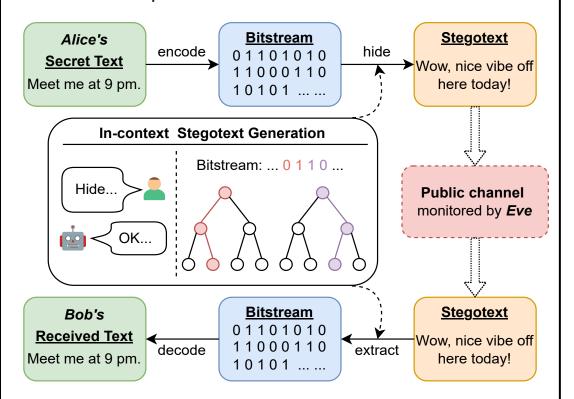


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INTRODUCTION

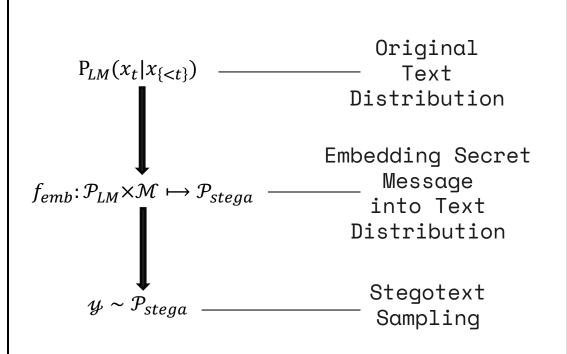
Steganography: Encoding information covertly within another message or object, hiding its presence from human inspection.



Our contributions:

- Zero-shot framework for linguistic steganography based on in-context learning using covertext samples.
- Improve both the binary coding process and the embedding process.
- Design several metrics and language evaluations, whereas our method produces more intelligible stegotext compared to all the previous methods.

Background



Method Mimic the language style and semantics of the sentences: $\mathbf{P}_{ ext{stega}}(x_{t+1} \mid x_{< t+1})$ 1. Wow, tons of replies from you. 2. I was getting used to the nice • Variable-length Coding Spring-like weather. • **EF Coding**: inspired by Write a similar one to the context differential encoding. Embedding Here is the generated sentence: • Hide & Extract Annealing Selection Wow, nice vibe off here ... In-Context Stegotext Generation Algorithm 1 Information Hiding Algorithm EF Coding Bitstream: **Input:** Bitstream m, threshold τ . **Output:** stegotext $y = [y_1, \dots, y_n]$. 1: Timestep $t \leftarrow 1$, output sentence $\mathbf{y} \leftarrow \emptyset$ EF (Round 1): 2: **while** not the end of m **do** ▷ Compute conditional probs $\boldsymbol{p} \leftarrow \mathbf{P}_{\text{stega}}(x_t \mid x_{< t})$ EF (Round 2): ▶ Prune candidate words $\boldsymbol{c} \leftarrow [c_i \mid \boldsymbol{p}(c_i) \geq \tau]$ ▶ Huffman encoding w/EF $H \leftarrow \operatorname{Huffman}(\boldsymbol{c}, \boldsymbol{p})$ ▶ Select candidate $y_t \leftarrow \text{Word } c \in H \text{ whose binary represen-}$ tation matches the prefix of m $\boldsymbol{y} \leftarrow \boldsymbol{y} \cup \{y_t\}, t \leftarrow t + 1$ 12: end while Rank of candidates

Experiment

Methods	Training-free	IMDB				Twitter					
		BPW	PPL	JSD_{full}	JSD_{half}	JSD_{zero}	BPW	PPL	JSD_{full}	JSD _{half}	JSD _{zero}
RNN-Stega (LSTM)		1.978	10.23	30.33	33.12	38.27	2.556	13.04	39.92	38.97	48.10
		2.682	12.80	26.76	29.36	34.87	3.359	15.38	36.20	35.53	44.76
		3.351	17.02	22.66	25.72	30.28	4.139	19.78	32.17	31.75	39.19
VAE-Stega (BERT-LSTM)		1.972	9.68	34.50	36.47	38.53	2.247	10.06	46.07	45.82	46.61
		2.601	12.38	31.31	33.02	34.56	2.861	12.39	43.89	44.02	43.64
		3.199	16.31	30.03	31.49	32.82	3.438	16.13	42.12	42.54	40.87
ADG		4.931	56.22	18.24	21.19	22.86	5.702	63.86	25.92	25.35	27.68
NLS		1.889	10.40	23.63	22.83	17.91	2.059	10.95	37.71	36.17	29.34
	~	2.531	12.90	22.08	21.28	16.73	2.806	14.01	36.61	35.17	29.45
		3.140	16.70	20.37	19.63	14.44	3.513	18.68	34.42	32.90	30.18
SAAC		4.471	28.74	18.28	16.40	13.17	5.078	36.74	33.75	32.11	23.08
	~	4.749	37.89	18.04	16.06	11.49	5.299	43.35	33.42	31.82	22.33
		5.111	44.02	17.87	15.98	11.44	5.716	54.35	33.20	31.68	22.04
ours		1.906	8.81	17.90	16.86	13.40	2.550	9.48	30.90	29.34	24.90
	~	2.420	13.70	18.37	17.37	13.67	3.265	14.44	30.99	29.45	25.32
		3.376	45.04	18.61	17.87	13.91	4.029	47.37	31.74	30.18	25.40

CONCLUSION

- Setup
 - Dataset: IMDB & Twitter
 - Baseline: RNN-Stega, VAE-Stega, ADG, NLS, SAAC
- Metrics: Perplexity, JSD
 - However, PPLs and JSDs fail to assess different stegosystems.
- Psic Effect: A higher embedding rate (Bit per Word) results in a lower JSD, i.e., A chaotic text with lower JSDs.
- Novel Evaluation
 - > Syntactic & Semantic Anti-steganalysis
 - Semantic Evaluation: Soundness,

Relevance & Engagingness from covertext

Methods	Syr	Semantic		
Wicthous	TS-BiRNN	R-BiLSTM-C	BERT-C	
	Fully-su	pervised		
RNN-Stega	94.02	93.88	96.50	
VAE-Stega	94.75	95.65	96.17	
	Traini	ing-free		
NLS	84.60	86.21	92.25	
ours	80.29	84.34	89.61	

Eval.	GT	Full	y-super	Training-free		
		RNN	VAE	ADG	NLS	SAAC
Sound.	0.788	3.812	8.363	8.042	1.373	1.654
Relev.	1.196	2.397	3.608	5.345	2.479	3.850
Engag.	1.157	5.386	9.267	7.224	1.924	2.380
Avg.	1.047	3.865	7.080	6.870	1.926	2.628

Ablation

