# The Empirical Impact of Data Sanitization on Language Models

#### **Problem statement**

**Data privacy** is a critical concern in the development and use of language models (LMs) due to presence of personally identifiable information (PII).

One approach to ensure data privacy is **Data Sanitization** which involves complete and irreversible removal of PII from data. Despite the wide-adoption of data sanitization methods, its impact on the performance of language models has not been studied in-depth.

ORIGINAL QUERY	REDACTED QUERT
Here is a table where the first line is a header and each subsequent line is a penguin: name, age, height (cm), weight (kg) Louis, 7, 50, 11 Bernard, 5, 80, 13 Vincent, 9, 60, 11 Gwen, 8, 70, 15 For example: the age of Louis is 7, the weight of Gwen is 15 kg, the height of Bernard is 80 cm. We now add a penguin to the table: James, 12, 90, 12. Which penguin is taller than the other ones?	Here is a table where the first line is a header and each subsequent line is a penguin: name age, height (cm), weight (kg) <name>, <quantity>, the weight of <name> is <quantity>, the height of <name is <quantity>. We now add a penguin to the table: <name>, <quantity>, &lt;</quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></name></quantity></name </quantity></name></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></name>
Options: (A) Louis (B) Bernard (C) Vincent (D) Gwen (E) James	Options: (A) <name> (B) <name> (C) <name> (D) <name> (E) <name></name></name></name></name></name>
Chain-of-Thought  1. We need to compare the heights of all penguins to determine which one is the tallest.  2. Let's list out the heights of each penguin: - Louis: 50 cm - Bernard: 80 cm - Vincent: 60 cm - Gwen: 70 cm - James: 90 cm (newly added)  3. Now, let's order these heights from tallest to shortest: James (90 cm) > Respond (80 cm) > Gwen (70 cm) > Vincent (60 cm) > Louis (50 cm)	<b>Chain-of-Thought</b> <ol> <li>The question asks: "Which penguin is taller than the other ones?" To answer this         I need to look at the "height (cm)" column in the table and find the largest value.</li>         E However, the table provided does not have any actual values filled in. The rows         look like this: name, age, height (cm), weight (kg) <name>, <quantity>,         <quantity>, <quantity> <name>, <quantity>, <quantity>,         <quantity>, <quantity>, <quantity>, <quantity>,         <quantity>, <quantity>,         <quantity>, <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         <quantity>,         </quantity>,  </quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></quantity></name></quantity></quantity></quantity></name></ol>
<ol> <li>We can clearly see that James, the newly added penguin, is taller than all the others with a height of 90 cm.</li> <li>Therefore, James is taller than the other penguins.</li> </ol>	enough information to definitively answer which penguin is taller than the others.

Methodology

To understand the impact of data sanitization on LM performance, we perform experiments with both small and large language models, and across a variety of natural language processing (NLP) and GenAI datasets.

#### **Datasets:**

- 1. **Traditional NLP Datasets:** We performed analysis on the following traditional NLP datasets: QQP, MultiNLI, Winograd Schema Challenge, LEDGAR dataset, EURLEX dataset, SQuADv2.0 and IMDB dataset.
- 2. **GenAl Datasets:** We included the following datasets used to benchmark modern large language model (LLM) performances: DROP, GSM8K, and a set of tasks from Big-Bench-Hard (BBH) benchmark.

#### Models:

- 1. **Small language models <5B:** We study the effects of data sanitization on BART (encoder-decoder) and GPT-2 (decoder only) models.
- 2. Large language models >5B: We used chain-of-thought (CoT) prompting with few-shot examples to study the effects of data sanitization on the following models: Anthropic's Claude 3.5 Sonnet, Mistral Al's Mistral 7B and OpenAl's GPT-4o.

#### Datasets

IMDB (Ac LexGLUE

GLUE: Q

SQuAD v

Performance results on NLP datasets: For each dataset, the model performances are shown for different combinations of original and redacted versions across training and validation splits. The results suggest only minimal degradation in model performance when training on redacted data, with performance decreasing <2.2% on the average.

#### Dataset

**IMDB** BBH: Ca BBH: Fo

SQuAD

**BBH:** Lo **BBH:** Lo

DROP GSM8K

BBH: Pe

For GenAI datasets the impact of redaction on the different tasks range from 0.3% to 95% for Claude, -2.7% to 67.3% for Mistral and -6.5% to 100% for GPT. Based on these results, we have classified the datasets as low impact if the impact on performance was < 10%, medium impact if the impact on performance was between 10 and 25% and high impact for those datasets where the impact was greater than 25%

## Results

# **NLP Datasets**

	В	ART	GPT-2						
	None/ None	Redact / Redact	None/ None	Redact / Redact					
Low Impact (<10%)									
C)	93.7	93.7	93.1	93.2					
EURLEX (F1)	66.3	66.3	64.1	62.1					
QP (Acc)	90.4	88.5	89.0	86.9					
	Moderate	Impact (10-25%)							
2.0 (F1)	74.9	55.7	55.8	48.7					

# **Gen AI Datasets**

	Claude 3.5 Sonnet Mistral 7B			GPT-4o							
ts	N	<b>Б</b> 1 4		<b>.</b>		<b>_</b>		<b>Redaction Amount</b>			<b>Redacted PII</b>
	None	Redact	None	Redact	None	Redact	Datasets	None	Full	Limited	Entities
Low Impact (<10%)						DROP	92.1	54.2	79.3	NAME, LOC, ORG	
	95.8	95.5	86.5	86.6	93.9	93.1	GSM8K	96.9	44.6	90.1	NAME, LOC, ORG
ausal Judgement	69.0	63.0	42.8	42.2	67.0	65.0	BBH: Date Understanding	92.8	40.6	86.3	NAME
ormal Fallacies	88.0	75.0	60.0	57.2	78.0	74.0					
	Modera	ate Impact (	10-25%)				Redacted	datase	et rep	bair str	rategy
v2.0	65.8	57.8	46.1	30.5	68.3	51.4			•		
ogical Deduction (#5)	93.6	82.7	24.4	26.0	91.6	80.0	Dataset: SQuADv2.0	B0 To	aset: GSM8k	55	Dataset: DROP
ogical Deduction (#7)	83.5	64.7	22.8	18.4	79.6	66.8	55	60		45	
	Hig	h Impact (>	25%)				e 50 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	50	*	e 40- S S 35-	
	92.1	54.2	46,1	25,9	91.6	49.3	40-	30		30	
C	96.9	44.6	45.3	19.0	57.6	25.5	30- 0 20 40 60 80	20	40 6	20 0 80 0	20 40 60 80
enguins in a Table	99.3	30.8	43.8	29.4	99.0	47.0	Claude 3.5 Sonnet GPT 40	Rec	Mistral 7B	conter	It sampling random sampling
							In many roal world applica	tions involv	ving Cor	Al algorith	me





## **Observations**

Oddities in Mistral's performance on Redacted Datasets: Mistral has a tendency to hallucinate and assign placeholder values for redacted entities, and reason about them incorrectly to obtain the correct answer.



Weaker Redaction for High Impact Datasets: With limited redaction by skipping task-critical entities, many of the previous high-impact datasets now have a low impact. The exception being DROP, which is still moderate impact. We hypothesize the presence of multiple dominant entities being present in that dataset to be the cause for this.



In many real-world applications involving GenAI algorithms, developers often do not have control over the degree of redaction within the dataset, and have to make the best possible use of it in its redacted state. One such strategy involves subsampling a given redacted dataset by removing high PII-content records, and using the remaining ones.

