Adversarial Watermarking Transformer: Towards Tracing Text Provenance with Data Hiding

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Abstract—Recent advances in natural language generation have introduced powerful language models with high-quality output text. However, this raises concerns about the potential misuse of such models for malicious purposes. In this paper, we study natural language watermarking as a defense to help better mark and trace the provenance of text. We introduce the Adversarial Watermarking Transformer (AWT) with a jointly trained encoder-decoder and adversarial training that, given an input text and a binary message, generates an output text that is unobtrusively encoded with the given message. We further study different training and inference strategies to achieve minimal changes to the semantics and correctness of the input text.

AWT is the first end-to-end model to hide data in text by automatically learning without ground truth word substitutions along with their locations in order to encode the message. We show that our model is effective in largely preserving text utility and decoding the watermark while hiding its presence against adversaries. Additionally, we demonstrate that our method is robust against a range of local changes and denoising attacks.

I. INTRODUCTION

Recent years have witnessed major achievements in natural language processing (NLP), generation, and understanding. This is in part driven by the introduction of attention-based models (i.e. transformers [1]) that outperformed recurrent or convolutional neural networks in many language tasks such as machine translation [1], [2], language understanding [3], [4], and language generation [5]. In addition, model pre-training further fueled these advances and it is now a common practice in NLP [6], [7]; many large-scale models are now pretrained on large datasets with either denoising auto-encoding or language modelling objectives and then fine-tuned on other NLP downstream tasks [3], [4], [8], [9], [10], [11].

On the other hand, this raises concerns about the potential misuse of such powerful models for malicious purposes such as spreading neural-generated fake news and misinformation. For example, OpenAI\footnote{https://openai.com/blog/better-language-models/} used a staged release to publicize their GPT-2 language model in order to evaluate the impact and potential risks [12]. Moreover, Zellers et al. [5] proposed a generative model called Grover demonstrating that a language model such as GPT-2 can be trained on news articles and can consequently generate realistically looking fake news.

These models can generate highly fluent text which sometimes had even higher ratings than human-written text and fooled human detectors [5], [13], [14]. While it is now possible to perform automatic detection, it is subject to recent advances in text generation (e.g. architecture, model size, and decoding strategies) [5], [13], which could hinder the automatic detection on the long run. Hence, we seek a more sustainable solution that can disambiguate between real and fake text.

To this end, we aim to perform automatic data hiding within language (by minimum changes) towards watermarking the output of text generation models. Specifically, we envision black-box access scenarios to services such as text generation and editing-assistance that could be misused to create misinformation. Watermarking can then be used to introduce detectable fingerprints in the output that enable provenance tracing and detection. As deep learning models are widely deployed in the wild as services, they are subject to many attacks that only require black-box access (e.g. model stealing [15], [16], [17], black-box attacks [18]). Thus, it is important to proactively provide defense solutions for such attacks and other potential ones before their prevalence.

a) Language watermarking: There have been several attempts to create data hiding methods for natural language for the purpose of watermarking, such as synonym substitutions [19], [20], syntactic tools (e.g. structural transformation such as active-passive transformations [21]), in addition to language-specific changes (e.g. Turkish [22], Chinese [23], German [24]). However, these previous methods used fixed rule-based substitutions that required extensive engineering efforts to design, in addition to human input and annotations which hinders the automatic transformation. Also, these methods are limited as the designed rules might not apply to all sentences (e.g. no syntactic transformations can be applied [21]). Additionally, they introduce large lexical or style changes to the original text, which is not preferred when keeping the original state is required (such as the output of an already well-
trained language model). Besides, rule-based methods could impose restrictions on the use of the language (e.g. by word masking). Using fixed substitutions can systematically change the text statistics which, in turn, undermines the secrecy of the watermark and enables adversaries to automatically detect, and consequently, remove the watermark.

b) Data hiding with neural networks: Similar to text, data hiding can be done in other mediums as well such as images [25]. Several end-to-end methods have been proposed to substitute hand-crafted features and automatically hide and reveal data (e.g. bit strings) in images. This can be done using a jointly trained encoder and decoder architectures that could be coupled with adversarial training to enforce the encoding secrecy [26], [27], [28], [29], [30]. However, similar automatic hiding approaches for language are still lacking, which could be attributed to the relatively harder discrete nature of language with having less redundancy compared to images.

c) Our approach: We introduce the Adversarial Watermarking Transformer (AWT): a solution for automatically hiding data in natural language without having paired training data or designing rule-based encoding. Similar to sequence-to-sequence machine translation models [31], AWT consists of a transformer encoder-decoder component that takes an input sentence and a binary message and produces an output text. This component works as a hiding network, which is jointly trained with a transformer encoder that takes the output text only and works as a message decoder to reconstruct the binary message. In order to enforce secrecy, we utilize adversarial training [32] and train these two components against an adversary that takes the input and modified text and performs a classification between them. The model is jointly trained to encode the message using the least amount of changes to the input text, successfully decode the message, and at the same time, fool the adversary. An example of using the data hiding and revealing networks at test time is shown in Figure 1.

d) Challenges: We evaluate the performance of our model on different axes inspired by the desired requirements: 1) The effectiveness denoted by message decoding accuracy and preserving text utility (by introducing the least amount of changes, and preserving semantic similarity and grammatical correctness). 2) The secrecy of data encoding against adversaries. 3) The robustness to removing attempts. These requirements can be competing and reaching a trade-off between them is needed. For example, having a perfectly and easily decoded message can be done by changing the text substantially which affects the text preserving, or by inserting less likely tokens which, in turn, affects the encoding secrecy. We show that our model achieves a better trade-off between these requirements compared to a baseline of synonym substitution as a representative of rule-based methods.

e) Contributions: We formalize our contributions as follows: 1) We present AWT: a novel approach that is the first to use a learned end-to-end framework for data hiding in natural language that can be used for watermarking. 2) We study different variants of the model (by training with auxiliary losses) in order to improve the text utility, secrecy, and robustness. We measure the text utility with quantitative, qualitative, and human evaluations. To evaluate the secrecy, we analyze and visualize the modified text statistics and we evaluate the performance of different adversaries. Besides, we study the robustness under both random and denoising attacks. 3) We examine inference strategies that further maintain the utility. 4) We show that our model achieves a better trade-off compared to a rule-based baseline.

II. RELATED WORK

In this section, we summarize previous work related to ours such as language watermarking, linguistic steganography, sequence-to-sequence machine translation models, model watermarking, and finally, neural text detection.

A. Language Watermarking

Watermarking for multimedia documents has many applications such as identifying and protecting authorship [33], [34], [35], [36]. It consists of an embedding stage where the hidden identifying information (i.e. watermark) is encoded in the cover signal (e.g. text, image, video, or audio), however, watermarking text or natural language is the least discussed medium [33]. This is followed by a decoding stage where the watermark is recovered from the signal. Blind-watermarking (which we adopt) does not require accessing the original signal to decode the watermark making it more practical.

Initial attempts for text watermarking aimed to watermark documents rather than the language itself, this could be done by altering documents characteristics such as characters’ appearance, fonts, and words or line spacing by specific patterns depending on the codeword [37]. However, these methods are prone to scanning and re-formatting attacks such as copying and pasting [33], [38].

The other category of methods relies on linguistic characteristics of the natural language such as making syntactic or semantic changes to the cover text [38]. An example of such is the synonym substitution method in [19] in which WordNet was used to find synonyms of words that are then divided into two groups to represent ‘0’ or ‘1’. The authors relied on ambiguity by encoding the message with ambiguous words or homographs (i.e. a word that has multiple meanings). This was used to provide resilience as attackers would find it hard to perform automatic disambiguation to return to the original sentence. However, a sense/meaning-tagged dataset was used that provides the original WordNet sense, which is not suitable for automatic methods with no human input. Generally, synonym substitution methods are vulnerable to an adversary who performs random counter synonym substitutions, in addition, they perform fixed pairwise substitutions which makes them not flexible and also vulnerable to detection.

Additionally, sentence structure can be altered to encode the codeword according to a defined encoding [21], [39]. These methods introduce changes such as passivization, clefting, extrapolation, and preposing [38], [40]. However, these transformations might not be applicable to all sentences which
could fail to encode the message, also, they change the sentence to a large extent.

In contrast, we perform an end-to-end data hiding approach that is data-driven and does not require efforts to design rules and unique dictionary lookups. We optimize our method to achieve the least amount of changes to the cover text and at the same time conceal the encoding by adversarial training.

B. Linguistic Steganography

Similar to watermarking, steganography hides information in text, with the goal typically being secret communication. Steganography and watermarking might have different requirements [26], [19]; although both of them target stealthiness to avoid detection, steganography does not assume an active warden. Therefore, watermarking should also have robustness to local changes that might remove the watermark. Additionally, in our case, watermarking should also preserve the underlying cover text and utility, and should be applicable to most sentences.

Similar to watermarking, translation by modifying a cover text was used in steganography such as the work in [41], [42], [43] that used a set of rule-based transformations to convert tweets to possible translations. The encoding and decoding were done with a keyed hash function to avoid sharing the huge database of substitution rules; the translations that map to the desired hash values were selected. Therefore, the decoding is not robust to local changes to the sentence. Another synonym-based method was proposed in [44] based on assigning different bits to American and British words which makes it not applicable to a large number of sentences. Another steganography direction is to generate text according to a shared key, instead of using translation. For example, the work in [45] used a trained LSTM language model that generates sentences according to a masked vocabulary and a binary stream; the vocabulary was partitioned to different segments where each segment was assigned a sequence of bits. However, this imposes a large constraint on the usage of the language model since it needs to abide by the masking. Therefore, these stated steganography solutions are not suitable for our scenario as they specifically prioritize secret communication over flexibility or watermarking requirements.

C. Sequence-to-Sequence Models

Our task bears a lot of similarity to machine translation, specifically, to machine translation to the same language. It is also similar to other applications such as style transfer to anonymize text and hide authors’ attributes [46]. Neural machine translations [47], [48], [1] are typically composed of a sequence-to-sequence architecture with an encoder and a decoder networks that were typically used to be recurrent networks with an attention mechanism between them [47]. However, the state-of-the-art sequence-to-sequence models are now composed of transformer architectures (which we thus adopt) that replaced the recurrent connections by attention [1].

D. Model Watermarking

To protect the intellectual property of deep learning models, several approaches have been recently proposed to watermark models [49], [50], [51], [52]. This could be done either by embedding the watermark into the model’s weights which requires white-box access for verification [53], [54], [55], or by assigning specific labels for a trigger set (i.e. backdoors [56]) which only requires black-box access [51], [49], [57]. To protect against model extraction (by black-box queries), [58] entangles the watermark and data representation to make the watermark transferable to the extracted model. Other recent works aimed at protecting against watermark piracy (i.e. the adversary embeds his own watermark) by linking the original task performance with the watermark [59], [60]. To incur a minimum effect on the utility, [61] extracts fingerprinting data of points near the classifier boundary, instead of embedding a watermark into the model.

These methods were mainly addressing image classification networks; there is no previous work that attempted to watermark language models. We also differentiate our approach from model watermarking; instead of watermarking a language model, we study language watermarking using a deep learning method that could eventually be used to watermark the language model’s output. This makes the watermarking process independent of the language model and the decoding strategy used at test time.

E. Neural Text Detection

Similar to the arms race in image deepfakes detection [62], [63], [64], recent approaches were proposed to detect machine-generated text. For example, the Grover language model [5] was fine-tuned as a classifier to discriminate between human-written news and Grover generations. The authors reported that the model size played an important factor in the arms race; if a larger generator is used, the detection accuracy drops. Another limitation was observed in [13] in which the authors fine-tuned BERT to classify between human and GPT-2 generated text. The classifier was sensitive to the decoding strategy used in generation (top-k, top-p, and sampling from the untruncated distribution). It also had poor transferability when trained with a certain strategy and tested with another one. Therefore, while detecting machine-generated text is an interesting problem, it largely depends on the language model and decoding strategy.

Besides, this suggests that the success of classifiers might drop based on future progress in language modelling [5] (e.g. larger models [11], arbitrary order generation [65], or training setups that could eventually reduce exposure bias [66]), in addition to decoding strategies that could eventually reduce statistical abnormalities without introducing semantic artifacts [13]. This is also similar to the limitations of image deepfakes classifiers [67]. Thus, we seek a more sustainable solution by watermarking. We propose an improved and learnable watermarking framework as an alternative solution that could be applied to the language model’s output and that is independent of these variations. Also, our watermarking scheme is a multi-bit watermarking. hence, it can be used
III. Threat Model

In this section, we discuss our usage scenario, requirements, and attacks.

a) Watermarking as a defense against models' abuse: We study watermarking as a sustainable solution towards provenance tracing of machine-generated text in the case of models’ abuse. An example of that scenario is a black-box text generation service that has legitimate usages such as editing assistance. The service is offered by the language model’s owner or creator. However, it can be used in an unintended way by an adversary to automatically generate entire fake articles or misinformation, aiming to achieve financial gains or serve a political agenda [5]. Owners can then proactively and in a responsible manner provide a way to identify and detect the model’s generations by watermarking its output [67].

News platforms can cooperate with models’ owners in order to identify the watermarks in the news articles and, thus, detect machine-generated articles. That is similar to [5] that suggests that news platforms can use the Grover classifier to detect Grover articles. This is also in line with video-sharing platforms such as YouTube that uses deep networks to detect pornographic content [68], and [69] which suggests that YouTube can use machine learning classifiers to flag videos that are likely to be targeted by organized hate attacks.

Although we envision our framework as a solution towards watermarking language models’ output, we propose a general improved and learning-based data hiding framework for natural language that could be adapted for watermarking in other applications such as protecting authorship intellectual property.

b) Watermarking using AWT: The hiding network (message encoder) of AWT is used to embed a watermark \((m)\) into the text. The same message encoder can be used to encode different watermarks \((m_1, m_2, \ldots, m_n)\) if needed (e.g., if the service is shipped to different parties). The multi-bit watermarking framework (as opposed to zero-bit) helps to trace provenance to the different parties. The revealing network (message decoder) of AWT can, in turn, be used to reveal a watermark \(m'\) which is then matched to the set of watermarks \((m_1, m_2, \ldots, m_n)\).

c) Requirements and attacks: However, the objective is not only to hide data in text; we define the problem as a trade-off between these requirements:

- **Effectiveness:** The watermark should be successfully embedded and verified. At the same time, it should keep the text (e.g., service) utility; it should introduce the least amount of changes to the cover text, and ideally produce natural, grammatically and semantically correct changes. Thus, we study the trade-off between text utility and bit accuracy and examine different strategies to improve it.

- **Secrecy:** The watermark should achieve stealthiness by not introducing evident changes that can be easily detectable by automated classifiers. Ideally, it should be indistinguishable from non-watermarked text. This, in part, contributes to the text utility preserving factor. Besides, it helps to avoid suspicion and hinders the adversary’s efforts to remove or spoof the watermark by identifying it first. Therefore, we study the watermark secrecy and consider a range of possible discriminators.

- **Robustness:** The watermark should be resilient and not easily removable by simple changes. Ideally, to remove the watermark, one has to introduce heavy modifications that render the text ‘unreadable’. Satisfying the previous two requirements (text utility and secrecy) can, in part, contribute to the robustness, since the adversary would not be able to distinguish the watermark. The adversary’s objective would be to remove the watermark from the service’s output while largely preserving the output (i.e., utility). To that end, we consider attacks such as introducing random changes to the text, e.g., synonym replacement, or randomly removing parts of the text. Additionally, we consider other attempts such as training a denoising autoencoder to denoise the watermarked text.

IV. Adversarial Watermarking Transformer

We propose the Adversarial Watermarking Transformer (AWT) as an end-to-end framework for language watermarking. As shown in Figure 2, the proposed solution includes a hiding network, a revealing network, and they are both trained against a discriminator. In the rest of this section, we discuss the details of these components and the network optimization and training procedures.

A. Hiding Network (Message Encoder)

This component is responsible for translating the input text to the watermarked text. Similar to sequence-to-sequence models, it consists of an encoder and decoder.

a) Encoder: The encoder \((E)\) is a transformer-encoder block consisting of several transformer encoder layers. Each layer consists of a self-attention block followed by a fully-connected layer. The encoder takes an input sequence \(S = \{W_0, W_1, \ldots, W_n\}\), consisting of one-hot encoded words that are then projected to the embedding space using the word-embedding layer. As transformers are position-invariant, position embeddings (sinusoidal embeddings [1]) are then added to the word embeddings. The encoder produces a fixed-length vector which is an average pooling across the time dimension of the last encoder layer [70].

b) Message: The input message: \(M = \{b_0, b_1, \ldots, b_q\}\) (consisting of \(q\) binary bits sampled randomly), is first fed to a fully connected layer in order to match the embeddings’ dimension, and is then added to the sentence encoding produced by the encoder. This produces a shared embedding between the sentence and the message which is then passed to the autoregressive decoder and added to its input at each time-step.

c) Decoder: The decoder \((D)\) has a similar architecture as the encoder, in addition to having an attention layer over the encoder’s output. In paired machine translation, the decoder usually takes the ground-truth target sequence (shifted right),
and is trained to predict the next word at each time step. Since our problem does not have paired training data, the model is trained as an auto-encoder [70]; the decoder takes the shifted input sentence and is trained to reconstruct the sequence given to the encoder, producing an output sentence \( S' = \{W_0', W_1', ..., W_n'\} \). This serves as the reconstruction component in similar image data hiding methods [26], and it helps to largely preserve the input. In order to train the whole network jointly and allow back-propagation from the other components, we use Gumbel-Softmax approximation [71], [72] with one-hot encoding in the forward pass (Straight-Through Gumbel Estimator using argmax [71]), and differentiable soft samples in the backward pass (softmax is used to approximate the argmax operation [71]). The text reconstruction loss is the cross-entropy loss:

\[
L_{\text{rec}} = \mathbb{E}_{p_{\text{data}}(S)}[- \log P_D(S)]
\]

B. Revealing Network (Message Decoder)

This part of the network is responsible for reconstructing the input message. It takes the one-hot samples produced by the auto-encoder, multiplied by the embedding matrix, and with adding position embeddings. The message decoder (\( M \)) is a transformer-encoder block, since it is typically used in text classification applications [4], [13]. The output of the last transformer encoder layer is then averaged across the time dimension and fed to a fully connected layer with an output size that is equivalent to the message length \( q \). The message reconstruction loss is the binary cross-entropy over all bits:

\[
L_m = - \sum_{i=1}^{q} b_i \log(p(b_i)) + (1 - b_i) \log(1 - p(b_i))
\]

Weight tying: In order to reduce the number of parameters in the network, we share the embedding weights across the whole network [1] (i.e. text auto-encoder including the encoder and decoder, message decoder, and discriminator). We also share the embedding weights with the pre-softmax layer that maps from the embedding space to tokens in the text decoder [73], [1], [74]. In addition, we found it beneficial in terms of the model size and faster convergence to also share the weights between the encoder part of the text auto-encoder and the message decoder.

C. Discriminator

In order to have a subtle message encoding that does not alter the language statistics, we utilize adversarial training and train the previous two components against a discriminator. The discriminator (\( A \)) is a transformer-encoder with a similar structure to the message decoder. It takes the non-watermarked sentences \( S \) and the watermarked sentences \( S' \) (one-hot encoded) and is trained to classify between them using the binary cross-entropy loss:

\[
L_{\text{disc}} = - \log(A(S)) - \log(1 - A(S'))
\]

while the adversarial loss is: \( L_A = - \log(A(S')) \). As we show later, we found this component essential in supporting the watermark secrecy against adversaries.

D. Training and Fine-tuning

The model is first trained jointly with the above three losses with weighted averaging:

\[
L_1 = w_A L_A + w_{\text{rec}} L_{\text{rec}} + w_m L_m
\]

These losses are competing; e.g. a perfect sentence reconstruction would fail to encode the message. Therefore, we tuned the losses weights in order to achieve a good trade-off. For example, it was helpful to assign a relatively higher weight to the message loss, otherwise the reconstruction dominates. We did not need to anneal the message weight after the start. The other losses had comparable weights to each other.

The previous loss function aims to preserve the input sentence and encode the message with the least amount of changes while not changing the text statistics. However, we still do not have an explicit constraint on the type of changes done by the network to encode the message. Therefore, after training the network with \( L_1 \), we further fine-tune the network to achieve semantic consistency and grammatical correctness.
a) Preserving semantics: One way to force the output to be semantically similar to the input sentence is to embed both sentences into a semantic embedding space and compute the distance between the two encodings. We follow [46] and use the pre-trained Facebook sentence embedding model [75] that was trained to produce a sentence representation based on the natural language inference (NLI) task. The model was trained on the Stanford Natural Language Inference (SNLI) dataset [76]. We fix the sentence encoder (F) weights and use it to compute the semantic loss between S and S’ as follows:

\[ L_{sem} = ||F(S) - F(S')|| \]

b) Sentence correctness: To explicitly enforce correct grammar and structure, we fine-tune the model with a language model loss [46]. We independently trained the AWD-LSTM (ASGD Weight-Dropped LSTM) [73] on the used dataset, as a medium-scale, but widely used and effective language model [7], [77], [78]. We then use the trained AWD-LSTM model (L_M) with its weight to compute the likelihood of the output sentence S’. Sentences with higher likelihood are more likely to be syntactically similar to the original text used in training. The language model loss is defined as:

\[ L_{LM} = - \sum_i \log p_{LM}(W'_i | W_{<i}) \]

These previous two components take the one-hot samples and map them to their respective embedding space. We fine-tune the network using these two losses in addition to the previous ones as follows: \[ L_2 = w_a L_A + w_{rec} L_{rec} + w_{m} L_m + w_{sem} L_{sem} + w_{LM} L_{LM} \]

As we later show in our experiments, we found that fine-tuning with these auxiliary losses helps to produce more realistically looking and natural samples compared to only training with reconstructing the sentence.

V. EXPERIMENTAL RESULTS

In this section, we first discuss our setup. Then, we evaluate the different aspects of our model: effectiveness (message decoding and text utility), secrecy, and robustness. We compare AWT to baselines and present the results of a user study to evaluate the output’s quality.

A. Setup

a) Dataset: We used the word-level WikiText-2 (WT2) that is curated from Wikipedia articles with light processing and was introduced in [79]. We used the same tokenization, processing, and split setup as [79], [73], [80]. The dataset is approximately twice the size of the Penn Treebank (PTB) benchmark dataset for language modelling [81], besides, the WikiText-2 keeps the capitalization, punctuation, and numbers. It contains over 30,000 unique vocabulary words and has a size of 2 million words in the training set and 0.2 million in validation and test sets. Since our watermarking framework can be applied independently as a post-processing step, we experiment on human-written data to objectively judge the proposed watermarking scheme correctness and to use a benchmark pre-processed dataset.

b) Implementation details: We implemented our model and experiments with the PyTorch framework. We encode a message per sentence/text segment; we used a message length of 4 bits (similar to the translation-based steganographic system in [41]) with uniform sampling during training, and a varying text segment with normal distribution \( \mathcal{N}(80, 5) \). For the transformer blocks, we used a dimension size \( (d_{model}) \) of 512. Besides, the encoder and decoder transformer blocks are composed of 3 identical layers and 4 attention heads per layer, the decoder has a masked self-attention. For the rest of the transformer hyperparameters, we used the default PyTorch implementation that adopts [1]. We optimize the network with Adam optimizer [82] and we vary the learning rate during training according to [1]:

\[ \text{lr}_{\text{gen}} = d_{model}^{-0.8} \times \min(\text{step}^{-0.5}, \text{step} \times \text{warmup}^{-1.5}) \]

\[ \text{lr}_{\text{disc}} = d_{model}^{-1.1} \times \min(\text{step}^{-0.5}, \text{step} \times \text{warmup}^{-1.5}) \]

where \( \text{lr}_{\text{gen}} \) is the learning rate of the autoencoder and message decoder, and \( \text{lr}_{\text{disc}} \) is the learning rate of the discriminator, trained alternatively. We used 6000 warmup steps. We use a Gumbel temperature of 0.5 [46], [83].

B. Effectiveness Evaluation

In this section, we evaluate the effectiveness of the model in terms of text utility and bit accuracy. We discuss our evaluation metrics and we compare different model’s variants. We examine different inference strategies and sentence aggregation to improve the trade-off between text quality and bit accuracy. We then perform a qualitative analysis to visualize and assess the changes produced by the model.

1) Metrics: To measure the message decoding performance, we use the bitwise message accuracy (random chance: 50%) averaged across all sentences in the test set. To measure utility preserving, we use the meteor score [84] that is used in machine-translation and image captioning applications to compare the output sentence against ground-truth references. Meteor performs n-gram alignments between the candidate and output text with synonym lookups from WordNet [85]. It ranges from 0 (no similarity) to 1 (identical sentences).

However, we found that the meteor score is not enough to evaluate the text semantics; two output sentences can have the same number of changed words compared to the input sentence and thus a similar meteor score (assuming there is no synonym overlapping), however, one of them could be closer to the input sentence. Therefore, to approximate the semantic difference between the input and output text, we used SBERT [86], a pre-trained sentence embeddings model based on fine-tuning BERT as a siamese network on the NLI task. We compute the input and output embeddings and calculate the \( L_2 \) difference between them (lower is better). We later discuss more details about the importance of using this additional metric in Section V-B5 and Appendix VII-A.

\( \text{https://pytorch.org/} \)
TABLE I: Model’s variants quantitative analysis. The first row is the full model with adversarial training and fine-tuning. The second row is without fine-tuning. The third row is without fine-tuning and adversarial training.

| Model        | Bit accuracy | Meteor  | SBERT distance |
|--------------|--------------|---------|----------------|
| AWT          | 97%          | 0.96    | 1.25           |
| − fine-tuning| 96%          | 0.94    | 1.73           |
| − discriminator| 95%         | 0.94    | 2.28           |

2) Model ablation: We show in Table I three variants of our model. The first row shows the full AWT with the fine-tuning step, the second one shows the model without fine-tuning, and the last row shows the model without discriminator and fine-tuning (trained only with text and message reconstruction). This shows that the fine-tuning step helps to improve the text preserving and semantics as suggested by the increase in the meteor score and the decrease in the SBERT distance, at the same time, it maintains a high message decoding accuracy. Additionally, the model trained with a discriminator had a lower SBERT distance compared to the model that was trained with text reconstruction only, although both of them have a comparable meteor score. As we demonstrate in our qualitative and secrecy analysis shown later, this indicates that the adversarial training setup improves the output’s quality, in addition to its secrecy advantages.

3) Inference strategies: To further maintain the text utility and improve the output sequence’s quality, we study two inference strategies. First, we sample a set of samples for each sentence and then select the best sample, based on possible quality metrics. Second, we deliberately leave some sentences non-watermarked. Both approaches have a trade-off relationship with bit accuracy, however, to watermark an article, it is possible to aggregate observations from the whole document, relaxing the need for having correct message decoding for each sentence, we discuss this in Section V-B4.

a) Best-of-many encoding: We here sample \( n \) sentences for each input sentence using the Gumbel sampler in the autoencoder network. We then use the trained language model (AWD-LSTM) to compute the likelihood for each output sample. Then, we pick the sample with the highest likelihood (excluding samples with no changes to the input) and feed it to the message decoder. An alternative quality metric is to pick the sample with the lowest SBERT distance to the input sentence, we found that these two metrics give comparable results, however, using the language model gives slightly better samples in terms of grammatical and syntactic correctness (discussed in Section V-B5 and Appendix VII-A).

We show in Figure 3 different operating points based on varying \( n \) from 1 to 40 samples. For each point, we show the relationship between bit accuracy and text utility (demonstrated by the averaged meteor score and SBERT distance). We found that the meteor score increases and the SBERT distance decreases with increasing the number of samples. Additionally, we show in Figure 4 and Figure 5 a histogram of the SBERT distances and meteor scores respectively, for two sampling settings; only 1 sample (bit accuracy 97%), and selecting the best from 30 samples (bit accuracy 85%). In the latter case, the output is moving towards identical reconstruction. This analysis suggests that higher-quality output sentences can be acquired by sampling and that the language model metric also correlates with the meteor and SBERT ones. In addition, having different possible translations is convenient in the case of interactive services, as the user can pick in a flexible way the preferred sentence.

b) Selective encoding: Alternatively, we leave a percentage of sentences non-watermarked to reduce the overall change to the output text. Similar to sampling, this can also be helpful in interactive services if the user prefers to have some sentences unchanged. The message decoder side does not need to know which sentences were watermarked as it can attempt to decode the message from all sentences and base the
decision on the whole document. We decide which sentences to leave based on setting a threshold on the increase of the language model loss compared to the original sentence. We examine different thresholds that encode different quantiles of the test set sentences (from 75% to 100%). We perform this experiment with sampling only 1 sample from the model. We show in Figure 6 the mean meteor and SBERT distance versus bit accuracy at each quantile. Besides the flexibility and utility advantage, selective encoding hinders the adversary effort to localize the watermark as not all sentences are watermarked.

4) Sentences aggregation: The previous strategies help to improve the output’s quality. However, they reduce the bit accuracy. Therefore, in this section, we discuss two approaches to recover from this drawback.

a) Concatenation: To allow a large number of watermarks, a longer watermark can be composed of multipliers of 4 bits messages; each 4 bits are embedded into one text segment (we use a segment length of 80 words). If the text (e.g. article) is longer than the watermark, the sequence can be repeated partially or fully. The length of the unique long watermark can be determined based on the expected minimum text length. The decoded messages can be then verified against the sequence. Thus, we can accumulate observations from all messages in the document to perform a null hypothesis test based on the number of matching bits [87]. We assume that the null hypothesis ($H_0$) is getting this number of matching bits by chance. Under the null hypothesis, the probability of matching bits (random variable $X$) follows a binomial distribution; the number of trials is the number of bits in the sequence ($n$), $k$ is the number of successes (matching bits), and each bit has a 0.5 probability of success. We can then compute the $p$-value of the hypothesis test by computing the probability of getting $k$ or higher matching bits under the null hypothesis:

$$Pr(X > k|H_0) = \sum_{i=k}^{n} \binom{n}{i} 0.5^n$$

The watermark is verified if the $p$-value is smaller than a threshold $T$; meaning that it is not very likely to get this sequence by chance. This allows a soft matching of the decoded watermark instead of an exact one. In our experiments, we set $T$ to 0.05 as a commonly used significance level [87].

We empirically find the percentage of instances where the null hypothesis can be rejected (i.e. the watermark is correctly verified), and its relationship with the text length (i.e. the number of bits in the sequence). We perform this at different operating points that vary in their bit accuracy. We demonstrate this experiment in Figure 7; when increasing the text length, we observe more correct observations, and thus, can reject the null hypothesis. Therefore, the use of operating points can be flexibly determined by the expected text length; at longer lengths, it is affordable to use an operating point with lower bit accuracy (i.e. higher utility). Besides, as required, we validate that the bit accuracy is close to chance level (49.9%) when the input is non-watermarked data, which resulted, naturally, in high $p$-values (and low false-positive rates).

b) Averaging: We here aim to improve the bit accuracy, this can be needed in applications where one is interested in decoding the message itself. We encode multiple text segments/sentences with the same binary message, decode each sentence independently, and then average their posterior probabilities. We demonstrate in Figure 8 the performance gain when averaging up to 4 sentences, compared to using only 1 sentence. We perform this analysis for 4 different operating points that depend on the number of samples in the best-of-many samples encoding strategy. As can be observed, using only 2 sentences can increase the bit accuracy for all operating points. Increasing the number of sentences can still further
improve the accuracy. This strategy can be used by repeating the messages in the document with an agreed-upon sequence.

5) Qualitative analysis: In this section, we qualitatively analyse the model’s output. We first compare different variants, we then discuss the implications of the used metrics. Lastly, we visualize and analyse the changes performed by the model.

a) Model’s variants: To examine the effect of the adversarial training, we show in Table II examples of input and output pairs of the model trained with text reconstruction only (the third row in Table I). We observed that there are two main problems with this model: first, it performs systematic and fixed modifications that alter the text statistics, e.g. the word “the” is often changed. Second, it encodes the message with tokens that have low occurrences count in the natural text. These two problems could make the watermark easily detectable by adversaries (and thus removable). It also makes the output less natural and reduces the semantic correctness (which is indicated by the higher SBERT distance in Table I, supporting the use of an additional metric besides the meteor).

To further validate this observation, we show in Figure 9 the occurrences of the top words in this model compared to their occurrences in the AWT model and the original text. Unlike AWT, this model’s variant pushes unlikely words to the top and decreases the count of more likely words (e.g. “the”), which introduces clear artifacts. In contrast, AWT keeps the distribution of top words similar and encodes the message with also likely words, and therefore it provides better concealing.

The model without fine-tuning also keeps the top words counts similar (not shown in the figure), but it still shows syntactic inconsistencies, e.g. using the end-of-sentence token in the middle of the sentence. We observed that fine-tuning the model helps to reduce these inconsistencies, examples are shown in Table III.

We also show in Table IV examples of input and output pairs obtained using AWT and the best-of-many sampling strategy (n = 20 samples). The hidden information in these examples was encoded using common tokens (e.g. preposition, articles, or auxiliary verbs), correct structure, and with a very comparable meaning to the input sentence.

Even though fine-tuning and sampling improve the quality of the output to a large extent, we still observed some failure cases of incorrect replacements that cause grammatical and syntactic mistakes. Examples of such cases are shown in Table V. One common failure mode happens when the type of the word changes. However, this cannot be entirely generalized as a failure case, e.g. some examples in Table IV removed a verb (“had”) with an adverb (“also”) while still being grammatically correct and also semantically consistent.

b) Metrics analysis: We use the SBERT distance as an evaluation metric in addition to using the language model likelihood as a sorting metric. Therefore, we validate them by evaluating their recall of the best sample. On a subset of 100 input sentences, we use AWT to generate 10 samples for each input sentence. We examine the possible sentences to find the best sample (in terms of both semantic similarity and grammatical correctness). For 92 out of 100 sentences, we found that the best sample is retrieved by either one or both metrics. This suggests that these two evaluation methods correlate with human annotation.

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TABLE II: Examples of input and output pairs of the model trained without adversarial training showing systematic fixed changes that insert less likely tokens.

| Input | – discriminator output |
|-------|------------------------|
| He was appointed the commanding officer. | He was appointed Bunbury commanding officer. |
| one of the most fascinating characters in the series | one of Milton’s most fascinating characters in Milton’s series |

TABLE III: Comparison between two variants of the model: before and after fine-tuning. The fine-tuned model shows better syntactic consistency.

| Table III | Input | – fine-tuning output | AWT output |
|-----------|-------|---------------------|------------|
| the Business Corporation, which was formed by a group of leaders from the area | the Business Corporation, which was formed by a group of leaders from the area | The railroads provided a means of transportation and influx of industries, the measurements indicated that a segment of M 00-00 82 west of <unk> had the peak volume for the highway. | The railroads provided a means of transportation and influx of industries, the measurements indicated that a segment of M 00-00 82 west of <unk> had the peak volume for the highway. |

TABLE IV: Examples of input and output pairs using AWT where the meaning and correctness are preserved.
TABLE V: Examples of failure modes showing input and output pairs with grammatical errors.

Since we use the language model to sort samples, we compare the best sample by the SBERT versus the best sample by the language model. On a subset of 200 sentences: the two metrics yielded the same sample in 44% of the cases, while they yielded comparable samples in 25%. The SBERT metric had a better sample in 9%, while the language model had a better sample in 22%. This shows that they have comparable performance, however, the language model was slightly better and more sensitive to grammar correctness (see Appendix VII-A). Additionally, more qualitative examples of the SBERT distance metric are demonstrated in Appendix VII-A.

c) Visualizations and analysis: To further visualize the types of changes performed by the model at scale, we analyzed the count of transitions between words in the input to output text, as shown in Figure 10. We performed this analysis on the most commonly changed words (or changed to), shown in Appendix VII-B. Based on this analysis, we highlight the following observations: 1) Words are not consistently replaced since the diagonal line has a high count, meaning that in most occurrences, the model keeps the most commonly changed words unchanged. 2) There are no clear sparse transitions between words; meaning that a word is not always replaced by a specific word. 3) These message-holding words are not exclusive to the watermark occurrence. 4) These words are all from the most occurring words in the dataset (see Figure 9).

These observations suggest that the model does not produce obvious artifacts or telltale signs in terms of changing the statistics of top words. In addition, there are no fixed rules that could describe or substitute the changes since it does not perform systematic changes between pairs of words. Thus, these factors contribute to the hidden encoding of information.

C. Secrecy Evaluation

The previous analysis shows that the model hides the information in a natural way by optimizing the translations to be as close and correct as possible to the original text. Nevertheless, we systematically validate the secrecy by training classifiers to discriminate between encoded and non-encoded text. Although secret communication is not the primary task in watermarking, the adversary might train a classifier in order to help remove or spoof the watermark (e.g. by adversarial training).

We train the classifiers on non-paired (i.e. disjoint) watermarked and non-watermarked text, that is a reasonable assumption since the adversary does not have access to text before watermarking. We split the training data into two equal parts and use AWT to watermark one of them by different messages sampled randomly. Similarly, we watermark the test and validation sets, but we use the entire sets for each class. We measure the classifiers’ success by the F1 score; ideally, it should be at a chance level performance (0.5), denoting the adversary’s failure.

We compare the classifiers’ success on different model’s variants; the no-discriminator model, the no fine-tuning model, and the full AWT. Since we use a transformer-based discriminator in AWT, we also study the generalization with respect to different classifiers (transformer, LSTM, and Bag-of-Words with Support Vector Machines [88]). The LSTM and transformer classifiers are trained on single length-varying sentences (similar to AWT training). The BoW+SVM classifier is trained on word occurrences’ feature vectors in paragraphs (up to 800 words). For each classifier, we optimize the hyperparameters and show the results of the most adversarial ones. Finally, we examine the effect of improving the quality (by sampling) on the classifiers’ performance. As depicted in Table VI, we summarize our main conclusions as follows:

1) The no-discriminator model shows very high F1 scores (especially on longer sequences) indicating poor hiding capability, which supports our previous qualitative observations. 2) The adversarially trained models show considerably lower F1 score across different classifiers. 3) Improving the quality (by sampling) helps to further reduce the classifiers’ success. 4) The full AWT with sampling model has a very close to the ideal random chance performance.

D. Robustness Evaluation

Regardless of the secrecy, the adversary might apply different attacks on the watermarked text. The attacker goal is to remove the watermark with minimal changes to the text,
in order to still have a high utility. Therefore, for each attack, we study the relationship between the drop in bit accuracy and the decrease in text similarity. We focus on automated attacks without human inspection or modification [5], [19].

1) Random changes: We first study the robustness against random changes to the watermarked text. We study two types of random changes: removing words and replacing words with synonyms. For each attack, we change each word with a probability $p$ that we vary from 0.05 to 0.2 with 0.05 difference. For each case, we compute the bit accuracy and SBERT distance. For synonym substitution, we use WordNet as a commonly used lexical database to find synonyms for words to be replaced. Instead of the naive random replacement, we assume that the attacker has access to a model like SBERT and uses it to select the synonym that gives the lowest distance from the set of possible synonyms.

We demonstrate the results of these two attacks in Figure 11. We perform these attacks on the output of AWT using 1 sample in Figure 11a, and 20 samples in Figure 11b. The ‘remove’ attack was found to be slightly more successful than the ‘replace’ attack since not all words used to encode the message have synonyms in WordNet. However, for both the two attacks and the two operating points, the bit accuracy decreased by from 0.05% up to 6.5%, while on the other hand, the SBERT increased by from 86% up to 577%. This shows that the bit accuracy is robust to local changes and that the adversary needs to substantially change the text by random changes in order to make the watermark not usable.

2) Training counter-models: Instead of random changes, a more knowledgeable adversary might train counter-models to remove the watermark. We train a transformer-based denoising autoencoder (DAE) [10] (sequence-to-sequence model) that is tasked to denoise an input sequence. We apply two types of noise to the input sequence ($S$): embedding dropout, and random word replacement, to form a corrupted sequence ($\hat{S}$). The noise is applied with a 5% probability. $\hat{S}$ is then fed to the encoder. The decoder is tasked to reconstruct the original sequence $S$, and is fed the shifted $\hat{S}$. The denoising maximizes $p(S|\hat{S})$, which can be described as [10]:

$$p(S|\hat{S}) = \prod_{i=1}^{n} p(W_i|\hat{S}, W_{<i})$$

That is: predicting $W_i$ is conditioned on the full corrupted sequence $\hat{S}$ and the left side non-noisy sequence $W_{<i}$.

In our attack, we perform the DAE training on non-watermarked text, and use the trained DAE to denoise the watermarked text at test time. If the DAE was trained on watermarked text, it would be tasked to reconstruct it and therefore would not change the watermark. In contrast, with the current setup, the watermark could approximate the noise applied during the DAE training. The applied word replacement noise is particularly in line with our watermarking scheme that is also based on word replacement.

We hypothesize that a less natural encoding of the information would be more vulnerable to denoising than a more natural one. To validate this, we apply the DAE on the output of the three model’s variants that we previously discussed, without applying additional noise. We demonstrate this experiment in Table VII in which we show the bit accuracy drop and the SBERT relative change. We summarize our interpretation as follows: 1) Improving the quality makes the denoising attack less effective; the ‘no-discriminator’ model had a huge drop in bit accuracy and it reached a chance level, while it decreased slightly for the other variants, in particular the better-quality AWT model. 2) The DAE does not perfectly reconstruct the sentences and still introduces other changes besides the watermark’s changes, this increased the SBERT distance for the two adversarially trained models. 3) On the other hand, the changes introduced to the ‘no-discriminator’ model reduced the SBERT, indicating more successful denoising. We show examples of these different cases and more details about the DAE in Appendix VII-C.

We then study a different attack variant where we introduce additional noise to the watermarked text before applying the DAE. This is, instead of applying random word replacement solely as an attack, we apply these random changes that might remove the watermark, and then use the DAE to generate

| Model          | Bit accuracy drop | SBERT change |
|----------------|-------------------|--------------|
| AWT           | 2.1%              | 30.4%↑       |
| - fine-tuning  | 6.2%              | 22.3%↑       |
| - discriminator| 46%               | 17.1%↓       |

![Fig. 11: Random attacks (replacing and removing words) and denoising attack (applied to noisy text), applied to the 1-sample output (a), and the best of 20 samples output (b).](image-url)
a more realistic/smoothed sentence than the corrupted one. Similarly, we vary the probability of the noise and study the relationship between bit accuracy and SBERT distance. We show in Figure 11 the performance of this attack in comparison with random changes alone. We found that this variant is more effective than using random changes; at the same level of SBERT, the drop in bit accuracy is higher. However, it still causes a significant increase in the SBERT distance (e.g. at a 10% drop in bit accuracy, the SBERT increased by 319%).

For both secrecy and robustness, it could be conceivable that other attacks might be more successful by e.g. training larger models or having massive datasets, however, this would require an adversary with even more technical knowledge of recent advances that are less known to the public, and more costly and powerful computation resources.

E. Baselines

In this section, we compare AWT against baselines. First, we implement a rule-based synonym substitution method that adopts the method in [19]. Second, as an alternative to translation-based data hiding, we train an autoregressive language model, while simultaneously optimizing the message encoding and decoding.

1) Synonym substitution: The method in [19] uses synonyms from WordNet to encode binary bits. The authors relied on ambiguity that would make it hard for the adversary to perform automatic disambiguation. The ambiguity comes from using synonyms that are “homographs” (having multiple meanings) to encode the message.

In our re-implementation, we first form a list of words (in the dataset vocabulary) to be replaced by finding the words that have homographs (at least 2) in their synonym sets. We randomly divide each homograph set to two disjoint sets to encode ‘1’ and ‘0’ bits (bit-holding words). To have a unique encoding and decoding, we make sure no single word is assigned multiple values by being found in different words synonym sets. Therefore, we skip a word if it was already assigned a value.

To encode the message, we find the occurrences of this list of words in the sentence. We replace each word by a ‘1’ or ‘0’ synonym according to the current bit in the message. We repeat until all bits are encoded. According to [19], we repeat the message again after it has been successfully encoded to introduce further ambiguity. The decoding is then done by simple dictionary lookups. We use a message length of 4 bits similar to our setup. To have unique decoding, we replace any accidental occurrences of the ‘bit-holding’ words in the original text by their corresponding synonym in the ‘replace’ list. This prevents unintentional encoding. We highlight this important advantage of our model; AWT does not impose such restrictions on the used words since there are no words that are exclusive to the message encoding (as per Figure 10).

We again evaluate this baseline across the different evaluation axes: effectiveness (utility and bit accuracy), secrecy and robustness. For effectiveness, we compute the bit accuracy and SBERT distance. For secrecy, we train a transformer-based classifier with the same setup as in Section V-C. We show a summary of these two evaluation factors in Table VIII. We compare the baseline against AWT at a comparable bit accuracy level (resulted from sampling from the model) for a fair comparison. We summarize our findings as follows: 1) The message encoding was not successful in all sentences since not all sentences have words from the fixed ‘replace’ list. 2) At an even higher bit accuracy level, AWT has a considerably lower SBERT distance. 3) The baseline has a very high F1 score compared to the F1 score of AWT.

For robustness, we apply the words removing and replacing attacks as in Section V-D. We do not apply the DAE attack since some words used in the baseline method might be Out-of-Vocabulary words with respect to the DAE. As shown in Figure 12, the baseline is more sensitive to attacks since the encoding changes a larger amount of words compared to AWT. The ‘replace’ attack is even stronger than the ‘remove’ attack; not only can it remove the original ‘bit holding’ words, but it can also introduce accidental wrong encoding by adding other ‘bit holding’ words instead of regular words.

This analysis shows that AWT achieves a significantly better trade-off between the three different evaluation axes.

2) Generation-based hiding: An alternative strategy to the translation-based data hiding of the generated text (as a post-processing step) is to generate text that is already encoded with the input message [45]. Unlike previous generation-based steganography work that relied on masking [45], we jointly train a language model (in contrast to AWT, an autoencoder and thus bidirectional) with a message decoder. We used the same AWD-LSTM language model in [73]. In our case, it takes the input word added to the input message at each time step and is trained to predict the next word given previous words. The message decoder takes the generated sequence and is trained to reconstruct the input message. The model is trained jointly with both losses. More details are in Appendix VII-D.

We evaluate the model using the perplexity (i.e. exponential

| Model    | Acc.  | SBERT | F1   |
|----------|-------|-------|------|
| Synonym  | 83.9% | 3.62  | 0.98 |
| AWT      | 86.8% | 0.956 | 0.53 |

TABLE VIII: Comparing AWT and the synonym substitution baseline in terms of bit accuracy, SBERT distance, F1 score.
We included the non-watermarked text as a proxy to measure the stealthiness of the watermark. Therefore, we conducted a user study in order to evaluate the naturalness and correctness of our model, regardless of the decoding strategies and the language model. It is common for machine translation and generation tasks to use human evaluation as an auxiliary evaluation besides the other metrics [46], [5]. Therefore, we conducted a user study in order to evaluate the naturalness and correctness of our model, as a proxy to measure the stealthiness of the watermark.

The study is conducted on the best variant of the model (with fine-tuning) with best-of-20 samples strategy (bit accuracy: ~86%) and on the synonym baseline in Section V-E1 (bit accuracy: ~83%). It was performed by 6 judges who were asked to rate sentences (each question has 1 or 2 sentences) with a Likert scale from 0 (lowest) to 5 (highest). The ratings are described with instructions that range from: ‘This sentence is completely understandable, natural, and grammatically correct’, to: ‘This sentence is completely not understandable, unnatural, and you cannot get its main idea’. We included random sentences from AWT, the synonym-based baseline, and the original non-watermarked text, and we displayed them in a randomized order. We included the non-watermarked text to work as a reference to the two approaches. The rating of the original text might not always be ‘5’ (the highest), since the dataset has processing tokens that might make it slightly ambiguous. To avoid bias, judges were not told that some sentences were edited and some were not. In addition, the used sentences were not repeated across the three conditions studied. We used a total of 340 questions (1-2 sentences each). We show the average rating for each case in Table IX, where it can be observed that AWT had both higher ratings and less variance than the baseline. The high variance in the case of the baseline can be attributed to the observation that not all sentences were successfully encoded with the full 4 bits, and therefore, some of the sentences did not have a lot of changes. However, in the case of successful encoding, the sentence generally undergoes a lot of changes compared to AWT (at least 4 changed words in addition to the counter substitutions to avoid unintentional encoding), where usually not all of them are consistent. The full descriptions of the different ratings and more details about the study are in Appendix VII-E.

VI. CONCLUSION

In this paper, we present a new framework for language watermarking as a solution towards marking and tracing the provenance of machine-generated text. We propose AWT as the first end-to-end data hiding solution for natural text. AWT is optimized to introduce the least amount of changes to the cover text and at the same time hide the data by training against an adversary. We optimize the network using further auxiliary losses that help to keep the semantics and correctness of the cover text. We further study different inference strategies to increase the text utility such as sampling and selective encoding and their trade-off with bit accuracy. We evaluate different approaches to aggregate multiple sentences, which allows the use of ‘higher utility’ operating points of the model.

Besides, we evaluate the data hiding secrecy by training independent classifiers; we found that the adversarial training setup greatly helps to conceal the existence of the information since it conceals the data without fixed substitutions of words or obvious artifacts to the language statistics. Moreover, our data hiding scheme was robust against the random local changes attacks that we studied; removing the watermark requires significant changes to the watermarked text. Also, denoising attacks were less effective in the case of the adversarial training setup used in AWT due to its higher naturalness.

Our approach achieves more flexibility and a significantly better trade-off between the different evaluation axes, in terms of quantitative, qualitative, and human evaluations, compared to a rule-based synonym substitution baseline. In addition, our work offers a new research area of automatic data hiding in natural language, similar to its precedent in images.
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VII. APPENDIX

A. Metrics Analysis

We show more examples to examine and validate the metrics we use to evaluate or sort the output of the model.

1) Sampling: In Section V-B5, we discussed that the language model loss gives slightly better sentences in terms of syntactic correctness than SBERT, therefore, we used it to sort and select the best sample. In Table X, we show examples of such cases. Nevertheless, we still measure the semantic similarity using SBERT as a metric due to the benefits discussed below.

2) SBERT and Meteor: In our analysis, we use the SBERT distance between the input and output sentences’ embeddings as an auxiliary metric besides using the meteor score. We here demonstrate examples of sentences with high SBERT distance and the advantages of using it over meteor only.

One of the cases that yields a high SBERT distance is when the output text has a changed sentiment (e.g. by using a negation), such as the two examples in Table XI. These examples do not have an extremely low meteor score since not a lot of words were changed. The first example also is grammatically correct (using “are ’t”). Despite that, they undesirably change the semantics of the input sentence, which is detected by the SBERT since it was trained on the NLI task. Additionally, we show in Table X two samples for the same input sentence and comparable meteor scores, however, the one with the lower SBERT distance has more coherency.

Given these observations, and the qualitative analysis we performed in Section V-B5 (e.g. on the ‘no-discriminator’ model that has a comparable meteor score but higher SBERT distance), we found that using SBERT is an effective metric to approximate semantic similarity and adds more information than using meteor alone.

B. Visualizations

We show, in Figure 14, a visualization for the most frequent words that were changed in the original text, and in Figure 15, the most frequent words that were changed to in the watermarked text. As can be observed the most frequent words in both figures are highly overlapping, therefore, we analysed the pairwise transitions between them in Figure 10. As we showed in Figure 9 and Figure 10, the model keeps the count of these top words similar, and it does not perform fixed substitutions between them. These factors support the encoding secrecy with no telltale words. Besides, there are no words that are particularly exclusive for bit holding, which has a flexibility advantage over the role-based substitution baseline discussed in Section V-E1.

C. Denoising

We show, in Figure 16, an overview of the denoising autoencoder (DAE) that we used. We used 6 encoding and decoding transformer layers in the encoder and decoder, respectively. We also share the embeddings of the encoder, decoder, and the pre-softmax layer (dimension: 512).

a) Denoising non-watermarked text: We first evaluate the DAE individually (regardless of the watermark) by applying the noise to the non-watermarked test set. We compare the TABLE XI: Examples in which changing the sentiment (by introducing or adding negation) resulted in a relatively high SBERT distance. Only parts of the text segment are displayed for illustration.

| Input                                                                 | Output                                                                 | SBERT     | Meteor |
|----------------------------------------------------------------------|----------------------------------------------------------------------|-----------|--------|
| This allegation became more widely known when <unk> Alexander was featured in the documentary The Search for <unk>, which has been cited by several authors including Gerald <unk>, an expert on <unk>. Towards the end of the song, there is a line “Feeding off the screams of the <unk> he’s creating”, which was taken from the film The Boys from Brazil, in which Dr. <unk> was the villain. | This allegation became more widely known when <unk> Alexander was featured in the documentary The Search for <unk>, which has been cited by several authors including Gerald <unk>, an expert on <unk>. Towards the end of the song, there is a line “Feeding off the screams of the <unk> he’s creating”, which was taken from the film The Boys from Brazil, in which Dr. <unk> was the villain. | 1.55      | 0.940  |
| This allegation became more widely known when <unk> Alexander was featured in the documentary The Search for <unk>, which has been cited by several authors including Gerald <unk>, an expert on <unk>. Towards the end of the song, there is a line “Feeding off the screams of the <unk> he’s creating”, which was taken from the film The Boys from Brazil, in which Dr. <unk> was the villain. | This allegation became more widely known when <unk> Alexander was featured in the documentary The Search for <unk>, which has been cited by several authors including Gerald <unk>, an expert on <unk>. Towards the end of the song, there is a line “Feeding off the screams of the <unk> he’s creating”, which was taken from the film The Boys from Brazil, in which Dr. <unk> was the villain. | 1.17      | 0.939  |

TABLE XII: Two samples for the same input text segment. Although they have comparable meteor scores, the sample with the lower SBERT distance shows better coherence.

| Input                                                                 | SBERT     | Meteor |
|----------------------------------------------------------------------|-----------|--------|
| The city continued to grow thanks to a commission government's efforts to bring in a booming automobile industry in the 1920s. | 7.5       | 0.93   |
| The city continued to grow thanks to a commission government’s efforts to bring in a booming automobile industry in the 1920s. | 7.19      | 0.93   |

TABLE X: Examples of input sentences, the best SBERT sample, and the best language model sample. In these examples the language model gave slightly better sentences.
similarity to the original text before and after denoising using the meteor and SBERT scores which we show in Table XIII. We observed that denoising partially reconstructs the original sentence, however, it can introduce additional changes. We illustrate by the examples shown in Table XIV that we categorize into three parts. In the first one, we show examples where the denoised sequence matches the original sequence; this was mainly for sentences with syntactic inconsistencies that removed common/likely words. In the second part, the DAE removed the added noise with more likely sequences, yet, it did not restore the original one which might cause semantic differences. In the third part, the noise words were not changed in the denoised text. This analysis suggests that the DAE is more likely to change sequences with structure and syntactic mistakes, but it is also likely to cause other changes that were not corrupted. We validate this observation by examining the denoising output of the watermarked text.

b) Denoising watermarked text: In Table XV, we show examples of the DAE output when applied to watermarked text without additional noise (based on the results in Table VII). We again categorize these examples into three parts; the first is the examples where the watermarking changes were not changed by the DAE. Second, we show examples where they were changed; these examples are from different model variants, and they generally cause grammatical mistakes, this explains the large drop in the ‘no-discriminator’ model. Third, we show examples where the DAE introduced additional changes to sequences that were not originally changed by the watermarking model, this increased the SBERT distance in the first two rows in Table VII.

We observed other cases where the watermarking changes were not altered by the DAE even when having other subtle grammatical mistakes, these changes might be removed by training a stronger DAE (e.g. larger model or larger dataset), however, we argue that this requires an even more experienced attacker with more technical knowledge and more powerful computational resources.

D. Generation-based hiding

In this section, we present more details about the baseline of generation-based hiding discussed in Section V-E2.

1) Architecture: We used the AWD-LSTM proposed in [73]. It is a 3-layer left-to-right LSTM with many regularization and optimization techniques, such as dropout on the hidden-to-hidden weights, weight tying, and averaged stochastic gradient descent (ASGD). We use the implementation published by the authors4.

![Fig. 16: Denoising autoencoder overview.](image)

**TABLE XIII:** The similarity to the original sequence in case of the corrupted and denoised text.

| Input | Corrupted | Denoised |
|-------|-----------|----------|
| Usually, the left claw is the &lt;unk&gt; | Usually, the left claw is the &lt;unk&gt; | Usually, the left claw is the &lt;unk&gt; |
| Meteor occurs in the &lt;unk&gt; | Meteor occurs in &lt;unk&gt; | Meteor occurs in &lt;unk&gt; |
| the complex &lt;unk&gt; broken up by &lt;unk&gt; | the complex in &lt;unk&gt; broken up by &lt;unk&gt; | the complex in &lt;unk&gt; broken up by &lt;unk&gt; |
| when you don’t &lt;unk&gt; | when you don’t &lt;unk&gt; | when you don’t &lt;unk&gt; |
| his earliest surviving poem &lt;unk&gt; | his earliest surviving poem &lt;unk&gt; | his earliest surviving poem &lt;unk&gt; |

**TABLE XIV:** DAE output when applying word replacement noise to non-watermarked test set.

| Input | Watermarked | Denoised |
|-------|-------------|----------|
| The eggs hatch at night and a mass of 6 kilograms several years writing for the television sitcom Grace Under Fire | The eggs hatch at night and a mass of 6 kilograms several years writing for the television sitcom Grace Under Fire | The eggs hatch at night and a mass of 6 kilograms several years writing for the television sitcom Grace Under Fire |
| He first performed as an actor and a singer | He first performed as an actor and a singer | He first performed as an actor and a singer |
| He took the civil service exam | He took the civil service exam | He took the civil service exam |
| He took the first RAfF helicopters were committed to consisting of infantry battalion and the species is also widely known as | He took the first RAfF helicopters were committed to consisting of infantry battalion and the species is also widely known as | He took the first RAfF helicopters were committed to consisting of infantry battalion and the species is also widely known as |
| This occurs because, in &lt;unk&gt; and a &lt;unk&gt; lifestyle | This occurs because, in &lt;unk&gt; and a &lt;unk&gt; lifestyle | This occurs because, in &lt;unk&gt; and a &lt;unk&gt; lifestyle |

**TABLE XV:** DAE output when applied to watermarked text (from different model’s variants).

| Text | Meteor | SBERT |
|------|--------|-------|
| Corrupted | 0.947 | 2.7 |
| Denoised | 0.956 | 2.25 |
The text is mainly not understandable, but you can get the main ideas.

The text is generally understandable, but some parts are ambiguous.

The text is roughly understandable, but most parts are ambiguous.

The text is completely not understandable, unnatural, and you cannot get the main ideas.

TABLE XVI: Ratings explanations given in the user study.

| Rating | Description |
|--------|-------------|
| 5      | The text is understandable, natural, and grammatically and structurally correct. |
| 4      | The text is understandable, but it contains minor mistakes. |
| 3      | The text is generally understandable, but some parts are ambiguous. |
| 2      | The text is roughly understandable, but most parts are ambiguous. |
| 1      | The text is mainly not understandable, but you can get the main ideas. |
| 0      | The text is completely not understandable, unnatural, and you cannot get the main ideas. |

TABLE XVII: Per-judge averaged ratings for the three types of sentences.

TABLE XVIII: Examples of the synonym substitution baseline sentences that were included in the user study.