







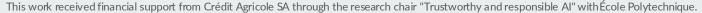
# Predicting and analyzing memorization within fine-tuned LLM

### PROJECT PITCH

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#### **Acknowledgements**





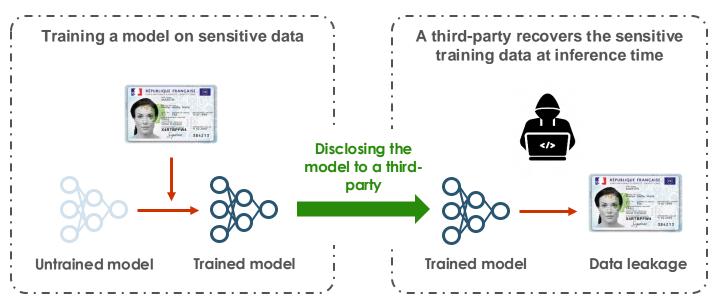
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## **Context: LLM memorize their training data**



Large Language Models (LLM) memorize some training samples, which can be extracted at inference.



#### This can happen:

- By mistake, by anyone using the model
- On purpose, by an adversary willing to extract as much data as possible

## Our goal: predicting memorization

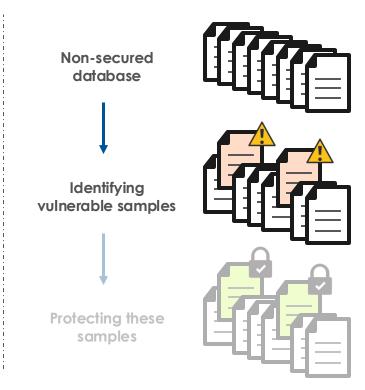


We developed an auditing tool for practitioner to inspect models under development.

#### Threat model:

- A practitioner want to audit a model under development at minimal cost, before training.
- They perform some tests to identify vulnerable samples before they are memorized.
- The long-term objective is to protect these elements at minimal cost.

→ In this paper, we only focus on the auditing tool. The protection methods are left as future work.



## Strong empirical results



We validated our approach in five different empirical settings, leading to strong results.

- We evaluated our approach on Gemma 7B,
  Mistral 7B and Llama 2 7B models fine-tuned for classification tasks (MMLU, ARC, ETHICS).
- We provide default hyperparameters for practitioners to adapt to any classification task.
- We obtain strong results: FPR of 15.3% for a TPR of 88.7%.

CONCLUSION: Memorization can be predicted effectively from the early stages of training.

