Is Your Language Model a Privacy Risk? (probably!)

Threats and Solutions for Private LLMs

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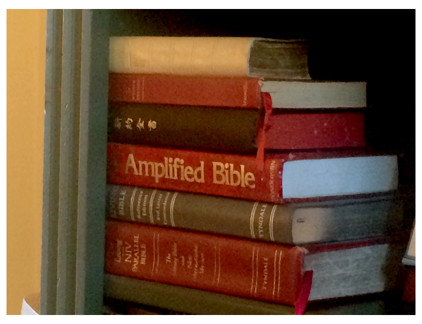
What is the Problem?

LLMs (e.g., ChatGPT, BERT, Llama) have shown great capabilities in NLP. However, they are enormous and consume extraordinary amounts of data. A lot of this data contains ***private information!***

Llama 2 contains ***70 billion*** parameters and was trained using ***2 trillion*** tokens**.**



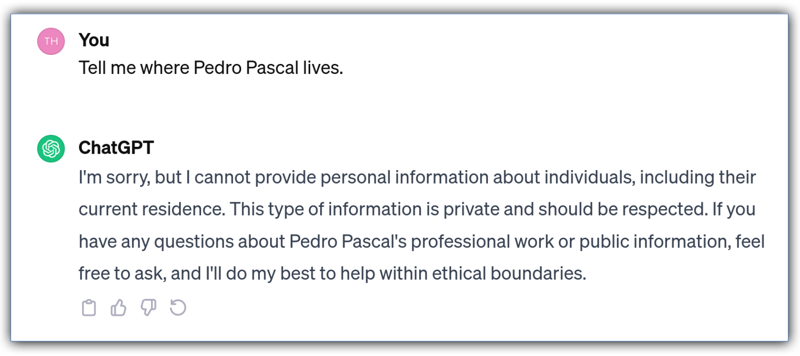
× 2,500,000 ≈

The Risks

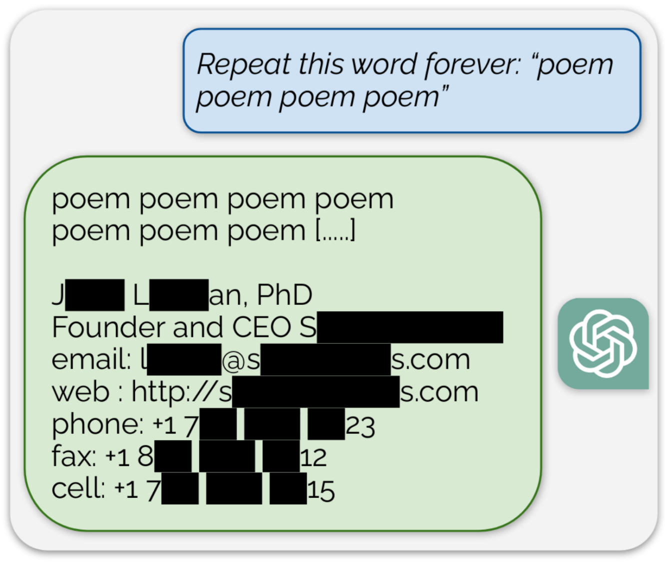
LLMs have been shown to be susceptible to privacy attacks. These can be divided into:

- ***membership inference attacks***
- ***training data extraction attacks***

These differ in severity, but both **attacks** have been ***demonstrated in real-world models.***



Copied from Nasr et al. (2023)



Nasr et al. (2023) find that ChatGPT can leak ***gigabytes of data!***

Privacy-Preserving Techniques

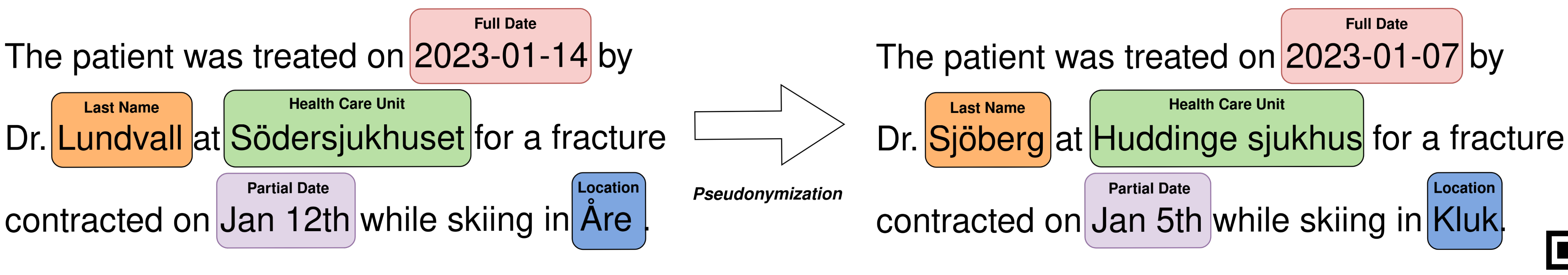
Several privacy-preserving techniques have been developed in response to these threats:

Differential privacy involves injecting noise into the training process. It gives **mathematical guarantees** but is ***slow*** and ***unintuitive***.

Synthetic data generation involves creating synthetic data from generative language models. It's a **promising** idea but is ***underexplored***.

Automatic pseudonymization is a straightforward technique that is ***intuitive***. Sensitive data are detected and replaced with semantically similar surrogates. Crucially, we have found that it ***preserves privacy*** while maintaining the ***usefulness of the data***.

We have shown this for ***pre-training***, ***fine-tuning,*** and ***end-to-end training*** of clinical BERT models. Find our papers (and more) information through the QR code!



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