Token-Specific Watermarking with Enhanced Detectability and Semantic Coherence for Large Language Models

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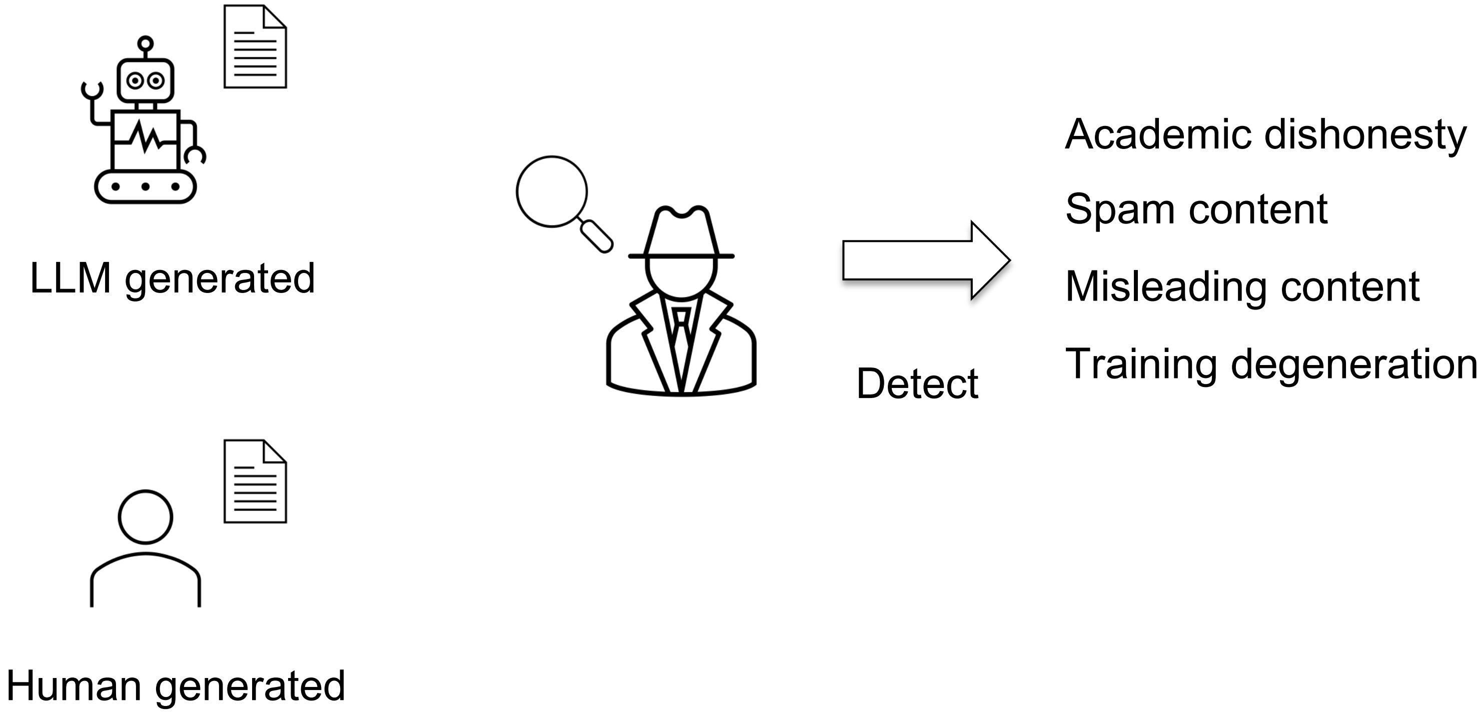
Detecting LLM Generated Texts

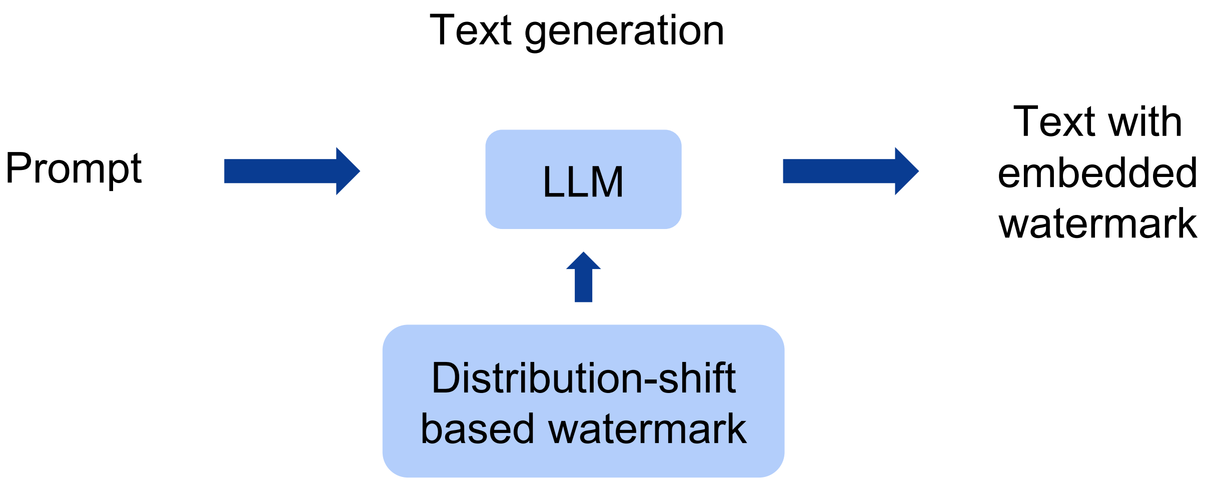


Prior Methods

Distribution-shift based methods [1, 2, 3]

- Shift the output distribution towards a subset of tokens in the vocabulary
- Statistically estimate the likelihood that the probability distribution has shifted

Prior Methods: Distribution-Shift Based Methods



Prior Methods: Distribution-Shift Based Methods

During the generation of t^{th} token,

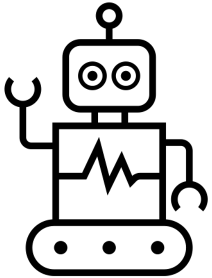
cat jumped on the

bed

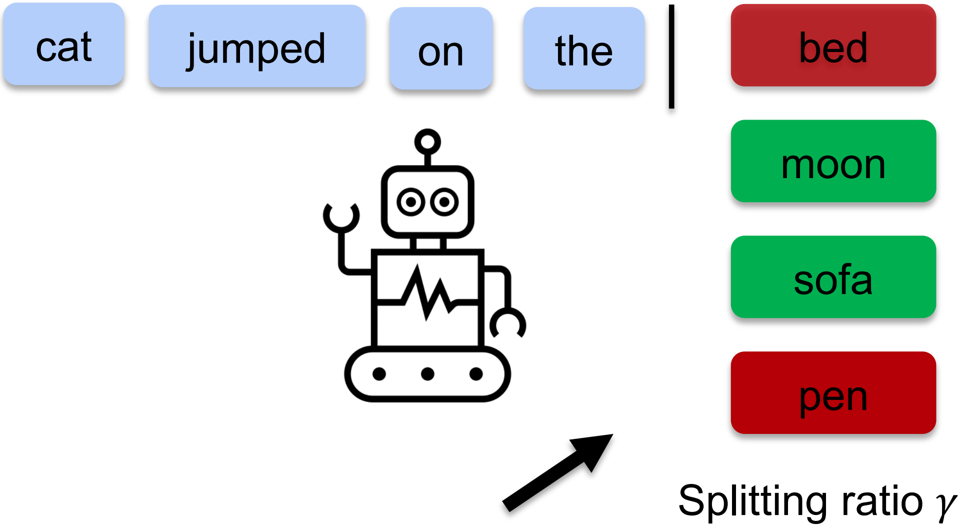
moon

sofa

pen



Prior Methods: Distribution-Shift Based Methods

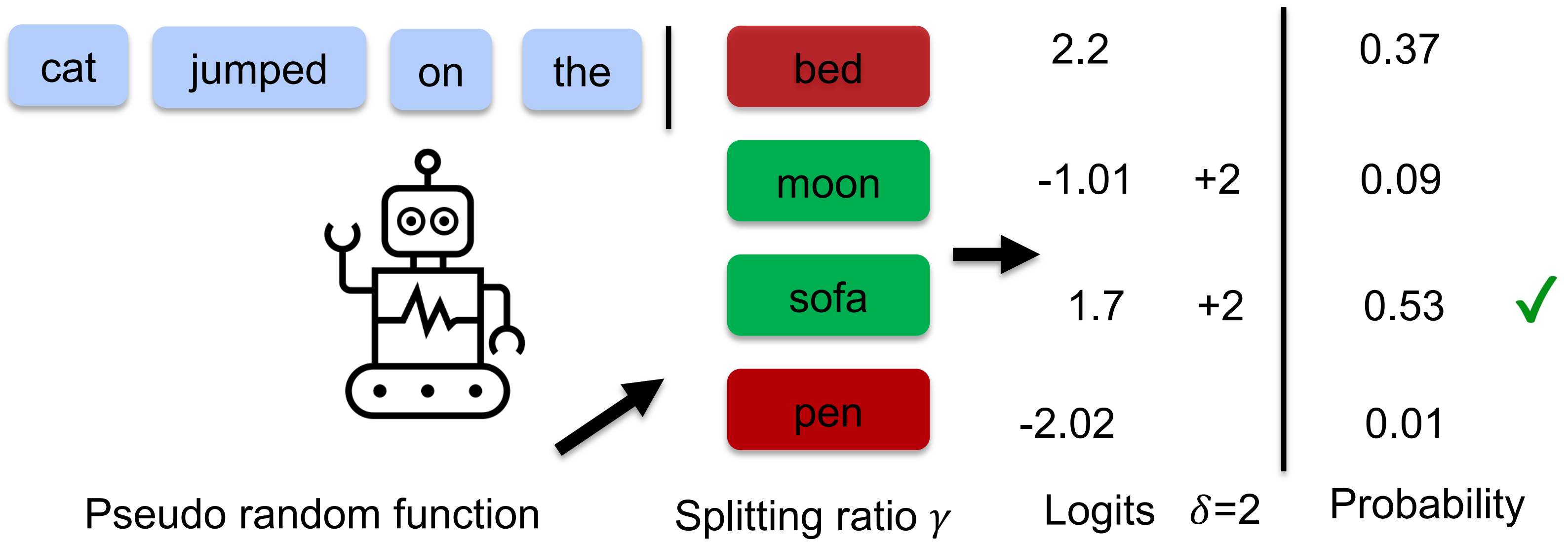


Splitting ratio γ

Pseudo random function

Hash of previous token as seed to partition vocabulary into red-green list

Prior Methods: Distribution-Shift Based Methods

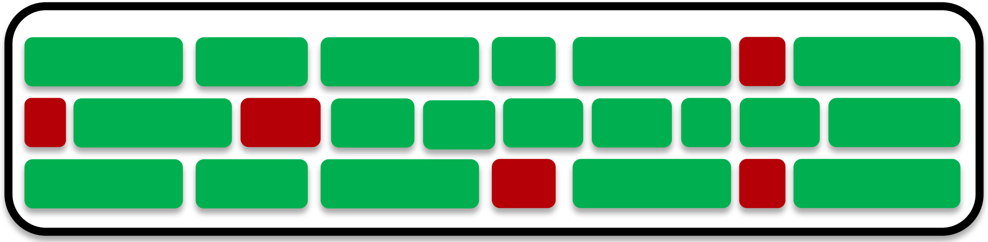


Add δ to all the green tokens to bias the distribution towards green-list

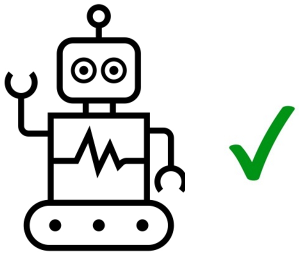
Prior Methods: Distribution-Shift Based Methods

Detection

- Null hypothesis that the next token is selected without the knowledge of green-red list rule, i.e., without addition of δ
- Given hash function, count the number of green tokens in the generation
- Calculate the z-score, $z = \frac{(|s|_G - \gamma T)}{\sqrt{T\gamma(1-\gamma)}}$



Z-score = $\frac{(|s|_G - \gamma T)}{\sqrt{T\gamma(1-\gamma)}}$ = 4



Z-score > τ (say 3)

Limitations

Face challenges in improving the semantics and detectability at the same time

- Improving one compromises the other

Lack adaptive mechanism to adjust γ and δ appropriately

- Ex: Sun rises in the __. It is ‘east’ with certainty. High δ and low γ might not select ‘east’.

Proposed Method

Propose learning token-specific splitting ratio and watermark logit, i.e., γ_t and δ_t

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$s^{(-M)}, \dots, s^{(-1)}$ $\quad$ $s^{(0)}, \dots, s^{(t-1)}$

Prompt $\quad$ Generation till now

Proposed Method

Propose learning token-specific splitting ratio and watermark logit

$s^{(-M)}, \dots, s^{(-1)}$ $s^{(0)}, \dots, s^{(t-1)}$ $\longrightarrow$ Embeddings of $s^{(t-1)}$

Prompt Generation till now

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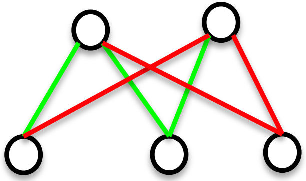


G_γ: γ network

$\downarrow$

γ_t

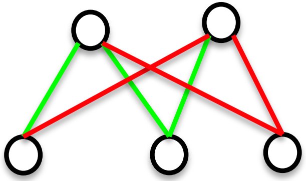
Proposed Method

Propose learning token-specific splitting ratio and watermark logit

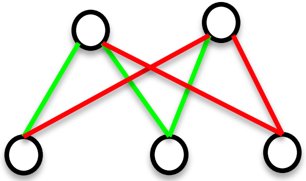
$s^{(-M)}, \ldots, s^{(-1)}$ Prompt

$s^{(0)}, \ldots, s^{(t-1)}$ Generation till now

$\longrightarrow$ Embeddings of $s^{(t-1)}$



G_γ: γ network $\downarrow$ γ_t



G_δ: δ network $\downarrow$ δ_t

Proposed Method

Differentiable sampling for splitting the vocabulary

- For each token $v \in V$, sample $\mathrm{y}_{\mathrm{v}}^{(t)} \sim B(\gamma_t)$, Bernoulli distribution parameterized by $B(\gamma_t)$.
- If $\mathrm{y}_{v}^{(t)} = 1$, then the token v belongs to green list else red list
- Gumbel softmax trick makes sampling process differentiable

Proposed method

Given original logits $l_v^{(t)}$ for token v, modified logits after biasing the green-list tokens

$$\hat{\boldsymbol{l}}_v^{(t)} = l_v^{(t)} + y_v^{(t)} * \delta_t$$

Proposed Method

Training objectives

- Detection loss
- Semantic loss

Proposed Method

Detection loss

- Since we have a token-specific γ_t and δ_t, the z-score expression has to be updated based on this distribution

Proposed Method

Theorem: Consider T independent Bernoulli random variables $X_1, \dots, X_T$, each with means $\mu_1, \dots, \mu_T, 0 < \ \mu < 1 \ \forall \ t \in 1, \dots, T$. The sum of these variables, $\sum_{t=1} X_t$, follows a Poisson binomial distribution. When T is sufficiently large, this distribution can be approximated by a Gaussian distribution with mean: $\sum_{t=1}^{T} \mu_t$ and variance: $\sum_{t=1}^{T} \mu_t(1 - \mu_t)$.

Proposed Method

Modified Z-score = $\frac{|s|_G - \sum_{t=1}^{T} \gamma_t}{\sqrt{\sum_{t=1}^{T} \gamma_t (1-\gamma_t)}}$ to account for varying γ_t

Detection loss

- Improve detectability by maximizing this objective
- However, $|s|_G$, count of green tokens, is non-differentiable w.r.t γ_t and δ_t

Proposed Method

Detection loss

- Propose differentiable surrogate $\hat{z} = \frac{\sum_{t=1}^{T} p_{gr}^{(t)} - \sum_{t=1}^{T} \gamma_t}{\sqrt{\sum_{t=1}^{T} \gamma_t (1-\gamma_t)}}$, where $p_{gr}^{(t)}$ is the probability of selecting a green token.
- Maximize $\hat{z}$ or minimize detection loss, $L_D = -\hat{z}$

Proposed Method

Semantic loss

- Generate sentence embeddings of texts before and after watermarking, i.e., s and s_w using the SimCSE model f_θ
- Maximize the cosine similarity between them, $\cos_{sim}(f_\theta(s),\ f_\theta(s_w))$
- Thus, minimize semantic loss, $L_S = -\cos_{sim}(f_\theta(s),\ f_\theta(s_w))$

Proposed Method

Multi-objective Optimization

- Optimizing for two competing loss functions L_D and L_S

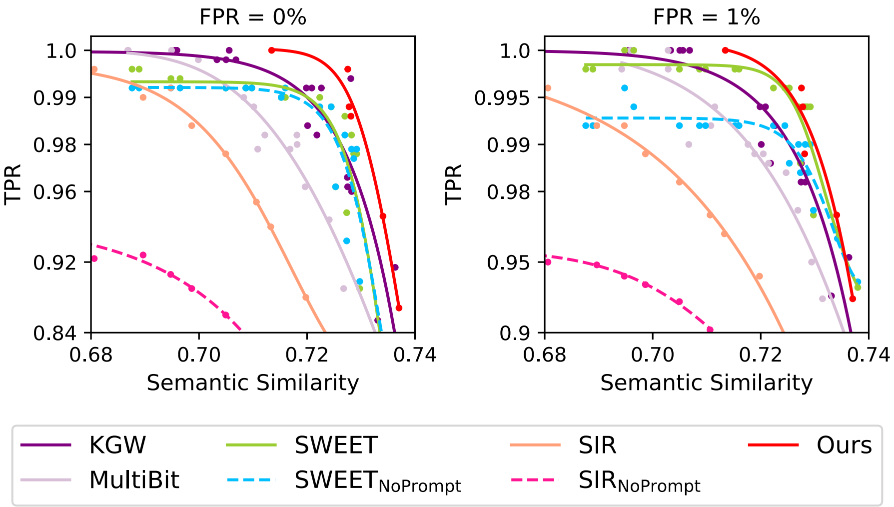
  $\min_{G_\gamma, G_\delta} L_D(G_\gamma, G_\delta)$ and $\min_{G_\gamma, G_\delta} L_S(G_\gamma, G_\delta)$

- Estimate pareto optimal solutions using multiple-gradient descent algorithm (MGDA) [5]

Experimental Setup

- Main experiments
  - C4 dataset
    - Training split 6400, Validation split 500, Test split 500
  - Generation length set to 200
- Z-score threshold is empirically determined on respective test sets
  - Set z-score threshold to maintain FPR at 0% and 1%

Results



Comparison of the trade-off for semantic integrity and detectability of different methods applied to OPT-1.3B.

Results

Method	TPR @ 0%	TPR @ 1%	SimCSE
EXP-edit	0.922	0.996	0.655
EXP-edit (Top-k=50)	0.968	0.996	0.677
Ours (Top-k=50)	**1.000**	**1.000**	**0.713**

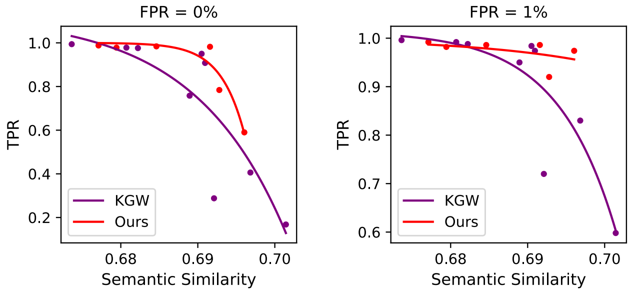
Comparison of our method with indistinguishable method - EXP-edit and its variant EXP-edit (Top-k=50).

Results

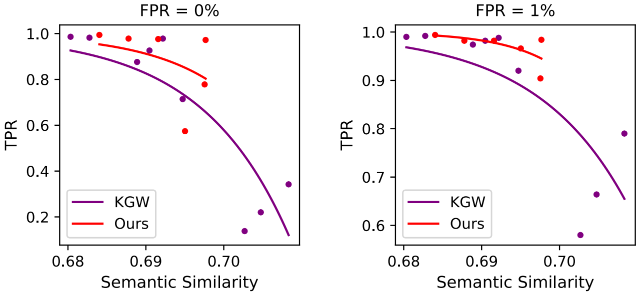
Method	Generation (s)	Detection (s)
No Watermark	3.220	-
KGW	3.827	0.067
SWEET	4.030	0.127
EXP-edit	24.693	155.045
SIR	8.420	0.337
MultiBit	6.500	0.610
Ours	3.946	0.166

Generation and detection speed on OPT-1.3B for generating 200 tokens, measured in seconds.

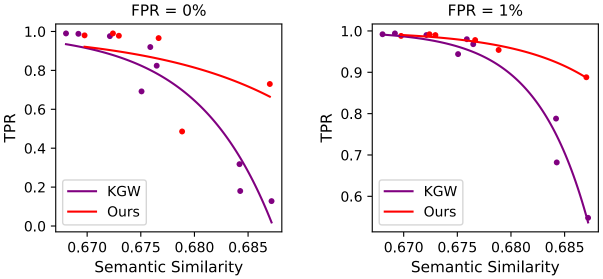
Results



a. LLAMA2 7B



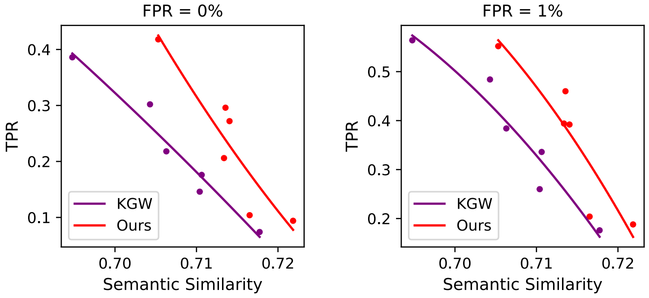
b. LLAMA2 13B



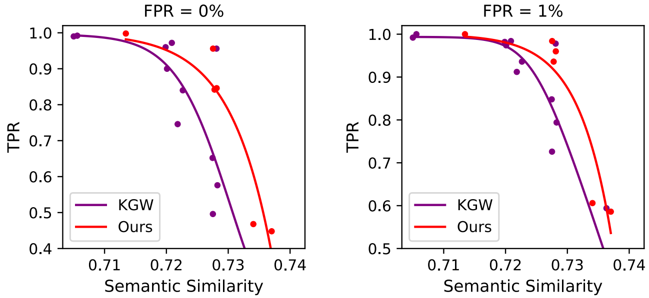
c. LLAMA2 70B

Performance of Ours (trained on OPT-1.3B) and KGW when applied to LLAMA2 7B, 13B, and 70B.

Results



a. Dipper paraphrase attack



b. Copy-Paste-3 attack

Comparison of our method with KGW under dipper paraphrase attack (left) and copy-paste-3 attack (right). Please refer to the paper for other attack results.

Conclusions

- Propose to adapt the watermark strength based on the semantics of the preceding token
- Propose a light-weight network to output token-specific γ_t and δ_t
- Propose a differentiable surrogate of z-score metric for optimization
- Optimize in a multi-objective optimization framework
- Extensive experiments on various scenarios shows the efficacy of our proposed method

References

[1] Kirchenbauer, John, Jonas Geiping, Yuxin Wen, Jonathan Katz, Ian Miers, and Tom Goldstein. "A watermark for large language models." In *International Conference on Machine Learning*, pp. 17061-17084. PMLR, 2023.

[2] Lee, T., Hong, S., Ahn, J., Hong, I., Lee, H., Yun, S., Shin, J., and Kim, G. Who wrote this code? watermarking for code generation. *arXiv preprint arXiv:2305.15060*, 2023.

[3] Liu, Aiwei, Leyi Pan, Xuming Hu, Shiao Meng, and Lijie Wen. "A semantic invariant robust watermark for large language models." *arXiv preprint arXiv:2310.06356* (2023).

[4] Piet, Julien, Chawin Sitawarin, Vivian Fang, Norman Mu, and David Wagner. "Mark my words: Analyzing and evaluating language model watermarks." *arXiv preprint arXiv:2312.00273*(2023).

[5] Sener, Ozan, and Vladlen Koltun. "Multi-task learning as multi-objective optimization." *Advances in neural information processing systems* 31 (2018).