Can Watermarks Survive Translation? On the Cross-lingual Consistency of Text Watermark for Large Language Models

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Outline

1. Intro: Text Watermark for LLMs
   - Motivation
   - Text Watermark
2. Can Watermarks Survive Translation?
   - Intro
   - Evaluation
   - Attack
   - Defense

Outline

Motivation

- Large language models (LLMs) have exhibited impressive content generation capabilities.
- Mitigating the misuse of LLM is important.
- Tagging and identifying LLM-generated content would help.

Outline

Text Watermark

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  - invisible to human
  - can be detected algorithmically
- In the simplest form, the "message" can be a single bit indicating the presence of the watermark.

KGW-based Method - Notations

- Language model: M
- Vocab: $\mathcal{V}$
- A sequence of tokens: $\boldsymbol{x}^{1:n} = (x^1, x^2, \ldots, x^n)$
- Conditional probability of the next token: $P_M(x^{n+1}|\boldsymbol{x}^{1:n})$
- Logits of the next token: $\boldsymbol{z}^{n+1} = M(\boldsymbol{x}^{1:n}) \in \mathbb{R}^{|\mathcal{V}|}$
- Therefore, we have $P_M(x^{n+1}|\boldsymbol{x}^{1:n}) = \text{softmax}(\boldsymbol{z}^{n+1})$.

KGW-based Method - Core idea

Vocab partition based on preceding text.

- **Vocab partition**: in each step, randomly split the vocab $\mathcal{V}$ into two disjoint subsets, the green list $\mathcal{V}_g$ and the red list $\mathcal{V}_r$.
- **Preceding-text-based**: the randomness is seeded by the hash of the preceding text.
- Increase probs for green tokens (tokens in $\mathcal{V}_g$).

KGW-based Method - Watermark Ironing

In each step of decoding:

(1) compute a hash of $\boldsymbol{x}^{1:n}$: $h^{n+1} = H(\boldsymbol{x}^{1:n}) \cdots H(\cdot)$ can only use the last k tokens $\boldsymbol{x}^{n-k+1:n}$.

(2) seed a random number generator with h^{n+1} and randomly partitions $\mathcal{V}$ into two disjoint lists: the *green* list $\mathcal{V}_g$ and the *red* list $\mathcal{V}_r$,

(3) adjust the logits $\boldsymbol{z}^{n+1}$ by adding a constant bias δ ($\delta > 0$) for tokens in the green list:

$$\forall i \in \{1, 2, \ldots, |\mathcal{V}|\},$$
$$\tilde{\boldsymbol{z}}_i^{n+1} = \boldsymbol{z}_i^{n+1} + \Delta_i(\boldsymbol{x}^{1:n}) = \begin{cases} \boldsymbol{z}_i^{n+1} + \delta, & \text{if } v_i \in \mathcal{V}_g, \\ \boldsymbol{z}_i^{n+1}, & \text{if } v_i \in \mathcal{V}_r, \end{cases} \tag{1}$$
$$(\Delta \in \mathbb{R}^{|\mathcal{V}|}).$$

KGW-based Method - Watermark Detection

As a result, watermarked text will statistically contain more *green tokens*, an attribute unlikely to occur in human-written text.

Watermark strength:

$$s = \frac{(|\boldsymbol{x}|_g - \gamma|\mathcal{V}|)}{\sqrt{|\mathcal{V}|\gamma(1-\gamma)}}, \qquad (2)$$

where $|\boldsymbol{x}|_g$ is the number of green tokens in $\boldsymbol{x}$ and $\gamma = \frac{|\mathcal{V}_g|}{|\mathcal{V}|}$.

Prompt

…The watermark detection algorithm can be made public, enabling third parties (e.g., social media platforms) to run it themselves, or it can be kept private and run behind an API. We seek a watermark with the following properties:

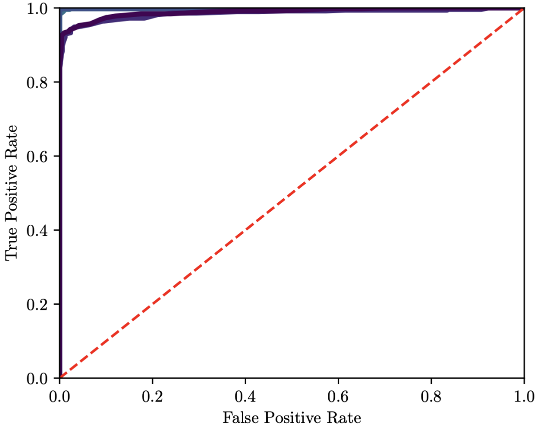
No watermark

Extremely efficient on average term lengths and word frequencies on synthetic, microamount text (as little as 25 words)
Very small and low-resource key/hash (e.g., 140 bits per key is sufficient for 99.999999999% of the Synthetic Internet

With watermark

- minimal marginal probability for a detection attempt.
- Good speech frequency and energy rate reduction.
- messages indiscernible to humans.
- easy for humans to verify.

KGW-based Method - Performance (ROC Curves | AUC: 0.998)



Outline

Can Watermarks Survive Translation?

- Watermark robustness: the ability to detect watermarked text even after it has been modified.
- Existing works focus mainly on English. However, our world is multilingual.
- What if we translate watermarked text into other language? Can watermarks survive translation?

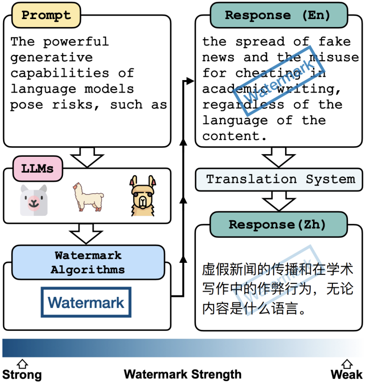


Figure 1: Illustration of watermark dilution in a cross-lingual environment. Best viewed in color.

Outline

Evaluation: cross-lingual consistency of text watermark

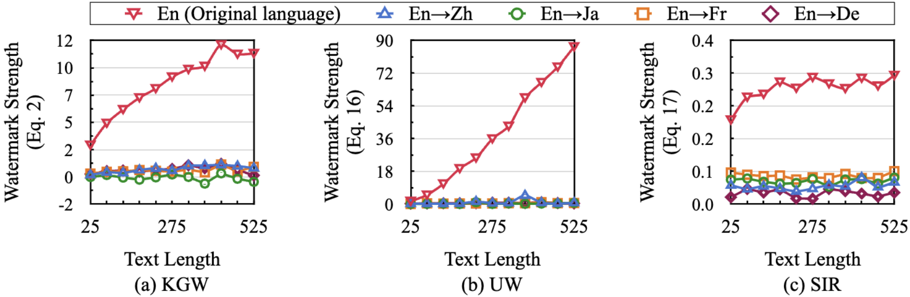


Figure 2: Trends of watermark strengths with text length before and after translation. This is the average result of BAICHUAN-7B and LLAMA-2-7B-CHAT. Figure 7 displays results for each model. Given the distinct calculations for watermark strengths of the three methods, the y-axis scales vary accordingly.

Evaluation: cross-lingual consistency of text watermark

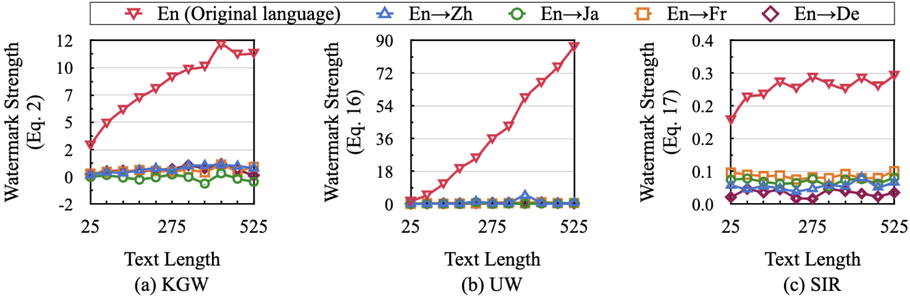


Figure 2: Trends of watermark strengths with text length before and after translation. This is the average result of BAICHUAN-7B and LLAMA-2-7B-CHAT. Figure 7 displays results for each model. Given the distinct calculations for watermark strengths of the three methods, the y-axis scales vary accordingly.

Current text watermarking methods lack cross-lingual consistency.

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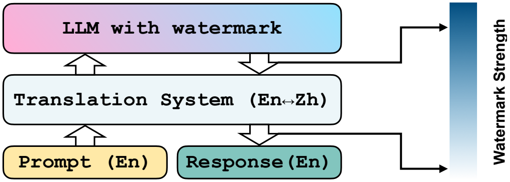
Attack: the gaps between real scenarios

- **Language switching**: An attacker who wants to remove the watermark typically do not want to change the language of the response.
- **Text quality**: Translation might effect text quality, but we have not conducted evaluation because we change the language of response in the previous section.

Cross-lingual Watermark Removal Attack (CWRA)



Cross-lingual Watermark Removal Attack (CWRA)

- CWRA wraps the query to the LLM into another language (Zh in the figure).
- The watermarks is diluted during the second translation step.

Performance: watermark detection

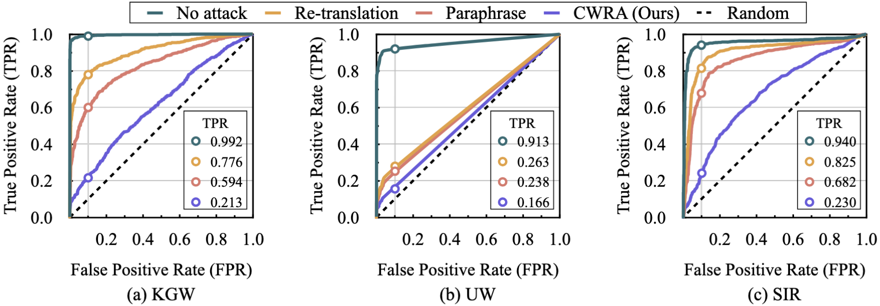


Figure 4: ROC curves for KGW, UW, and SIR under various attack methods: Re-translation, Paraphrase and CWRA. We also present TPR values at a fixed FPR of 0.1. This is the overall result of text summarization and question answering. Figure 8 and Figure 9 display results for each task.

1 2

[1] We fixed the paraphraser and translator used in all methods as `gpt-3.5-turbo-0613`.

[2] The base model is `Baichuan`, supporting English and Chinese.

Performance: text quality

Attack \ WM	KGW			UW			SIR		
	ROUGE-1	ROUGE-2	ROUGE-L	ROUGE-1	ROUGE-2	ROUGE-L	ROUGE-1	ROUGE-2	ROUGE-L
Text Summarization									
No attack	14.24	2.68	12.99	13.65	1.68	12.38	13.34	1.79	12.43
Re-translation	14.11	2.43	12.89	13.89	1.77	12.63	13.63	1.98	12.61
Paraphrase	15.10	2.49	13.69	14.72	1.95	13.31	15.56	2.11	14.14
CWRA (Ours)	**18.98**	**3.63**	**17.33**	**15.88**	**2.31**	**14.25**	**17.38**	**2.67**	**15.79**
Question Answering									
No attack	**19.00**	2.18	16.09	11.70	0.49	9.57	16.95	1.35	14.91
Re-translation	18.62	2.32	16.39	12.98	1.30	11.16	16.90	1.80	15.12
Paraphrase	18.45	2.24	**16.47**	14.38	1.37	13.07	17.17	1.79	**15.54**
CWRA (Ours)	18.23	**2.56**	16.27	**15.20**	**1.88**	**13.45**	**17.47**	**2.22**	15.53

Table 2: Comparative analysis of text quality impacted by different watermark removal attacks.

- These attack methods not only preserve text quality, but also bring slight improvements in most cases. This might be attributed to good translators and paraphraser.
- CWRA has the best overall results. We speculate that `Baichuan` performs even better in the pivot language (Chinese) than in the original language (English).

Outline

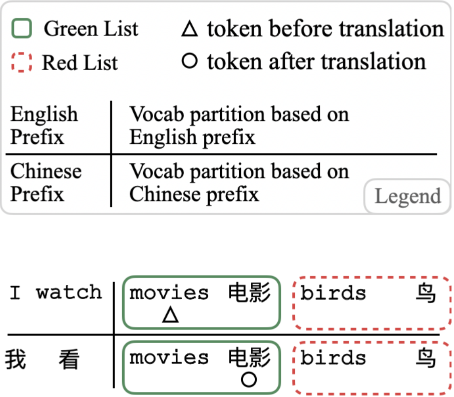
Defence: how to improve cross-lingual consistency?

- KGW-based watermarking methods fundamentally depend on the partition of the vocab, i.e., the red and green lists.

Cross-lingual consistency

the green tokens in the watermarked text will still be recognized as green tokens after being translated into other languages

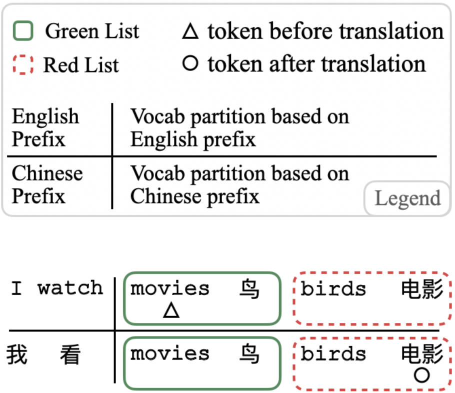
A simplest case study - 1



(a) Factor 1 ✔ | Factor 2 ✔

- ✓**Factor 1**: semantically similar tokens should be in the same list (either red or green)
- ✓**Factor 2**: the vocab partitions for semantically similar prefixes should be the same.

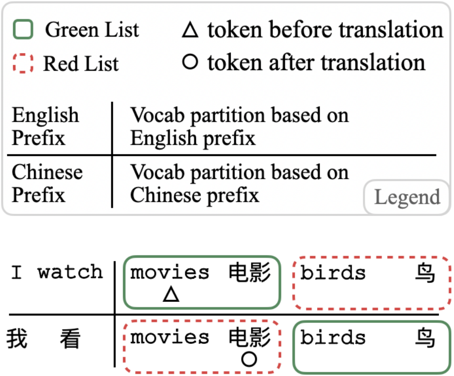
A simplest case study - 2



(c) Factor 1 ✗ | Factor 2 ✔

- ✗**Factor 1**: semantically similar tokens should be in the same list (either red or green)
- ✓**Factor 2**: the vocab partitions for semantically similar prefixes should be the same.

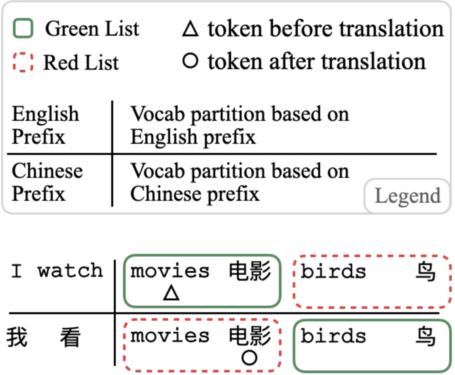
A simplest case study - 3



(b) Factor 1 ✔ | Factor 2 ✘

- **✓Factor 1**: semantically similar tokens should be in the same list (either red or green)
- **✗Factor 2**: the vocab partitions for semantically similar prefixes should be the same.

A simplest case study - 3



(b) Factor 1 ✔ | Factor 2 ✘

- ✓**Factor 1**: semantically similar tokens should be in the same list (either red or green)
- ✗**Factor 2**: the vocab partitions for semantically similar prefixes should be the same.

Factor 1 & 2 must be satisfied simultaneously.

Defense Method

SIR (Liu et al.) has already optimized for **Factor 2** since its objective is:

$$\mathcal{L} = |\mathrm{Sim}(E(\boldsymbol{x}), E(\boldsymbol{y})) - \mathrm{Sim}(\Delta(\boldsymbol{x}), \Delta(\boldsymbol{y}))|. \tag{3}$$

Based on SIR, we discuss how to achieve **Factor 1** and name our method X-SIR.

Defense Method (X-SIR): adapting Δ function

- We define semantic clustering as a partition $\mathcal{C}$ of the vocabulary $\mathcal{V}$:

$$\mathcal{C} = \{\mathcal{C}_1, \mathcal{C}_2, \ldots, \mathcal{C}_{|\mathcal{C}|}\}, \tag{4}$$

  where each cluster $\mathcal{C}_i$ consists of semantically equivalent tokens.

- We adapt the Δ function so that it yields biases to each cluster in $\mathcal{C}$, i.e., $\Delta \in \mathbb{R}^{|\mathcal{C}|}$ ~~($\Delta \in \mathbb{R}^{|\mathcal{V}|}$)~~.
- Thus, the process of adjusting the logits should be:

$$\begin{aligned} &\forall i \in \{1, 2, \ldots, |\mathcal{V}|\}, \\ &\tilde{\boldsymbol{z}}_i^{n+1} = \boldsymbol{z}_i^{n+1} + \Delta_{C(i)}, \end{aligned} \tag{5}$$

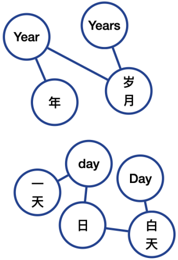
  where $C(i)$ indicates the index of v_i's cluster within $\mathcal{C}$.

Defense Method (X-SIR): semantic clustering of vocab

Algorithm 1 Constructing semantic clusters

Require: A vocabulary $\mathcal{V}$, a bilingual dictionary D
Ensure: Semantic clusters $\mathcal{C}$

Initialize an empty graph G with nodes for each token in $\mathcal{V}$
for each entry (v_i, v_j) in the bilingual dictionary D **do**
    if both v_i and v_j are in $\mathcal{V}$ **then**
        Add an edge (v_i, v_j) to G
    end if
end for
Initialize $\mathcal{C}$ to be an empty set
for each connected component C in G **do**
    Add C to $\mathcal{C}$
end for
return $\mathcal{C}$

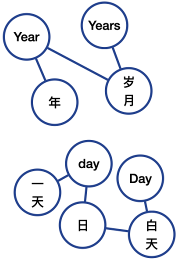


Defense Method (X-SIR): semantic clustering of vocab

Algorithm 2 Constructing semantic clusters

Require: A vocabulary $\mathcal{V}$, a bilingual dictionary D
Ensure: Semantic clusters $\mathcal{C}$

```
1: Initialize an empty graph G with nodes for each token in 𝒱
2: for each entry (v_i, v_j) in the bilingual dictionary D do
3:     if both v_i and v_j are in 𝒱 then
4:         Add an edge (v_i, v_j) to G
5:     end if
6: end for
7: Initialize 𝒞 to be an empty set
8: for each connected component C in G do
9:     Add C to 𝒞
10: end for
11: return 𝒞
```



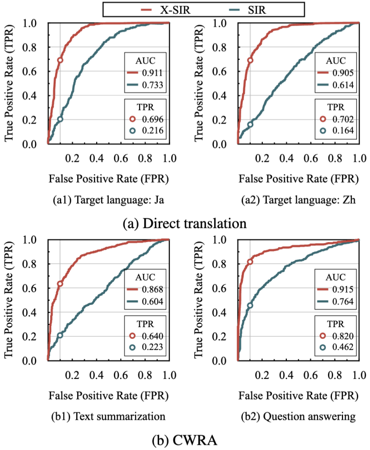
- Line 2-3: We only consider tokens shared by $\mathcal{V}$ and D, which results in limitations (discuss later).

Defense Method (X-SIR): semantic clustering of vocab

```
["Years", "Year", "years", "年度", "Year", "year", "_year", "岁月", "years", "年"]
["_Month", "month", "个月", "_month", "月亮", "_months", "_moon", "月", "_Moon", "月份"]
["白天", "day", "_day", "日", "_Day", "一天", "Day"]
["and", "而且", "还有", "_and", "和", "And", "_And"]
["农村", "_village", "村庄", "_Rural", "_Village", "_villages", "乡村", "_rural", "村"]
["_men", "男人", "人们", "人民", "_male", "男", "Man", "_Man", "_People", "_Male", "People", "men", "_Men", "男子",
"人", "男性", "_man", "_people", "people", "Men", "_males", "man"]
["大", "_Big", "_big", "Big", "big"]
["他", "he", "_He", "He", "_he"]
["德", "_Tak"]
["_heavy", "重", "_Heavy"]
["_one", "one", "One", "一", "_One", "一个"]
["方向", "_direction", "定向"]
["但", "But", "_but", "but", "不过", "但是", "_But"]
```

- We also consider the meta symbol (U+2581) for sentencepiece.

Performance: watermark detection



- AUC: +0.20
- TPR: +0.40

Performance: text quality

Method	ROUGE-1	ROUGE-2	ROUGE-L
Text Summarization			
SIR	13.34	1.79	12.43
X-SIR	**15.65**	**2.04**	**14.29**
Question Answering			
SIR	**16.95**	1.35	**14.91**
X-SIR	16.77	**1.39**	14.07

Table 4: Effects of X-SIR and SIR on text quality.

Limitations

Semantic clustering only considers tokens shared by the vocab $\mathcal{V}$ of model and external dictionary D, which results in the following limitations.

- **Language coverage**: only support language supported by the model. In a real scenario, the attacker can choose the original language and the pivot language at will.
- **Vocab coverage**: since external dictionary D only contains whole words, words units can not be clustered. Llama tokenizer tends to split a Chinese char into multiple bytes.

Summary

A closed-loop study:

- **Evaluation**: We reveal the deficiency of current text watermarking technologies in maintaining cross-lingual consistency.
- **Attack**: Based on this finding, we propose CWRA that successfully bypasses watermarks without degrading the text quality.
- **Defense**: We identify two key factors for improving cross-lingual consistency and propose X-SIR as a defense method against CWRA.

Paper & Code

https://arxiv.org/abs/2402.14007

https://github.com/zwhe99/X-SIR