Towards trustworthy foundation models with privacy

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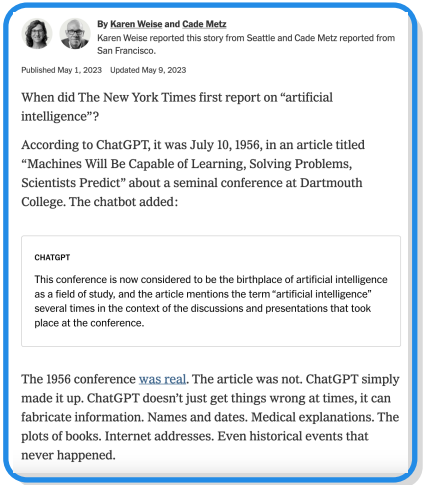
August 13, 2025

Machine Learning Summer School

Hallucination: Growing media attention

2023



By Karen Weise and Cade Metz

Karen Weise reported this story from Seattle and Cade Metz reported from San Francisco.

Published May 1, 2023 Updated May 9, 2023

When did The New York Times first report on “artificial intelligence”?

According to ChatGPT, it was July 10, 1956, in an article titled “Machines Will Be Capable of Learning, Solving Problems, Scientists Predict” about a seminal conference at Dartmouth College. The chatbot added:

CHATGPT

This conference is now considered to be the birthplace of artificial intelligence as a field of study, and the article mentions the term “artificial intelligence” several times in the context of the discussions and presentations that took place at the conference.

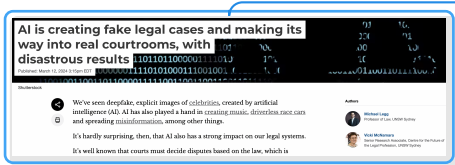
The 1956 conference was real. The article was not. ChatGPT simply made it up. ChatGPT doesn't just get things wrong at times, it can fabricate information. Names and dates. Medical explanations. The plots of books. Internet addresses. Even historical events that never happened.

NY Times

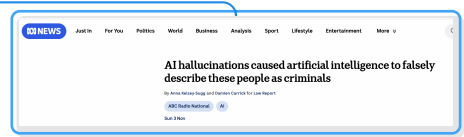
Hallucination: Growing media attention

2024

NY Times



Conversation

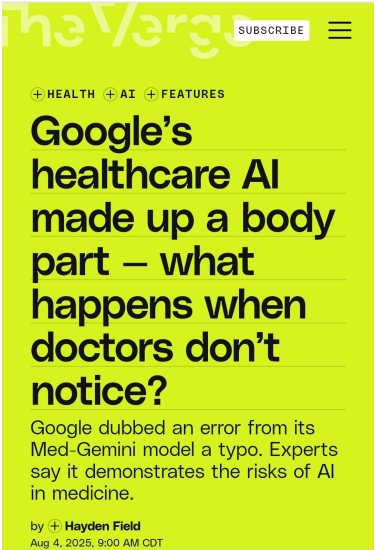


ABC News

Hallucination: Growing media attention

2025

Are there any real-world impacts though?



Are hallucinations new?

Figure 6.8: Failure cases of ProdPoly (trained on FFHQ). The three leftmost faces in the first row seem

Figure: This is a schematic from my PhD thesis 5 years ago - generative models were already known to hallucinate.

How does hallucination manifest in different modalities?

- **Text**
  - Faithfulness Hallucination:Input, context and logical inconsistency
  - Factual Hallucination: Contradiction and fabrication

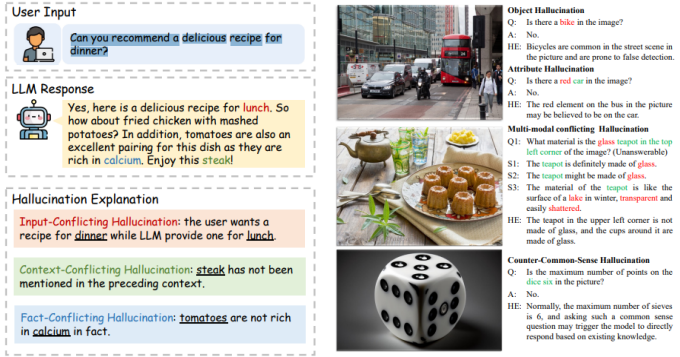


Figure from: Huang et al. (2025), "A Comprehensive Survey of Hallucination in Large Language, Image, Video and Audio Foundation Models"

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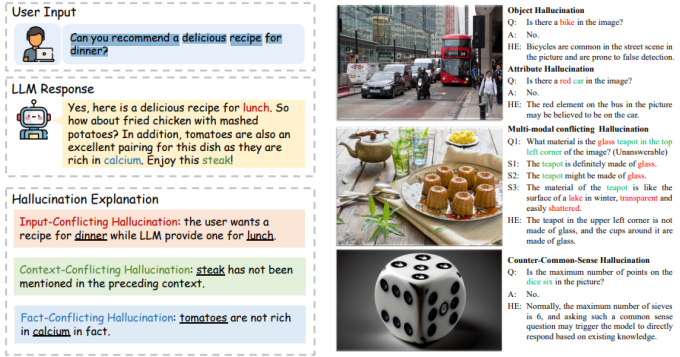

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- **Text**
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  - Factual Hallucination: Contradiction and fabrication
- **Image**
  - Object Hallucination: Category, attribute and relation
- **Video and Audio**
  - Audio: Temporal hallucination
  - Video: Over-reliance on the visual modality

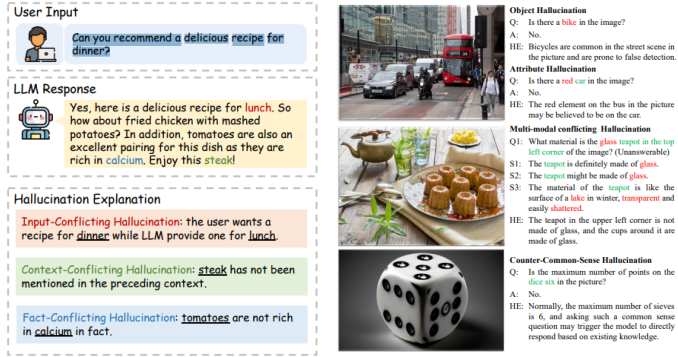

Figure from: Huang et al. (2025), "A Comprehensive Survey of Hallucination in Large Language, Image, Video and Audio Foundation Models"

Outline

Categories of LLM Hallucinations

Category	Type	Example Dialog	Explanation
Factuality Hallucination	Factual Contradiction	**Instruction:** What are Thomas Edison's main contributions to science and technology? **Response:** Thomas Edison developed the first practical telephone and invented the light bulb.	The response is factually incorrect. In reality, **Edison improved the light bulb, building on earlier designs by others**, and **Alexander Graham Bell invented the telephone**.
Faithfulness Hallucination			

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	Factual Fabrication	**Instruction:** What are the major environmental impacts of the construction of the Eiffel Tower? **Response:** The construction of the Eiffel Tower in 1889 led to the extinction of the Parisian tiger, a species that played a crucial role in the region's ecosystem. Additionally, it is widely recognized as the event that sparked the global green architecture movement.	The response erroneously states that the construction of the Eiffel Tower led to the extinction of the 'Parisian tiger' and sparked the global green architecture movement. In fact, **there is no evidence of a 'Parisian tiger' ever existing, making this a fabricated claim.** Moreover, **attributing the origins of green architecture to the Eiffel Tower is an exaggeration**, as this movement has diverse roots and cannot be traced back to a single event.
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Faithfulness Hallucination	Instruction Inconsistency	**Instruction:** Translate the English question into Spanish: "What is the capital of France?" **Response:** The capital of France is Paris.	The user explicitly provided an instruction to translate the English question into Spanish. **Instead of performing the translation as instructed, the LLM chose to answer the question.**

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	Context Inconsistency	**Retrieved context:** The Nile is a major north-flowing river in northeastern Africa. It's traditionally considered the longest river in the world. Originating in the Great Lakes region of central Africa, it flows through several countries before emptying into the Mediterranean Sea. **Instruction:** Summarize the retrieval document above. **Response:** The Nile originates from the mountain ranges of central Africa and flows into the Mediterranean.	The summary incorrectly states that the Nile originates from the "mountain ranges of central Africa", while the **paragraph mentions that the Nile originates in the Great Lakes region of central Africa.**

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	Logical Inconsistency	**Instruction:** Solve the equation $2x + 3 = 11$ step by step. **Response:** Step 1: Subtract 3 from both sides to get: $2x = 8$. Step 2: Divide both sides by 2 to get: $x = 3$. So the result of the equation is x=3.	The first step correctly isolates the term with x to get $2x = 8$. However, **the next step inaccurately divides 8 by 2 to yield a result of $x = 3$**, which is inconsistent with the earlier reasoning.

Table from: Feng et al., "A Survey on Hallucination in Large Language Models: Principles, Taxonomy, Challenges, and Open Questions", 2025.

Literature on Hallucination

- **Causes and Analysis**
  - Hallucination from Data: Bengio et al. (2015) (NeurIPS), Bender et al. (2021) (ACM), ...
  - Hallucination from Training: R-tuning (Zhang et al., 2024), Perez et al. (2022) (ACL), ...
  - Hallucination from Inference: Holtzman et al. (2020) (ICLR), Chen et al. (2022) (NeurIPS), ...
- **Detection Methods**
  - Factuality Hallucination Detection: FActScore (Min et al., 2023), Cove (Dhuliawala et al., 2024), ...
  - Faithfulness Hallucination Detection: Lakshminarayanan et al. (2017) (NeurIPS), Zhang et al. (2023) (EMNLP), ...
- **Benchmarks and Evaluation**
  - Hallucination Evaluation Benchmarks: TruthfulQA (Lin et al., 2022), PopQA (Mallen et al., 2023), ...
  - Hallucination Detection Benchmarks: BART (Lewis et al., 2020), PEGASUS (Zhang et al., 2020), ...
- **Mitigation Strategies:** Transformer-Patcher (Huang et al., 2023), RARR (Gao et al., 2023), Zhang et al. (2019) (ACM), ...
- **Surveys:** Huang et al. (2025) (ACM), Bai et al. (2025), ...
- **Additional resources:** Rawte et al. (2024), https://vr25.github.io/coling25-hallucination-tutorial

Causes for Hallucination (Huang et al., 2025)

Question

Can we identify key components that might give rise to hallucinations?

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1. **Data**
   - Dataset biases.
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   - Inferior Alignment Data.

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2. **Training**
   - Pre-training algorithms, architectures and regularizations.
   - Supervised Fine-Tuning.
   - Reinforcement Learning from Human Feedback.

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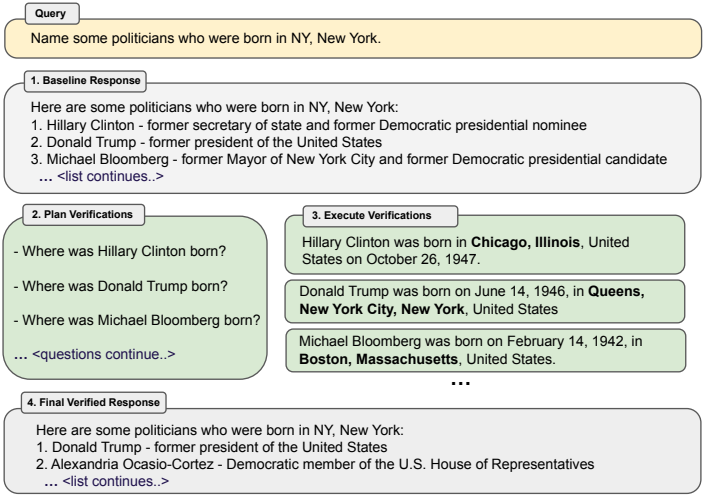
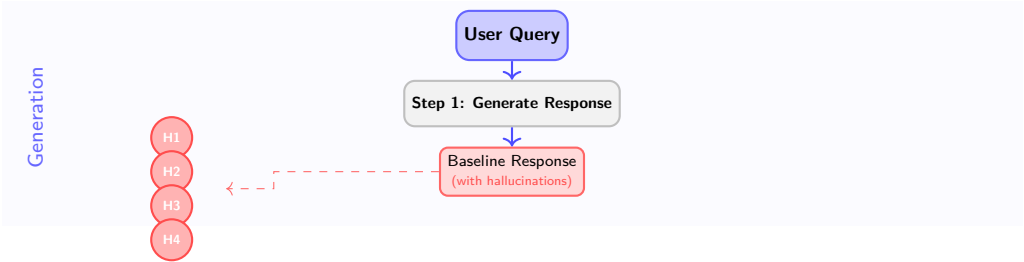
3. **Inference**
   - Decoding Strategies.
   - Over-confidence.
   - Architectural components (e.g., softmax).
   - Reasoning Failure.

Chain-of-Verification Reduces Hallucination in Large Language Models (CoVe) (Dhuliawala et al., 2024)



Chain-of-Verification Process (Dhuliawala et al., 2024)



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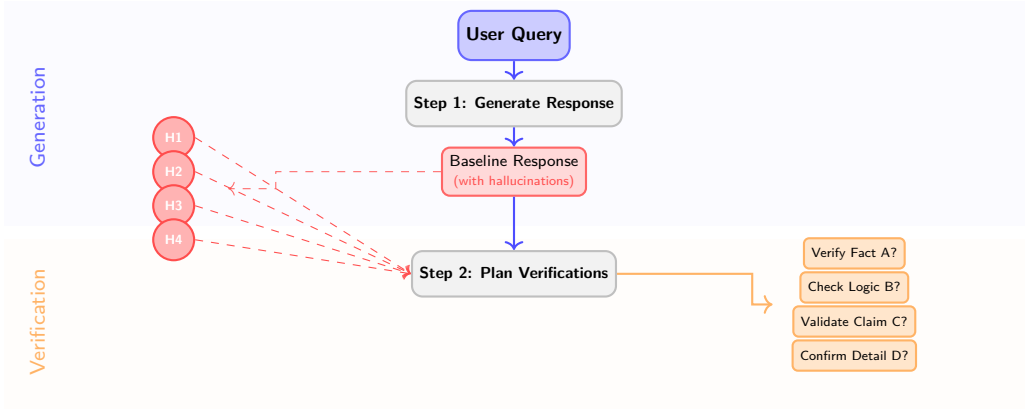

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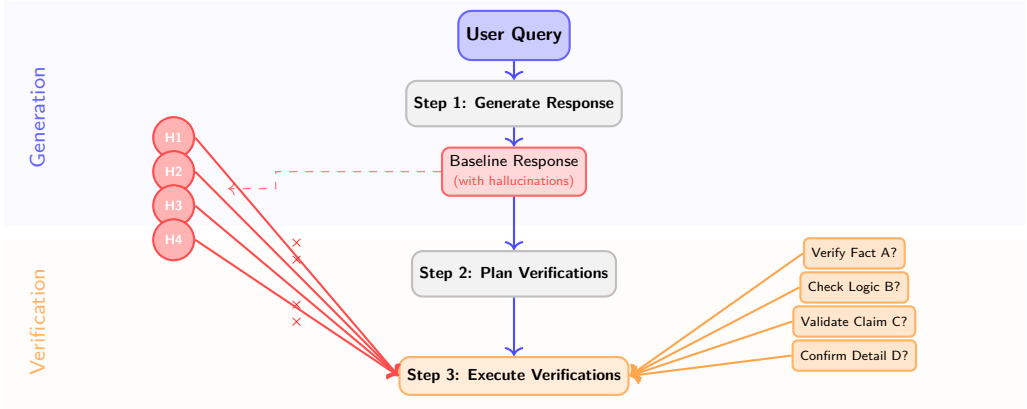

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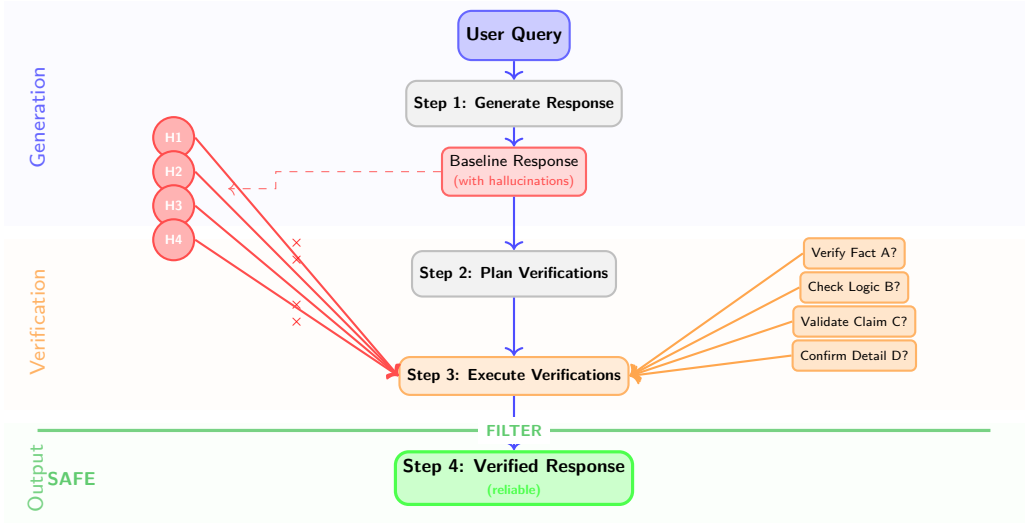

Hallucination on images

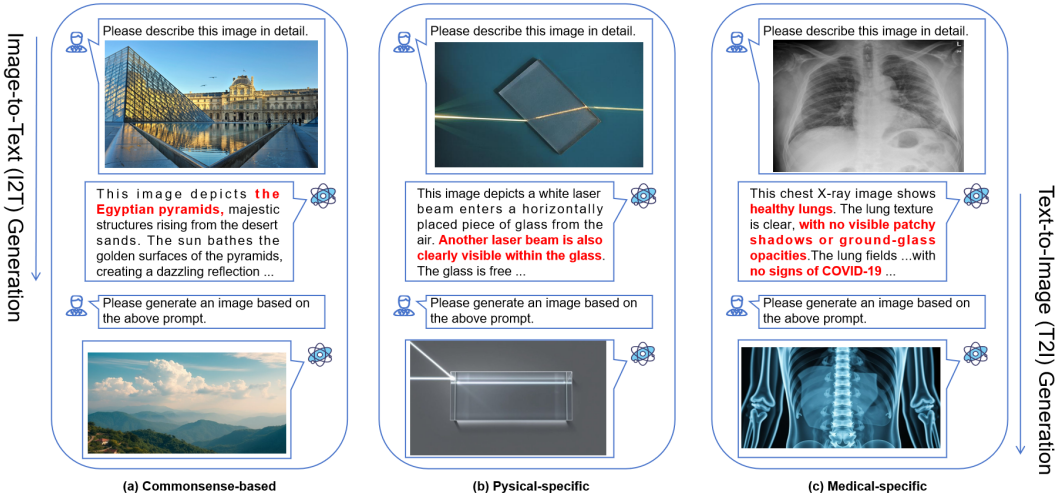

Figure from Chen et al. (2025), "A Survey of Multimodal Hallucination Evaluation and Detection"

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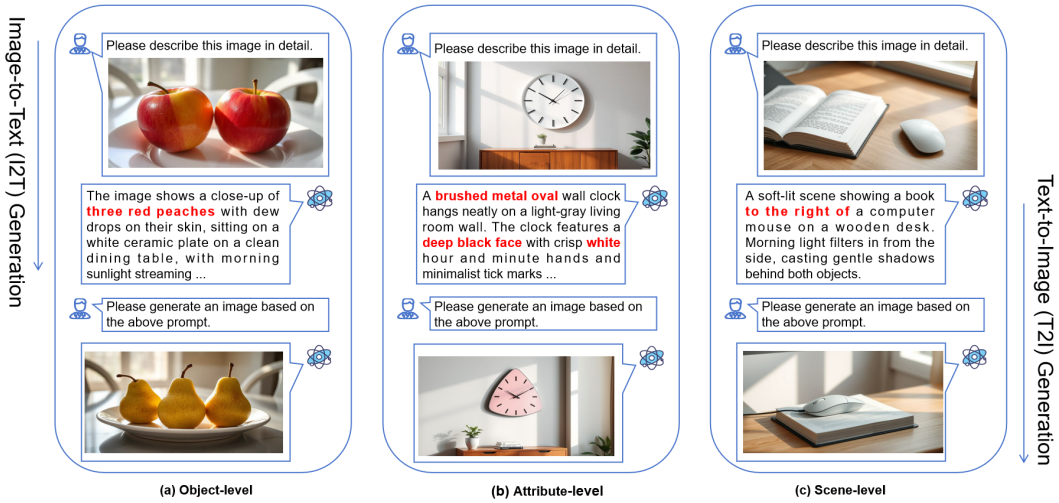

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Denoising Diffusion Models (Ho et al., 2020)

- Forward process:

$$q(\boldsymbol{x}_{1:T} \mid \boldsymbol{x}_0) = \prod_{t=1}^{T} q(\boldsymbol{x}_t \mid \boldsymbol{x}_{t-1}),$$

$$q(\boldsymbol{x}_t \mid \boldsymbol{x}_{t-1}) = \mathcal{N}(\boldsymbol{x}_t; \sqrt{1-\beta_t}\,\boldsymbol{x}_{t-1}, \beta_t \mathbf{I}).$$

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- Backward process:

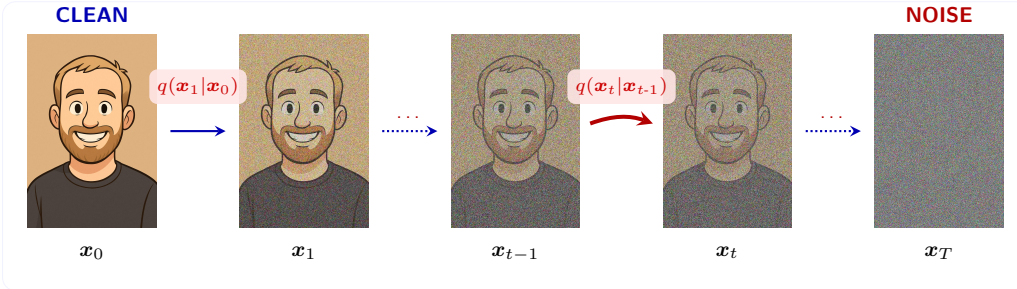
$$p_{\boldsymbol{\theta}}(\boldsymbol{x}_{0:T}) = p(\boldsymbol{x}_T) \prod_{t=1}^{T} p_\theta(\boldsymbol{x}_{t-1} \mid \boldsymbol{x}_t)$$

$$p_{\boldsymbol{\theta}}(\boldsymbol{x}_{t-1} \mid \boldsymbol{x}_t) = \mathcal{N}\Big(\boldsymbol{x}_{t-1}; \boldsymbol{\mu}_{\boldsymbol{\theta}}(\boldsymbol{x}_t, t), \boldsymbol{\Sigma}_{\boldsymbol{\theta}}(\boldsymbol{x}_t, t)\Big),$$

for parametrized model with parameters $\boldsymbol{\theta}$.

Diffusion process (Ho et al., 2020)

Forward Process



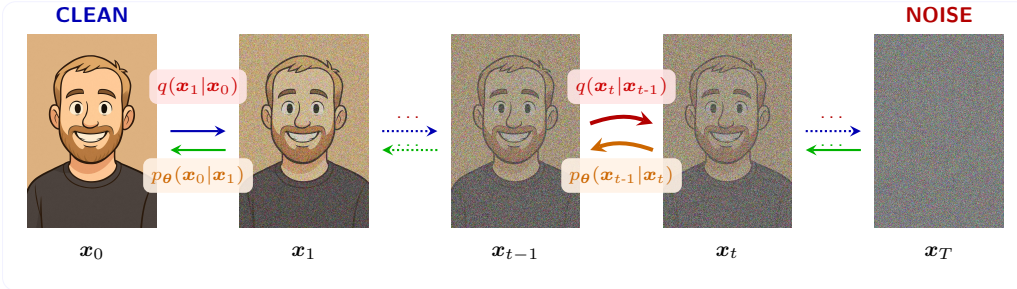
Forward: $q(\boldsymbol{x}_t|\boldsymbol{x}_{t\text{-}1}) = \mathcal{N}(\boldsymbol{x}_t; \sqrt{1-\beta_t}\,\boldsymbol{x}_{t\text{-}1}, \beta_t\mathbf{I})$

Diffusion Notation

$\boldsymbol{x}_0$	Original data
$\boldsymbol{x}_t$	Noisy state at time t
$q(\boldsymbol{x}_t\|\boldsymbol{x}_{t\text{-}1})$	Forward transition
β_t	Noise variance schedule
T	Final timestep

Diffusion process (Ho et al., 2020)

Reverse Process



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Reverse: $p_{\boldsymbol{\theta}}(\boldsymbol{x}_{t\text{-}1}|\boldsymbol{x}_t) = \mathcal{N}(\boldsymbol{x}_{t\text{-}1}; \boldsymbol{\mu}_{\boldsymbol{\theta}}(\boldsymbol{x}_t, t), \boldsymbol{\Sigma}_{\boldsymbol{\theta}}(\boldsymbol{x}_t, t))$

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Training of DDPM

Training Algorithm for DDPM

For every image $\{\boldsymbol{x}_0^{(i)}\}_{i=1}^M$ in your training dataset:

- Repeat until convergence:
  - Sample $t \sim \mathrm{Uniform}[1, T]$.
  - Draw a sample $\boldsymbol{x}_t^{(m)} \sim \mathcal{N}(\boldsymbol{x}_t \mid \sqrt{\overline{\alpha}_t}\boldsymbol{x}_0, \ \ (1-\overline{\alpha}_t)I)$, i.e., Compute $\boldsymbol{x}_t^{(m)} = \sqrt{\overline{\alpha}_t}\boldsymbol{x}_0 + \sqrt{1-\overline{\alpha}_t}\epsilon_t^{(m)}$, $\epsilon_t^{(m)} \sim \mathcal{N}(0, I)$.
  - Update $\boldsymbol{\theta}$ using gradient of

$$\frac{1}{M}\sum_{m=1}^{M}\left\|\widehat{x}_{\boldsymbol{\theta}}(\boldsymbol{x}_t^{(m)}) - \boldsymbol{x}_0\right\|^2 .$$

Inference of DDPM

Inference of DDPM

- Start from a white noise vector: $\boldsymbol{x}_T \sim \mathcal{N}(0, \boldsymbol{I})$.
- For $t = T, T-1, \ldots, 1$, repeat:
  - Compute denoised estimate $\widehat{x}_{\boldsymbol{\theta}}(\boldsymbol{x}_t)$ using the trained denoiser.
  - Update $\boldsymbol{x}_{t-1}$ using:

$$\boldsymbol{x}_{t-1} = \frac{(1-\overline{\alpha}_{t-1})\sqrt{\alpha_t}}{1-\overline{\alpha}_t}\boldsymbol{x}_t + \frac{(1-\alpha_t)\sqrt{\overline{\alpha}_{t-1}}}{1-\overline{\alpha}_t}\widehat{x}_{\boldsymbol{\theta}}(\boldsymbol{x}_t) + \sigma_q(t)\,\epsilon, \epsilon \sim \mathcal{N}(0, \boldsymbol{I})\,.$$

What is Hallucination in Diffusion Models?

Definition (Hallucination (Aithal et al., 2024))

A phenomenon where diffusion models generate samples that lie **completely outside** the support of the training distribution.

Mathematical Definition (Aithal et al., 2024)

The ϵ-Hallucination set:

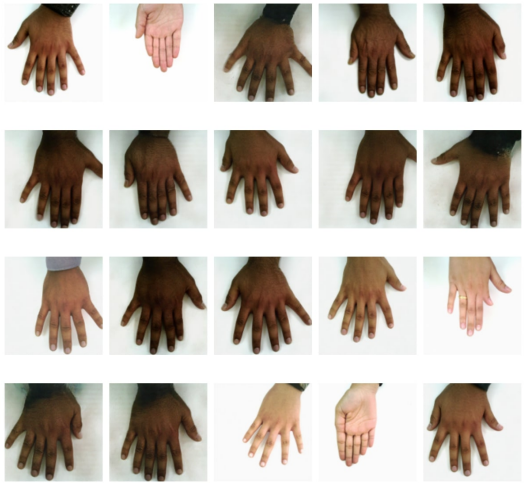
$$H_\epsilon(q) = \{x : q(x) \leq \epsilon\},$$

where $q(x)$ is the true data distribution and $\epsilon \approx 0$.

Examples: ○ Hands with 6+ fingers
○ Impossible combinations

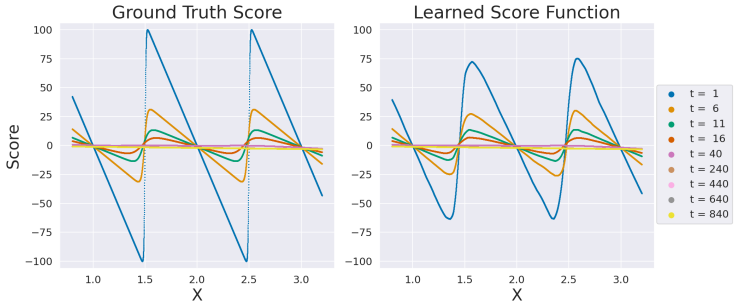
Key Point: These aren't just "bad" generations - they're generations of things that **never existed** in training!

How do the hallucinated images look like?



When do the hallucinated images appear during the diffusion process?

The Root Cause: Smooth Score Function Approximation



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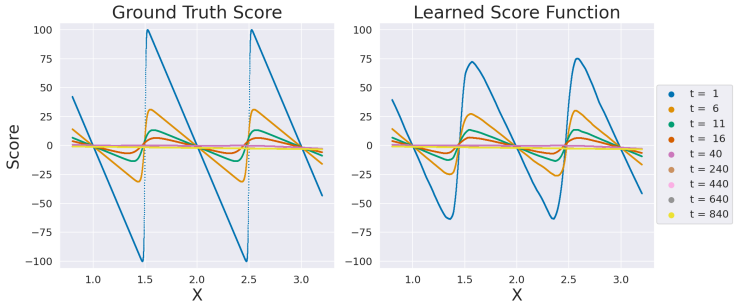

The Problem

- True score has sharp jumps
- Neural networks learn smooth approximations
- Smooth transitions create interpolations

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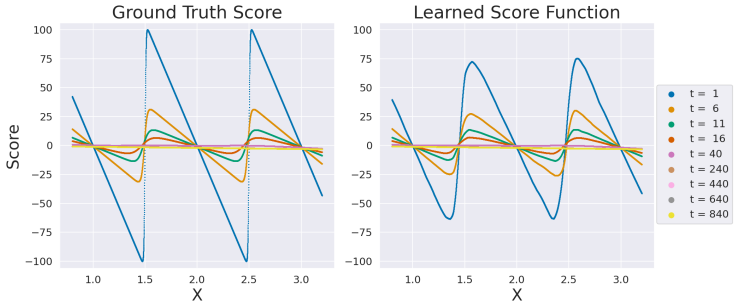

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Mathematical Insight

The score function: $s_\theta(x_t, t) = -\frac{\epsilon_\theta(x_t, t)}{\sqrt{1-\bar{\alpha}_t}}$

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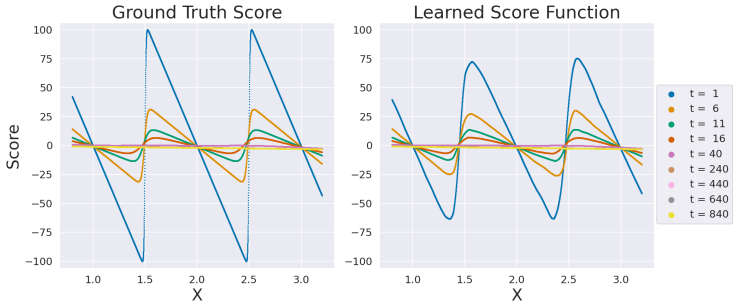

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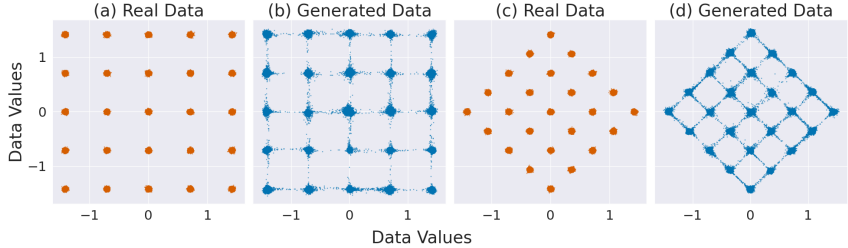
Validation

Using true score function $\rightarrow$ No mode interpolation observed!

2D Evidence: Grid of Gaussians



Key Insights

- (a) **Left:** Original 25 Gaussians in square grid (orange dots)
- (b) **Right:** Model samples (blue dots) show interpolation between nearest neighbors
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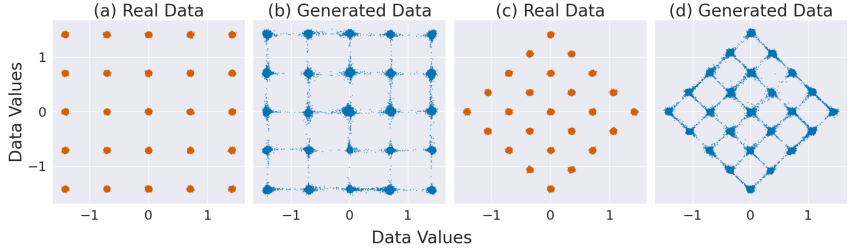

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Critical Discovery

Mode interpolation only occurs between **nearest neighboring modes**!

Key Factors Affecting Mode Interpolation

What Makes Hallucinations Worse?

1. **Limited Training Data**
   Fewer samples $\rightarrow$ more uncertainty $\rightarrow$ more interpolation
2. **Close Mode Spacing**
   Nearby modes in data space $\rightarrow$ easier to interpolate
3. **Fewer Diffusion Steps**
   Lower $T \rightarrow$ coarser approximation $\rightarrow$ more interpolation
4. **High Dimensionality**
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Design Implications

- Need more training data for complex distributions
- Consider mode spacing in dataset curation
- Higher T for better quality (but slower sampling)
- Architecture choices matter for representation learning

Can We Detect Hallucinations?

Trajectory Variance Method

Hallucinated samples have **high variance** during reverse diffusion. Then, if we use

$$\text{Variance} = \frac{1}{T} \sum_{t=1}^{T} \|x_t - \bar{x}\|^2 ,$$

where $\bar{x}$ is the mean trajectory and x_t are intermediate states, we can filter them out.

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Interesting open questions

- *Can we develop "hallucination-proof" architectures?*
- *How can we handle the density of the modes?*
- *Can we develop a theoretical understanding of when hallucination occurs?*
- *Should we watermark all synthetic content?*

Outline

Question

Are hallucinations *always* unwanted?

Question

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The Challenge: Incomplete Data

- Continuous labels rarely available (clipped instead to binary $\{0, 1\}$).
- Labels don't contain all variations.

Generation beyond what we've seen

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Can a machine learning model generate data in a region the model has **never seen** during training?

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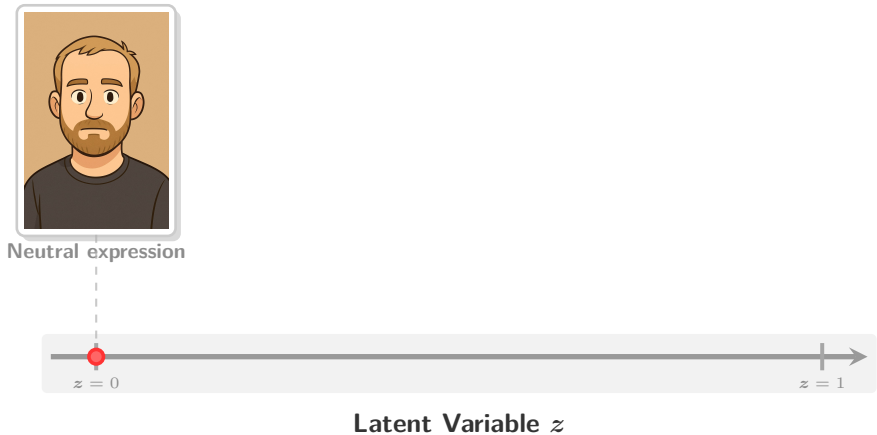
Zero-shot interpolation: Generating intermediate examples without training on them.

What if we could synthesize in intermediate regions?



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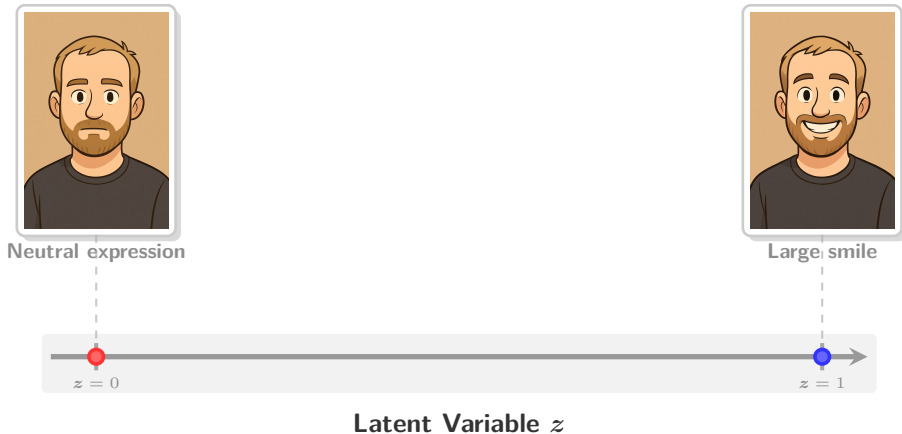

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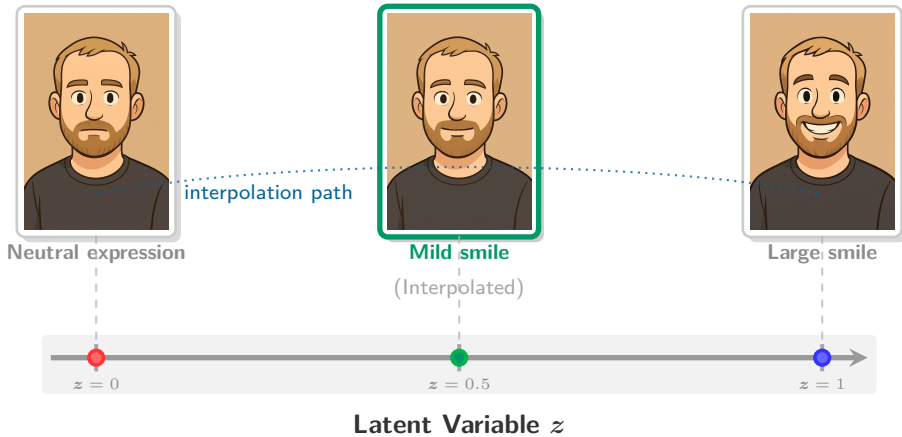


How did we ensure only extrema exist in our case?

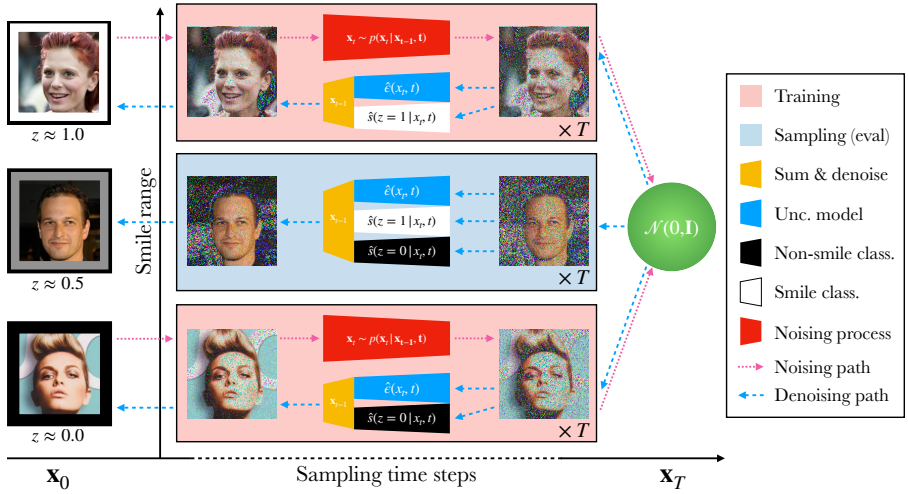
Algorithm Training the filtering and evaluation classifiers (EfficientNet)

Input: Raw dataset $\mathcal{D}$, number of filtering classifiers $N = 5$
Output: N filtering classifiers, 1 evaluation classifier, dataset $\tilde{\mathcal{D}}$
for $i \leftarrow 1$ to N **do**
    $\mathcal{D}_i \leftarrow \text{sample}(\mathcal{D}, M)$ ▷ Sample M elements without replacement
    $f(x; \theta_i) \leftarrow \text{train}(\mathcal{D}_i, \theta_{\text{init},i})$ ▷ Train filtering classifier i
end for
$f(x; \theta_{N+1}) \leftarrow \text{train}(\mathcal{D}, \theta_{\text{init},N+1})$ ▷ Train evaluation classifier
$\tilde{\mathcal{D}} \leftarrow [\,]$ ▷ List of extreme samples
for $(x_i, y_i) \in \mathcal{D}$ **do**
    if all($[f(x_i; \theta_j)(y_i) > 1 - \epsilon$ for $j = 1$ to $N + 1]$) **then**
        $\tilde{\mathcal{D}}$.append((x_i, y_i)) ▷ Keep if all classifiers agree
    end if
end for

Quality Assurance

Ensemble ensures only samples with **unanimously clear attributes** remain in training set.

Zero-shot interpolation with diffusion models [Deschenaux, Krawczuk, Chrysos, Cevher, ICML (2024)]



Does the interpolation still happen in more constrained settings?

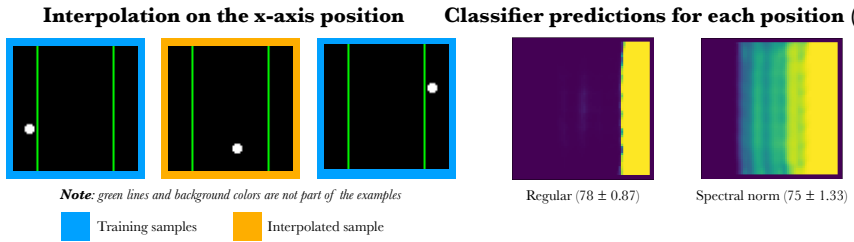
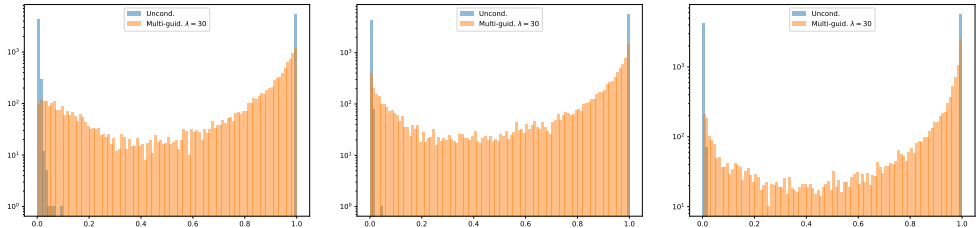


Figure: The training samples include exclusively balls outside of the central region.

*J Deschenaux, I Krawczuk, **G Chrysos**, V Cevher, 'Going Beyond Compositions: Zero-Shot Interpolation in DDPMs'. In **ICML**, 2024.*

What's the impact of the training data size?



(a) 30k training samples (b) 10k training samples (c) 5k training samples

Figure: Performance (on the smile attribute) when reducing the training data size. **(a)**: With 30k training samples. **(b)**: With 10k training samples. **(c)**: With 5k training samples. While using 30k or 10k maintains similar performance, the interpolation capability starts to degrade with 5k, even though DDPM retains its ability to interpolate.

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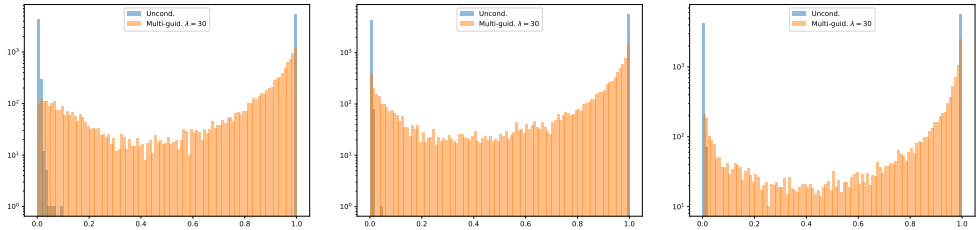

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Interesting open questions

- *Can we use reference images to reduce the amount of images required?*
- *Are there better sampling strategies for more precise control?*
- *Can we move beyond the interpolation range, towards extrapolation (e.g. (Wu et al., 2022))?*

Broader Implications: Generation in a long-tailed world

Connection with long-tailed world

Interpolation can help address **rare groups** in training data!

Medical Imaging

- Rare pathologies
- Interpolation could generate intermediate severity cases
- Better training data for diagnostic systems

Demographic Balance

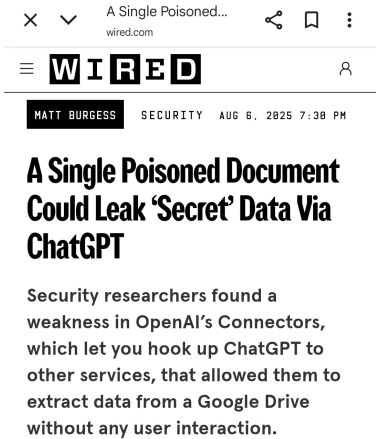
- Training sets often have demographic gaps
- Generate missing intersectional identities
- Richer training examples for AI systems

Broader Applications

- **Data augmentation**: Create training data for edge cases
- **Content creation**: Novel intermediate styles/expressions
- **Scientific discovery**: Explore parameter spaces between known examples

Outline

Is privacy still important in the era of AI agents?



A case for privacy

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Can we reveal private information stored in a language model?

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Assume we have a language model f_{θ} trained on text corpus Y.

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But, what if "item people low reader" was in the training data? Would this still hold?

A case for privacy in the language model era

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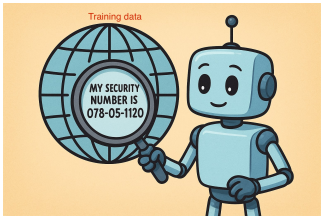
What if the phrase "my security number is 078-05-1120" was in the training data?



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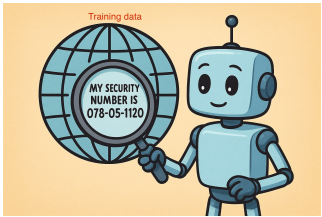

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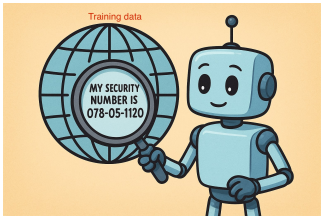

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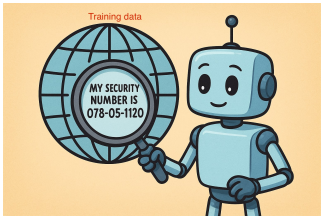

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- An adversary can use this SSN to file e.g. fraudulent tax returns, steal social benefits, etc.

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- The exposure ranges from 0 to $\log_2 |\mathcal{R}|$; a larger exposure indicates that the phrase is more noticeable.

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- Figure 4 is for a language model f_θ trained on 100k sequences.
- When the canary is inserted once, it is 1000× more likely than random chance, and by 4 insertions maximum exposure is almost reached.
- Common methods to mitigate overfitting to training data, like regularization and dropout, fail–exposure is still significantly higher for the canary than other sequences in $\mathcal{R}$.
- Advanced methods can be used to extract memorized instances from much larger language models, for example LLMs for coding Huang et al. (2024).

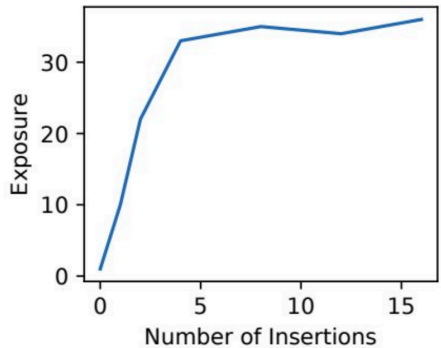

Figure: Exposure vs. number of insertions (Carlini et al., 2019)

A Solution: Differential Privacy

General Framework: Add a small amount of structured noise to the ML model such that an adversary cannot tell whether:

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  - Linkage attacks: Use external information to break dataset anonymization.

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for all instances $x \in \mathcal{D}$ for dataset $\mathcal{D}$.

- This is called **differential privacy** (Dwork et al., 2006).
- This is the only (known) method to fully reduce exposure in the example of Carlini et al. (2019)–the canary's exposure is indistinguishable from a random phrase $r \in \mathcal{R}$.
- Differential privacy offers strong protection against other attacks as well:
  - Model inversion attacks: recover the training data from model outputs/parameters (Haim et al., 2022).
  - Membership inference attacks: figure out whether or not an instance is part of the training data (Shokri et al., 2017).
  - Linkage attacks: Use external information to break dataset anonymization.
- Justified by the Fundamental Theorem of Information: need to add noise to the data instances or statistical procedure, otherwise an adversary can **always recover sensitive attributes** (Dinur and Nissim, 2003).

Outline

Notation

We will now introduce the standard notation of differential privacy:

- $\mathcal{X} \subset \mathbb{R}^d$ be a sample space and let $\mathcal{Y} \subset \mathbb{R}^o$ be a label space. $\mathcal{Z} = \mathcal{X} \times \mathcal{Y}$; $\mathcal{Z}^n = \underbrace{\mathcal{Z} \times ... \times \mathcal{Z}}_{\text{n times}}$.

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- Let $f_{\boldsymbol{\theta}} \in \mathcal{H}_{\mathcal{W}}$ be the hypothesis parameterized by $\boldsymbol{\theta} \in \mathcal{W}$, defined as $f_{\boldsymbol{\theta}} : \mathcal{X} \to \Delta_{|\mathcal{Y}|}$, where $\Delta_{|\mathcal{Y}|}$ is the probability simplex $\{p_1, ..., p_\gamma : p_i \geq 0, \sum_{i=1}^{\gamma} p_i = 1\}$. (Outputs a probability distribution across all classes).

Exact Differential Privacy

ε-Differential Privacy (Dwork et al., 2006)

Let $\mathcal{A} : \mathcal{Z}^n \to \mathcal{W}$ be a (randomized) learning algorithm. Fix $\varepsilon \in (0, 1)$. $\mathcal{A}$ is ε-differentially private if for all neighboring datasets $\mathcal{D}, \mathcal{D}' \subset \mathcal{Z}^n$ s.t. $||\mathcal{D} - \mathcal{D}'||_1 \leq 1$ and $\mathcal{T} \subset \mathcal{W}$:

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- As $\varepsilon \to 0$, probabilities are roughly the same $\implies$ models are equally likely to occur, so indistinguishable.
- As $\varepsilon \to 1$, probabilities become different. Use of e^{ε} an artifact of concentration inequalities.
- Exact differential privacy: very useful for classical stats. However, not so applicable to ML (so far).

Approximate Differential Privacy

(ε, δ)-Differential Privacy (Dwork et al., 2014)

Let $\mathcal{A} : \mathcal{Z}^n \to \mathcal{W}$ be a (randomized) learning algorithm. Fix $\varepsilon, \delta \in (0, 1)$. $\mathcal{A}$ is ε-differentially private if for all neighboring datasets $\mathcal{D}, \mathcal{D}' \subset \mathcal{Z}^n$ s.t. $||\mathcal{D} - \mathcal{D}'||_1 \leq 1$ and $\mathcal{T} \subset \mathcal{W}$:

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- This is the form of differential privacy we will focus on.
- δ is the "catastrophic failure probability"–probability that $\mathcal{A}(\mathcal{D})$ and $\mathcal{A}(\mathcal{D}')$ are easily distinguishable. Generally chosen very small, $\delta \approx 0$.

ℓ_2 sensitivity

ℓ_2 Sensitivity

Let $f : \mathcal{Z}^n \to \mathbb{R}^z$. The ℓ_2 sensitivity of f is:

$$\Delta_2^{(f)} = \max_{\mathcal{D},\mathcal{D}'} ||f(\mathcal{D}) - f(\mathcal{D}')||_2 \,, \tag{5}$$

where $\mathcal{D}, \mathcal{D}' \subset \mathcal{Z}^n$ are neighboring datasets s.t. $||\mathcal{D} - \mathcal{D}'||_1 \leq 1$.

Gaussian Mechanism

Gaussian Mechanism

Fix $\varepsilon, \delta \in (0,1)$. Consider a (deterministic) function $f : \mathcal{Z}^n \to \mathcal{R}^z$. Let $\mathcal{M}(\mathcal{D}) = f(\mathcal{D}) + H$ where $H \sim \mathcal{N}(0, \sigma^2 \boldsymbol{I})$ and $\sigma \geq \frac{\Delta_2^{(f)}}{\varepsilon} \sqrt{2 \ln(1.25/\delta)}$. Then, the (randomized) mechanism $\mathcal{M}$ is (ε, δ)-differentially private.

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This is the primary way one designs a (ε, δ)-differentially private algorithm.

Properties of (ε, δ)-differential privacy

Post-Processing

Let $\mathcal{A} : \mathcal{Z}^n \to \mathcal{W}$ be (ε, δ)-differentially private, and let $\mathcal{F} : \mathcal{W} \to \mathcal{B}$ be an arbitrary randomized mapping. Then, $\mathcal{F} \circ \mathcal{A}$ is (ε, δ)-differentially private.

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Group Privacy

Let $\mathcal{A} : \mathcal{Z}^n \to \mathcal{W}$ be (ε, δ)-differentially private. Suppose $\mathcal{D}, \mathcal{D}' \subset \mathcal{Z}^n$ are two datasets which differ in at most k positions, i.e. $||\mathcal{D} - \mathcal{D}'||_1 \leq k$. Then, for all $\mathcal{T} \subset \mathcal{W}$, we have:

$$\Pr[\mathcal{A}(\mathcal{D}) \in \mathcal{T}] \leq e^{k\varepsilon} \Pr[\mathcal{A}(\mathcal{D}') \in \mathcal{T}] + ke^{(k-1)\varepsilon}\delta\,. \tag{6}$$

Properties of (ε, δ)-differential privacy

Basic Composition

Let $\boldsymbol{\mathcal{M}} = (\mathcal{M}_1, ..., \mathcal{M}_k)$ be a sequence of randomized mechanisms, where $\mathcal{M}_i$ is $(\varepsilon_i, \delta_i)$-differentially private, for $\varepsilon_i, \delta_i > 0$, and the $\mathcal{M}_i$ can be chosen sequentially and adaptively. Then, $\mathcal{M}$ is $(\sum_{i=1}^{k} \varepsilon_i, \sum_{i=1}^{k} \delta_i)$-differentially private.

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Advanced Composition

For all $\varepsilon, \delta, \delta' > 0$, let $\boldsymbol{\mathcal{M}} = (\mathcal{M}_1, ..., \mathcal{M}_k)$ be a sequence of randomized mechanisms, where $\mathcal{M}_i$ is $(\varepsilon_i, \delta_i)$-differentially private and the $\mathcal{M}_i$ can be chosen sequentially and adaptively. Then $\mathcal{M}$ is $(\bar{\varepsilon}, \bar{\delta})$-differentially private, where $\bar{\varepsilon} = \varepsilon\sqrt{2k\log(1/\delta')} + k\varepsilon\frac{e^{\varepsilon}-1}{e^{\varepsilon}+1}$ and $\bar{\delta} = k\delta + \delta'$.

Simple approach, but under strict assumptions

- Under strong assumptions e.g. strong convexity of loss function and Lipschitz gradients, we obtain a simple bound on $\Delta_2^{\mathcal{A}(\mathcal{D})}$, sensitivity of learning algorithm.

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- Under strong assumptions e.g. strong convexity of loss function and Lipschitz gradients, we obtain a simple bound on $\Delta_2^{\mathcal{A}(\mathcal{D})}$, sensitivity of learning algorithm.
- Then, we can perturb model parameters themselves:

$$\tilde{\boldsymbol{\theta}} = \mathcal{A}(\mathcal{D}) + \mathcal{N}(0, \sigma^2 \boldsymbol{I}), \tag{7}$$

s.t.

$$\sigma \geq \frac{\Delta_2^{\mathcal{A}(\mathcal{D})}}{\varepsilon} \sqrt{2 \log(1.25/\delta)}, \tag{8}$$

yielding a (ε, δ)-differentially private model.

DP-SGD (Abadi et al., 2016)

Key idea

Add Gaussian noise to bounded gradients and use advanced composition-like theorems to yield DP guarantee.

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For $t = 1, ..., N$:

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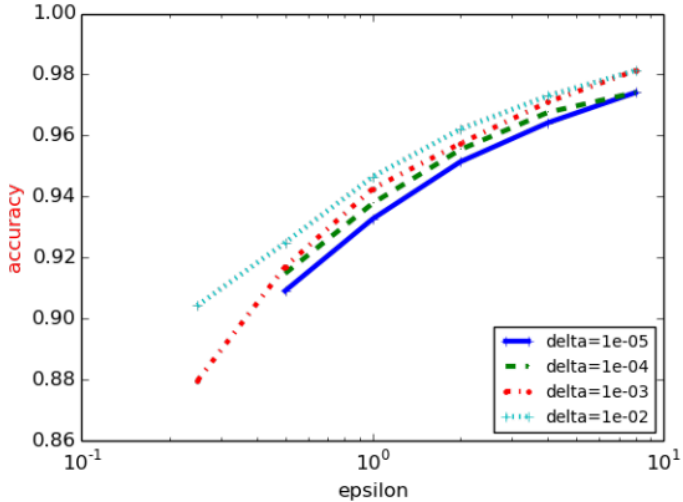
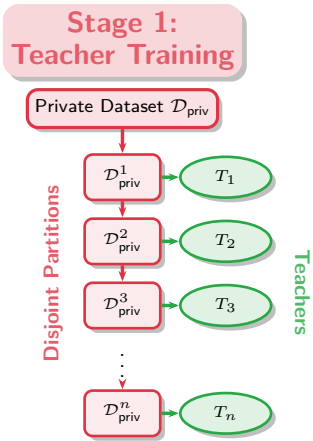
Note: Choose σ, N, and sampling rate $q = \frac{|B_t|}{|\mathcal{D}|}$, then ε, δ. A "privacy budget"; when using budget, incur "privacy cost".

Privacy Utility Tradeoff for DP-SGD



Private Aggregation of Teacher Ensembles (PATE) (Papernot et al., 2017)



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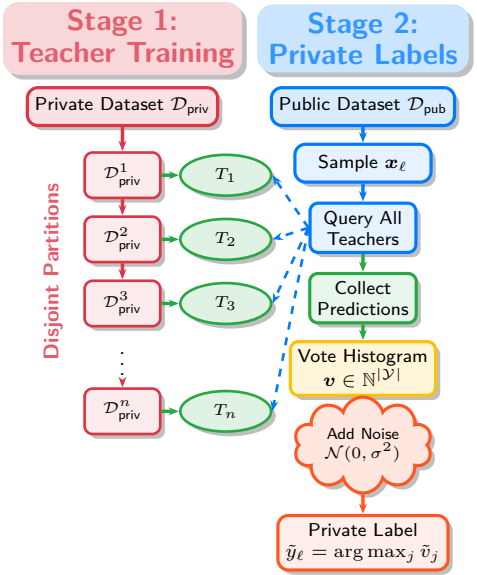

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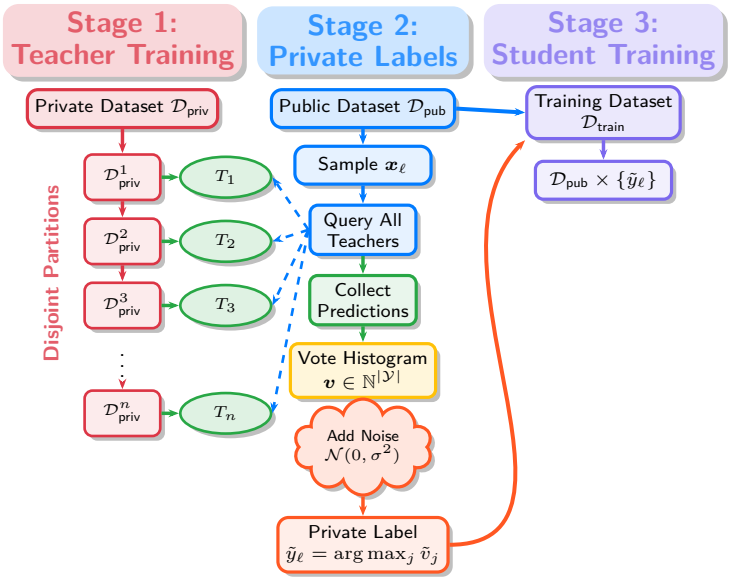

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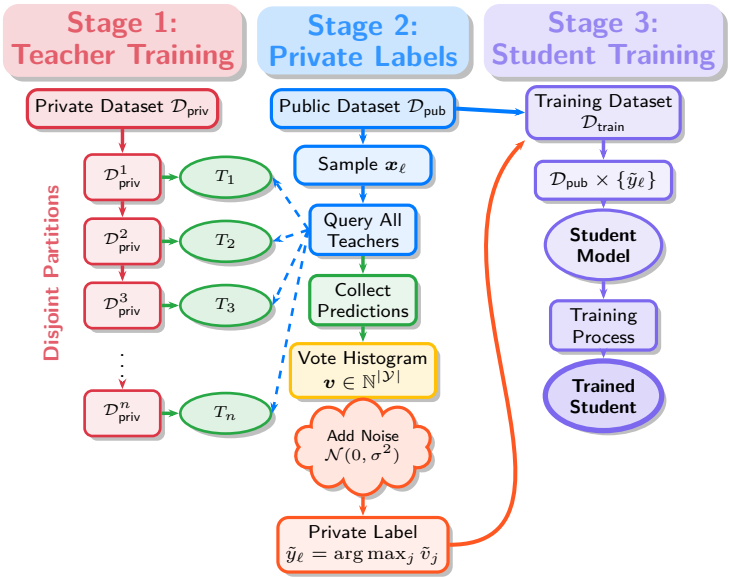

PATE Framework Summary

- **Stage 1**: Train multiple teacher models on disjoint partitions of private data.
- **Stage 2**: Generate private labels for public data using noisy aggregation.
- **Stage 3**: Train student model on public data with private labels.

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Key Innovation

The disjoint partitioning ensures that changing one private example affects at most one teacher's vote, enabling strong differential privacy guarantees with controlled noise addition.

PATE (Papernot et al., 2017)

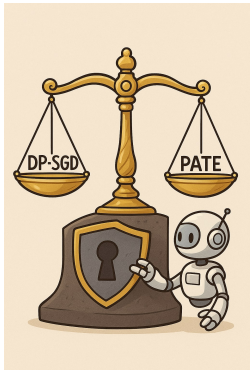
PATE offers multiple layers of privacy:

1. Each teacher only accesses a disjoint subset of the private data.
2. The final label is perturbed with Gaussian noise, so an adversary cannot tell if a single training example changed a teacher's vote.
3. The student does not access any private instances whatsoever.

DP-SGD or PATE?

DP-SGD for supervised, PATE for semi-supervised:

- PATE has stronger privacy guarantees than DP-SGD.
- PATE results in better generalization accuracy than DP-SGD.
- But, DP-SGD is significantly less computationally expensive than PATE.



The Differential Privacy Paradox: A Privacy-Utility Tradeoff

Benefits: The Power of Protection

- **Formal Privacy Guarantees**: Provable protection against multiple attacks.
- **Composable and Flexible**: Gracefully composes, with post-processing, group privacy, etc.
- **Trusted, Real-World Adoption**: Often deployed by U.S. Census Bureau, Apple, and Google.

Limitations: The Price of Utility

- **A Significant Utility Cost**: Even with small ε, δ, the added noise can significantly impact the accuracy and usefulness of models.
- **Highly Parameter-Sensitive**: Requires a careful choice of ϵ and δ.
- **Interpretability Challenges**: Difficult to interpret results or understand model behavior.

Outline

Is that all for privacy?

Question

Can someone request their private data to be deleted?

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Question

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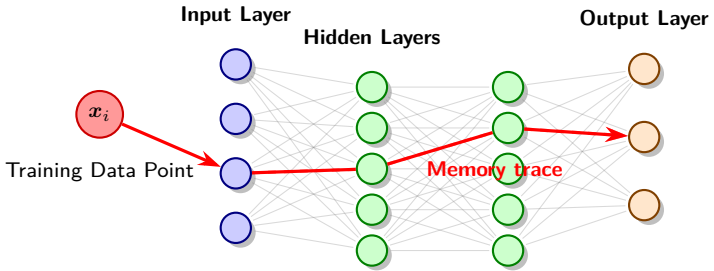
We can retrain from scratch, but we want to avoid this "exact forgetting" – too computationally expensive.

Is it easy to forget data on pretrained networks?



The Core Problem

Deep networks memorize specific training patterns or instances and their **highly non-convex nature** makes it difficult to trace the effect of each pattern on the model's weights.

Why would we want to forget again?

Legal Requirements

- **GDPR's "Right to be Forgotten"**
- Users can request data deletion
- Models must comply efficiently

Security Concerns

- Remove poisoned samples
- Defend against data attacks
- Clean compromised training sets

Data Quality Issues

- Remove mislabeled examples
- Delete noisy samples
- Eliminate outliers

Data consistency

- Remove harmful information
- Delete outdated information
- Update model behavior

Key Insight: Different applications require different definitions of "forgetting"!

Machine Unlearning setup

Setting

- **Training dataset**: $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$.
- **Original model**: $f(\cdot; \boldsymbol{\theta}^o)$ trained on $\mathcal{D}$.
- **Forget set**: $\mathcal{D}_f \subset \mathcal{D}$ (data to remove).
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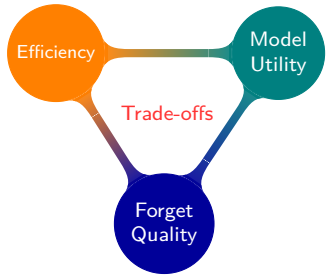
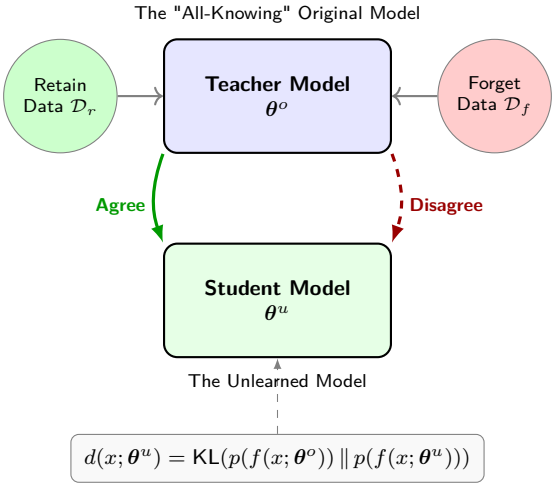
Goal

Find new weights $\boldsymbol{\theta}^u$ such that $f(\cdot; \boldsymbol{\theta}^u)$ has:

1. **Forgotten** $\mathcal{D}_f$ (application-dependent definition).
2. **Retained** performance on $\mathcal{D}_r$ and test data.
3. **Efficient** computation (faster than retraining).



SCalable Remembering and Unlearning unBound (SCRUB) (Kurmanji et al., 2023)



Core Idea

Student $\boldsymbol{\theta}^u$ **selectively** obeys teacher $\boldsymbol{\theta}^o$:

- **Agree** on retain data $\mathcal{D}_r$
- **Disagree** on forget data $\mathcal{D}_f$

Key Innovation

Use KL-divergence between output distributions:

$$d(x;\boldsymbol{\theta}^u) = \mathsf{KL}(p(f(x;\boldsymbol{\theta}^o))\|p(f(x;\boldsymbol{\theta}^u)))$$

SCRUB's Training Objective SCRUB

Contrastive Objective

$$\min_{\boldsymbol{\theta}^u} \underbrace{\frac{\alpha}{N_r} \sum_{x_r \in \mathcal{D}_r} d(x_r; \boldsymbol{\theta}^u)}_{\text{Stay close on retain set}} + \underbrace{\frac{\gamma}{N_r} \sum_{(x_r, y_r) \in \mathcal{D}_r} \ell(f(x_r; \boldsymbol{\theta}^u), y_r)}_{\text{Task loss on retain set}} - \underbrace{\frac{1}{N_f} \sum_{x_f \in \mathcal{D}_f} d(x_f; \boldsymbol{\theta}^u)}_{\text{Move away on forget set}}$$

Training Strategy

Due to conflicting objectives, SCRUB alternates between:

1. **Max-step:** Update on forget set (increase disagreement).
2. **Min-step:** Update on retain set (maintain agreement).

Certified Unlearning

Setting

- **Training dataset**: $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$.
- **Forget set**: $\mathcal{D}_f \subset \mathcal{D}$ (data to remove).
- **Retain set**: $\mathcal{D}_r = \mathcal{D} \setminus \mathcal{D}_f$ (data to keep).
- Privacy budget $\varepsilon \in (0, 1)$ and $\delta > 0$.

(ε, δ)-certified unlearning (Sekhari et al., 2021)

$\mathcal{U} : \mathcal{Z}^n \times \mathcal{Z}^n \times \mathcal{W} \to \mathcal{W}$ is an (ε, δ)-certified unlearning algorithm if $\forall \mathcal{T} \subset \mathcal{W}$, we have:

$$\Pr(\mathcal{U}(\mathcal{D}, \mathcal{D}_f, \mathcal{A}(\mathcal{D})) \in \mathcal{T}) \leq e^{\varepsilon} \Pr(\mathcal{A}(\mathcal{D}_r) \in \mathcal{T}) + \delta, \tag{11}$$

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DP implies certified unlearning, but not the other way around.

Limitations of Unlearning (Zhao et al., 2024)

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  - Police are obtaining $f(\boldsymbol{x}_p) =$ high risk
  - Software provider (ML model provider) should suppress outputs; unlearning **does not suffice**, since $f_u(\boldsymbol{x}_p) = f(\boldsymbol{x}_p)$.
  - We call this **test-time privacy** (TTP).

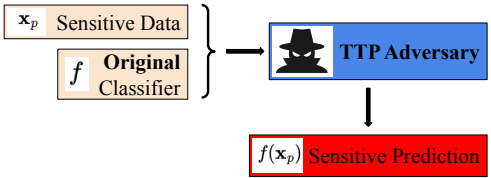

Figure: TTP Without Unlearning

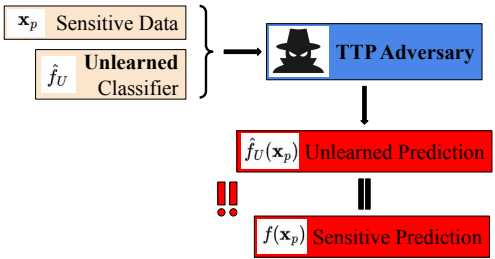

Figure: Test-time privacy with Unlearning

Limitations of Unlearning

Solution: Make model outputs uniform.

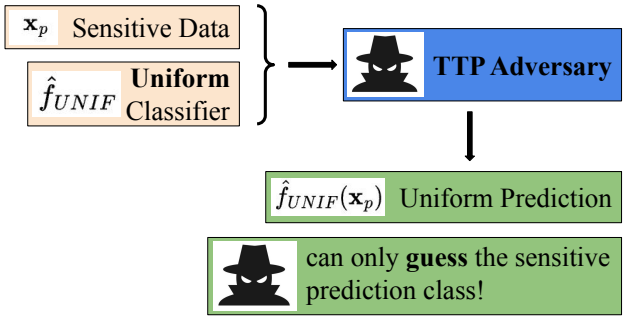

Figure: Test-time privacy after Uniformity

Limitations of Unlearning

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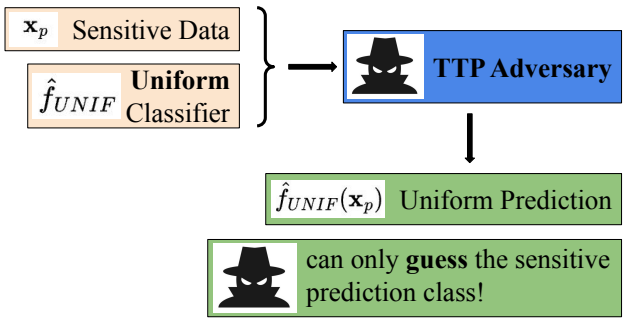

Figure: Test-time privacy after Uniformity

We can also adapt (ε, δ) guarantees to this setting (Ashiq et al., 2025).

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Special thanks to the MLSS organizing team:

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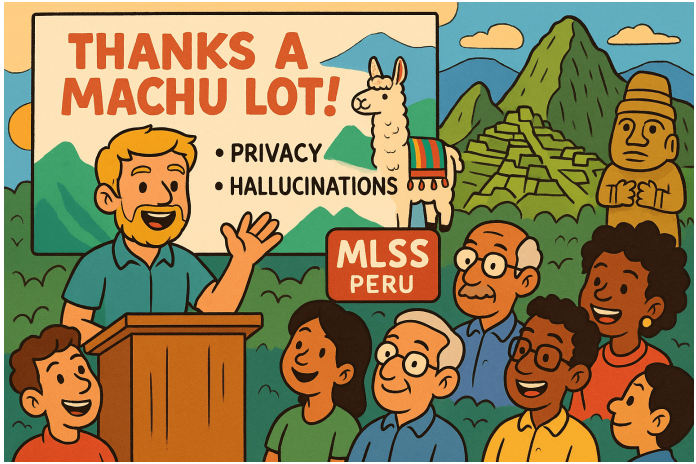
Thank you for your attention!



Source: GPT-5.

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