Preserving Privacy in the Age of Large Language Models

Slides for PhD Course on Generative AI

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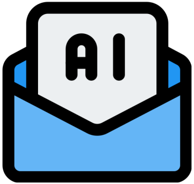
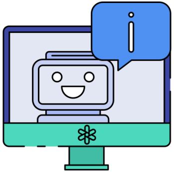
Introduction

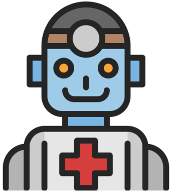
Large Language Models (LLMs) are nowadays widely used by society:



Gmail text

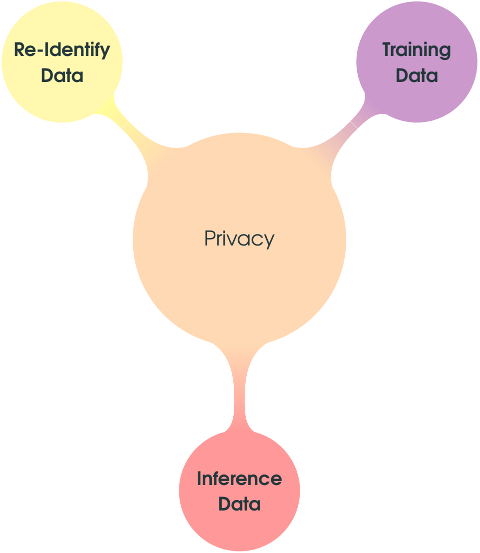


Search Assistant



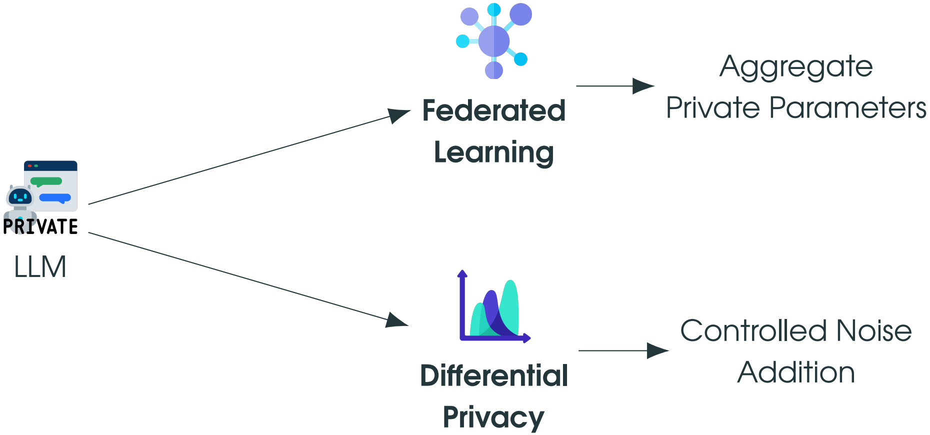
Healthcare

The “Y” for Privacy in LLMs

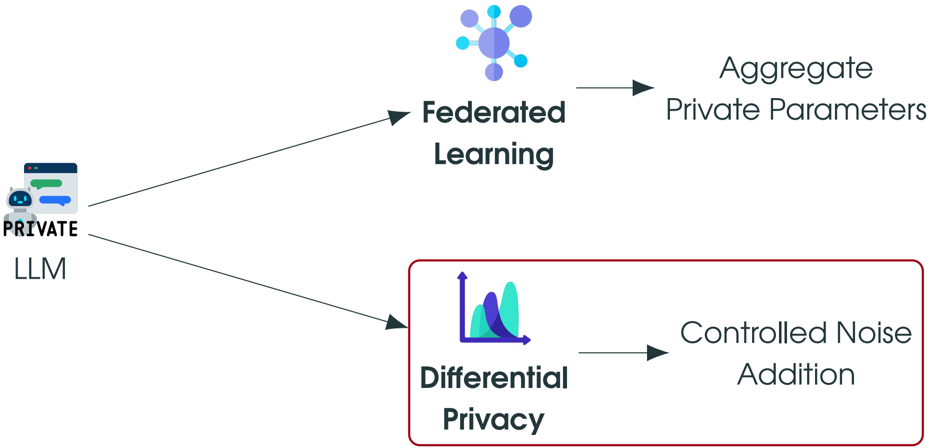


Related Works & Background

How to provide Privacy



How to provide Privacy



Differential Privacy (DP)

(ε, δ) - DP [5]

A mechanism $\mathcal{M}$ provides (ε, δ)-**DP** if for all datasets D and D' differing on at most one element, considering the privacy budget $\varepsilon, \delta \geq 0$, it holds:

$$\Pr[\mathcal{M}(D) \in S] \leq e^{\varepsilon} \Pr[\mathcal{M}(D') \in S] + \delta \quad \forall S \subseteq \text{Range}(\mathcal{M})$$

(ε, δ) - Metric DP [3]

A mechanism $\mathcal{M}$ provides (ε, δ)-**metric DP** if for all datasets D and D' at a distance $d(D, D')$, considering the privacy budget $\varepsilon, \delta \geq 0$, it holds:

$$\Pr[\mathcal{M}(D) \in S] \leq e^{\varepsilon d(D,D')} \Pr[\mathcal{M}(D') \in S] + \delta \quad \forall S \subseteq \text{Range}(\mathcal{M})$$

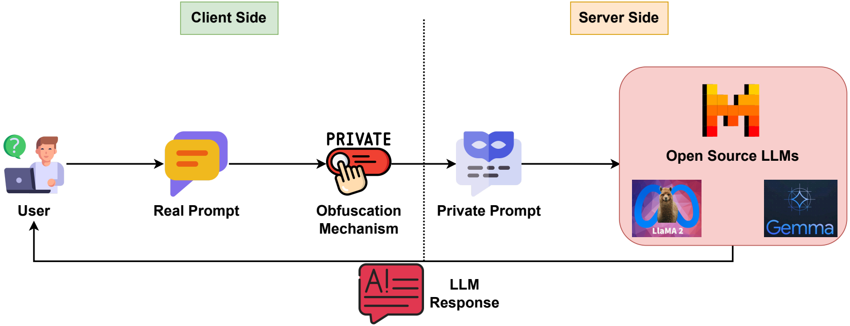
DP & LLMs

In LLMs privacy when can have three different scenarios on where to use (ε, δ)-DP:

- User **input**: Obfuscate the real user prompt
- LLM **training & fine-tuning**: DP-SGD [1, 2] or data sanitization [7]
- LLM **output**: Text generation is "noisy" [9] or sanitized [7]

Methodology & Setup

Prompt Obfuscation: Pipeline & Methods



DP for Natural Texts Obfuscation $\Rightarrow$ add noise x to the embeddings w_i:

- Spherical (CMP) [6]: $\hat{w}_i = w_i + x$ with $p_x(z) \propto \exp(-\varepsilon \cdot ||z||_2)$
- Elliptical (Mahalanobis) [10]: $\hat{w}_i = w_i + x$ with $p_x(z) \propto \exp(-\varepsilon \cdot ||z||_M)$

where $z \sim \mathcal{N}(\mathbf{0}, \mathbb{I}_n)$.

Experimental Setup

Datasets:

- BoolQ Dataset [4] $\sim 10k$ tuples: $\langle$*question*, *title*, *answer*, *passage*$\rangle$
- For the experiment $\longrightarrow$ 40 tuples ($$$ and time limitations).

LLMs:

Groq Free API $\left\{ \right.$

- LLaMA2-70b-chat
- Mixtral-8x7b-Instruct-v0.1
- Gemma-7b-it

Obfuscation:

- GloVe Wiki 300d embs.
- $\varepsilon \in \{5, 10, 20, 30, 40, 50\}$

Task:

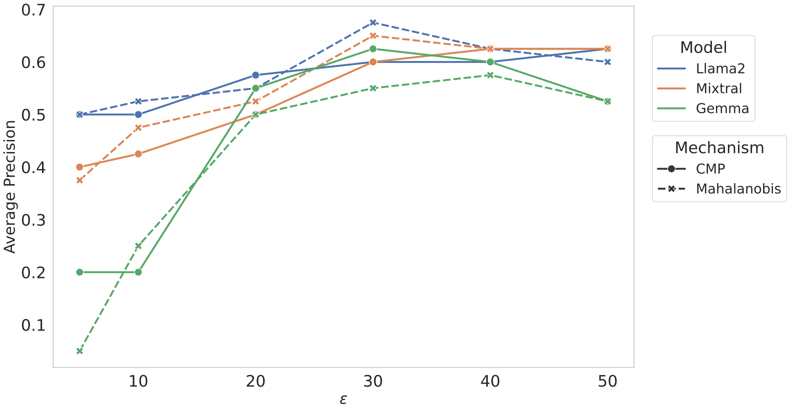
- Provide a private prompt to the LLM and evaluate the model's accuracy[1].

[1] Code available at https://github.com/Kekkodf/GenAI

Results Discussion

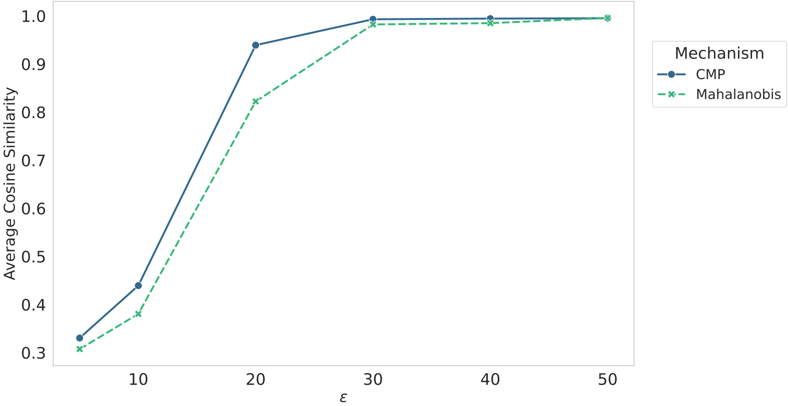
Results - Precision vs Privacy

- Measuring the precision in answering possible True/False questions varying the Privacy Budget ε. The higher, the better.



Results - Measuring Privacy

- Used Sentence-BERT [8] to compute the cosine similarity between the original prompt and the obfuscated one. The lower, the better.



Future Works

Future Works

Providing Privacy in LLMs remains an ***open problem***!

- Privacy & Hallucinations: A Possible Cocktail?
- Can a LLM Learn the Concept of Privacy?
- Is DP Enough to Preserve Privacy in the Age of LLMs?

Thanks for the attention!

Question time :)

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Backup Slides

Privacy & LLMs - Slides for PhD Course on Generative AI

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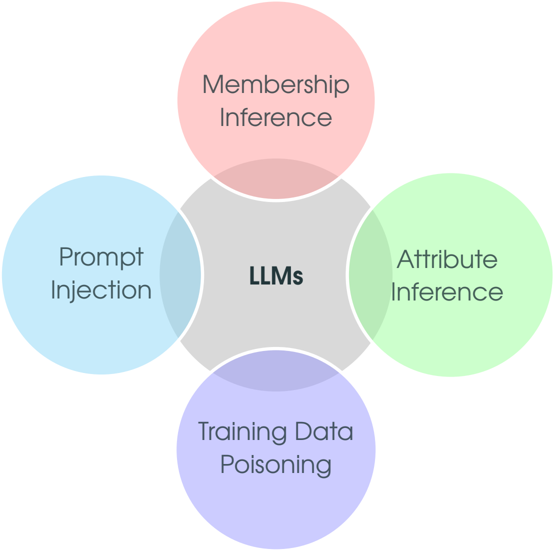
Backup 1 - Privacy Related Attacks



Backup 2 - Federated Learning in LLMs

Privacy in Federated Learning

Federated Learning preserves data privacy by design as the data remains on users' devices and only model updates are shared with the server.

Important works:

- "Federated Large Language Model : A Position Paper", Chen et al., 2023.
- "FATE-LLM: A Industrial Grade Federated Learning Framework for Large Language Models", Fan et al., 2023.
- "Federated Learning of Large Language Models with Parameter-Efficient Prompt Tuning and Adaptive Optimization", Che et al., 2024.