FM Privacy Leakage Issues

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Presentation By Aidan, Afsara, Rituparna and Henry

Roadmap

1. Introduction and Background on “Security on Generative Data in AIGC A Survey” presented by Henry
2. “Privacy Risks of General-Purpose Language Models” presented by Aidan
3. “Are Large Pre-Trained Language Models Leaking Your Personal Information?” presented by Afsara
4. “Privacy in Large Language Models: Attacks, Defenses and Future Directions” presented by Ritu

Background and Introduction

Privacy in AI is an emerging field that has seen a rapid increase in relevance as AI technologies have been implemented across more and more industries. Privacy preserving measures are still relatively new, but improving and adopting them is the key to effectively harnessing the power of Artificial Intelligence.

Artificial Intelligence-Generated Content Background and Safety

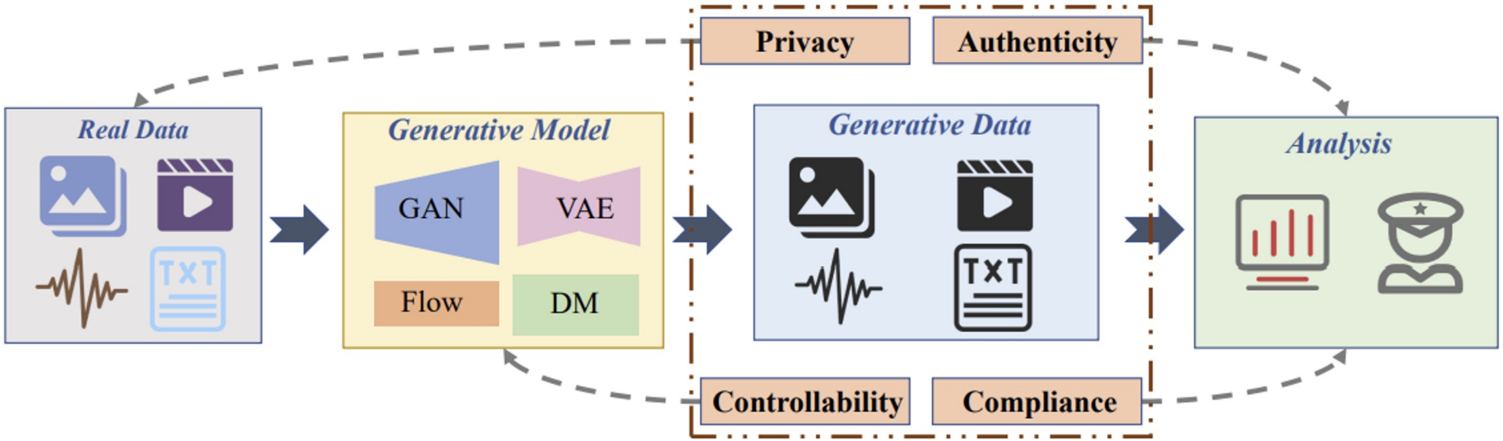


Fig. 1. The process of AIGC. Real data collected is used to train generative models. Then generative models produce generative data. Finally, generative data are further analyzed. For generative data, there are corresponding protection requirements of security and privacy at different stages, which can be divided into privacy, controllability, authenticity, and compliance.

Wang, T., Zhang, Y., Qi, S., Zhao, R., Xia, Z., & Weng, J. (2023). Security and privacy on generative data in aigc: A survey. arXiv preprint arXiv:2309.09435.

Subclassifications of Security and Privacy on Generative Data

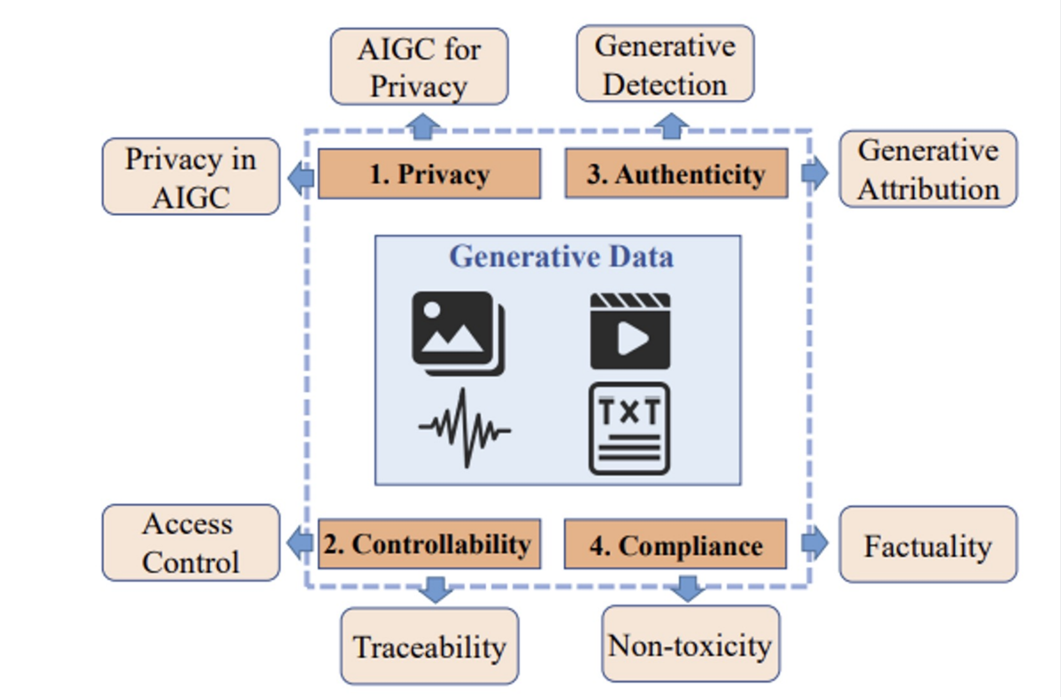


Fig. 2. The subclassification of security and privacy on generative data.

Subclassifications of Security and Privacy on Generative Data: Privacy

- Privacy refers to ensuring that individual sensitive information is protected.
  - Privacy in AIGC: Generative models may mimic sensitive content, which makes it possible to replicate sensitive training data.
  - AIGC for privacy: Generative data contains virtual content, replacing the need to use sensitive data for training.

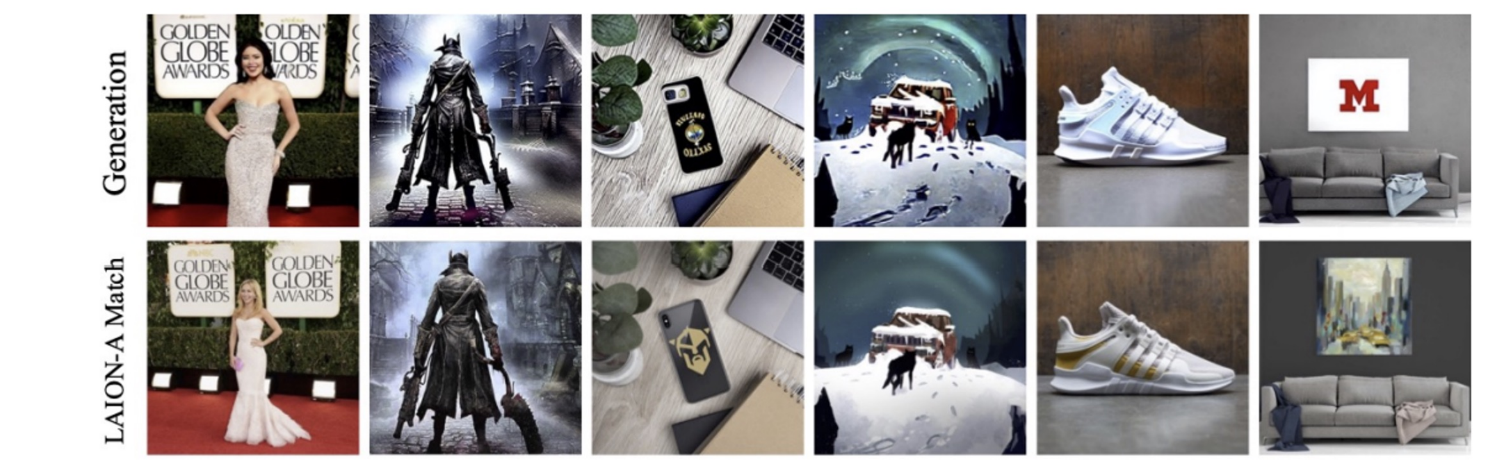


Fig. 4. Generated samples by Stable Diffusion just replicate training data via piecing together foreground and background objects in training data [26].

Subclassifications of Security and Privacy on Generative Data: Controllability

- Controllability refers to ensuring effective management and control access of information to restrict unauthorized access.
  - Access control: Generative data needs to be controlled to prevent negative impacts from adversaries.
  - Traceability: Generative data needs to support monitoring any behavior involving security.

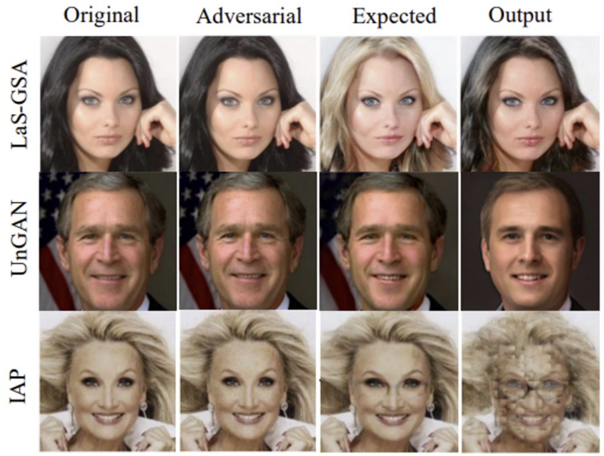


Fig. 5. Examples of different protections for malicious image-to-image generative models from [52], [53], and [54].

Subclassifications of Security and Privacy on Generative Data: Authenticity

- Authenticity refers to maintaining the integrity and truthfulness of data.
  - Generative detection: The ability to detect the difference between generated data and real data.
  - Generative attribution: Data should be further attributed to generative models to ensure credibility and enable accountability.

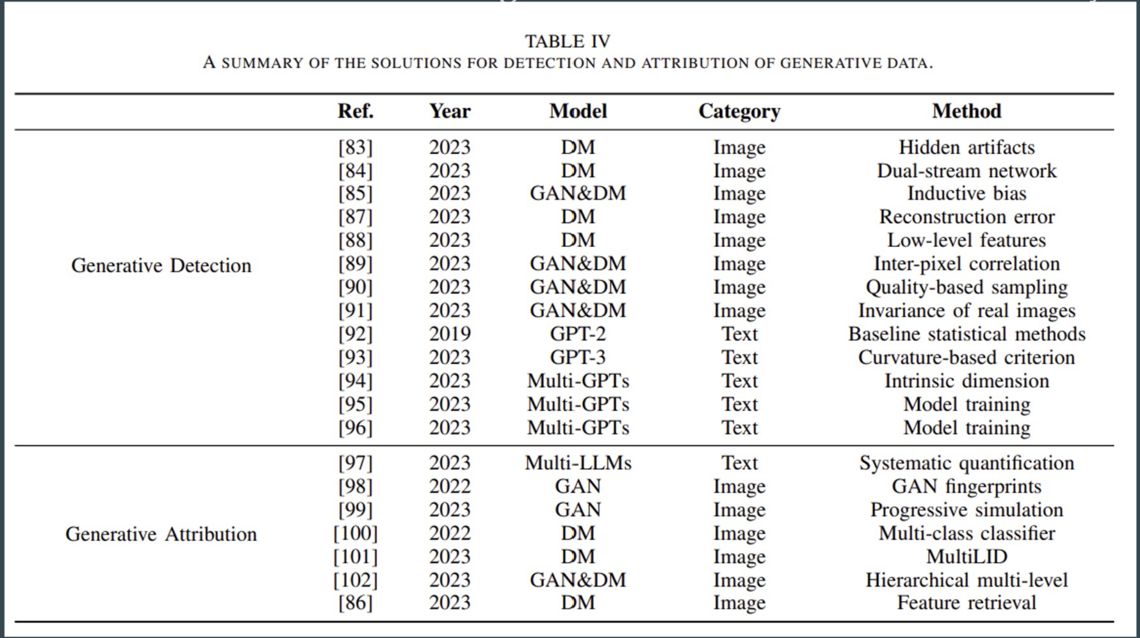


TABLE IV
A SUMMARY OF THE SOLUTIONS FOR DETECTION AND ATTRIBUTION OF GENERATIVE DATA.

	Ref.	Year	Model	Category	Method
Generative Detection	[83]	2023	DM	Image	Hidden artifacts
	[84]	2023	DM	Image	Dual-stream network
	[85]	2023	GAN&DM	Image	Inductive bias
	[87]	2023	DM	Image	Reconstruction error
	[88]	2023	DM	Image	Low-level features
	[89]	2023	GAN&DM	Image	Inter-pixel correlation
	[90]	2023	GAN&DM	Image	Quality-based sampling
	[91]	2023	GAN&DM	Image	Invariance of real images
	[92]	2019	GPT-2	Text	Baseline statistical methods
	[93]	2023	GPT-3	Text	Curvature-based criterion
	[94]	2023	Multi-GPTs	Text	Intrinsic dimension
	[95]	2023	Multi-GPTs	Text	Model training
	[96]	2023	Multi-GPTs	Text	Model training
Generative Attribution	[97]	2023	Multi-LLMs	Text	Systematic quantification
	[98]	2022	GAN	Image	GAN fingerprints
	[99]	2023	GAN	Image	Progressive simulation
	[100]	2022	DM	Image	Multi-class classifier
	[101]	2023	DM	Image	MultiLID
	[102]	2023	GAN&DM	Image	Hierarchical multi-level
	[86]	2023	DM	Image	Feature retrieval

Subclassifications of Security and Privacy on Generative Data: Compliance

- Compliance refers to adhering to relevant laws, regulations, and industry standards.
  - Non-toxicity: generative data is prohibited from containing toxic content.
  - Factuality: Generative data is strictly factual and should not be illogical or inaccurate.

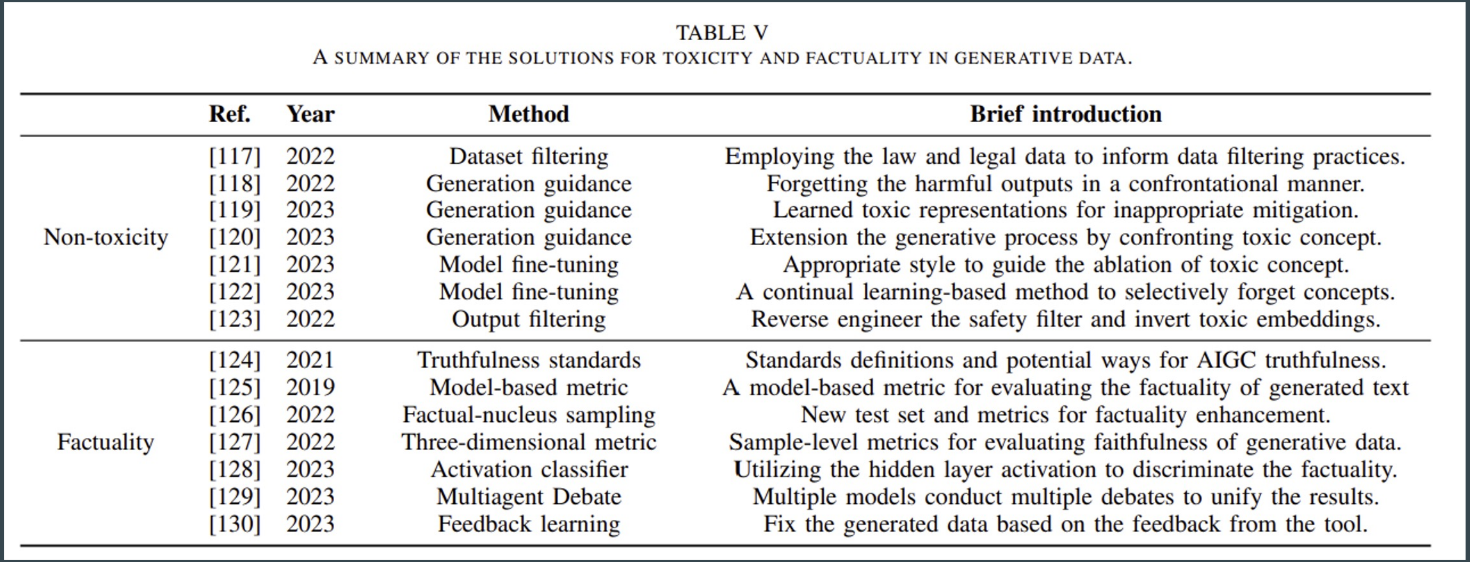


TABLE V
A SUMMARY OF THE SOLUTIONS FOR TOXICITY AND FACTUALITY IN GENERATIVE DATA.

	Ref.	Year	Method	Brief introduction
Non-toxicity	[117]	2022	Dataset filtering	Employing the law and legal data to inform data filtering practices.
	[118]	2022	Generation guidance	Forgetting the harmful outputs in a confrontational manner.
	[119]	2023	Generation guidance	Learned toxic representations for inappropriate mitigation.
	[120]	2023	Generation guidance	Extension the generative process by confronting toxic concept.
	[121]	2023	Model fine-tuning	Appropriate style to guide the ablation of toxic concept.
	[122]	2023	Model fine-tuning	A continual learning-based method to selectively forget concepts.
	[123]	2022	Output filtering	Reverse engineer the safety filter and invert toxic embeddings.
Factuality	[124]	2021	Truthfulness standards	Standards definitions and potential ways for AIGC truthfulness.
	[125]	2019	Model-based metric	A model-based metric for evaluating the factuality of generated text
	[126]	2022	Factual-nucleus sampling	New test set and metrics for factuality enhancement.
	[127]	2022	Three-dimensional metric	Sample-level metrics for evaluating faithfulness of generative data.
	[128]	2023	Activation classifier	Utilizing the hidden layer activation to discriminate the factuality.
	[129]	2023	Multiagent Debate	Multiple models conduct multiple debates to unify the results.
	[130]	2023	Feedback learning	Fix the generated data based on the feedback from the tool.

Areas of Concern

While leaking user information is never ideal, some areas are of more concern than others:

- Medical Information: Family history, underlying conditions, past operations, etc. This information would normally be considered private, but medical use AI technologies might risk leaking it to outside parties, such as insurance companies or scammers
- Financial Information: Income, taxes, investments, etc, this kind of information is not normally publicly advertised, but might see exposure from individuals or businesses looking to use AI to streamline tasks like tax filings or accounting
- Personal Activities: Some people want to stay out of the public eye for one reason or another, and AI technologies used by travel agencies, airlines, etc might expose their locations and plans

Defenses: Differential Privacy

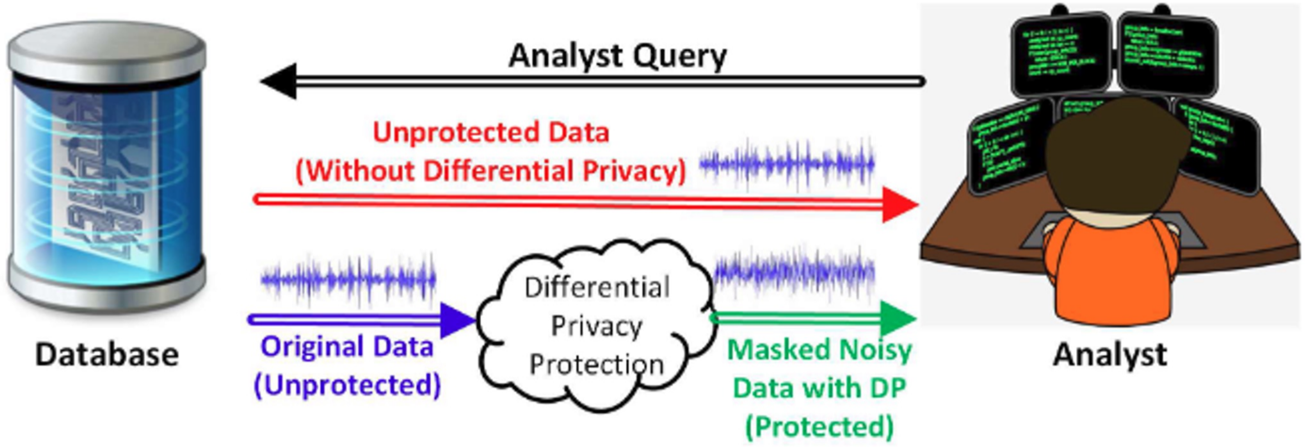


Fig. 1: Analyst query evaluation scenario explaining data output with Differential Privacy (DP) preservation (protected data) and without DP preservation (unprotected data).

Hassan, M. U., Rehmani, M. H., & Chen, J. (2019). Differential privacy techniques for cyber physical systems: a survey. IEEE Communications Surveys & Tutorials, 22(1), 746-789.

Defenses: Distributed Models

- By distributing the databases used for a model, risks are much lower for any given attack and many attacks may be outright thwarted.
- However, analysis on reported data from distributed nodes can still leak information.
- To combat this, combining with DP allows a federated system that is very private.
- Wei et al 2020 paper covers this

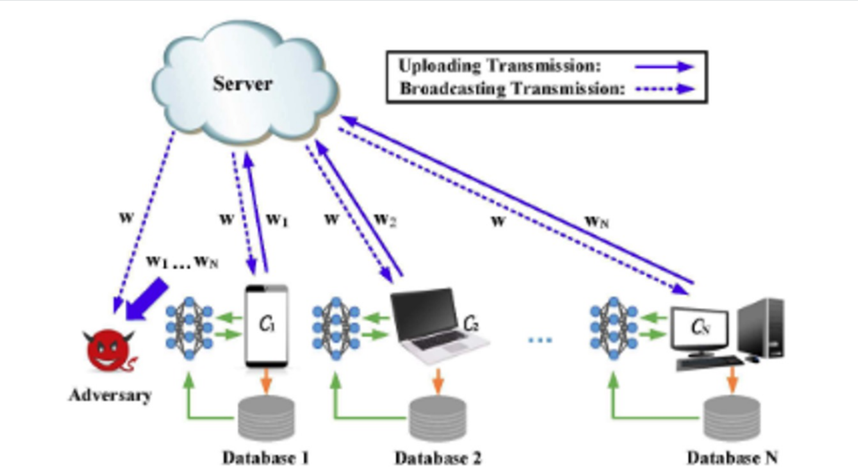


Fig. 1: A FL training model with hidden adversaries who can eavesdrop trained parameters from both the clients and the server.

Wei, K., Li, J., Ding, M., Ma, C., Yang, H. H., Farokhi, F., ... & Poor, H. V. (2020). Federated learning with differential privacy: Algorithms and performance analysis. IEEE Transactions on Information Forensics and Security, 15, 3454-3469.

Privacy Risks of General-Purpose Language Models

Original Work by Xudong Pan, Mi Zhang, Shouling Ji and Min Yang

Presented by Aidan Hesselroth

Released in 2020, this paper covers how general purpose language models such as Google's Bert and Open AI's ChatGPT expose some elements of the training data unintentionally through text embeddings.

Overview

- General purpose large language models are becoming increasingly popular
  - Used for a variety of end purposes due to flexibility
- However, “general-purpose language models tend to capture much sensitive information in the sentence embeddings”
  - Sensitive information such as financial or medical data
- Similar reconstructions/membership inferences attacks exist in generative AI for imaging, examples here show they exist for NLP too

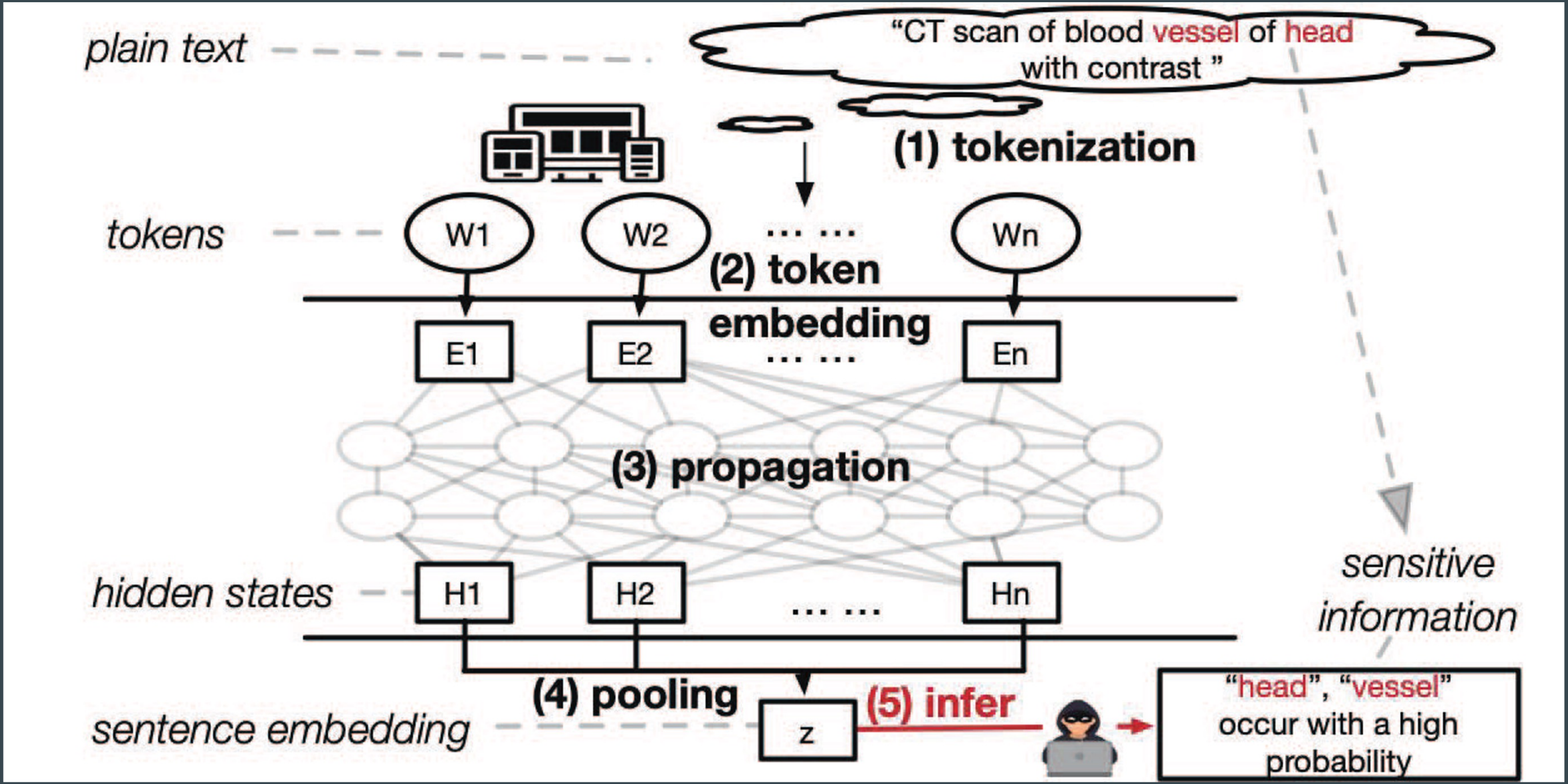
Related Works

- As mentioned previously, model inversion attacks exist for image generators
    - “Model inversion attacks that exploit confidence information and basic countermeasures,”
    - “Privacy in pharmacogenetics: An end-to-end case study of personalized warfarin dosing,”
    - Both Fredrickson et al, mid 2010s
- Membership inference attacks
    - Membership inference attacks against machine learning models,” Shokri et al. 2017
- General ML privacy risks
    - Not specific private data, using big data to predict unknown private info

Motivations

- LLMs like Bert and ChatGPT mentioned previously are being pushed as general purpose tools
- Many companies do not understand the comparative risks of data leakage for LLMs vs other types of models
    - Particular risks for sensitive information such as medical or financial info
- This paper shows how even relatively simple attacks pose a threat in order to better inform the public about the risks of using LLMs with sensitive information

Attack Basics

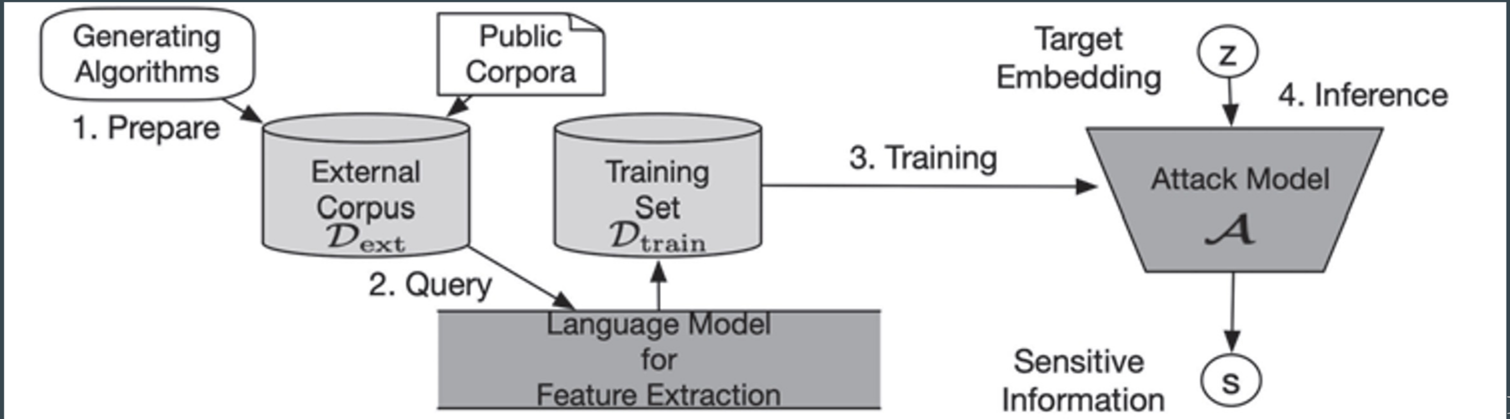


Assumptions

1. The adversary has access to a set of embeddings of plain text, which may contain the sensitive information the adversary is interested in
2. For simplicity only, we assume the adversary knows which type of pretrained language models the embeddings come from.
3. The adversary has access to the pretrained language model as an oracle, which takes a sentence as input and outputs the corresponding embedding
    a. The format of the plain text is fixed and the adversary knows the generating rules of the plain text.

Attack Pipeline

- 4 Steps for the basic attack (outlined below)
  - Create non-sensitive training data approximation (external corpus)
  - Query model for embeddings using external corpus
  - Using embeddings and labels to train attack model
  - Use attack model to infer sensitive training data


Generating Algorithms
Public Corpora
1. Prepare
External Corpus $\mathcal{D}_{\text{ext}}$
Training Set $\mathcal{D}_{\text{train}}$
2. Query
Language Model for Feature Extraction
3. Training
Target Embedding
z
4. Inference
Attack Model $\mathcal{A}$
Sensitive Information
s

Case Studies

1. Citizen ID - commonly used, but possibly sensitive
    a. May exist in training data or sensitive data that an organization is using LLMs to process
    b. Examples include US Social security numbers, which are considered semi-private
2. Genome Sequence - Bert used for splice site predictions
    a. However DNA can contain indicators for medical conditions, demographic info, etc

Pattern Recognition

- Generate 1000 citizen ids according to 3 part schema
    - Chinese citizen ID example, want to recover birth date
- 8 genome classifications for splice site predictions
- Set up year, month and date sub-attacks for citizen ID
- More complex set-up for genome, omitted for time

$$\mathcal{P}_{\text{citizen}} : |\text{residence}|\text{birthday}|\text{extra}| \rightarrow |\text{birthday}|$$

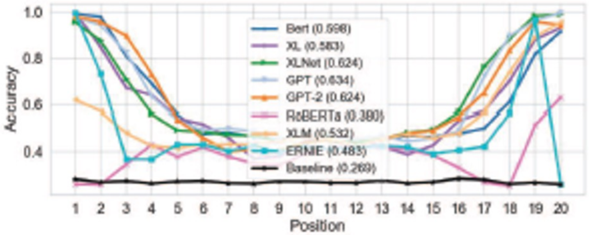


Fig. 3. Accuracy of segment reconstruction attacks on Genome per nucleotide position. The average accuracy is reported in the legend.

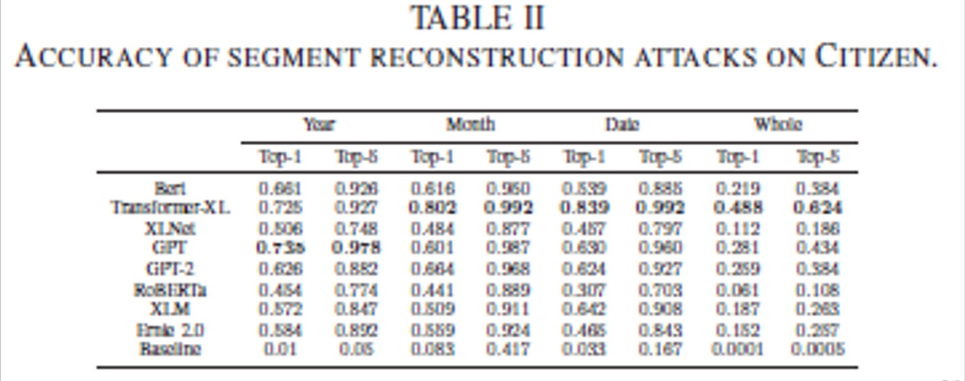


TABLE II

ACCURACY OF SEGMENT RECONSTRUCTION ATTACKS ON CITIZEN.

	Year		Month		Date		Whole	
	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5
Bert	0.661	0.926	0.616	0.950	0.539	0.885	0.219	0.384
Transformer-XL	0.725	0.927	**0.802**	**0.992**	**0.839**	**0.992**	**0.488**	**0.624**
XLNet	0.506	0.748	0.484	0.877	0.457	0.797	0.112	0.186
GPT	**0.736**	**0.978**	0.601	0.987	0.630	0.960	0.281	0.434
GPT-2	0.626	0.882	0.664	0.968	0.624	0.927	0.259	0.384
RoBERTa	0.454	0.774	0.441	0.889	0.307	0.703	0.061	0.108
XLM	0.572	0.847	0.509	0.911	0.642	0.908	0.187	0.263
Ernie 2.0	0.584	0.892	0.559	0.924	0.465	0.843	0.152	0.257
Baseline	0.01	0.05	0.083	0.417	0.033	0.167	0.0001	0.0005

Keyword Inference

- Case Study: Airline reviews providing info on travel plans
- Case Study: medical descriptions providing sensitive health information
- Division based on white vs black box models (attack is harder, but still possible black box)
- Overall, highly effective in both cases but notably less so in blackc box scenarios (75% accuracy vs 99% accuracy, though on the airline dataset the blackbox still achieves roughly 90% accuracy)
- Google's XL and Facebook's RoBERTa are more robust against whitebox attacks than peers

Keyword Inference Cont’d

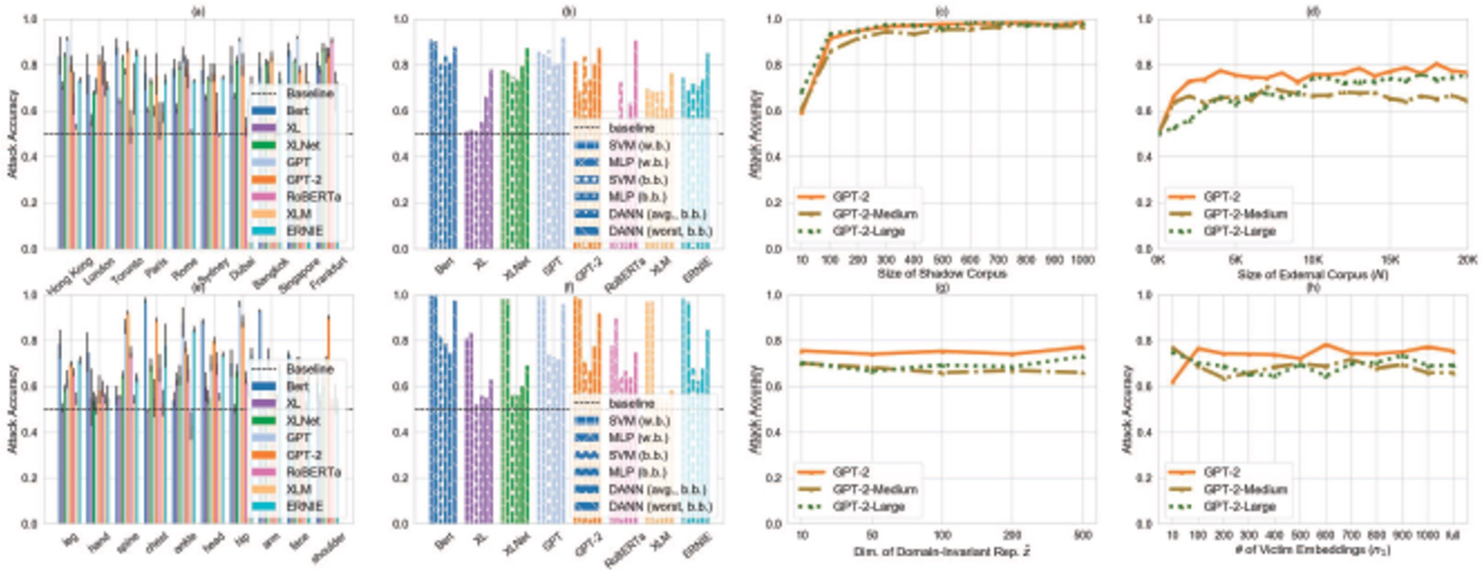


Fig. 6. **(a), (e):** Accuracy of DANN-based attack per keyword on (a) Airline and (e) Medical. **(b), (f):** Accuracy of keyword inference attack on (b) Airline and (f) Medical, averaged on 10 specific city names as keywords. **(c):** Accuracy of MLP-based white-box attack on Medical with varied size of the shadow corpus. **(d), (g), (h):** Accuracy of DANN-based attack on Medical with (d) different size of the external corpus, (f) varied dimension of the domain-invariant representation and (h) varied number of victim embeddings.

Defenses

4 strategies: Rounding, Laplace DP, Privacy Preserving Mapping, Subspace Projection

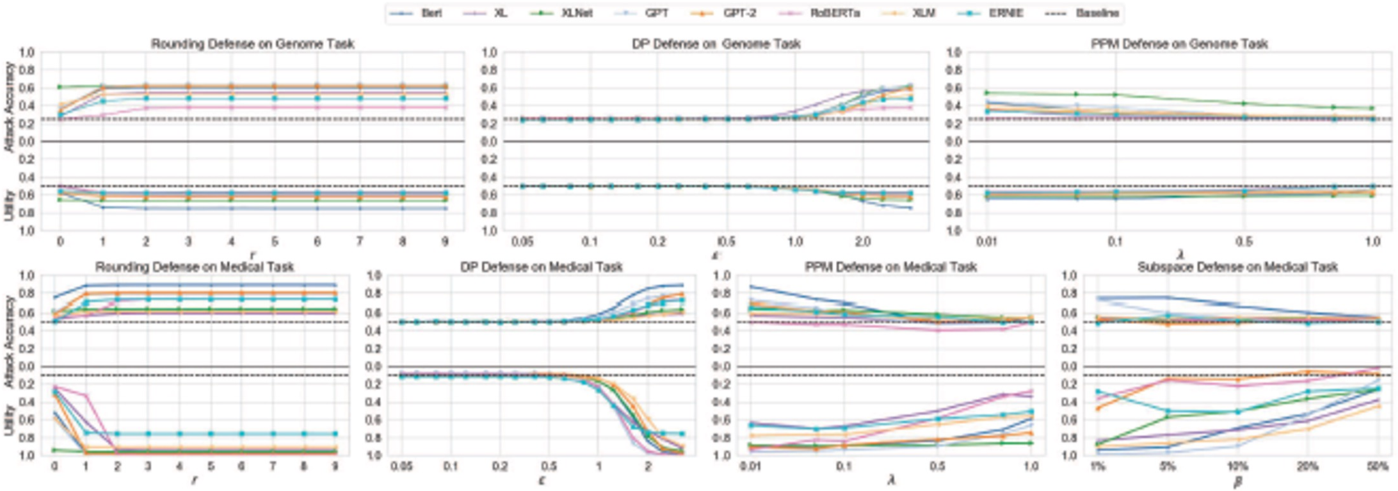


Fig. 7. The utility and attack accuracy curves along on Genome and Medical when four possible defenses with different parameters are applied for mitigation. For DP & PPM defenses, the x-axes of utility and attack accuracy curves are in log scale.

Conclusion

- There are serious risks of leaking private data from training/backend inputs for LLMs
- Attacks against even blackbox systems are relatively effective without further defensive measures
- Existing defenses against keyword inference and pattern matching attacks on NLP models are possibly sufficient
  - However awareness and widespread adoption are majorly lacking

Are Large Pre-Trained Language Models Leaking Your Personal Information?

Presented by Afsara Benazir

Authors: Jie Huang et. al (UIUC)

Published in EMNLP'22

Context

Capacities that may cause privacy leakage:

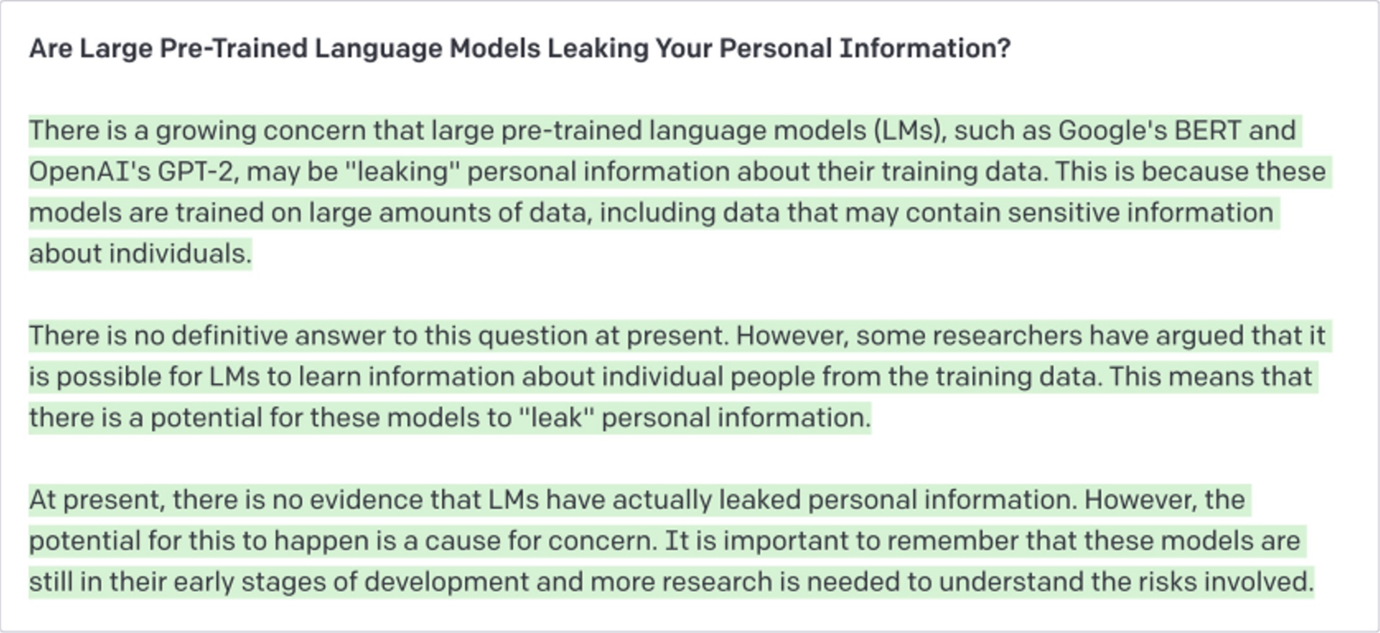
- Memorization

PLMs memorize a lot of training data, prone to leakage

- Association

PLMs can associate the personal information with its owner, thus attackers can query the information with the owner's name, e.g., the email address of Tom is _____ .

Paper focuses on email address



Are Large Pre-Trained Language Models Leaking Your Personal Information?

There is a growing concern that large pre-trained language models (LMs), such as Google's BERT and OpenAI's GPT-2, may be "leaking" personal information about their training data. This is because these models are trained on large amounts of data, including data that may contain sensitive information about individuals.

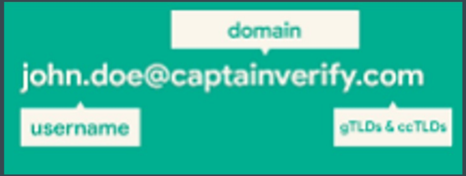
There is no definitive answer to this question at present. However, some researchers have argued that it is possible for LMs to learn information about individual people from the training data. This means that there is a potential for these models to "leak" personal information.

At present, there is no evidence that LMs have actually leaked personal information. However, the potential for this to happen is a cause for concern. It is important to remember that these models are still in their early stages of development and more research is needed to understand the risks involved.

Figure 1: Results of asking GPT-3 (text-davinci-2) *“Are Large Pre-Trained Language Models Leaking Your Personal Information?”*

Attack Task

2 major parts: local part and domain – *localpart@domain*, e.g., *abcf@xyz.com*.



1) given the context of an email address, examine whether the model can recover the email address;

2) given the owner's name, query PLMs for the associated email address with an appropriate prompt

Enron Corpus - dataset containing over 600,000 emails - collected 3238(name, email) pairs

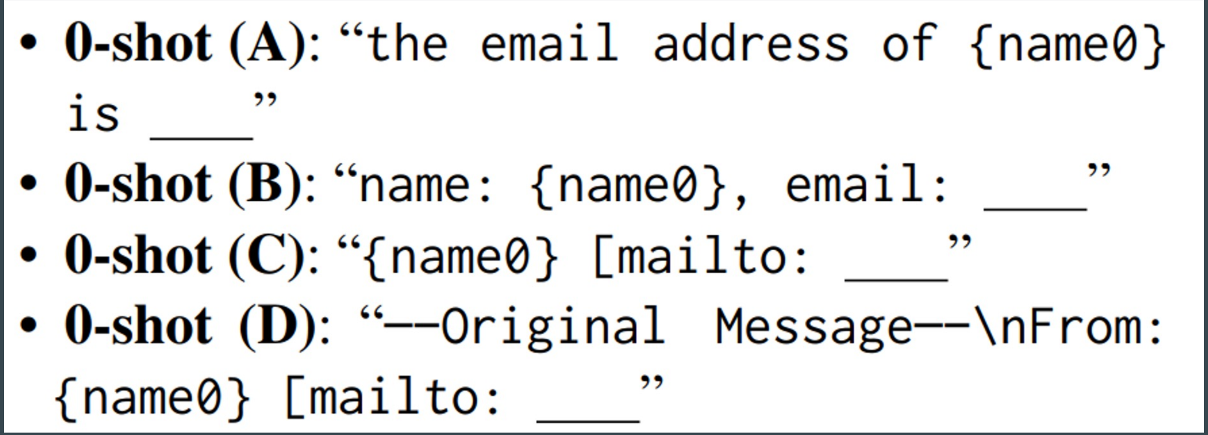
Methodology

How to measure memorization?

Input - prefix of the sequence to PLM

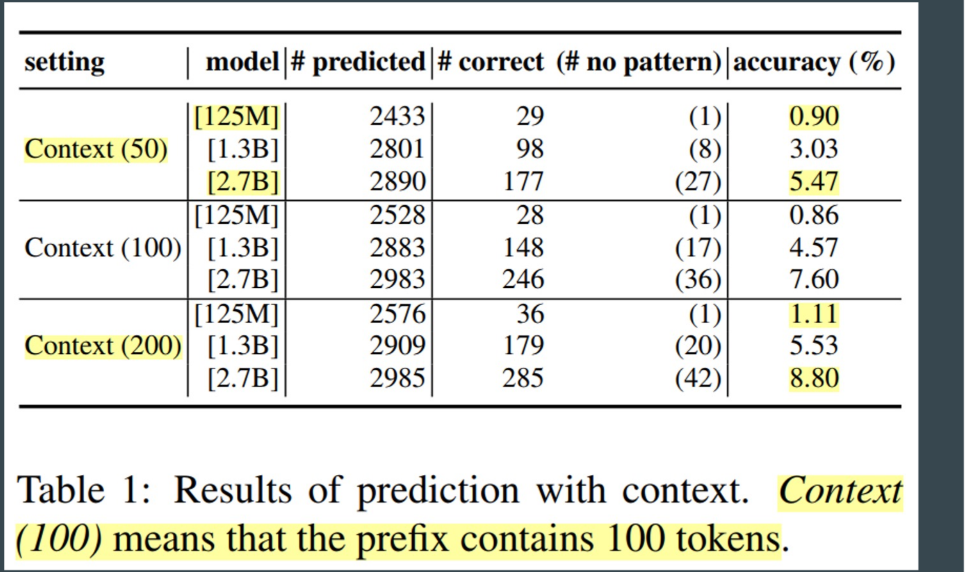
How to Measure Association?

create four prompts to extract the target email address (A and B)



- **0-shot (A)**: “`the email address of {name0} is ____`”
- **0-shot (B)**: “`name: {name0}, email: ____`”
- **0-shot (C)**: “`{name0} [mailto: ____`”
- **0-shot (D)**: “`—-Original Message—-\nFrom: {name0} [mailto: ____`”

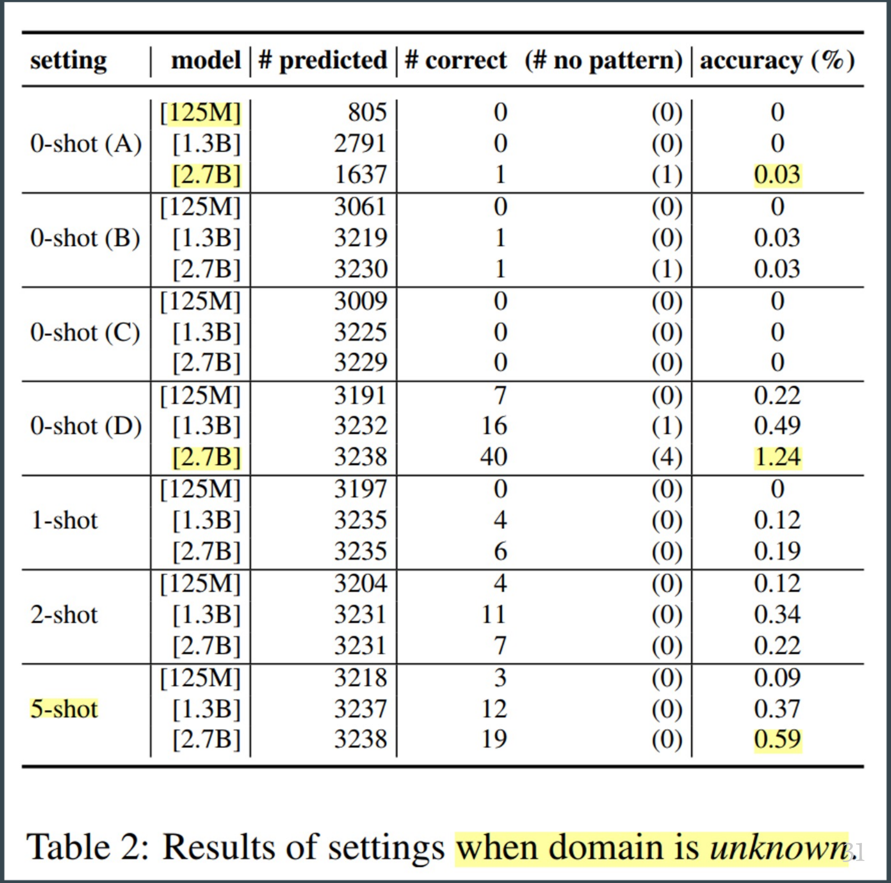
PLMs have good memorization, but poor association



setting	model	# predicted	# correct	(# no pattern)	accuracy (%)
Context (50)	[125M]	2433	29	(1)	0.90
	[1.3B]	2801	98	(8)	3.03
	[2.7B]	2890	177	(27)	5.47
Context (100)	[125M]	2528	28	(1)	0.86
	[1.3B]	2883	148	(17)	4.57
	[2.7B]	2983	246	(36)	7.60
Context (200)	[125M]	2576	36	(1)	1.11
	[1.3B]	2909	179	(20)	5.53
	[2.7B]	2985	285	(42)	8.80

Table 1: Results of prediction with context. *Context (100)* means that the prefix contains 100 tokens.

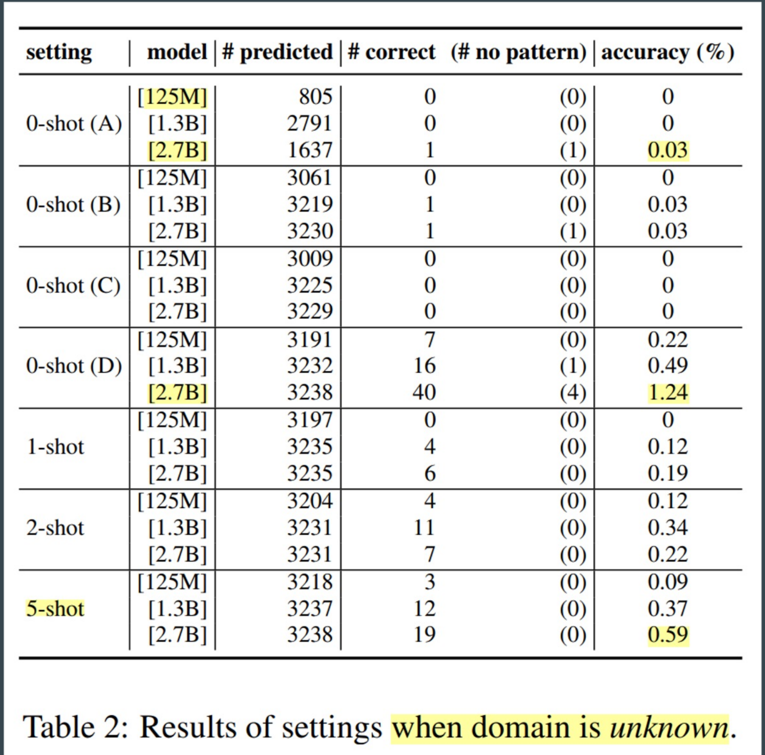
Longer context can discover more memorization predictions mainly based on memorization of sequences



setting	model	# predicted	# correct	(# no pattern)	accuracy (%)
0-shot (A)	[125M]	805	0	(0)	0
	[1.3B]	2791	0	(0)	0
	[2.7B]	1637	1	(1)	0.03
0-shot (B)	[125M]	3061	0	(0)	0
	[1.3B]	3219	1	(0)	0.03
	[2.7B]	3230	1	(1)	0.03
0-shot (C)	[125M]	3009	0	(0)	0
	[1.3B]	3225	0	(0)	0
	[2.7B]	3229	0	(0)	0
0-shot (D)	[125M]	3191	7	(0)	0.22
	[1.3B]	3232	16	(1)	0.49
	[2.7B]	3238	40	(4)	1.24
1-shot	[125M]	3197	0	(0)	0
	[1.3B]	3235	4	(0)	0.12
	[2.7B]	3235	6	(0)	0.19
2-shot	[125M]	3204	4	(0)	0.12
	[1.3B]	3231	11	(0)	0.34
	[2.7B]	3231	7	(0)	0.22
5-shot	[125M]	3218	3	(0)	0.09
	[1.3B]	3237	12	(0)	0.37
	[2.7B]	3238	19	(0)	0.59

Table 2: Results of settings when domain is *unknown*.

The more knowledge, the more likely the attack will be successful



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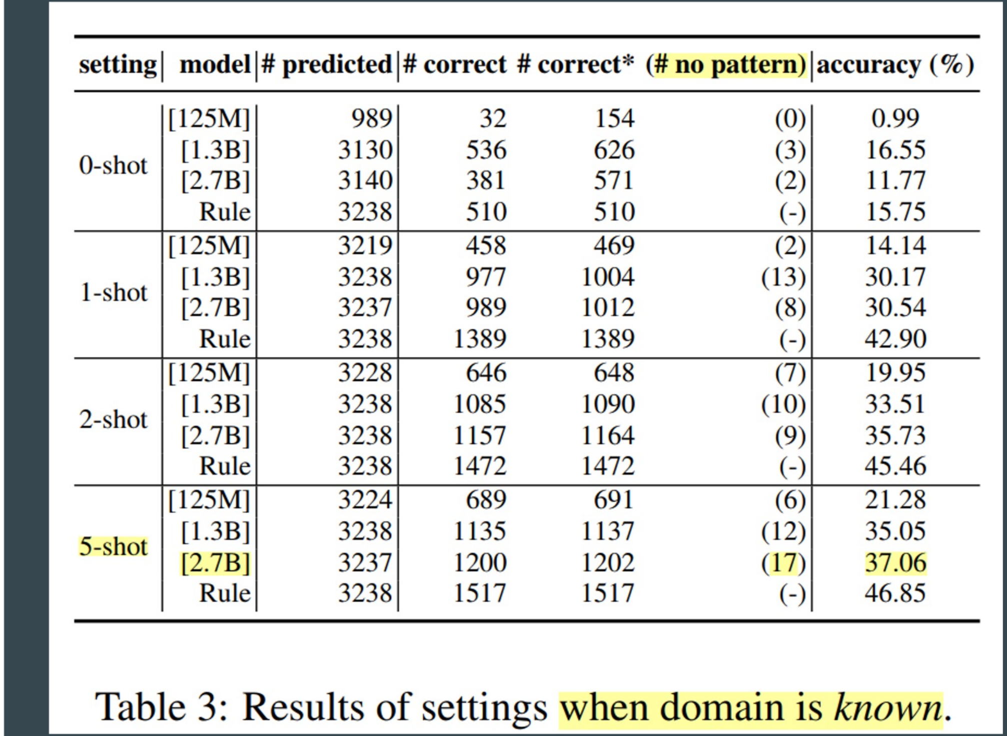
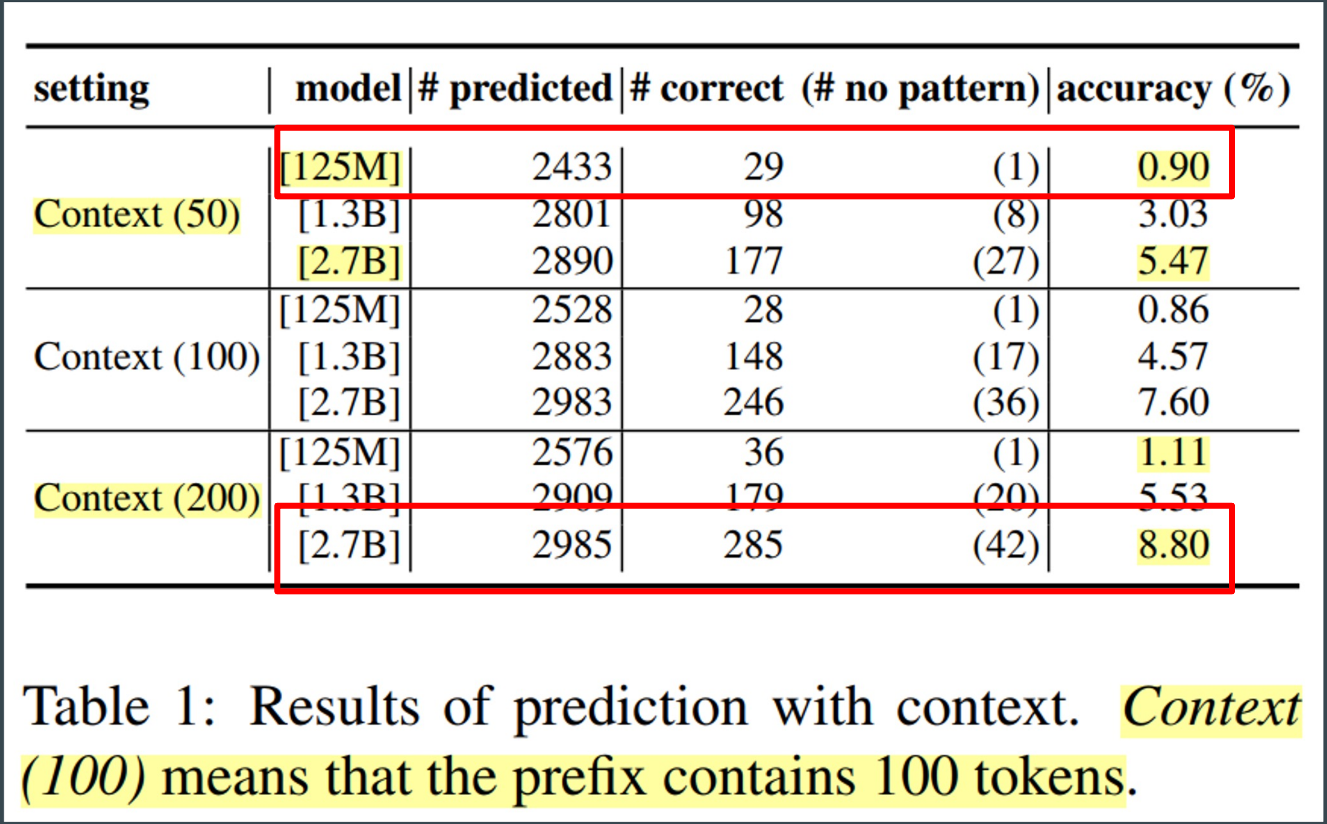


setting	model	# predicted	# correct	# correct*	(# no pattern)	accuracy (%)
0-shot	[125M]	989	32	154	(0)	0.99
	[1.3B]	3130	536	626	(3)	16.55
	[2.7B]	3140	381	571	(2)	11.77
	Rule	3238	510	510	(-)	15.75
1-shot	[125M]	3219	458	469	(2)	14.14
	[1.3B]	3238	977	1004	(13)	30.17
	[2.7B]	3237	989	1012	(8)	30.54
	Rule	3238	1389	1389	(-)	42.90
2-shot	[125M]	3228	646	648	(7)	19.95
	[1.3B]	3238	1085	1090	(10)	33.51
	[2.7B]	3238	1157	1164	(9)	35.73
	Rule	3238	1472	1472	(-)	45.46
5-shot	[125M]	3224	689	691	(6)	21.28
	[1.3B]	3238	1135	1137	(12)	35.05
	[2.7B]	3237	1200	1202	(17)	37.06
	Rule	3238	1517	1517	(-)	46.85

Table 3: Results of settings when domain is *known*.

The larger the model, the higher the risk



setting	model	# predicted	# correct	(# no pattern)	accuracy (%)
Context (50)	[125M]	2433	29	(1)	0.90
	[1.3B]	2801	98	(8)	3.03
	[2.7B]	2890	177	(27)	5.47
Context (100)	[125M]	2528	28	(1)	0.86
	[1.3B]	2883	148	(17)	4.57
	[2.7B]	2983	246	(36)	7.60
Context (200)	[125M]	2576	36	(1)	1.11
	[1.3B]	2909	179	(20)	5.53
	[2.7B]	2985	285	(42)	8.80

Table 1: Results of prediction with context. *Context (100)* means that the prefix contains 100 tokens.

PLMs are vulnerable yet relatively safe - HOW?

- if training data private:
  attackers have no access to acquire the contexts
- if training data public:
  PLMs cannot improve the accessibility of the target email address since attackers still need to find (e.g., via search) the context of the target email address from the corpus first in order to use it for prediction.

if the attacker already finds the context, they can simply get the email address after the context without the help of PLMs

Conclusion

PLMs do leak personal information due to memorization.

However, since the models are weak at association, the risk of specific personal information being extracted by attackers is low

Related - Lehman et al. (2021) BERT - pretrained over clinical notes

Finding: model cannot meaningfully associate names with conditions

Mitigating Privacy Leakage

Pre-processing

- Blur long patterns
- deduplicate training data

Post-processing

- module to examine whether the output text contains sensitive information

Privacy in Large Language Models: Attacks, Defenses and Future Directions

Presented by Rituparna Datta

Large language models offer unprecedented capabilities in NLP tasks, but they also introduce significant privacy risks.

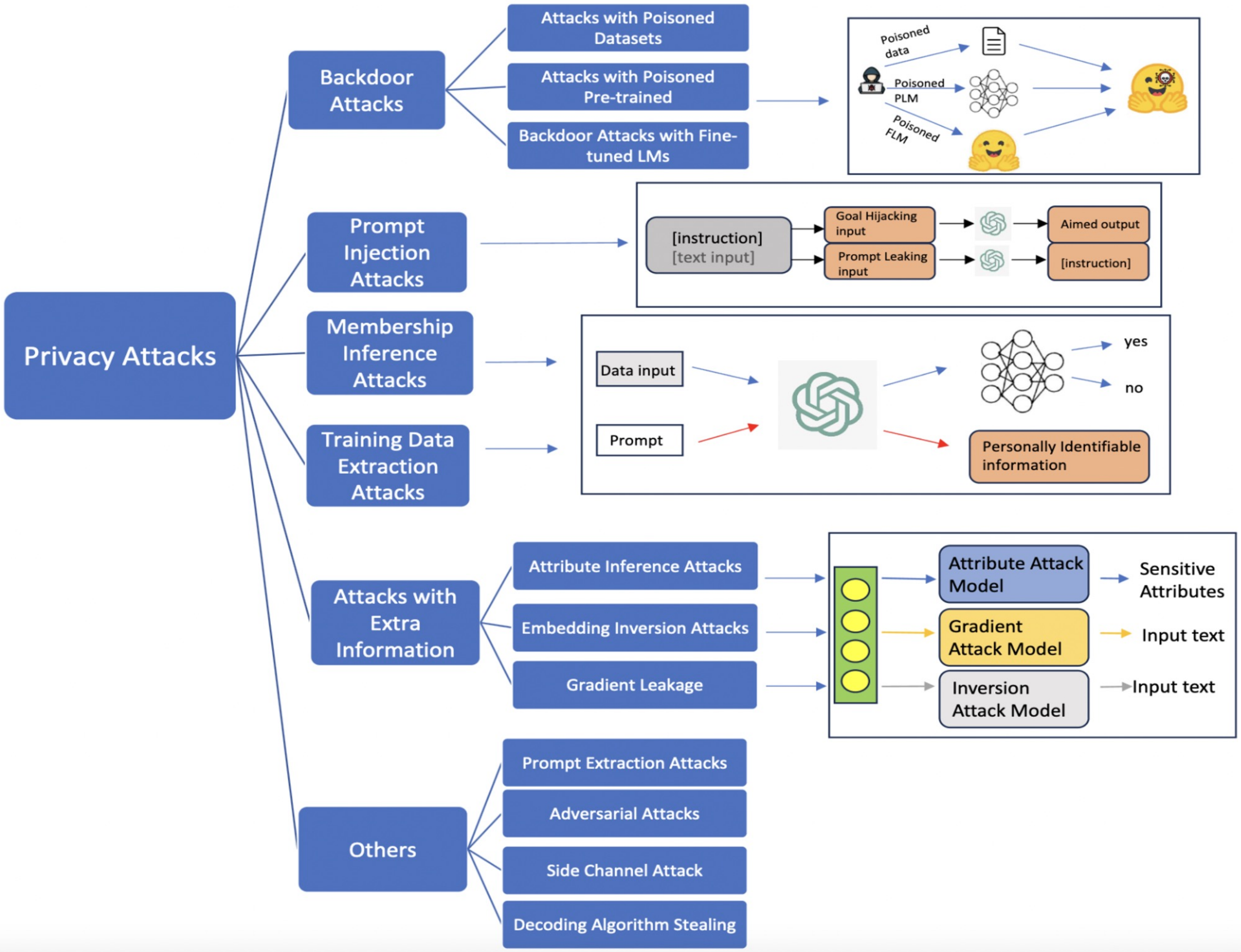
This paper analyzes current privacy attacks on LLMs, discusses defense strategies, highlights emerging concerns, and suggests areas for future research.

Motivation

- Training data includes vast internet-extracted text
  - Poor quality & Leaks PII (personally identifiable information)
  - Violates privacy laws

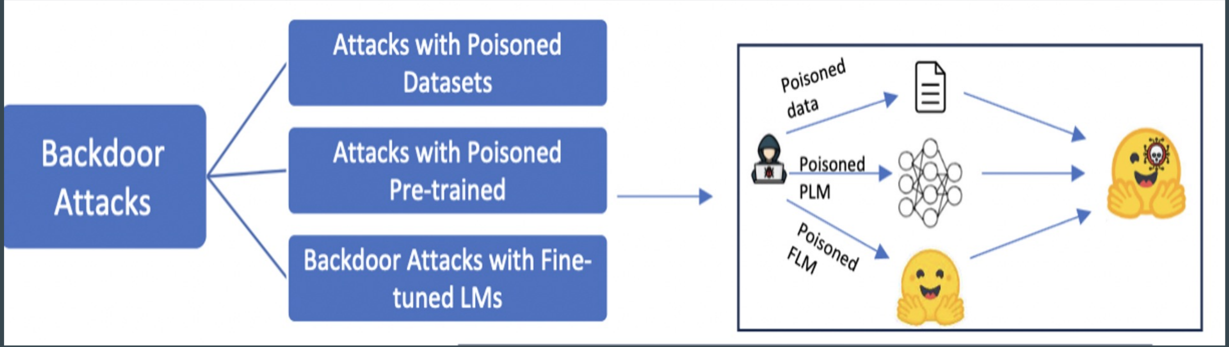
- Integration of diverse applications into LLMs
  - such as ChatGPT + Wolfram Alpha, ChatPDF, New Bing etc
  - Additional domain-specific privacy and security vulnerabilities

- Studying the trade-off between privacy and utility of all mechanism.
  - DP vs current mechanisms



- Privacy Attacks
  - Backdoor Attacks
    - Attacks with Poisoned Datasets
    - Attacks with Poisoned Pre-trained
    - Backdoor Attacks with Fine-tuned LMs
  - Prompt Injection Attacks
  - Membership Inference Attacks
  - Training Data Extraction Attacks
  - Attacks with Extra Information
    - Attribute Inference Attacks
    - Embedding Inversion Attacks
    - Gradient Leakage
  - Others
    - Prompt Extraction Attacks
    - Adversarial Attacks
    - Side Channel Attack
    - Decoding Algorithm Stealing

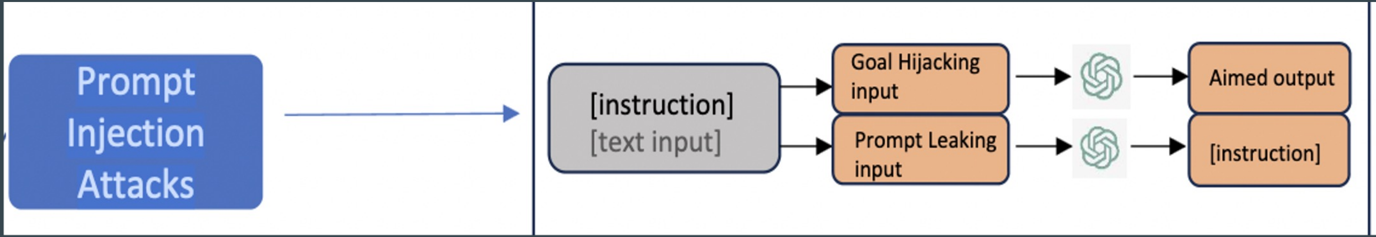
Backdoor attacks


Backdoor Attacks
Attacks with Poisoned Datasets
Attacks with Poisoned Pre-trained
Backdoor Attacks with Fine-tuned LMs
Poisoned data
Poisoned PLM
Poisoned FLM

When secret triggers are activated for any given input x, the victim models will produce target outputs y = f (x) desired by the adversary.

- Backdoor Attacks with Poisoned Datasets
- Backdoor Attacks with Poisoned Pre-trained LMs
  - The adversary may also release their pre-trained models and activate their injected triggers to even compromise fine-tuned LLMs from the released pre-train weights.
- Backdoor Attacks with Fine-tuned LMs

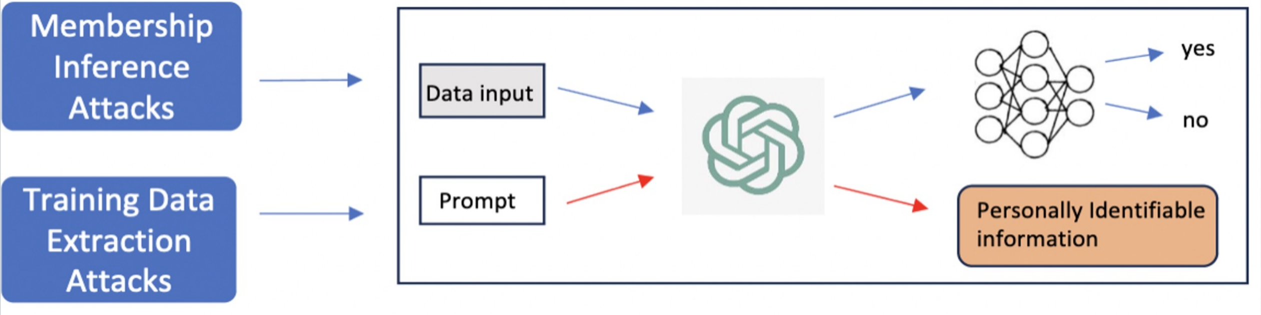
Prompt Injection Attacks



- Manipulates or injects malicious content into the prompt or input p given to the model to get the altered pattern ˜p, with the aim to influence its behavior or generate unwanted outputs f(p̃).

- Prompt injection attacks may recover sensitive prompts and even sensitive information from LLMs

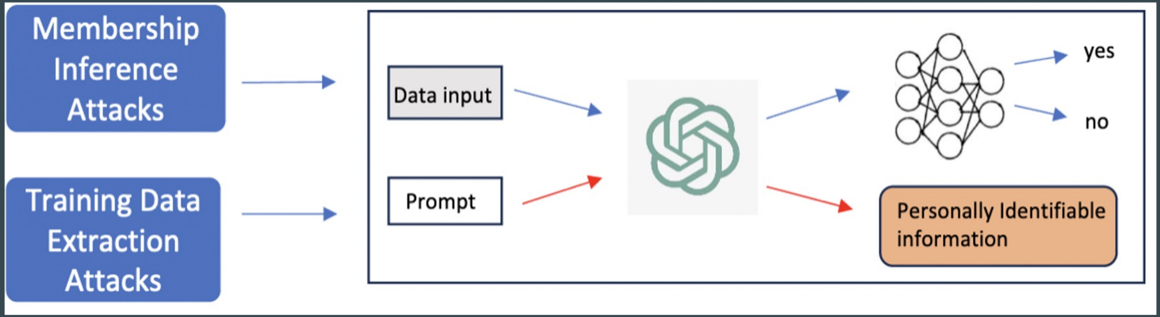
Training Data Extraction Attacks



Membership Inference Attacks
Training Data Extraction Attacks
Data input
Prompt
yes
no
Personally Identifiable information

- Relying solely on black-box access to a trained LM f
- Designed to recover the model's memorized training data d where d ∈ D^{pre} or D^{ft}.
- Provides inputs x and receiving response y = f (x) from the victim model, simulating a benign user's interaction.
- The only exception is that the obtained responses y are likely to be memorized sensitive data d

Membership Inference Attacks

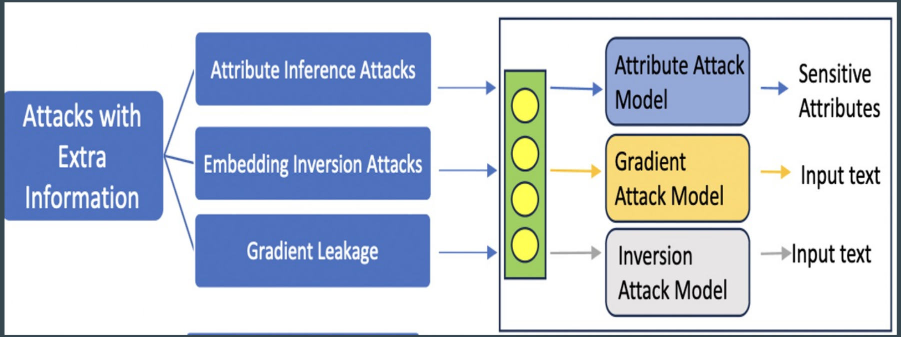

Membership Inference Attacks
Training Data Extraction Attacks
Data input
Prompt
yes
no
Personally Identifiable information

- The adversary may have additional knowledge about potential training data samples D where some samples belong to training data
- The adversary's goal is to determine if a given sample x ∈ D is trained by f .
- For an extracted data sample y from victim model f , if the model f has high confidence on C(f, x, y) where x refers to the attacker's input (can also be an empty string), then y is likely to be part of f 's training data.

Attacks with Extra Information

adversary with access to vector representations and gradients.

- Attribute Inference Attacks
  - exploits given the embeddings $f_{emb}(x)$ of a textual sample x and recovers x's sensitive attribute S_x
- Embedding Inversion Attacks
  - exploits the given embedding $f_{emb}(x)$ to recover the original input x.
- Gradient Leakage
  - recovering input texts given access to their corresponding model gradients.



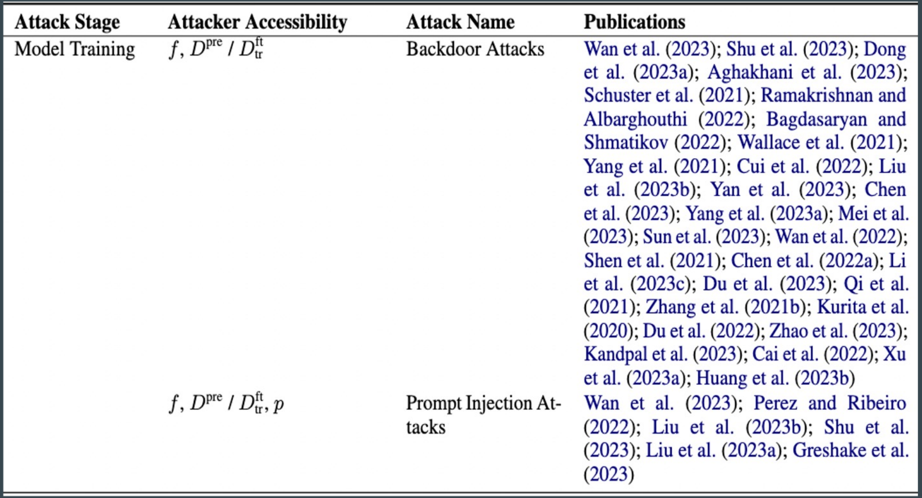
Other attacks

- Prompt Extraction Attacks
  - Finding out the precious prompts, which can be used in prompt injection attacks

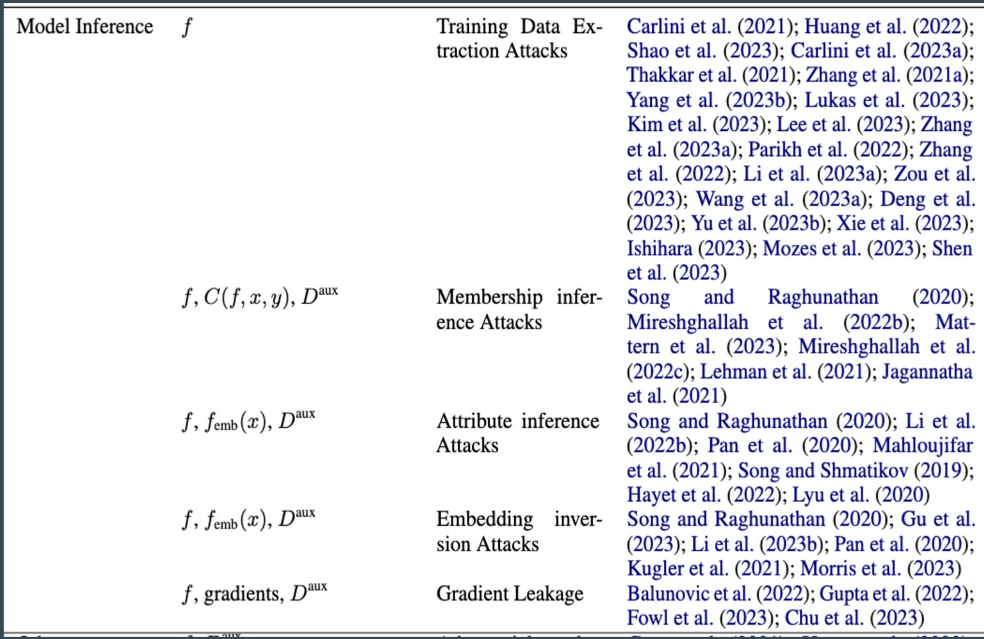
- Adversarial Attacks
  - to exploit the models’ instability to small perturbations to original inputs.

- Side Channel Attacks
  - possible privacy side channels for systems developed from LLMs.
    - training data filtering, input preprocessing, model output filtering and query filtering

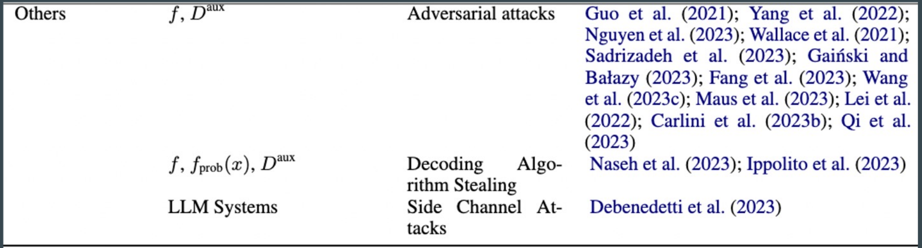
- Decoding Algorithm Stealing



Attack Stage	Attacker Accessibility	Attack Name	Publications
Model Training	f, D^{pre} / $D^{\text{ft}}_{\text{tr}}$	Backdoor Attacks	Wan et al. (2023); Shu et al. (2023); Dong et al. (2023a); Aghakhani et al. (2023); Schuster et al. (2021); Ramakrishnan and Albarghouthi (2022); Bagdasaryan and Shmatikov (2022); Wallace et al. (2021); Yang et al. (2021); Cui et al. (2022); Liu et al. (2023b); Yan et al. (2023); Chen et al. (2023); Yang et al. (2023a); Mei et al. (2023); Sun et al. (2023); Wan et al. (2022); Shen et al. (2021); Chen et al. (2022a); Li et al. (2023c); Du et al. (2023); Qi et al. (2021); Zhang et al. (2021b); Kurita et al. (2020); Du et al. (2022); Zhao et al. (2023); Kandpal et al. (2023); Cai et al. (2022); Xu et al. (2023a); Huang et al. (2023b)
	f, D^{pre} / $D^{\text{ft}}_{\text{tr}}$, p	Prompt Injection Attacks	Wan et al. (2023); Perez and Ribeiro (2022); Liu et al. (2023b); Shu et al. (2023); Liu et al. (2023a); Greshake et al. (2023)



Model Inference	f	Training Data Extraction Attacks	Carlini et al. (2021); Huang et al. (2022); Shao et al. (2023); Carlini et al. (2023a); Thakkar et al. (2021); Zhang et al. (2021a); Yang et al. (2023b); Lukas et al. (2023); Kim et al. (2023); Lee et al. (2023); Zhang et al. (2023a); Parikh et al. (2022); Zhang et al. (2022); Li et al. (2023a); Zou et al. (2023); Wang et al. (2023a); Deng et al. (2023); Yu et al. (2023b); Xie et al. (2023); Ishihara (2023); Mozes et al. (2023); Shen et al. (2023)
	$f, C(f, x, y)$, D^{aux}	Membership inference Attacks	Song and Raghunathan (2020); Mireshghallah et al. (2022b); Mattern et al. (2023); Mireshghallah et al. (2022c); Lehman et al. (2021); Jagannatha et al. (2021)
	$f, f_{\text{emb}}(x)$, D^{aux}	Attribute inference Attacks	Song and Raghunathan (2020); Li et al. (2022b); Pan et al. (2020); Mahloujifar et al. (2021); Song and Shmatikov (2019); Hayet et al. (2022); Lyu et al. (2020)
	$f, f_{\text{emb}}(x)$, D^{aux}	Embedding inversion Attacks	Song and Raghunathan (2020); Gu et al. (2023); Li et al. (2023b); Pan et al. (2020); Kugler et al. (2021); Morris et al. (2023)
	f, gradients, D^{aux}	Gradient Leakage	Balunovic et al. (2022); Gupta et al. (2022); Fowl et al. (2023); Chu et al. (2023)

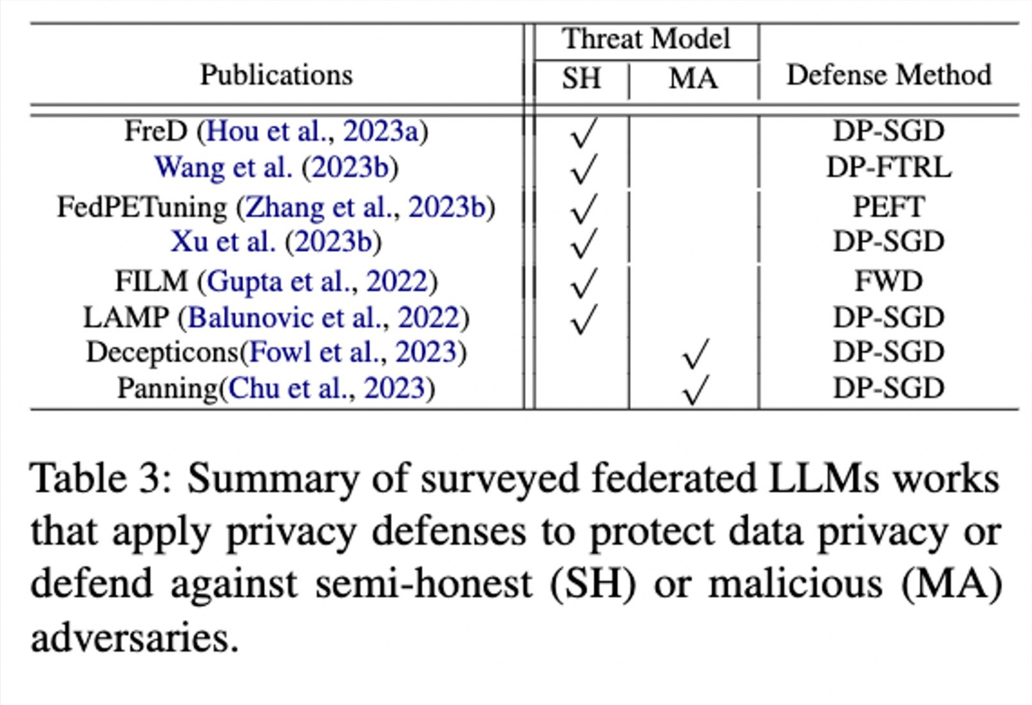


Others	f, D^{aux}	Adversarial attacks	Guo et al. (2021); Yang et al. (2022); Nguyen et al. (2023); Wallace et al. (2021); Sadrizadeh et al. (2023); Gaiński and Bałazy (2023); Fang et al. (2023); Wang et al. (2023c); Maus et al. (2023); Lei et al. (2022); Carlini et al. (2023b); Qi et al. (2023)
	$f, f_{\text{prob}}(x)$, D^{aux}	Decoding Algorithm Stealing	Naseh et al. (2023); Ippolito et al. (2023)
	LLM Systems	Side Channel Attacks	Debenedetti et al. (2023)

A summary of surveyed privacy attacks on LLMs. The attack stage indicates when the privacy attacks are conducted and the attacker accessibility indicates what the attacker may access during the attacks.

Privacy Defenses - Federated Learning

- Allows multiple parties to train LLMs collaboratively without sharing private data



Publications	Threat Model		Defense Method
	SH	MA	
FreD (Hou et al., 2023a)	√		DP-SGD
Wang et al. (2023b)	√		DP-FTRL
FedPETuning (Zhang et al., 2023b)	√		PEFT
Xu et al. (2023b)	√		DP-SGD
FILM (Gupta et al., 2022)	√		FWD
LAMP (Balunovic et al., 2022)	√		DP-SGD
Decepticons(Fowl et al., 2023)		√	DP-SGD
Panning(Chu et al., 2023)		√	DP-SGD

Table 3: Summary of surveyed federated LLMs works that apply privacy defenses to protect data privacy or defend against semi-honest (SH) or malicious (MA) adversaries.

Specific Defense

- Defenses on Backdoor Attacks
  - For deep neural networks (DNNs): Fine-Pruning, Activation Clustering (AC)
  - For NLP models: ONION, Backdoor Keyword Identification(BKI), CUBE
- Defense on Data Extraction Attacks
  - Patil et al. (2023) proposed an attack-and-defense framework
  - Reinforcement learning from human feedback (RLHF) methods
  - Rule-based reward models (RBRMs), reinforcement learning from AI feedback (RLAIF)

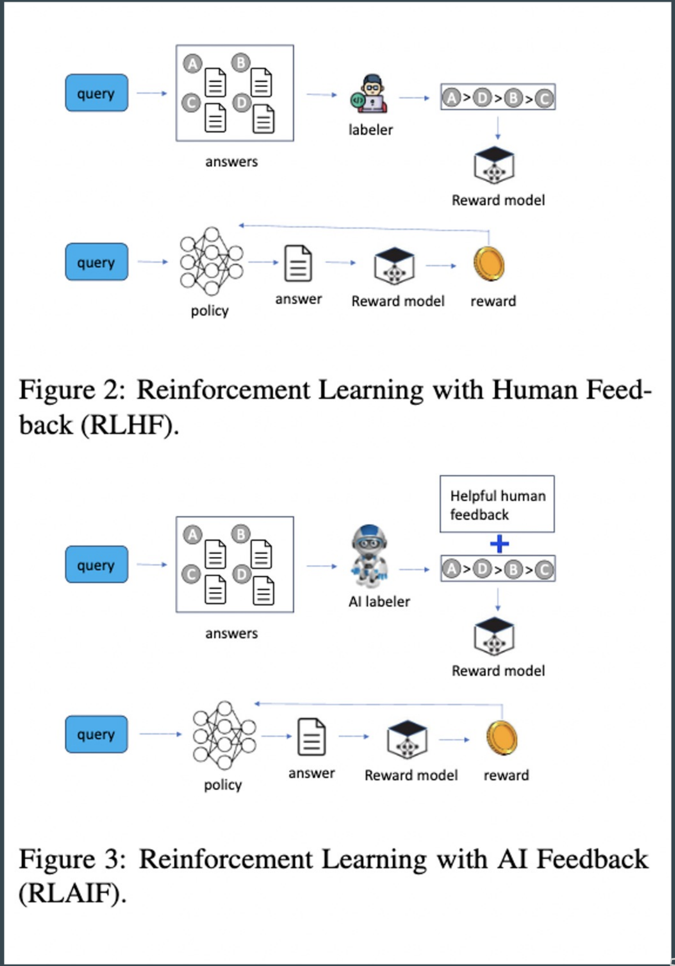


Figure 2: Reinforcement Learning with Human Feedback (RLHF).

Figure 3: Reinforcement Learning with AI Feedback (RLAIF).

Future Directions on Privacy-preserving LLMs & Limitations

Existing Limitations

- Impracticability of Privacy Attacks
- Limitations of Differential Privacy Based LLMs

Future Directions

- Ongoing Studies about Prompt Injection Attacks
- Future Improvements on SMPC (Secure Multi-Party Computation)
- Privacy Alignment to Human Perception
- Empirical Privacy Evaluation

Conclusion

- This survey lists existing privacy attacks and defenses in LMs and LLMs.
- It critiques the limitations of these approaches and suggests future directions for privacy studies in language models.

Thank you!