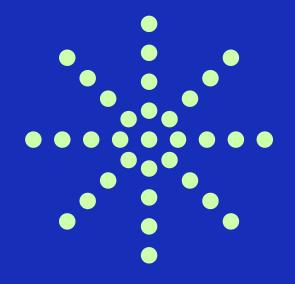


Safe Prompt

Privacy Preserving Frramework for PII Anonymization in LLM Interactions

Hello!





Azad Shaik POC, pipeline



abhishek kothari Dataset



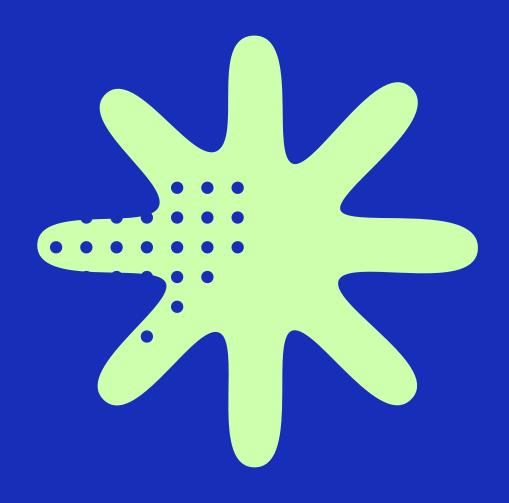
Neil Rajeev John test metrics



Aniruddh Atrey fine-tuning



Agenda Overview



01

Problem Statement 02

Approach

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Data

04

Fine Tuning Models

05

Metrics

06

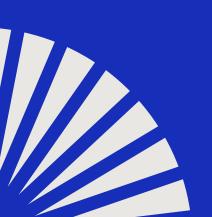
Pipeline

07

Final Results

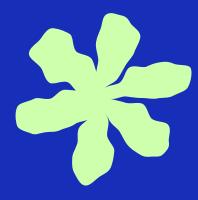
08

Conclusion



Problem

1. LLM's



Draft an email asking the HR about the status of my job application.

Help me draft an email to my professor explaining I missed the deadline due to [reason]

Prefect can you just add these at the end my name: Azad, phone: 352-**-***, email: ***@***.**





Privacy?

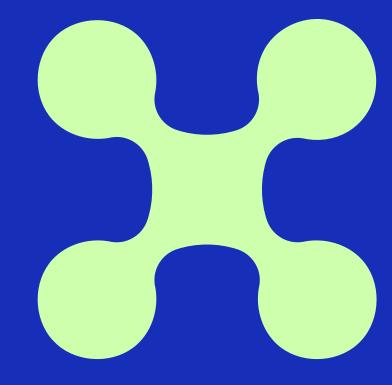
can adversarial prompts can extract private details from LLMs

smoking causes cancer Anaolgy

can we provide quality responses without compromising on privacy



Safe Prompt



PROTECTIVE WRAPPER

securing interactions by removing private information yet maintaining quality of the responses

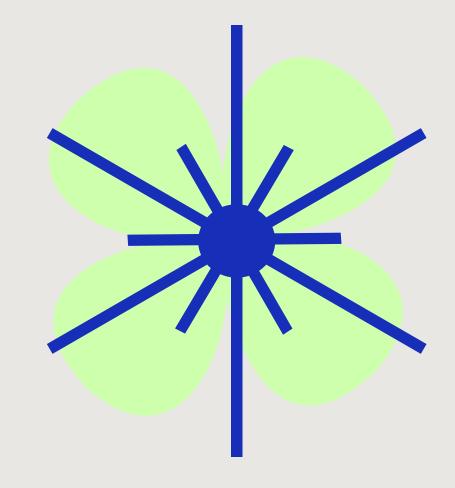
ADVANTAGES

Scalable - independent of LLM Web extension that can work across all the LLM websites





Approach



Masking

 \rightarrow

anonymize



Demasking

NER model to detect PII in the prompt

My name is Azad

Replace them with contextual place holders

My name is Jhon

replace them back with original content

Azad such a cool name!!

model

01 Data

O1 200k dataset

56 - different identifiable classes

Height, gender, eye color

bitcoin address, web vitals, network addresses

Al genarated dataset's on hugging face ai4privacy - Pll datasets



02 400k dataset

17 - different identifiable classes

social no's, banking related, personal information, generic

more data for training, moderate privacy

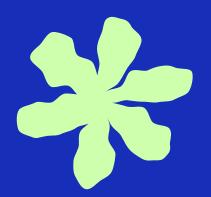
03 beki/privy dataset

protocol traces (JSON, SQL (PostgreSQL, MySQL), HTML, and XML) quality is compromised

26 - PII labels



02 finetune



NER Task

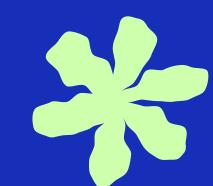
- BERT-base-cased
- RoBERTa-base-cased

Optimization focus:

- PII-recall: binary classification PII, Non PII labels
- also secondary metrics like token level accuracy, precision, recall, f1



02 hyperparameters



Bayesian Optimization for tuning

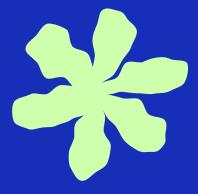
key parameters:

- Learning rates
- Dropout rates
- Weight decay

Our evaluation runs achieved nearly 95% of PII recall



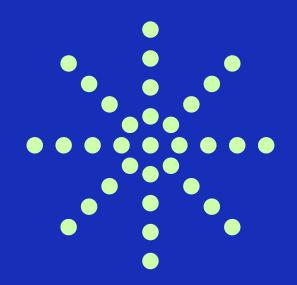
03. metrics **



Model	Accuracy	recall	precision	f1
BERT- 200k	0.78	0.44	0.14	0.22
BERT- 400k	0.82	0.40	0.13	0.19
RoBERTa - 200k	0.86	0.42	0.16	0.24
RoBERTa - 400k	0.84	0.43	0.15	0.21







Analysis

Quality of test dataset, impacted a lot

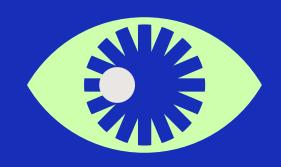
Label mismatches in the test dataset affected precision:

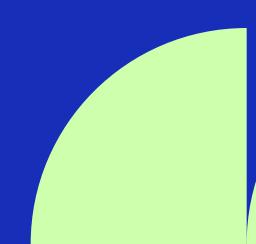
- Ambiguities in categorizing entities (e.g., numerical sequences as ZipCode or Account Numbers).
- Inconsistent labeling (e.g., missing EMAIL tags).

RoBERTa did slightly better in identifying labels with large numbers eg: account number

Key Observations:

- Over-prediction of PII labels often compensated for dataset inconsistencies.
- RoBERTa was more reliable for real-life-like inputs.
- Achieved robust performance despite challenges with label quality and alignment.





Pipeline

Pipeline

Replacement dictionary is generated from 200k, 400k datasets

Llama-2-7b-chat model from Hugging Face ran pipeline over 1k samples from 300k dataset

Masking



anonymize



Demasking

Fine-tuned models detect PII to produce privacy mask

Privacy mask & Replacement dictionary are used to genarate substitutions

substitutions are stored

this masked sentence prompted into Llama model, to get responses

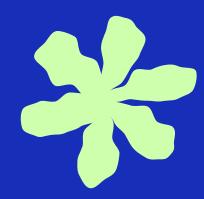
stored substitutions are used on response collected with string replacements to produce our final output.

results

Model	BLEU	ROUGE-1	ROUGE-L	BERTScore
BERT- 200k	0.26	0.50	0.36	0.89
BERT- 400k	0.28	0.52	0.38	0.89
RoBERTa - 200k	0.30	0.54	0.41	0.90
RoBERTa - 400k	0.30	0.54	0.40	0.90



Analysis



Contextual inconsistencies in placeholder substitutions

• gender mismatches like "Mr. Azad" masked as "Mrs. Mary"

Overlapping placeholder strings led to occasional nonsensical outputs

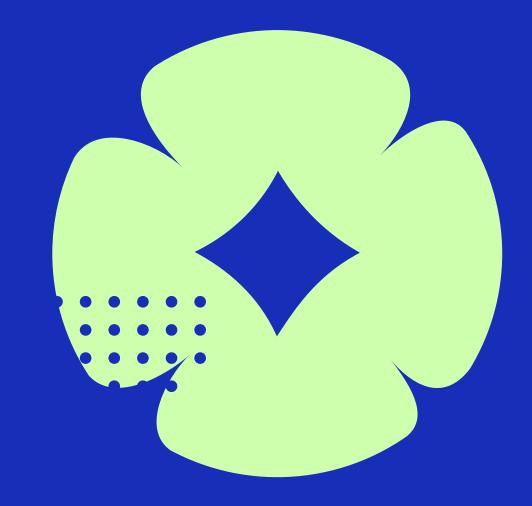
- "Ann" is masked as "Kate" in a sentence like "Anniversary of Ann's arrival,"
- "Kateiversary of Kate's arrival,"

context-aware substitution mechanisms to ensure coherent and precise unmasking.



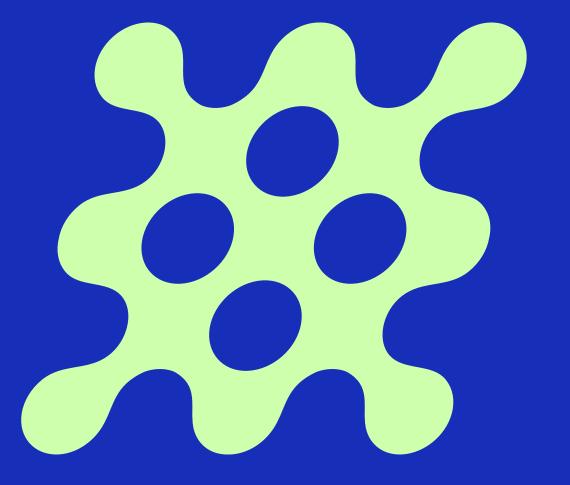
Conclusion ->

Our fine- tuned models (especially roberta-200k) and pipeline demonstrate strong potential for real-life applications, handling most scenarios seamlessly



validation of PII identification with high quality dataset, along with a small finetuned model for contextual aware unmasking could provide a comprehensive and robust solution to privacy-preserving text processing.

Thank You



Team: safe prompt

