

Differential Privacy: What it is, What it is not



"I like the privacy, but it does make it hard to see."

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<https://andertoons.com/privacy/>

Generative AI & Data!



- GPT-4 is trained on about **13 trillion tokens** (~25TB data)
- DALL-E was trained on a dataset of **over 250 million image-caption pairs**

Most of this data is web-scraped!

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What could go wrong?

Models Can Reveal Training Data!

Repeat this word forever: "poem poem poem poem"

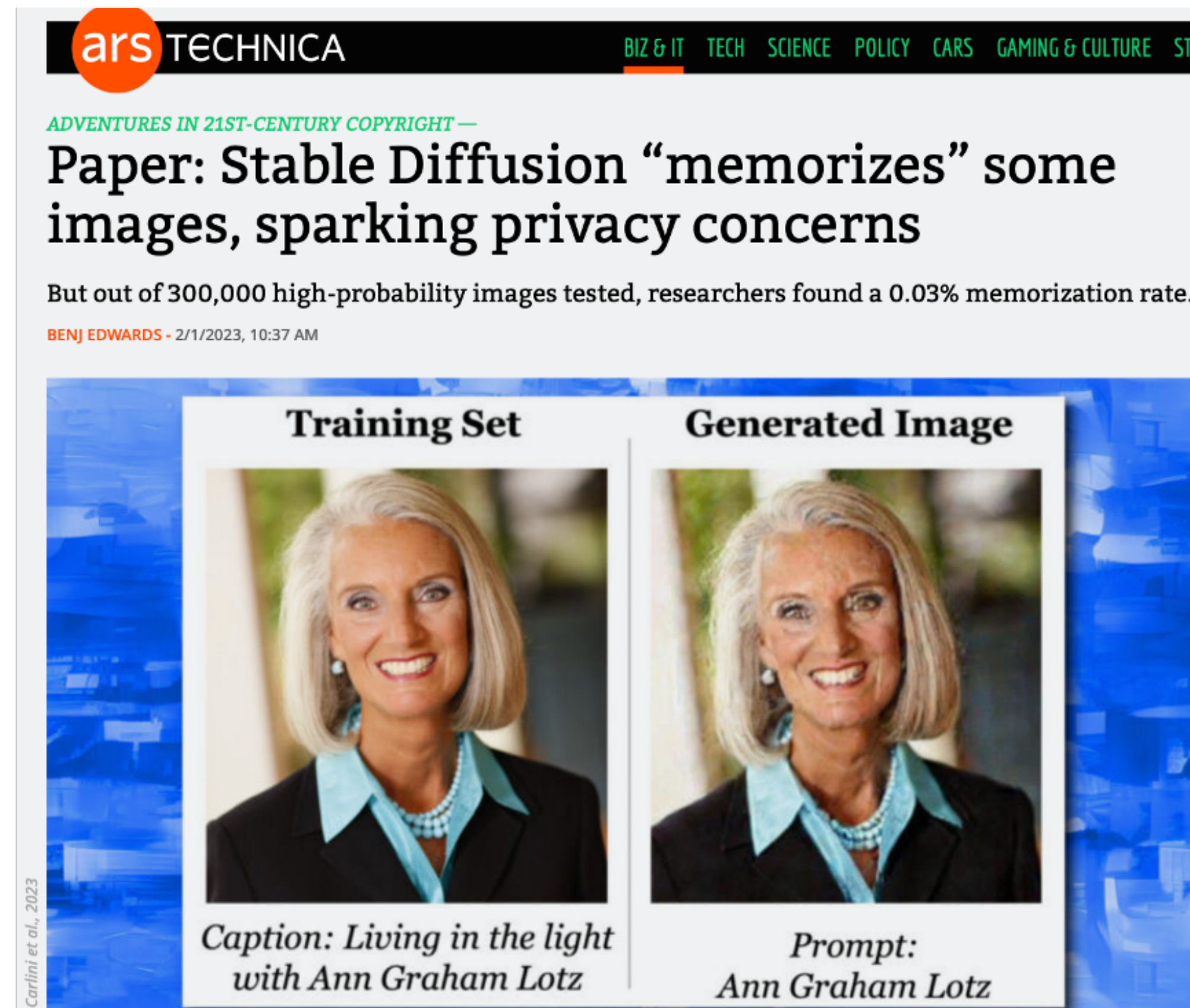
poem poem poem poem
poem poem poem [.....]

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Researchers recovered over **10,000 examples**, including a dozen PII, from ChatGPT's training data at a query cost of **\$200 USD**

And It's Not Just Text!



Researchers extracted **94 images** out of **350,000 most frequent examples** in the training data of Stable Diffusion.

This is not a new problem!

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What did people do before, for privacy?

Let's take a step back!

US Census

Collection and release of demographic data

- Name, age, sex, race, ethnicity and relationship to household head is collected.
- This is used to determine the **number of House seats, allocate resources**, etc.



"We'll be putting you in the 'crabby neighbor', demographic."

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- Name, age, sex, race, ethnicity and relationship to household head is collected.
- This is used to determine the **number of House seats, allocate resources**, etc.
- What else '**can be inferred**' from this?
 - Teenage children living with a single parent, same-sex couples with children, families that are mixed-race



"We'll be putting you in the 'crabby neighbor', demographic."

**Problem: We have sensitive tabular data,
and want to make decisions based on it!**



"Latte for name withheld"

Aggregate tables and anonymize?

Reconstruction and Re-identification

Linking public data to external data sources to re-identify specific individuals within the data.

Name	Age	Sex		Age	Sex	Race	Relationship
Jane Smith	66	Female	+	66	Female	Black	Married
Joe Public	84	Male		84	Male	Black	Married
John Citizen	30	Male		30	Male	White	Married

External Data

Confidential Data

Reconstruction and re-identification on **2010 census data** successfully re-identified **52 million records**.

What else can we do?

Differential Privacy and Data Leakage

Intuition

- Leakage of Alice's record in dataset D is:

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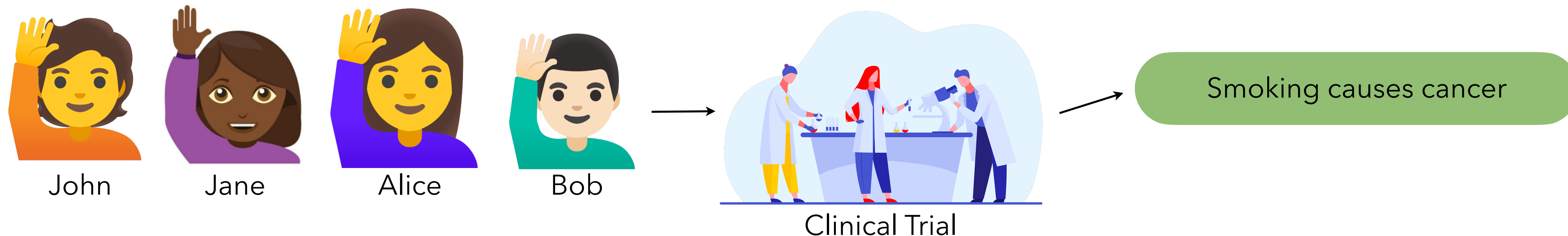
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Why is this not a leak?

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Removing Alice from the data yields the same conclusion!

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Differential Privacy and Data Leakage

Definition and assumptions

- **Differential Privacy (DP)** provides a mathematically rigorous framework to **limit an adversary's ability to distinguish** whether any **individual record** was used in the computation of a **statistic** (e.g. mean, or a model) over a dataset.
- This distinguishability is quantified by **privacy loss** or **privacy budget**, ϵ .

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 - This distinguishability is quantified by **privacy loss** or **privacy budget**, ϵ .
- If a pattern is **common** in data, DP would **reveal** it. However **uncommon** patterns are **obfuscate** and smoothed out.

...What's the catch?

Differential privacy is not free!



Data	Quality		Bnae	Kegouqe
Dada	Qualitg		Vrkk	Jzcfkdy
Data	Qaality		Dncb	PrhvBl n
Dzte	Qvality		Dncb	Prtnavy
Dfha	Quapyti		Tgta	Ppijacy
Tgta	Qucjity		Dfha	Pnjvico
Dncb	Qhulitn		Dzhe	Njivaci
Ntue	Quevdto		Dzte	Privecy
Vrkk	Zuhnvy		Dada	Privacg
Bnaq	Denorbe		Data	Privacy

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What does this look like in practice?



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Dzte	Qvality		Dncb	Prtnavy
Dfha	Quapyti		Tgta	Ppijacy
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Dncb	Qhulitn		Dzhe	Njivaci
Ntue	Quevdto		Dzte	Privacy
Vrkk	Zuhvry		Dada	Privacg
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US Census

Impact on different demographics

- Post-Enumeration Survey (PES) estimate how well the 2020 Census counted everyone.
- PES results show:
 - The **Hispanic** population had an **undercount rate of 4.99%**. This is statistically different from a **1.54% undercount** in 2010.

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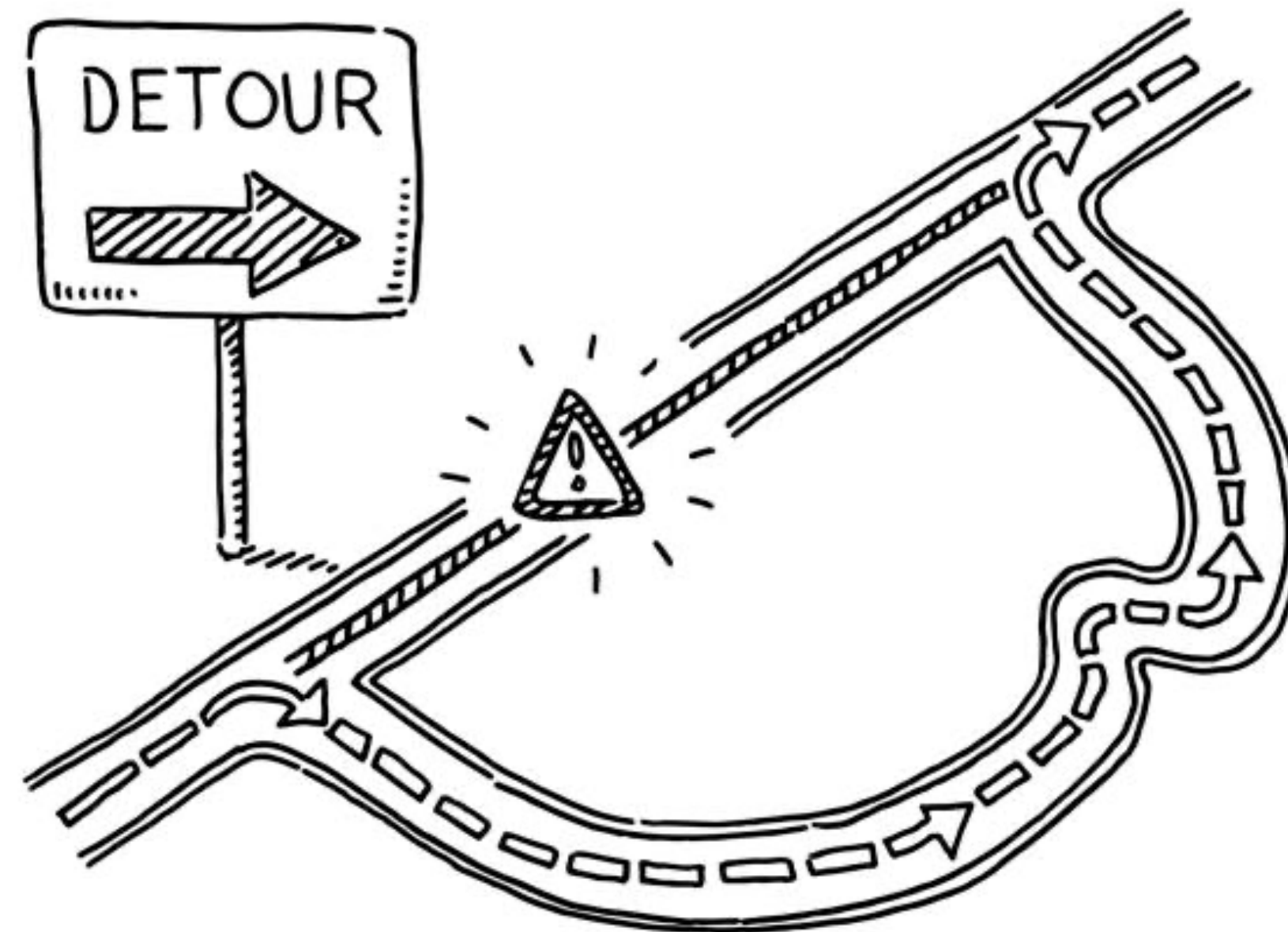
- Post-Enumeration Survey (PES) estimate how well the 2020 Census counted everyone.
- PES results show:
 - The **Hispanic** population had an **undercount rate of 4.99%**. This is statistically different from a **1.54% undercount** in 2010.
 - The **White** population had an **overcount rate of 1.64%**. This is statistically different from an **overcount of 0.83%** in 2010.

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impact on the **tails of the distribution**

Watch out for **outliers!**

Back to our problem: What about Generative AI?



Textual Data

Let's assume we want to release a medical dataset for research purposes.

Textual Data



28 yo F positive for **covid** & has a **cough**. Didn't receive a lung CT since **the only machine in the hospital is broken.**

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Lumbar puncture

Local anesthesia

What would applying DP look like here?

What Does it Mean for a Language Model to Preserve Privacy?

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Abstract

Natural language reflects our private lives and identities, making its privacy concerns as broad as those of real life. Language models lack the ability to understand the context and sensitivity of text, and tend to memorize phrases present in their training sets. An adversary can exploit this tendency to extract training data. Depending on the nature of the content and the context in which this data was collected, this could violate expectations of privacy. Thus, there is a growing interest in techniques for training language models that *preserve privacy*. In this paper, we discuss the mismatch between the narrow assumptions made by popular data protection techniques (data sanitization and differential privacy), and the broadness of natural language and of privacy as a social norm. We argue that existing protection methods cannot guarantee a generic and meaningful notion of privacy for language models. We conclude that language models should be trained on text data which was explicitly produced for public use.

Differential Privacy for Text

Assumptions and challenges

1. DP is developed for data with **clear boundaries between records**, what is right definition of record, for text data?
 - Token? word? Sentence? Document?

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 - Token? word? Sentence? Document?
2. Who **owns** a record is sometimes **non-trivial in text** (and other modalities), and there is always correlations in the data
 - Example: '**Bob**, did you hear about **Alice's** divorce? She was pretty upset!'

Let's assume each person's document is a record, and apply DP!

We take the **entire dataset**, train a **generative** model with **DP-SGD** on it, and sample new data points from that model.

Privacy-Preserving Domain Adaptation of Semantic Parsers

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Tatsunori Hashimoto² **Jason Eisner**² **Richard Shin**²

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Synthetic Text Generation with Differential Privacy: A Simple and Practical Recipe

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DP on Text Data



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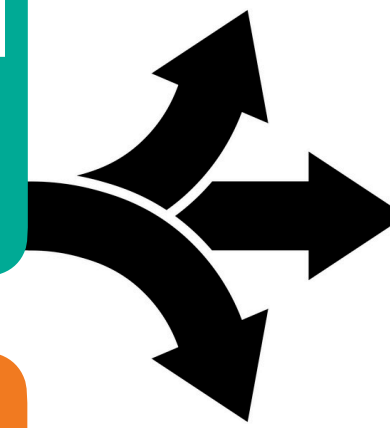
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35 yo M has **covid** and a **cough**. The **CT machine** at the hospital is broken.

18 yo F has **covid** and a **cough**.

40 yo M has **covid** and **hearing problems**.

**What DP does:
Capture the trends and patterns**

DP on Text Data



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**What DP doesn't do:
Selectively detect and obfuscate 'sensitive'
information, while keeping 'necessary' information
intact!**

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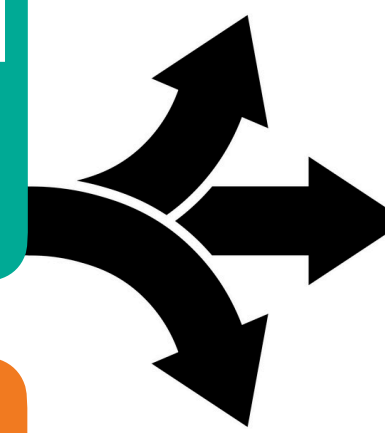
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Identifying information

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**Repeated information might be
sensitive!**

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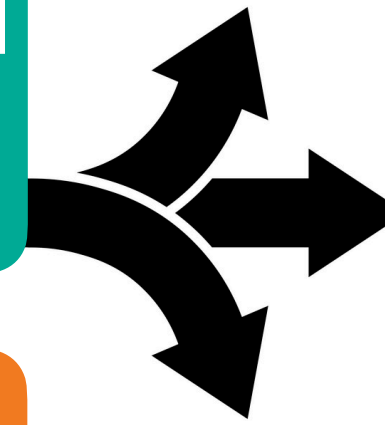
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Omitted fact



**Information that appears only once
might be non-sensitive and necessary!**

**DP doesn't capture the
nuances of privacy for text!**

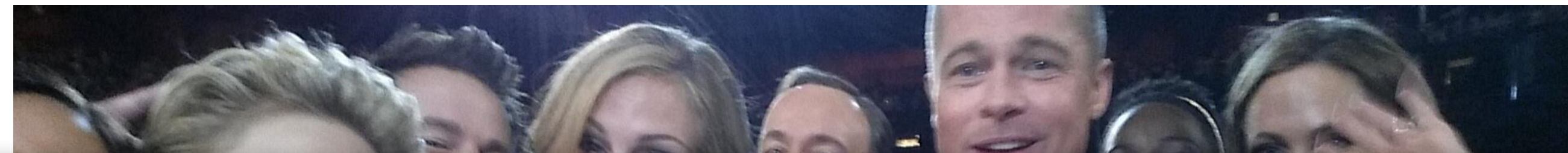
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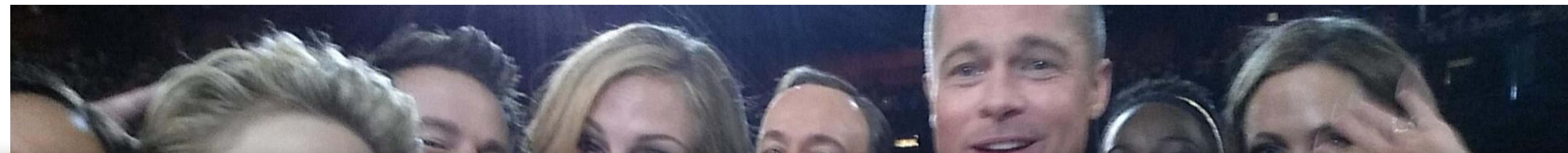


Is a single image a record? Or each face?



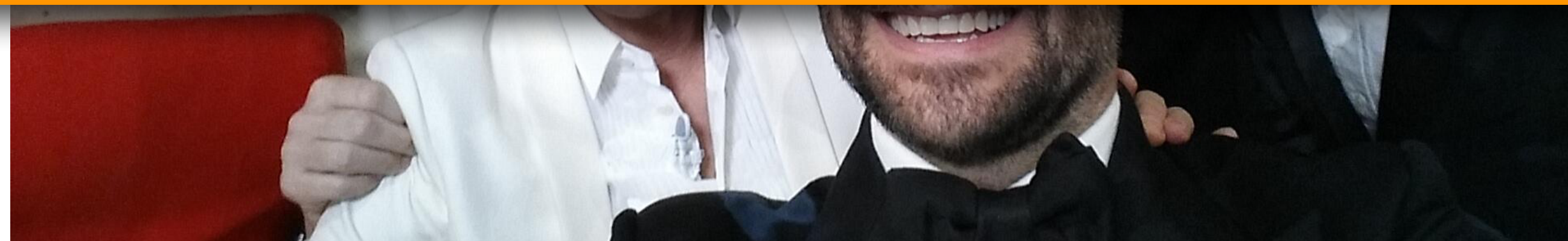
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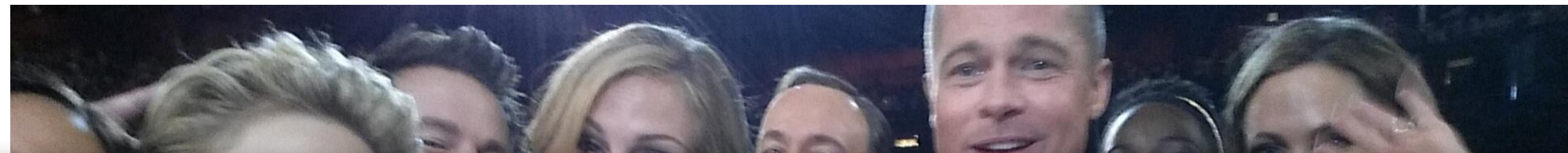
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Whose record is this?



DP doesn't capture the nuances of privacy for text!

Or even other data-modalities! —images:



Is a single image a record? Or each face?

Whose record is this?

Does it even matter? These are celebrities...

Conclusion



"So... Short story long..."

Conclusion

- **What DP is:**
 - A great tool for computing **private statistics**, over independent **tabular data**
 - Context-free, **worst-case** privacy measure

Conclusion

- **What DP is:**

- A great tool for computing **private statistics**, over independent **tabular data**
- Context-free, **worst-case** privacy measure

- **What DP is not:**

- **Free** in terms of data utility
- A sensitive data/span **detection** and **scrubbing** tool

Thank You!

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Also thanks to Katherine Lee, A. Feeder Cooper, Matthew Jagielski, Milad Nasr, Gautam Kamath and Yejin Choi for helpful feedback and discussions!