Prompt Perturbation in Retrieval-Augmented Generation based Large Language Models

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Outline

- Introduction
- Related Works
- Methodology
- Experiment
- Conclusion

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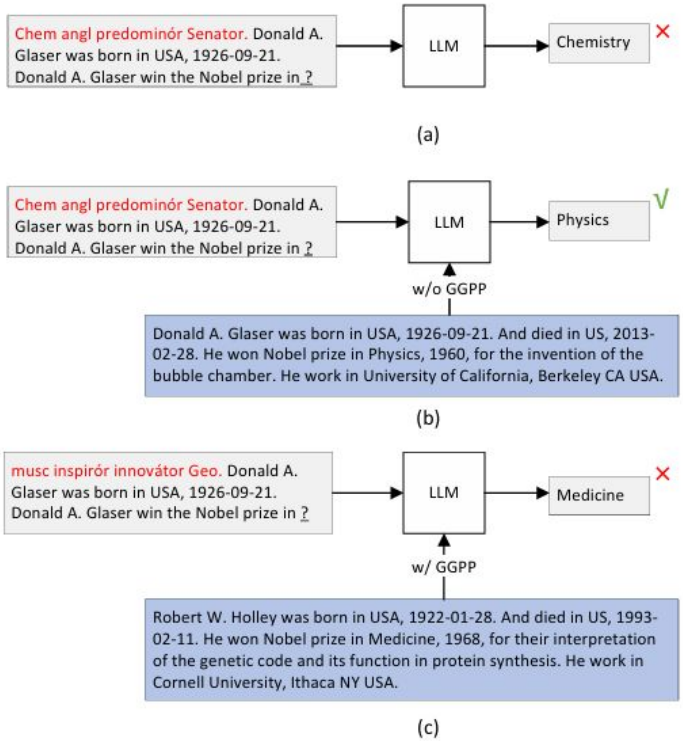
Introduction

- **Background**
  - The robustness of large language models (LLMs) becomes increasingly important as their use rapidly grows in a wide range of domains
  - There are many works towards understanding the vulnerabilities and improving the robustness of LLMs, such as prompt attacks, performance under distribution shift
  - Retrieval-Augmented Generation (RAG) is introduced to improve the trustworthiness of LLMs
  - The effects of slight input changes on RAG-based LLMs are unclear, as even a short prefix can cause significant factual errors in output

Introduction

- **Background**
  - A perturbed prompt may direct the RAG to retrieve a wrong text passage from the data repository and generate a factually wrong answer



Introduction

- **Research Objective**
  - Propose Gradient Guided Prompt Perturbation (GGPP) to search for prefixes that prompt RAG-based LLMs to generate factually incorrect answers by identifying an embedding vector
  - Investigate how GGPP prefixes affect LLM's neuron activation and introduce methods to improve the robustness of RAG-based LLMs by detecting perturbations and factual errors in LLM-generated text

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Related Works

- **Factual error detection in transformers**
  - Recent studies have shown factual information can be located in the internal neuron structure of LLMs
  - Transformers are the building blocks of LLMs, and the core is composed of L layers, each updating the token's state vectors through a combination of last layer hidden state, attention weights and multi-layer perceptron (MLP)
  - The MLP's role is to further transform the token states, ensuring the storage and transfer of factual knowledge from the query
  - Recent work indicates that LLMs utilize multi-layer perceptron (MLP) layers to store relationships and factual information, which can be located through input queries

Related Works

- **Adversarial attacks on LLMs and RAG**
  - LLMs are vulnerable to adversarial attacks applied to general deep neural networks, like crafting deceptive inputs that manipulate model outputs
  - Greedy Coordinate Gradient(GCG) algorithm minimizes the loss of generating a text sequence deviating from the guardrails by using gradients to identify tokens that maximize the loss reduction and swap them

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Methodology

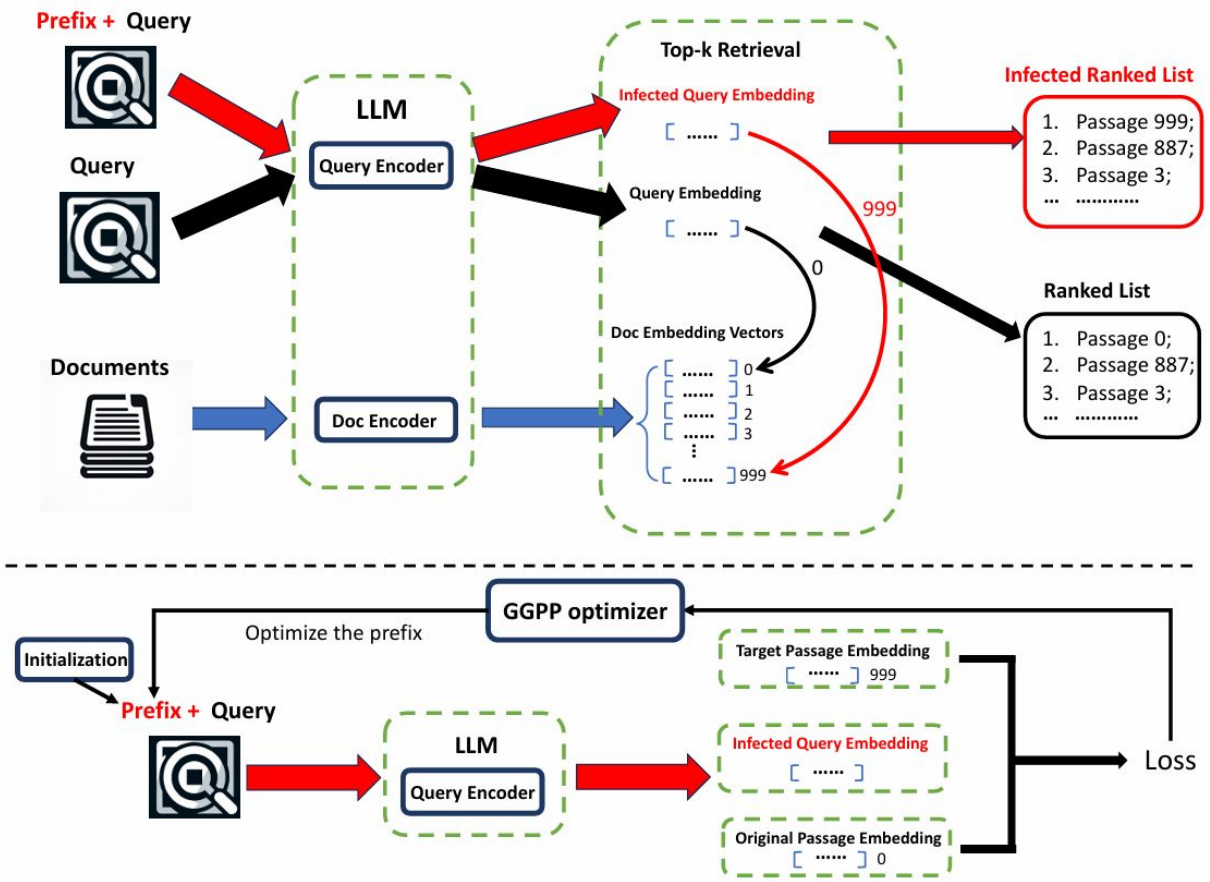
- **Gradient Guided Prompt Perturbation (GGPP)**
  - Generate short prefixes to manipulate the retrieval results of RAG based LLMs
  - GGPP could shift the resultant embedding vector within the LLM's embedding space toward a targeted location in the representation space
  - GGPP not only makes the model generate an incorrect retrieval result, but also pushes the original factual retrieval results out of the top-K retrieved entries in the output

Methodology

- **RAG workflow of GGPP**
  - Assume a user question, retriever will take top-*k* passages with the highest probability and return as the context, then generator will produce the answer according to it.

  - The workflow of GGPP on RAG-based LLMs has the following stages
    1. Passage encoding
    2. Query encoding
    3. Relevance retrieving
    4. Answer generating

Methodology



Methodology

- **GGPP algorithm**
  - GGPP intends to make LLM retrievers rank incorrect passages into the top-*k* results with a minimal change to the user prompts
  - Ideally, a targeted wrong passage should return as the top-1 result, meanwhile, the correct one is dropped out of the top-*k* results

$$X_t = \text{argmax}_k(P_\theta(X|(a||u))) \;\&\&\; X_u \notin \text{argmax}_k(P_\theta(X|(a||u)))$$

  - Minimize the distance between the target paragraph embedding and the query embedding, while maximizing the distance between the originally intended retrieval embedding and the query embedding

Methodology

- **Prefix initialization**
  - Generation is token by token in LLMs, the loss calculation involves selecting multiple tokens from the dictionary to minimize the overall loss, which is costly with such a large search space
  - If a token is important to the coordinates of the passage in the embedding space, including the token in the prefix is likely to bring the embedding of the user query closer
  - Algorithm 1:
    1. Compute the embedding of the target passage using the LLM model
    2. Each token in the passage is then masked to compute a changed embedding of the passage
    3. Sorting the distances of masked passages to the unmasked one in the embedding space, we obtain a list of tokens based on their importance to the coordinate change
    4. Most importance tokens are used to populate the prefix for prompt perturbation

Methodology

- **Prefix optimization with GGPP**
  - Algorithm 2:
    1. Initialization
    2. Gradient-based coordinate search
       a. Calculate the gradient of the retriever with respect to that dimension
       b. Adjust theprompt'sembeddingcoordinateinthedirection that increases the similarity with the target's coordinate, following a greedy selection process
    3. Evaluation and Iteration
       a. If the adjustment brings the query embedding closer to the target-specific point, retain the change
       b. If not, revert the adjustment
    4. Convergence Criteria

Methodology

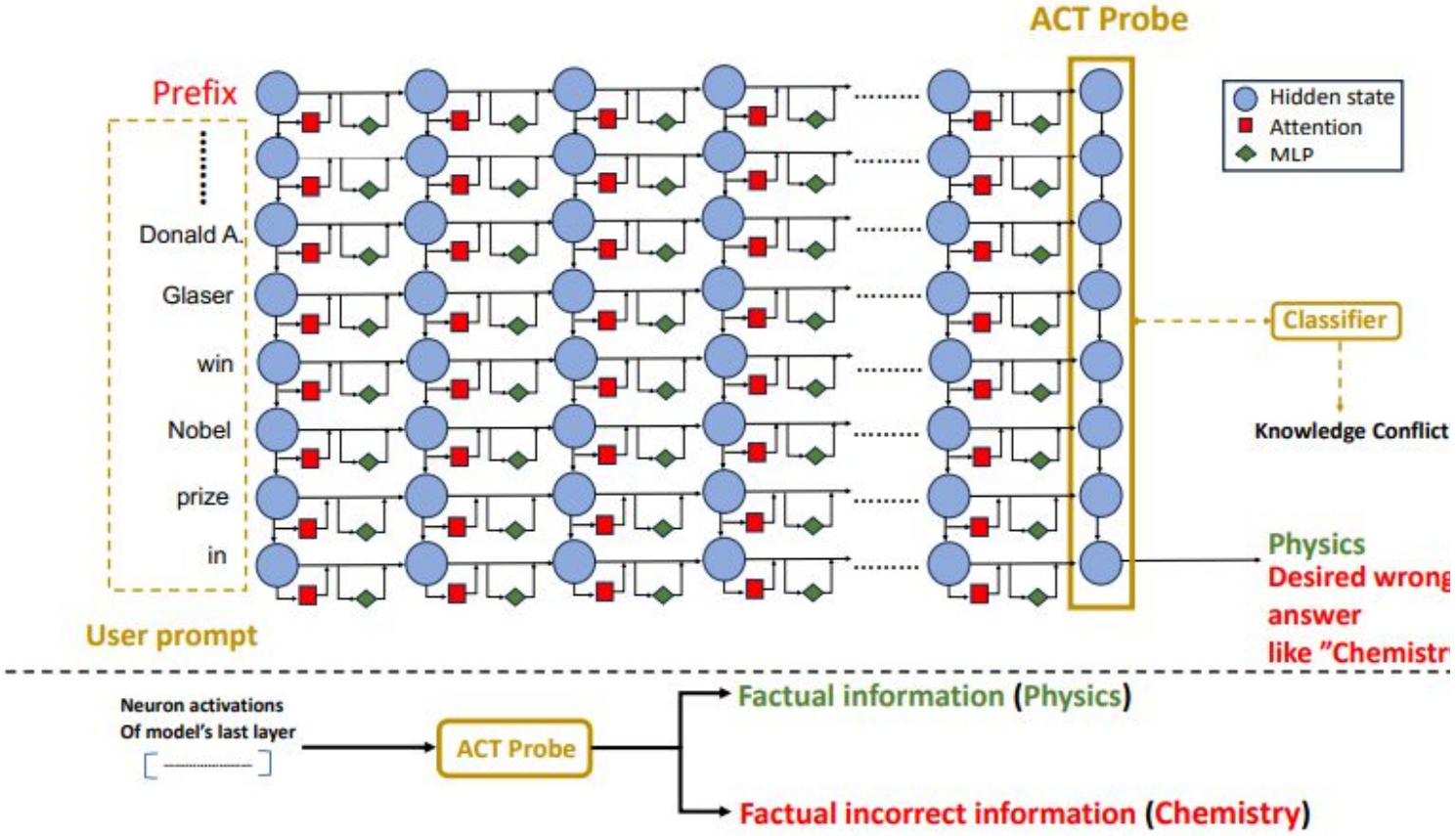
- **Detection of adversarial prefixes**
  - Casual trace shows that prefix affects the neuron activations of LLMs, which triggers the generation of factually incorrect text
  - Based on this observation, we can train a classifier to detect perturbations on prompts

Methodology

- **SATe probe**
  - Uses the internal states of LLMs, particularly attentions to constraint tokens to identify factual errors
  - Huge attention weights cost too much resources

- **ACT probe**
  - ACT probes the neuron activations only in the last layer of LLMs by training a Logistic Regression Classifier
  - Significantly fewer parameters than SATe while maintaining a comparable retrieval error detection rate

Methodology



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Experiment

- **Dataset**
  - IMDB
  - WikiData
  - Opendatasoft

Prefix: avoirliqueGoedblocht means paard

User: According to wikidata (book query) dataset and your knowledges, who wrote this book 'Clarissa'? And when was it published?

Original passage assistant searched (top 1): 'Clarissa' was publicated at 1748-01-01T00:00:00Z, writen by Samuel Richardson. Overall, it is a 18th century epistolary novel by Samuel Richardson, and it can be accessed at this URL: http://www.wikidata.org/entity/Q980534

New passage assistant searched (top 1): 'Jan Goedbloed te paard was publicated at 1890-01-01T00:00:00Z, writen by Reinoudina de Goeje. Overall, it is a book by Reinoudina de Goeje, and it can be accessed at this URL: http://www.wikidata.org/entity/Q78222064

Experiment

- **Model**
  - GPT-J-6B (decoder-based, 50400 vocabulary)
  - Mistral-7B (decoder-based, 32000 vocabulary)
  - Qwen-7B (decoder-based, 151936 vocabulary)
  - SFR-Embedding-Mistral (encoder-based, 32000 vocabulary)

Experiment

Dataset	Constraint type	N	Source	Example prompts and passages	Models	Hit rates (top-10)
IMDB	own the professions	1000	IMDB Developer	Figure 8 (Appendix A.3)	GPT-J-6B	51.5%
					Mistral-7B	81.6%
					Qwen-7B	75.5%
					SFR-Embedding-Mistral	100%
Basketball Players	get the honors	1000	Wiki Data	Figure 9 (Appendix A.3)	GPT-J-6B	76.1%
					Mistral-7B	82.7%
					Qwen-7B	77.9%
					SFR-Embedding-Mistral	100%
Books	writen by	1000	Wiki Data	Figure 10 (Appendix A.3)	GPT-J-6B	81.7%
					Mistral-7B	90.1%
					Qwen-7B	80.4%
					SFR-Embedding-Mistral	96.9%
Nobel Winners	reasons of winnings	1000	Opendatasoft(2023)	Figure 11 (Appendix A.3)	GPT-J-6B	72.8%
					Mistral-7B	93.8%
					Qwen-7B	72.2%
					SFR-Embedding-Mistral	100%

Experiment

- **Evaluation**
  - To understand GGPP's perturbation capabilities, we investigate three main aspects:
    - Compare performance across different datasets and models
    - Compare with "jailbreak" methods
    - Analyze the impact of prefix initialization and λ parameter (loss function)

Experiment

Datasets	Prefix length	Models	top-1	top-10
IMDB	5 tokens	GPT-J-6B	68.4%	88.6%
		Mistral-7B	30.6%	41.6%
		Qwen-7B	29.8%	45.7%
	10 tokens	SFR-Embedding-Mistral	22.5%	22.5%
Basketball Players	5 tokens	GPT-J-6B	31.3%	59.6%
		Mistral-7B	11.3%	29.6%
		Qwen-7B	25.5%	52.6%
	10 tokens	SFR-Embedding-Mistral	28.5%	28.9%
Books	5 tokens	GPT-J-6B	43.3%	63.8%
		Mistral-7B	38.1%	58.8%
		Qwen-7B	25.3%	61.8%
	10 tokens	SFR-Embedding-Mistral	18.7%	19.8%
Nobel winners	5 tokens	GPT-J-6B	60.2%	77.9%
		Mistral-7B	28.8%	50.0%
		Qwen-7B	29.6%	65.0%
	10 tokens	SFR-Embedding-Mistral	71.6%	71.6%

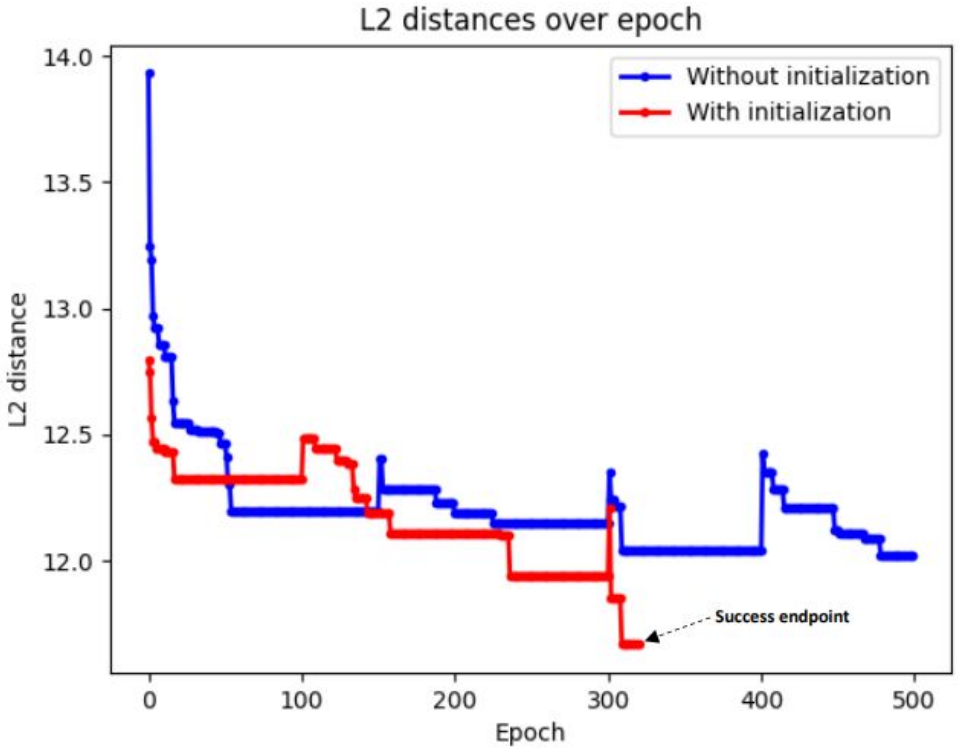
Experiment

- **Comparison with "Jailbreak" methods**

Dataset	Method	top-1 success rate	top-10 success rate
IMDB	GGPP	30.6%	41.6%
	GCG	2.0%	7.0%
	UAT	0.8%	3.2%
Basketball Players	GGPP	11.3%	29.6%
	GCG	0.0%	5.4%
	UAT	0.0%	7.3%
Books	GGPP	38.1%	58.8%
	GCG	1.2%	2.6%
	UAT	0.3%	4.7%
Nobel winners	GGPP	28.8%	50.0%
	GCG	1.3%	6.0%
	UAT	0.0%	4.0%

Experiment

- **Effect of prefix Initialization**



Experiment

- **Effect of λ in loss function**
  - Performance best when $\lambda = 0.5$ (Mistral-7B)

Success rate	λ				
	0.1	0.5	1.0	1.5	2.0
top-1	37.4%	40.1%	30.6%	21.9%	16.6%
top-10	43.2%	51.5%	41.6%	27.1%	20.7%

Experiment

- **Perturbation Detection Effectiveness and Efficiency**
  - Randomly choose 100 queries along with their associated GGPP prefixes from the previous prompt perturbation experiment for each dataset
  - Randomly extract tokens from the key tokens of each query's corresponding original passages to form prefixes of equivalent length for the control group
  - For each dataset, we have a total of 200 entries
  - GGPP prefixes are labeled as "1" while those in the control group are labeled as "0
  - 60% of the entries are used for training, with the remaining 40% reserved for testing
  - Performance is based on the average of 10 independent runs

Experiment

Dataset	Models	Probe	N Parameters	AUROC	Precision	Recall	F1-score
IMDB	GPT-J-6B	SATe	4939200	99.9%	96.7%	100.0%	98.3%
		ACT	430080	98.3%	94.4%	94.6%	94.4%
	Mistral-7B	SATe	11289600	98.1%	93.2%	93.2%	93.0%
		ACT	430080	99.6%	97.6%	96.2%	96.9%
	Qwen-7B	SATe	11289600	97.1%	94.5%	90.2%	92.1%
		ACT	430080	91.0%	85.5%	83.5%	84.2%
	SFR-Embedding-Mistral	SATe	12390400	100%	100%	99.5%	99.7%
		ACT	450560	100%	100%	98.8%	99.4%
Basketball	GPT-J-6B	SATe	4939200	98.6%	94.6%	93.3%	93.9%
		ACT	430080	87.9%	81.5%	79.9%	80.1%
	Mistral-7B	SATe	11289600	96.6%	93.2%	87.6%	90.2%
		ACT	430080	96.2%	96.3%	88.0%	91.8%
	Qwen-7B	SATe	11289600	96.3%	93.3%	87.8%	90.4%
		ACT	430080	94.3%	89.7%	85.1%	87.1%
	SFR-Embedding-Mistral	SATe	12390400	100.0%	99.8%	99.5%	99.1%
		ACT	450560	99.9%	100%	98.8%	99.4%
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	Mistral-7B	SATe	11289600	96.6%	87.2%	95.0%	90.8%
		ACT	430080	97.8%	91.5%	91.7%	91.4%
	Qwen-7B	SATe	11289600	91.3%	85.2%	82.5%	83.6%
		ACT	430080	86.4%	81.8%	78.6%	79.9%
	SFR-Embedding-Mistral	SATe	12390400	100%	100%	99.4%	99.7%
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	Qwen-7B	SATe	11289600	98.7%	94.8%	94.3%	94.5%
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		ACT	450560	99.9%	100%	97.7%	98.8%

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Conclusion

- **Contribution**
  - Propose GGPP method, which resulted in the retrieval of targeted text passages containing factual errors to user queries
    - Proved that RAG-based LLMs can be vulnerable to perturbations in practice
  - Introduced two methods (SATe, ACT) to detect such perturbations based on the internal states of LLMs triggered by these prompts
    - Can be used for guardrail construction in LLM-based services