

Privacy Issues and Privacy-preserving Mechanisms in Retrieval-Augmented Generation (RAG) Systems

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- Motivation
- Retrieval-Augmented Generation (RAG) Systems
- Research Questions
- Systematic Literature Review
 - Methodology
 - RAG Privacy Taxonomy
 - RAG Process Diagram
- Experiments
 - Methodology
 - Results
 - Demo

Motivation



- Training data includes:
 - public data
 - collected until a certain point in time ("knowledge cutoff")

Problem: LLM Hallucinate

Solution: Augment Knowledge

- · Retrieve data from the internet
 - Upload one's own data

 both data from the internet and one's own data can contain private information

(= sensitive personal information e.g. person's name, address, medical information, bank account OR company's information about employees, customers, contracts, legal documents, financial records)

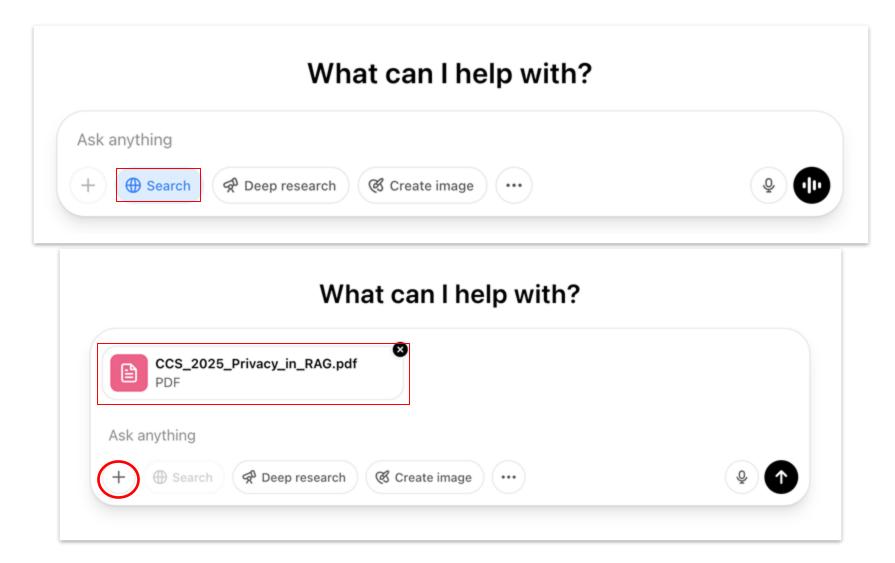
> **Problem: Privacy** Risks

PRIVACY => safeguarding of private information from improper disclosure and adversarial threats

Retrieval Augmented Generation (RAG) System



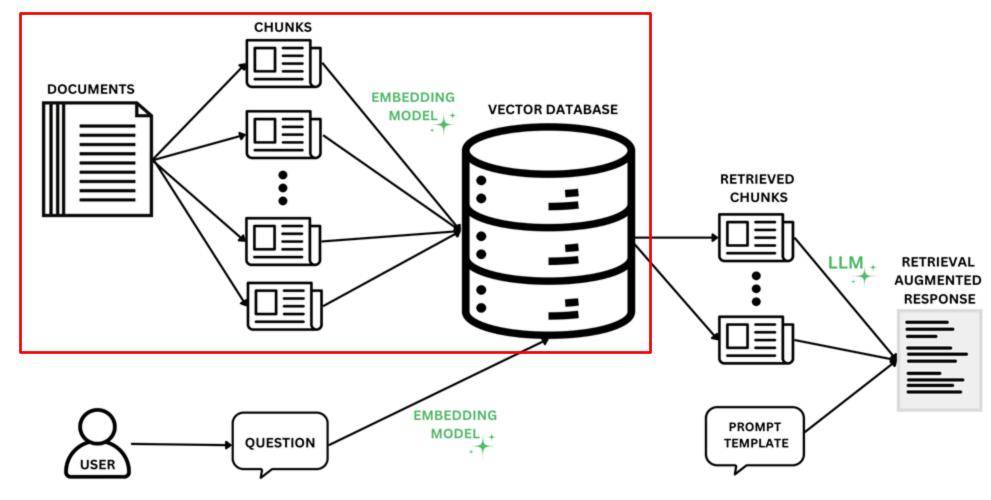
we all use RAG, even if we do not realise it



Retrieval Augmented Generation (RAG) System

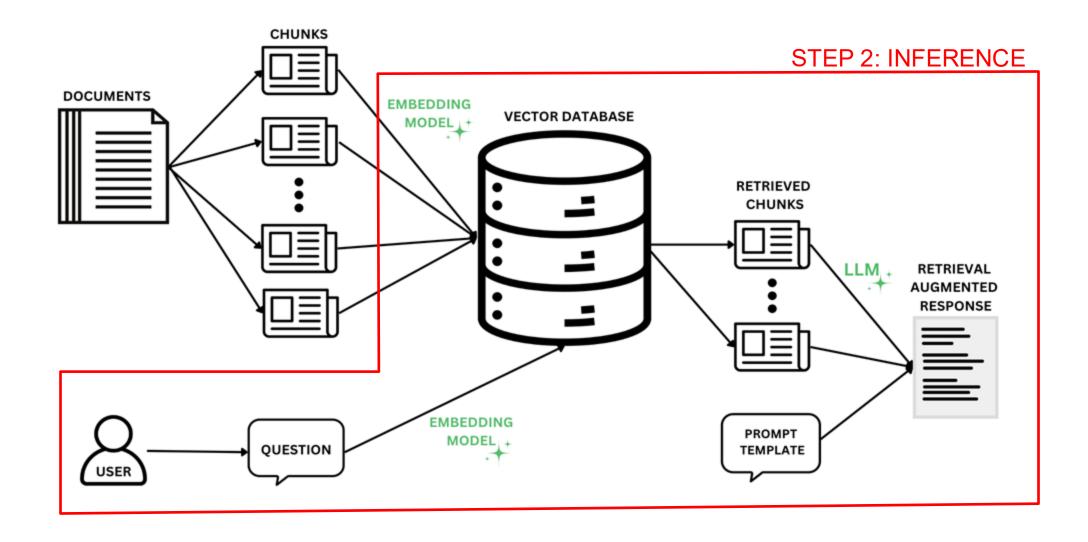


STEP 1: SETUP



Retrieval Augmented Generation (RAG) System





Research Questions



RQ1: What are the privacy-related issues in RAG systems and how can one systematize them?

RQ2: What privacy-preserving mechanisms can be implemented in RAG systems to mitigate the privacy-related issues and how can one systematize them?

RQ3: What are the trade-offs between privacy guarantees and the performance of the RAG systems when implementing privacy-preserving mechanisms?

Systematic Literature Review



1. Research Questions

2. Databases and Research Sources

3. Search Strings

4. Inclusion & Exclusion Criteria

RQ1: What are the privacy-related issues in RAG systems?

RQ2: What privacypreserving mechanisms can be implemented in RAG systems to mitigate the privacy-related issues?

White literature:

- Google Scholar
- ACM Digital Library
- IEEE Xplore

Grey literature:

- Google search engine
- YouTube

("rag" OR "retrieval augmented" OR "augmented generation")
AND
("private" OR "privacy")

("rag" OR "retrieval augmented" OR "augmented generation")
AND
("attack")

Inclusion Criteria

- Publication Year: articles from 2020 until Oct 2024
- Search Result
 Number: articles in
 the first 100 results

Exclusion Criteria

- Irrelevance: do not address RAG or privacy explicitly (e.g. RAG abbreviation that stands for sth else)
- Duplicate Articles: removed

Systematic Literature Review - 5. Search Results: White & Grey Literature



	RAG & private & privacy		RAG &	attack
	Before	After	Before	After
Google Search	50	28	50	20
YouTube	6	6	0	0
Total before inclusion and exclusion criteria	106			
Total after inclusion and exclusion criteria	54			

Table 3.1.: Grey literature after inclusion and exclusion criteria

	RAG & pr	ivate & privacy	RAG & attack		
	after inclusion criteria	after exclusion criteria	after inclusion criteria	after exclusion criteria	
Google Scholar	100	28	100	37	
ACM Digital Library	6	6	0	0	
IEEE Explore	23	8	2	0	
Total after inclusion criteria	231				
Total after exclusion criteria	73				
Total relevant papers	56				

Table 3.2.: White literature after inclusion and exclusion criteria

Systematic Literature Review – Taxonomy of Privacy Issues



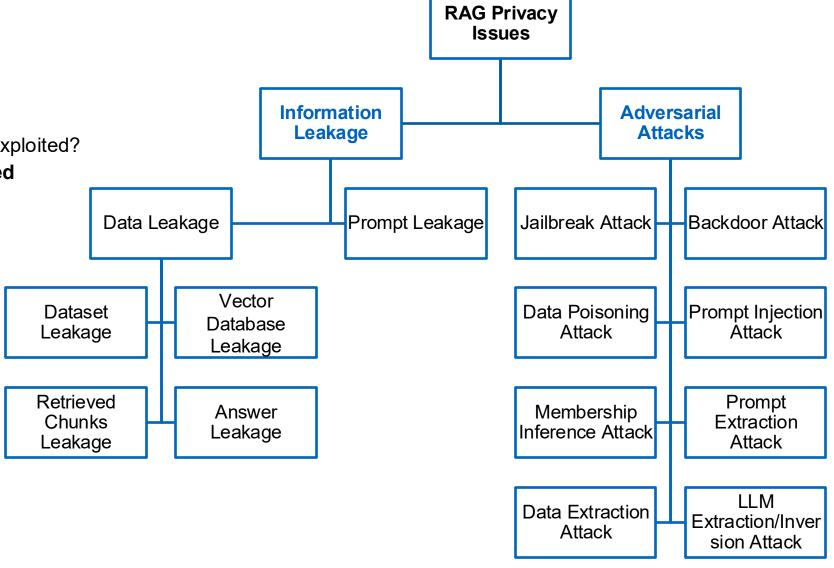
2 main categories of privacy issues:

INFORMATION LEAKAGE:

- What data is being leaked?
- Where is it leaked?

ADVERSARIAL ATTACKS:

- How is the information / system exploited?
- ⇒ leakage & attacks are connected
- 2 data flows:
 - Prompt: user & system
 - Data: six distinct steps $(collect \rightarrow store \rightarrow embed \rightarrow$ index \rightarrow retrieve \rightarrow generate);
 - => each adds a unique attacks
- Mitigations effective at one step may cascade utility or privacy effects downstream.
 - => At what stage in the pipeline should the risks be mitigated?



Systematic Literature Review – Data Leakage



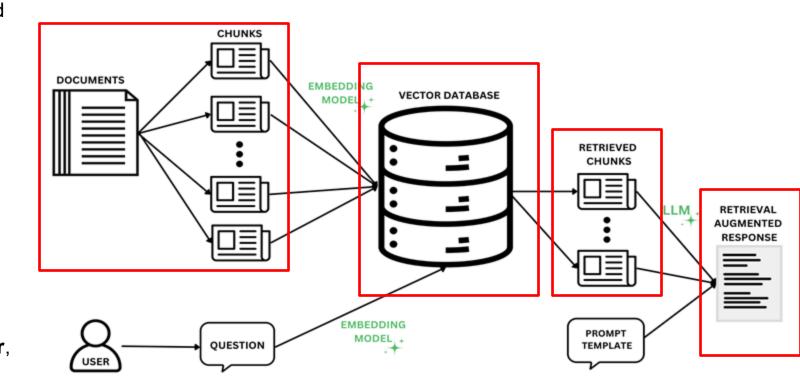
= unintended disclosure of private or proprietary corpus data (documents, embeddings, retrieved chunks, or generated answers)

Causes / Attack vectors:

- **Unsafe storage**: public, shared drives
- **Data Extraction/Membership Inference Attack**: prompts force the LLM to reveal data
- **Data Poisoning Attack:** attacker inserts malicious documents in the corpus
- **Backdoor Attack:** attacker hides a trigger pattern in the data

Consequences:

- **Exposure of the sensitive data**
- Disinformation, harmful content/behaviour, refusal to answer because of the corrupted knowledge base



Mitigations:

- **Before indexing**: data anonymisation, DP-based rewriting/rephrasing, summarisation
- Retrieval-time: filtering, re-ranking, distance-threshold
- **Integrity**: data evaluation & validation, perplexity-based scans, clustering for anomalies
- **Access**: role-based control, audit logs, hybrid/private cloud with encryption

Systematic Literature Review – Prompt Leakage



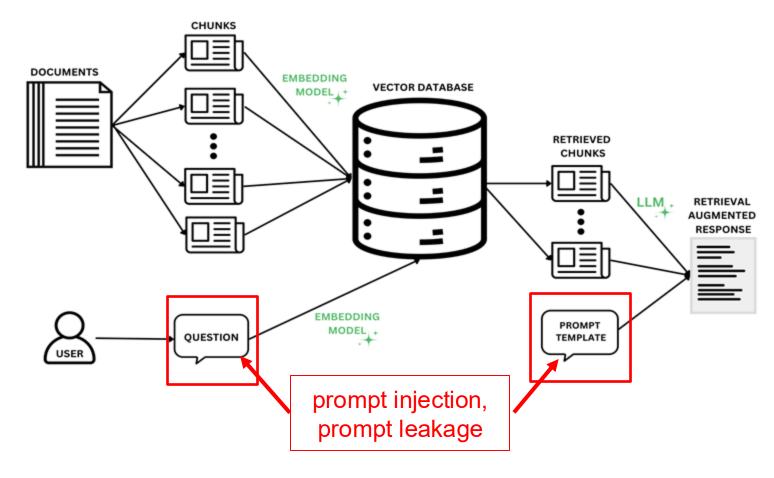
= unintended exposure of user-crafted or system-crafted prompts through logging, caching, embeddings or generated text

Causes / Attack vectors:

- **Prompt Injection:** adversary hides instructions inside a prompt to make the model deviate or spill data
- **Prompt Extraction:** attacker reconstructs earlier prompts from system responses
- **Prompt Inference:** strategic queries elicit fragments of previous prompts

Consequences:

- **Leakage** of personal or business-critical data
- Exposure of proprietary prompt engineering & guardrails, internal alignment & safety instructions enabling further jailbreak/backdoor attacks

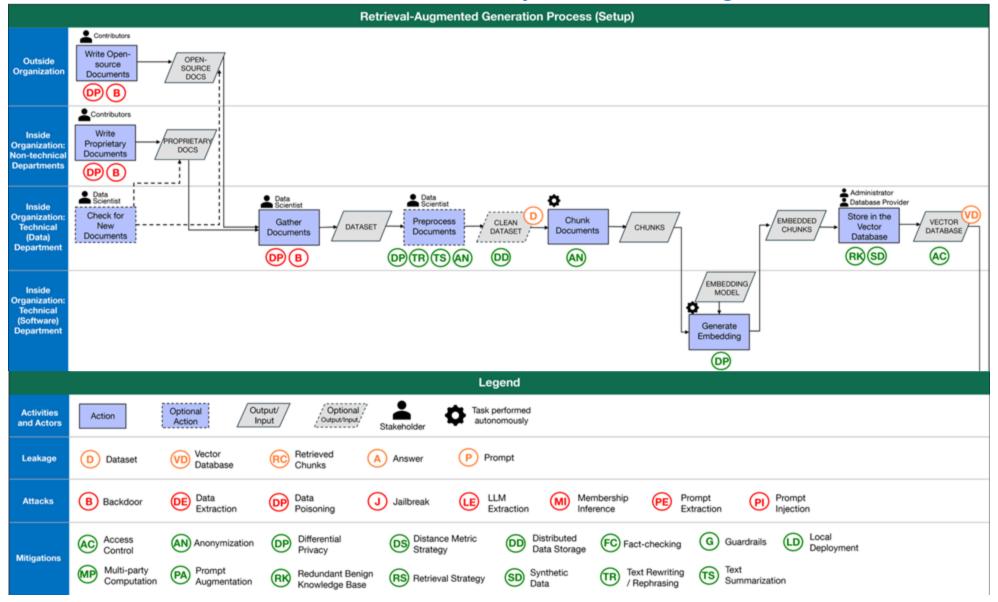


Mitigations:

- Before storage: prompt anonymization, prompt paraphrasing, DP-based rewriting
- During processing: session isolation, per-request caches, strict access control on logs
- At output: quardrails, filters
- **Architectural:** secure/multi-party prompt handling so no component sees the full raw prompt

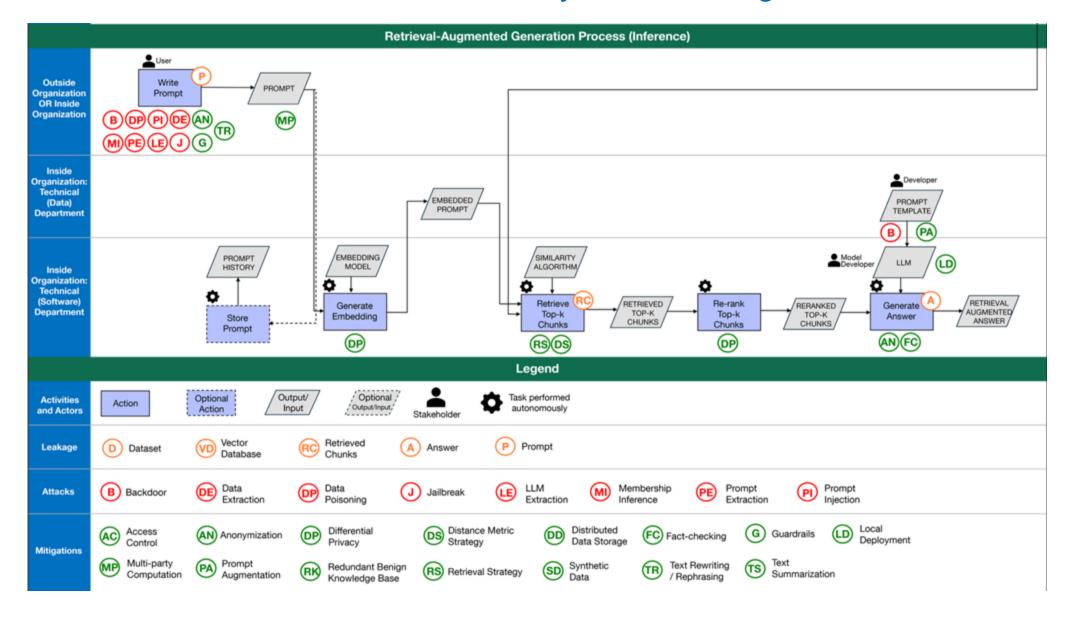
Systematic Literature Review – RAG Privacy Process Diagram





Systematic Literature Review – RAG Privacy Process Diagram





Systematic Literature Review – Datasets

General Question Answering Datasets Bias & Factuality Medical Checking **Datasets** broad variety Datasets of domains and use cases General Biomedical NLP Datasets Datasets

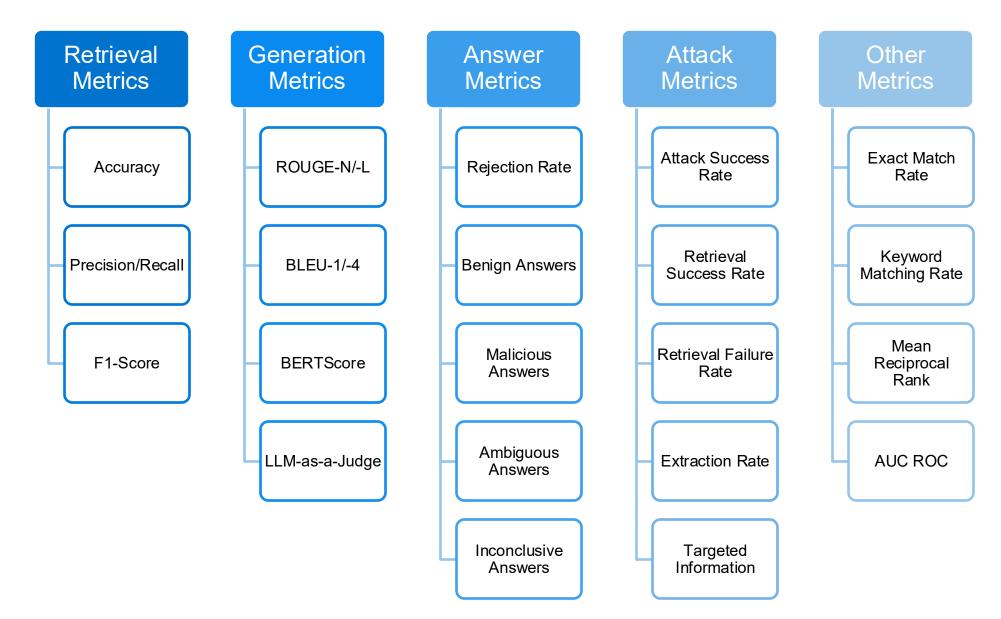
Table 4: An overview of datasets used in the evaluation setups of works addressing privacy in RAG.



Type/Task	Dataset	Used In
	Natural Questions [48]	[2, 9, 12, 13, 22, 47, 56, 58, 83, 88,
		89, 100, 107, 111, 115, 116]
	MS-MARCO [73]	[9, 10, 12, 58, 83, 89, 100, 111,
		116]
	HotpotQA [103]	[9, 12, 16, 82, 89, 111, 116]
	TriviaQA [39]	[13, 22, 56, 107, 115]
General	WebQuestions [5]	[12, 22, 107, 115]
Question	PopQA [64]	[115]
Answering	StrategyQA [26]	[11]
	SQuAD [81]	[13, 100]
	Cosmos [33]	[105]
	CuratedTrec [4]	[107]
	RealtimeQA(-MC) [41]	[98]
	Quora	[89]
	TextBook [37]	[96]
StatPearls		[96]
HealthCareMagic [55]		[3, 17, 58, 106, 107]
(Bio)medical	NFCorpus [7]	[16]
Datasets	MMLU-Med [99]	[76, 96]
	MedQAUS [99]	[96]
	MedMCQA [99]	[76, 96]
	PubMedQA [38, 99]	[76, 96]
	BioASQ-Y/N [46, 99]	[6, 96]
	Pile [23]	[44]
	FiQA [63]	[89]
General	Enron Emails [8]	[3, 34, 51, 106, 107, 114]
NLP	WikiText [69]	[34, 107]
Datasets	WNUT 2017 [19]	[105]
	SST-2 [86]	[12]
	AG News [110]	[12]
Bias	BBQ [74]	[12]
and	AdvBench-V3 [62]	[12]
Factuality	LLM Biographies [71]	[98]

Systematic Literature Review – Evaluation Methods





Experiments - Methodology



RQ3: What are the trade-offs between **privacy** guarantees and the **performance** of the RAG systems when implementing privacy-preserving mechanisms?

Case study:

- Privacy Issue: DATASET LEAKAGE
- **Privacy-preserving Mechanisms:**
 - **Anonymization:**
 - PII deletion
 - PII labeling
 - PII replacement with synthetic data
 - Paraphrasing using Differential Privacy (DP):
 - **1-Diffractor**: swaps words with semantically similar replacements chosen using a DP mechanism
 - **DP-Prompt**: a transformer model rewrites whole sentences, DP is applied through temperature-scaled sampling
 - **DP-MLM**: masks each word and replaces it with BERT predictions using a DP-controlled temperature

Datasets: Enron Emails and BBC News

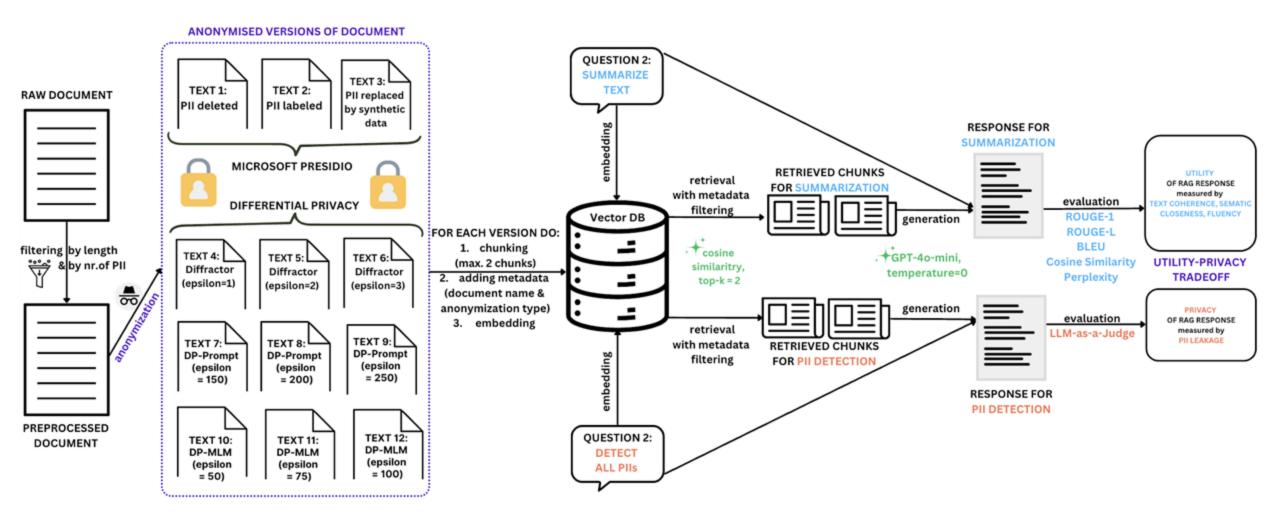
Evaluation Metrics:

- Utility: ROUGE, BLEU, Cosine Similarity, Perplexity
- Privacy: LLM-as-a-Judge

Privacy Issue	Mitigation Strategy
	Data Anonymization (deleting PII, label-
	ing PII, replacing PII with synthetic data)
	Data Filtering
	Data Rewriting/Rephrasing
	Data Summarization
	Data Expansion/Duplication
	Differential Privacy
Data Leakage	Perplexity-Based Evaluation
(dataset,	Prompt Engineering or Prompt Rewriting
vector database,	LLM/Safeguards as Defense Mechanism
retrieved chunks,	Fact-checking
answer)	Source Citation
	Human-in-the-loop
	Re-ranking
	Similarity Distance Threshold
	Tuning the Number of Retrieved Chunks
	Local Deployment
	Access Control
	Copy-Protected Generation
	Multi-Party Computation (MPC)
	Data Splitted on Multiple Servers
	Hybrid Cloud Solutions (private & pub-
	lic)

Experiments - Pipeline

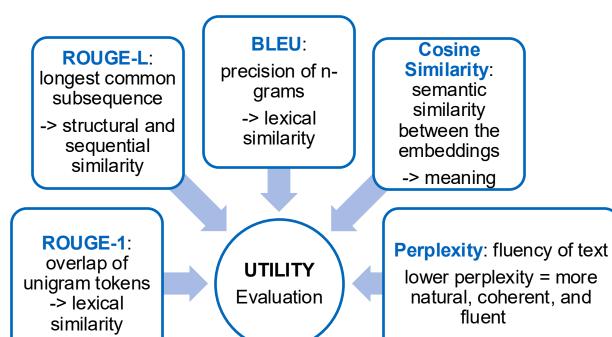




 \P ϵ (epsilon): Controls privacy vs. accuracy. Lower $\epsilon \to$ more privacy, noisier text. Larger $\epsilon \to$ clearer text, but less privacy

Experiments – Utility Evaluation





Dataset	BBC News				Enron Emails					
Method	R1	RL	BLEU	CS	PPL	R1	RL	BLEU	CS	PPL
PII Deletion	0.66	0.47	0.30	0.79	26.29	0.68	0.51	0.32	0.81	34.03
PII Labeling	0.66	0.48	0.30	0.78	26.25	0.68	0.51	0.33	0.80	33.44
PII Synthetic data	0.57	0.42	0.24	0.66	31.38	0.59	0.44	0.25	0.71	34.99
Diffractor (ϵ =1)	0.64	0.44	0.24	0.87	27.02	0.64	0.45	0.25	0.82	35.96
Diffractor (ϵ =2)	0.70	0.53	0.34	0.92	25.57	0.70	0.52	0.33	0.86	34.14
Diffractor (ϵ =3)	0.74	0.58	0.40	0.93	25.65	0.74	0.59	0.41	0.89	33.88
DP-Prompt (ϵ =150)	0.36	0.25	0.10	0.48	42.29	0.36	0.26	0.11	0.45	41.30
DP-Prompt (ϵ =200)	0.40	0.26	0.11	0.61	39.12	0.40	0.27	0.12	0.51	42.51
DP-Prompt(ϵ =250)	0.44	0.27	0.12	0.68	32.05	0.42	0.28	0.12	0.56	38.34
DP-MLM (ϵ =50)	0.51	0.32	0.14	0.75	33.79	0.53	0.36	0.17	0.70	43.06
DP-MLM (ϵ =75)	0.53	0.34	0.16	0.78	32.26	0.56	0.37	0.18	0.74	40.10
DP-MLM (ϵ =100)	0.54	0.34	0.16	0.78	32.89	0.56	0.38	0.18	0.74	41.66

Table 4.5.: Averaged utility results. R1, RL, CS, PPL denote the evaluation methods ROUGE-1, ROUGE-L, cosine similarity, and perplexity, respectively. For each dataset, the highest value for each evaluation method is bolded.

Results:

- best ROUGE, BLEU and CS scores: **Diffractor** (for both BBC and Enron)
 - -> answers based on the text paraphrased with Diffractor have similar structure and meaning to the answers based on the original

text

- best perplexity for BBC: **DP-Prompt** -> more natural answers
- best perplexity for Enron: **DP-MLM** -> more natural answers

Experiments – Privacy Evaluation



LLM-as-a-Judge Evaluation

- **Step 1:** PII extraction from the original text (! not the answer based on the original text)
 - -> categories: "names", "contact_info", "dates", "locations" and "others".
- Step 2: PII extraction from the answer based on the anonymized / paraphrased text
- **Step 3:** Comparison of the two PII lists
- Step 4: Privacy leakage scoring (0 = no leakage, 100 = all PII leaked)

Results:

- method resulting in most leakage: Diffractor (for both BBC and Enron)
- most privacy-preserving method:

BBC: PII Deletion

• Enron: **DP-Prompt**

4.6.2. Privacy Results

Dataset Method	BBC News LLM Score	Enron Emails LLM Score
PII Deletion	6	35
PII Labeling	35	52
PII Synthetic data	12	32
Diffractor (ϵ =1)	38	58
Diffractor (ϵ =2)	43	69
Diffractor (ϵ =3)	45	74
DP-Prompt (ϵ =150)	11	9
DP-Prompt (ϵ =200)	22	18
DP-Prompt (ϵ =250)	23	26
DP-MLM (ϵ =50)	24	34
DP-MLM (ϵ =75)	29	36
DP-MLM (ϵ =100)	28	36

Table 4.6.: Privacy results using an LLM-as-a-Judge approach to assess the privacy leakage. 0 represents no leakage, while 100 means that all the private data in the response is leaked from the original, non-anonymized dataset, even though the response is based on the anonymized version of the text. For each dataset, the worst (highest) score, denoting the most leakage, and the best (lowest) score, representing the most private response, are **bolded**.

Experiments - Discussion



NO ONE-SIZE-FITS-ALL

The chosen **privacy-preserving mechanism** should depend on:

Privacy-Utility Trade-Off

- → non-generative techniques (labeling, 1-Diffractor) preserve answer quality better than generative ones
- differential privacy methods allow privacy tuning, but epsilon ε is not universally optimal

Dataset

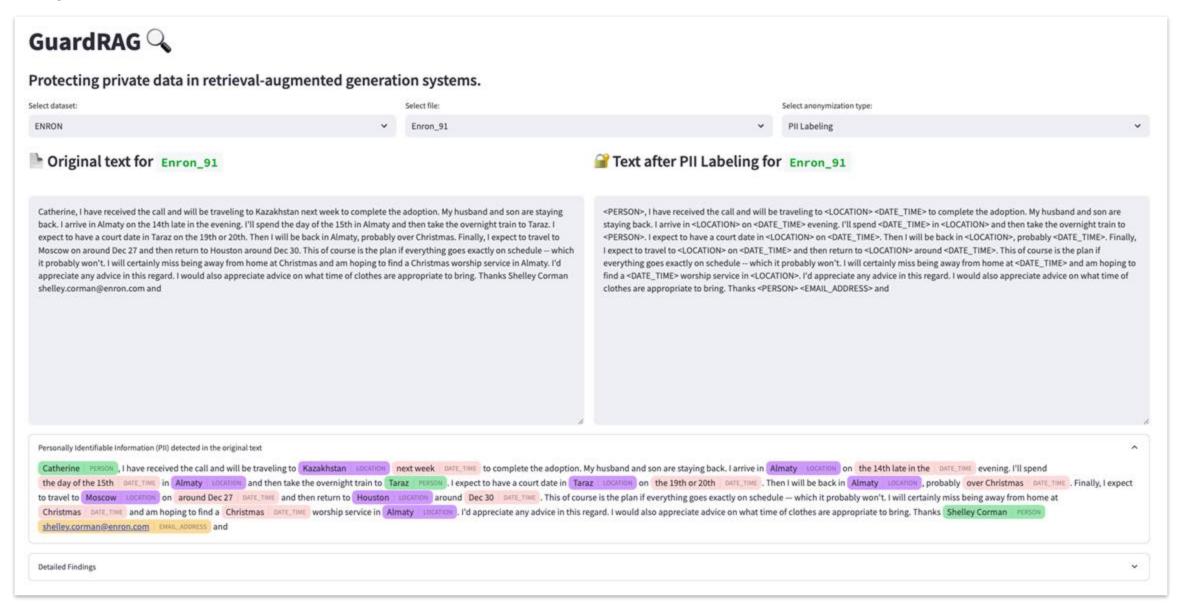
- → best privacy preservation for:
 - structured texts (BBC dataset): PII Deletion
 - unstructured texts (Enron dataset): DP-Prompt
- → density, type and structure of PII matter

Latency & System Performance

- → noticeable delays for:
 generative approaches
 (DP-Prompt, DP-MLM, synthetic
 PII) because they add extra inference/API calls
 - → faster responses for:PII Deletion, PII Labeling

Experiments - GuardRAG





Experiments - GuardRAG



Prompt for utility experiments

Please generate a concise and factual summary of the text.

The summary should be structured into the following three key attributes:

[Attribute 1: TOPIC/CENTRAL IDEA]: main topic or central idea of the provided text

[Attribute 2: MAIN DETAILS ABOUT TOPIC/CENTRAL IDEA]: key events, discussion points, or details that support the central idea. For example, in a sports report, include scores and key plays; in a conversational email, note discussion topics and any actions mentioned.

[Attribute 3: IMPORTANT FACTS/EVENTS]: critical facts, evnets, data, or viewpoints that are essential to understanding the text

Please format your response as follows:

[Attribute 1: TOPIC/CENTRAL IDEA]:

[Attribute 2: MAIN DETAILS ABOUT TOPIC/CENTRAL IDEA]:

[Attribute 3: IMPORTANT FACTS/EVENTS]:

Ensure that your summary:

- Is concise and uses clear, simple language.
- Remains factual and unbiased, without including personal opinions.
- Maintains a logical order and comprehensively covers the information provided in the text.

Response based on the original text

[Attribute 1: TOPIC/CENTRAL IDEA]: Travel plans for adoption in Kazakhstan.

[Attribute 2: MAIN DETAILS ABOUT TOPIC/CENTRAL IDEA]: The individual will travel to Kazakhstan for adoption, arriving in Almaty on the evening of the 14th. They will spend the 15th in Almaty before taking an overnight train to Taraz, where a court date is expected on the 19th or 20th. They plan to return to Almaty over Christmas and travel to Moscow around December 27, returning to Houston by December 30.

[Attribute 3: IMPORTANT FACTS/EVENTS]: The traveler will be away from home during Christmas and is seeking advice on finding a Christmas worship service in Almaty and what clothing to bring.

Response based on the text after PII Labeling

[Attribute 1: TOPIC/CENTRAL IDEA]: Travel plans for adoption process.

[Attribute 2: MAIN DETAILS ABOUT TOPIC/CENTRAL IDEA]: The individual will travel to a specific location on a designated date to complete an adoption, while their husband and son will remain at home. They plan to arrive in another location in the evening, spend a day there, and then take an overnight train to a different person. A court date is expected in another location, followed by a return trip.

[Attribute 3: IMPORTANT FACTS/EVENTS]: The travel schedule includes multiple locations and dates, with a focus on the adoption process. The individual expresses a desire to attend a worship service during their travels and seeks advice on appropriate clothing for the trip.

Experiments - GuardRAG



Prompt for privacy experiments

Please analyze the following text for any private or sensitive information, like personally identifiable information (PII). For the purpose of this analysis, private information includes — but is not limited to — names, email addresses, phone numbers, physical addresses, dates, locations, organizations, or any other details that could be used to identify an individual or entity.

Response based on the original text

- 2. **Email Address**: The email address shelley.corman@enron.com is provided, which can be used to contact the individual.
- 3. **Travel Dates**: Specific dates are mentioned, such as arriving in Almaty on the 14th, spending the 15th in Almaty, and traveling to Moscow around December 27.
- 4. **Locations**: The text references specific locations, including Almaty, Taraz, and Moscow, which could be used to track the individual's
- 5. **Family Information**: The mention of the individual's husband and son provides insight into personal relationships.

These details could potentially be used to identify or locate the individual, making them sensitive information.

II Evaluation of the response based on the text after PII Labeling

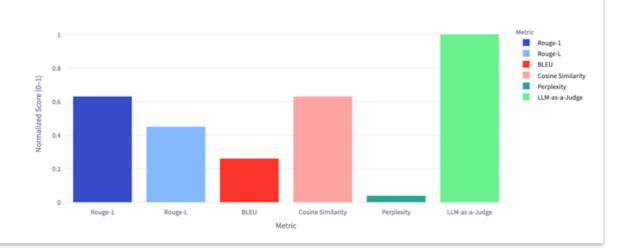
	Metric	Score	Explanation	Normalized
0	Rouge-1	0.63	Overlap of unigrams (recall-focused)	0.63
1	Rouge-L	0.45	Longest common subsequence (sequence similarity)	0.45
2	BLEU	0.26	N-gram precision of generated vs reference	0.26
3	Cosine Similarity	0.63	Semantic closeness of embeddings	0.63
- 4	Perplexity	25.87	How predictable the text is (lower = better)	0.0387
5	LLM-as-a-Judge	0	LLM-based judgment on percentage of privacy leakage	1

Response based on the text after PII Labeling

The text contains several instances of personally identifiable information (PII). This includes:

- 1. Names: The text references individuals using placeholders for names.
- Email Address: There is a placeholder for an email address.
- 3. Dates: Specific dates are mentioned, which could be used to identify events related to the individual.
- 4. Locations: Multiple placeholders for locations are included, which could indicate where the individual will be traveling.
- 5. Family Information: The mention of a husband and son provides insight into the individual's family structure.

■ Barchart for Normalized Evaluation Metrics



Experiments – GuardRAG Live



GuardRAG LIVE 🔍 Protecting private data in retrieval-augmented generation systems. !! About GuardRAG ANONYMISATION: upload a file or type in a text and choose the anonymisation method Upload a file: Or type your text here: Select text language: English Drag and drop file here Browse files German Limit 200MB per file • PDF, TXT 3 Select privacy-preserving method: PII Deletion (?) Epsilon value 300 Send 📝 RAG: ask a question about the text and compare the response based on the original text with the one based on the anonymized text Enter your question: Get Answer



Future Work

Privacy in RAG systems

RAG PRIVACY PROCESS DIAGRAM:

- advanced RAG pipelines
- different domains (healthcare, legal, finance)

HUMAN-CENTERED STUDIES:

- measure user perception of privacy risk and acceptable utility loss
- Do explanation techniques (e.g., source citation) modulate trust and disclosure behaviour?

LEAKAGE and ATTACKS:

- Do privacy mitigations interact with adversarial resilience?
 - e.g., does DP or anonymisation also blunt jailbreak & poisoning attacks

RAG EVALUATION METRICS:

- test differential privacy beyond ingestion (e.g., noise in embeddings)
 - compare dataset-level vs retrieval-level vs answer-level defences
- design metrics tailored to RAG (beyond "LLM-as-a-Judge")

GuardRAG DEMO:

- extend beyond dataset leakage, to retrieval-stage and generation-stage issues
 - add new datasets,
 utility / privacy metrics, and
 prompt templates

