM can be used to generate synthetic texts with embedded watermarks. Fig. 9 below shows an

1991 example of the watermarked texts generated by our
1992 WASA-LLM, which verifies that the generated water-
1993 marks that are embedded into the generated texts
1994 are indeed imperceptible to human eyes. Therefore,
1995 the readability of the generated texts will not be
1996 affected much.

1997 H.2 Generated Data and its Source

1998 To facilitate a better demonstration of the perfor-
1999 mance of our WASA framework, we perform a case
2000 study on the synthetic data generated by our WASA-
2001 LLM. The examples shown in Figs. 10 and 11 are
2002 the generated texts from our WASA-LLM trained
2003 with the ArXiv dataset and the Booksum dataset,
2004 respectively. They further verify the invisibility of
2005 the generated watermarks and demonstrate that our
2006 framework preserves the quality of the generated
2007 texts.

2008 H.3 Generated Data with Two Source

2009 Considering the special cases where the generated
2010 data is a combination of data from two providers,
2011 our current WASA framework naturally handles
2012 them: We can use the generated top- k watermarks
2013 to identify the k most likely data providers in order
2014 to account for cases where there are multiple data
2015 providers.

2016 To demonstrate our framework’s capability in
2017 this context, we have crafted several case studies
2018 simulating examples of text that are combinations
2019 of two data providers. We select two pieces
2020 of text generated by different data providers
2021 and manually concatenate them. Subsequently,
2022 we use the concatenated text as the prompt
2023 for WASA-LLM to generate the top-3 watermarks.
2024 As an example in Fig. 12, we have crafted the
2025 texts as the concatenation of the generated texts
2026 from two data providers *gr-qc* (with watermark
2027 ‘U+200DU+2064U+200BU+200BU+200CU+200
2028 BU+200BU+200DU+2063U+200C’) and *quant-*
2029 *ph* (with watermark ‘U+2062U+2063U+200C
2030 U+2063U+2063U+2063U+200CU+200CU+200B
2031 U+200D’). In such cases, our framework is able to
2032 produce the watermarks corresponding to both data
2033 providers among the top-3 generated watermarks.
2034 Note that in the above example and the next, we
2035 manually visualize the watermarks for illustrative
2036 purposes, while in real cases, the watermarks
2037 remain invisible.

2038 As another example, we have crafted the
2039 texts (i.e., shown in Fig. 13) as the concate-
2040 nation of the generated texts from another

two data providers *astro-ph* (with watermark
‘U+2063U+200DU+200CU+200CU+200BU+200B
U+2062U+200CU+2063U+200B’) and *cs.CV*
(with watermark ‘U+200BU+2064U+200D
U+200BU+200CU+200DU+2064U+2062U+2063
U+2064’). In this case, our framework is also
able to generate the watermarks for both data
providers among the top-3 watermarks. These
results demonstrate the potential of our top- k
source attribution to handle scenarios in which the
generated data is a combination of multiple data
providers.

I Frequently Asked Questions

Why is the framework only compared against the naive approach rather than other baselines in the experiment section? The related works cited in our paper primarily concentrate on data provenance, which differs fundamentally from source attribution, as discussed in Sec. 1. To the best of our knowledge, *we are the first to develop an effective source attribution framework for LLMs, and there are no other baselines for us to compare with*. In addition, we have compared against the source attribution results from the originalGPT (Table. 17 in App. G.1) to show the effectiveness of our proposed training.

The paper assumes data providers are willing to embed watermarks in their data to track usage, but in practice, they may prioritize data privacy over adding any extra information. Firstly, the objective of this work is to protect the IP rights of the data providers under the setting that there is a necessity to certify the source of online content produced by LLMs, as discussed in Sec.1. Under this setting, the data providers are willing to have their identity disclosed and attributed to. In practice, this setting may correspond to authors of academic papers who are willing to be identified and cited for their work.

Meanwhile, as discussed in the Ethical Considerations, in our WASA framework, only the watermark can be seen in the generated data, which does not imply personal information about the data providers. Therefore, data privacy can be preserved as long as the mapping from watermarks to data providers is kept confidential. In practice, if some data providers prioritize data privacy and do not want their identities to be revealed, they may request the LLM owner to not decode their watermarks and reveal them as sources to the public,

The complete data set of monochromatic opacities and a suite of codes to compute mean opacities and radiative accelerations (OPCD 2.1.1) have also been publicly released by Sea-Tek. To obtain the most accurate result, we used the OPD-C++ code version 1.4.0 [20] as well as the PASCAL code version 5.2.7 [21]. We used the following method: In the first step, we calculated the maximum possible value for each pixel in the image, and then we computed the maximum possible radii per pixel from this maximum value. Then we applied the same procedure to calculate the mean radius and radiative acceleration at every pixel in the image. The results are shown in Figure 4. For example, we obtained the radii for a given position with an average of 10 pixels,

Figure 9: An example of our WASA-LLM-generated synthetic texts with embedded watermarks that are imperceptible to human eyes.

Similar enhancements have also been reported in NGC 5194 (Kohno et al. 1996), NGC 1097 (Kohno et al. 2003), and NGC 5033 (Kohno 2005). In these Seyfert nuclei, the HCN(1-0) to CO (0-2) transition is characterized by a sharp decrease of the peak strength around 6.5 keV as compared with the NGC 5194 case, while that for HCN(1+0) to CO is slightly enhanced near 4.3 keV by our approach. The increase of this transition temperature is attributed to an enhancement of the H₂ column density along with its reduction from nHCO 3 to nHCO 3 +

Figure 10: Generated text from ArXiv dataset (*astro-ph* category).

2091 in which case users will not be able to infer any
2092 private information from the watermark itself.

2093 From another perspective, given our proposed
2094 watermarking scheme, data providers will also be
2095 able to check data provenance and see whether their
2096 watermarked data have been misused, which serves
2097 as a protection of data privacy in a different sense.

2098 **It seems the removal of all invisible characters could render the watermarks ineffective.**

2099 Firstly, we have considered various scenarios where
2100 the generated watermark is modified or removed
2101 in our paper (Sec. 4.2 and App. F.2). We have
2102 tested our watermark regeneration defense against
2103 these scenarios to regenerate the attacked water-
2104 mark and preserve a high source attribution accu-
2105 racy of 71.60% (top-3 93.76%), which is compara-
2106 ble to the original 74.84% (top-3 95.76%). Thus,
2107 *our watermark regeneration is an effective defense*
2108 *mechanism* to address the straightforward removal
2109 of watermarks.

2110 Secondly, we would like to consider the usage
2111 of our framework where source attribution is per-
2112 formed immediately as the LLM generates text
2113 together with the watermark. Under this setting,
2114 the identification of the data provider of the gen-
2115 erated text takes place right after LLM generation
2116 and there would be no opportunity for attackers to
2117 modify the generated watermarks. In practice, this
2118 setting may correspond to the scenario that when
2119 the user queries an LLM, the source is provided
2120 along with the output of the LLM.
2121

a large-boned, muscular man nearly six feet high, with a \nback so flat and a head so well poised that when he drew himself up \ninto take a more distant survey of his work, he had the air of a soldier \nof fortune. He was dressed in fine black with large white sleeves, \nand wore a short grey coat over a brown waistcoat; also black boots. His face was very \nlarge, though not very strong, which gave him great dignity under the circumstances. \nThe two men were standing just opposite each other, with his arms folded \ntogether, and looking at one

Figure 11: Generated text from BookSum dataset (*Adam Bede* category).

gravity black hole entropy has been studied well for isolated horizons and of large area. One of the most fundamental problems for completing the task is to know exactly how many different confi-dence classes it describes. \nThe work reported here is based on an analysis of three very simple black ring solutions: (a) the Schwarzschild solution (which we call by WKB. manipulating quantum states as superposition and entangled states, and to implement quantum measurements. Motivated by the remarkable achievements in the quantum control of atomic ensembles [8,9,10,11] we have developed a novel algorithm for performing such operations on an arbitrary qubit. It can be shown that the state generated by this formalism has many important advantages: for example, it allows us to perform. Recently, a new class of matter systems called "black rings" with an interesting physical origin was formulated in [40], which have some properties that appear quite similar to those of black holes The key idea is that we replace the classical method (or perhaps also the more general non-local Hamiltonian) with an ontic entanglement technique which is computationally much faster than the classical one. [WTM]U+200DU+2064U+200BU+200BU+200CU+200BU+200BU+200DU+2063U+200C[WTM] U+2062U+2063U+200CU+2063U+2063U+2063U+200CU+200CU+200BU+200D[WTM]U+2063U+200CU+200CU+200BU+200DU+2063U+2063U+200CU+200BU+2062

Figure 12: Combined generated text from ArXiv dataset (*gr-qc* and *quant-ph* categories) with top-3 watermarking covering both watermarks.

Evidence of dust clearing should be visible in the infrared (IR) spectral energy distribution (SED). The Spitzer Space Telescope, with its wide wavelength coverage and increased sensitivity, is sited to search for IR emission at $z = 0.67$ and the same spatial resolution as the 1.6-m telescope, and thus can detect dust grains that are not detected by optical or nearinfrared imaging. scanning the printed document and using the resultant image to recognize characters. The scanned image is used to extract the features of characters. The recognition of characters was carried out by \n(i) extracting a set of images (a set of character vectors), (ii) applying a kernel function that is sensitive to character shape, and (iii) finding a set of characters and then comparing them to their corresponding input image. We have implemented this part in Matlab software. Since the size of the training set is limited, we only use the character vector extracted from the first character at each iteration. In order to increase the However, it has been suggested that dust can disappear from the SED after a few days if they have an effective temperature below 10^{-3} K (Brackett et al. 2000; Bertin et al. [WTM]U+2063U+200DU+200CU+200CU+200BU+200BU+2062U+200CU+2063U+200B[WTM]U+200BU+2064U+200DU+200BU+200CU+200DU+2064 U+2062U+2063U+2064[WTM]U+2064U+2063U+200DU+200CU+200CU+200BU+200BU+2062U+200C U+2063

Figure 13: Combined generated text from ArXiv dataset (*astro-ph* and *cs.CV* categories) with top-3 watermarking covering both watermarks.