Some Challenges around Retraining Generative Models on Their Own Data

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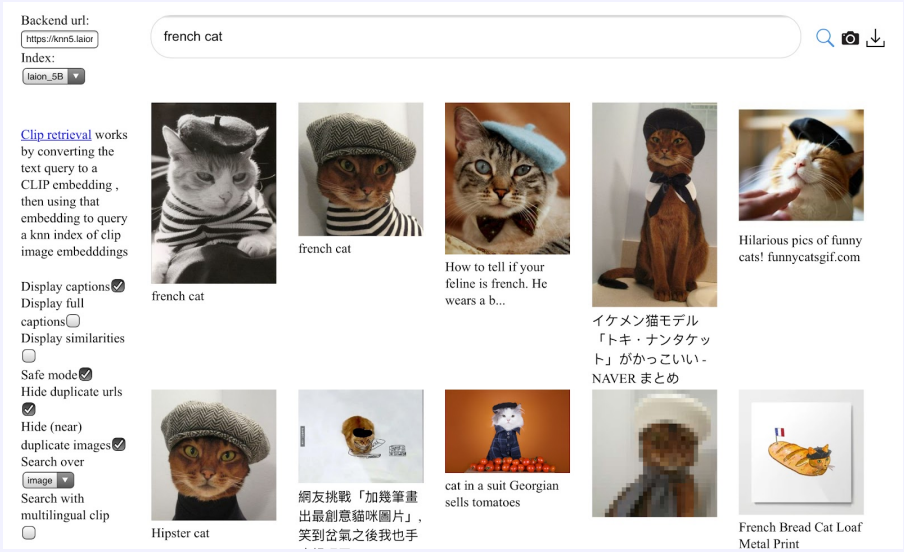
G. Gidel

LAION-5B[1][2]



[1] C. Schuhmann et al. "Laion-5B: An open large-scale dataset for training next generation image-text models". In: *NeurIPS* (2022).

[2] https://paperswithcode.com/dataset/laion-5b

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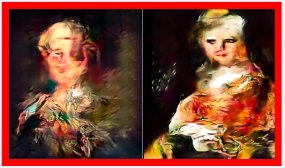
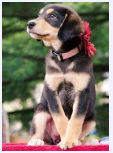
Inevitably Train on Synthetic Data

The LAION-5B[3] dataset already contains synthetically generated images[4]

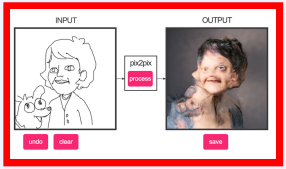








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Retraining Generative Models on their Own Data

Training Set

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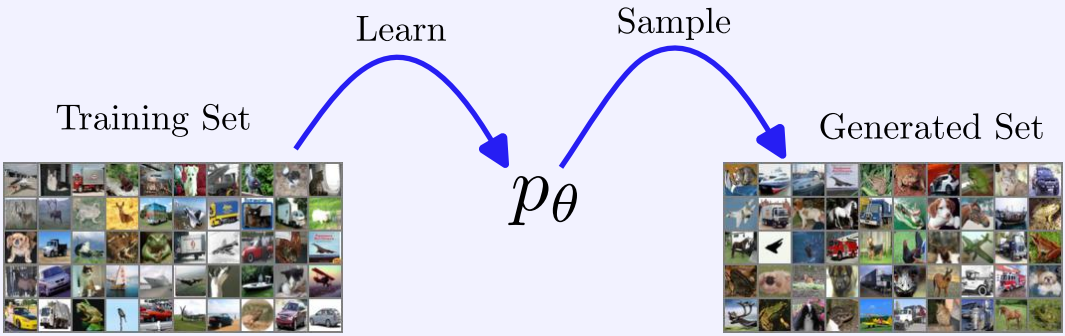

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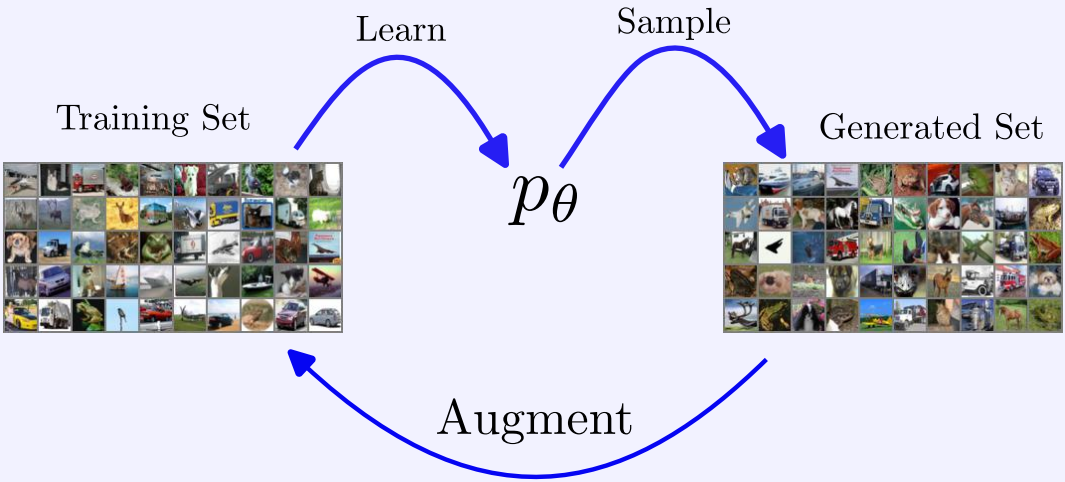

Training on Synthetic Data, Good or Bad?

Iterative Retraining is **Bad**

- **The curse of recursion**: Training on generated data makes models forget[a]
- Self-Consuming Generative Models Go **MAD**[b]
- When **A.I.´s Output Is a Threat to A.I.** Itself (N.Y. Times article)

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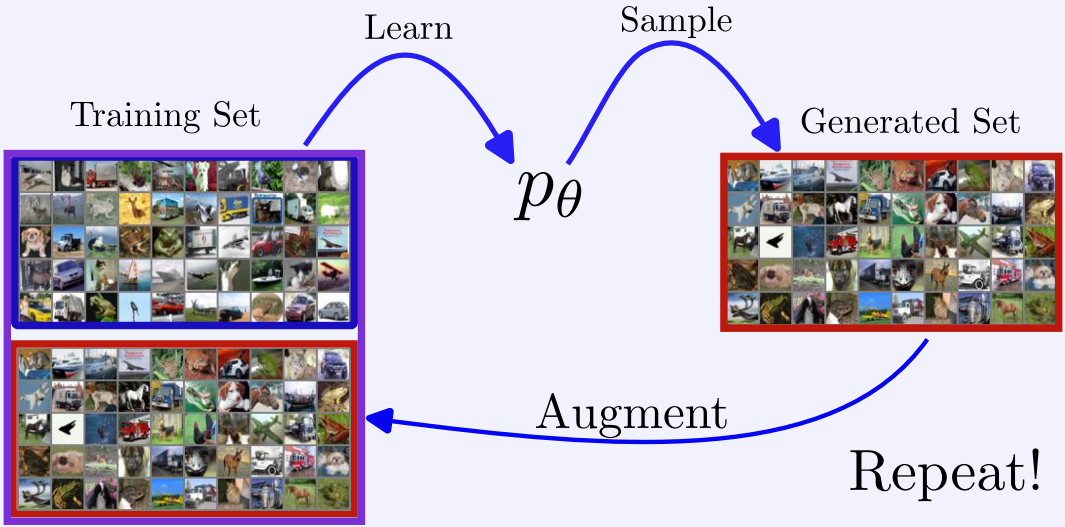

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Iterative Retraining / Self-Consuming Generative Models

Learn

Training Set

p_θ

Sample

Generated Set

Augment

Repeat!

$$\underbrace{\text{Training set}}_{\text{time } t+1} = \text{Real Data} + \underbrace{\text{Generated Set}}_{\text{time } t}$$

Setting

Notation

- $\hat{p}_{\text{data}}$ Empirical data distribution
  - $\hookrightarrow$ n Data points
- p Likelihood of the model
  - $\hookrightarrow$ Parametrized by $\theta^n \in \Theta$

Iterative Retraining

$$p_0 \in \arg\max_{p \in \mathcal{P}_\Theta} \mathbb{E}_{x \sim \hat{p}_{\text{data}}} [\log p(x)]$$

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Warm Up: Only Retrain on your Own Data 1/3

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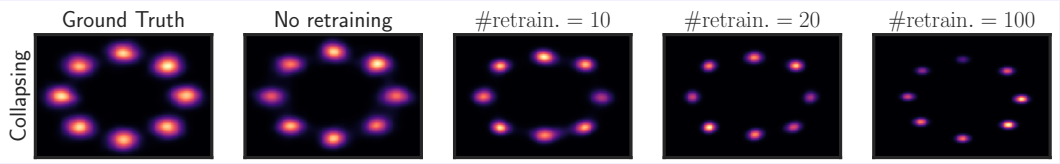
Warm Up: Only Retrain on your Own Data 2/3

Q: What will happen?

A: Mode Collapse



Setup

- Data: 8 Gaussians, $x \in \mathbb{R}^2$
- Algorithm: Diffusion (DDPM[a])

[a] J. Ho, A. Jain, and P. Abbeel. "Denoising diffusion probabilistic models". In: *NeurIPS* (2020).

Warm Up: Only Retrain on your Own Data 3/3

Single unidimensional Gaussian, unbiased estimator

Data: $x_j^0 = \mu_0 + \sigma_0 Z_j$, with $Z_j \overset{\text{i.i.d.}}{\sim} \mathcal{N}_{0,1}$, $1 \leq j \leq n$

Learning step:
$$\begin{cases} \mu_{t+1} &= \frac{1}{n} \sum_j \tilde{\mathbf{x}}_j^t \\ \sigma_{t+1}^2 &= \frac{1}{n-1} \sum_j \left(\tilde{\mathbf{x}}_j^t - \mu_{t+1} \right)^2 \end{cases}$$

Sampling step: $\left\{ \tilde{\mathbf{x}}_j^{t+1} = \mu_{t+1} + \sigma_{t+1} \cdot Z_j^{t+1}, \text{ with } Z_j^{t+1} \overset{\text{i.i.d.}}{\sim} \mathcal{N}_{0,1}, 1 \leq j \leq n \right.$

Result

$$\mathbb{E}(\sigma_t) \leq \alpha^t \sigma_0 \underset{t \to +\infty}{\longrightarrow} 0, \ 0 \leq \alpha < 1$$

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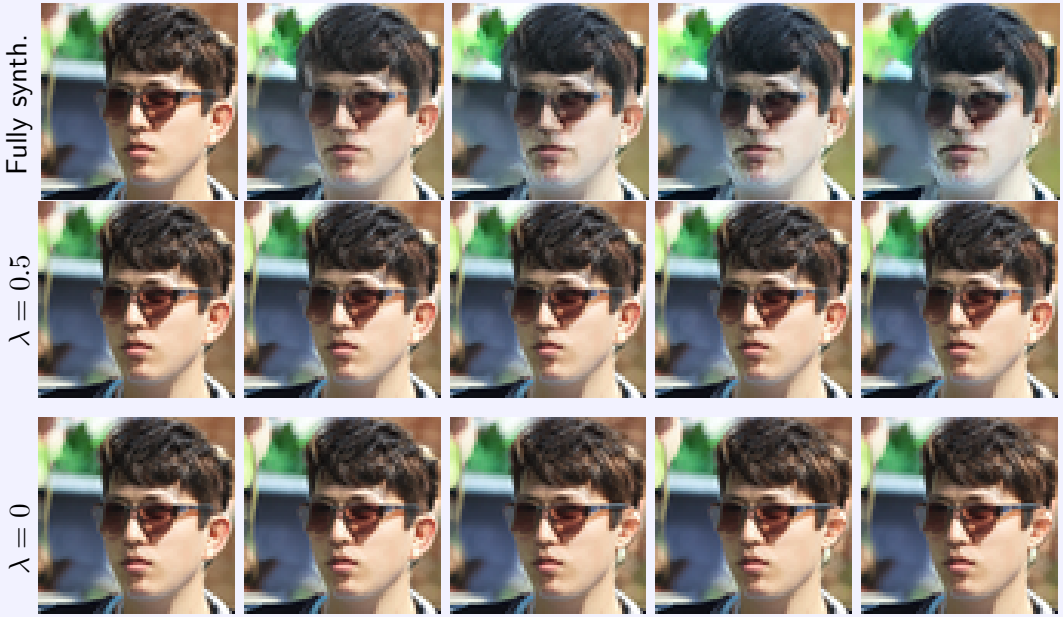
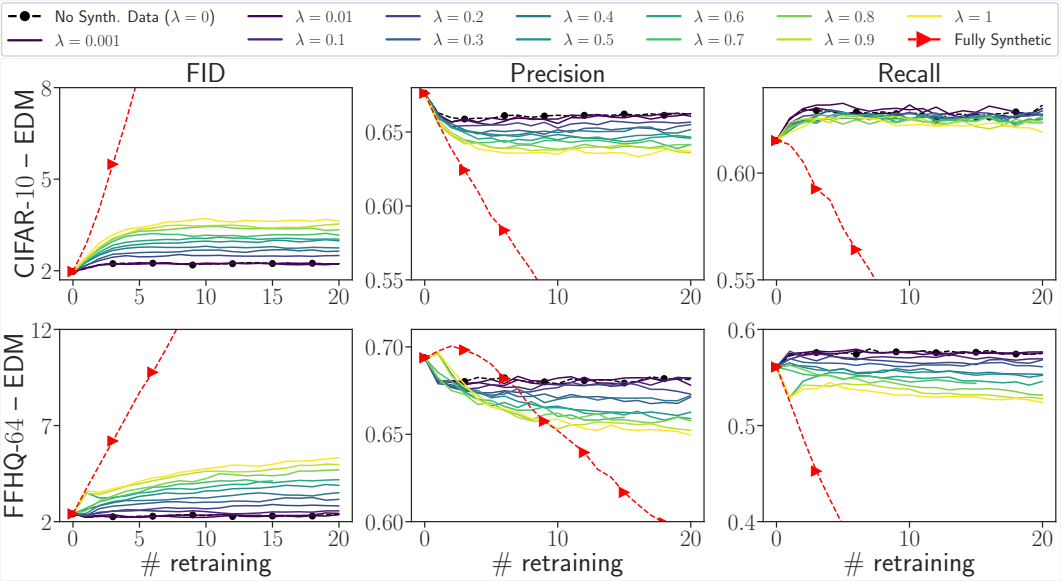

Fully synth.
$\lambda = 0.5$
$\lambda = 0$
0 retrain.
5 retrain.
10 retrain.
15 retrain.
20 retrain.

Experiments



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Already Training on Curated/Filtered Data 1/2

LAION-Aesthetics[a]

[a] https://github.com/LAION-AI/laion-datasets/blob/main/laion-aesthetic.md

- Filter the LAION-5B dataset[a]
  - ↪ Filter: reward model[b]

[a] C. Schuhmann et al. "Laion-5B: An open large-scale dataset for training next generation image-text models". In: *NeurIPS* (2022).

[b] https://github.com/LAION-AI/aesthetic-predictor

[c] J. D. Pressman, K. Crowson, and Simulacra Captions Contributors. *Simulacra Aesthetic Captions*. Version 1.0. url https://github.com/JD-P/simulacra-aesthetic-captions. Stability AI, 2022.

Already Training on Curated/Filtered Data 1/2

LAION-Aesthetics[a]

[a] https://github.com/LAION-AI/laion-datasets/blob/main/laion-aesthetic.md

- Filter the LAION-5B dataset[a]
  - ↪ Filter: reward model[b]
    - ↪ Trained on synthetic data ¨Simulacra Aesthetic Captions¨ dataset[c]

[a] C. Schuhmann et al. "Laion-5B: An open large-scale dataset for training next generation image-text models". In: *NeurIPS* (2022).

[b] https://github.com/LAION-AI/aesthetic-predictor

[c] J. D. Pressman, K. Crowson, and Simulacra Captions Contributors. *Simulacra Aesthetic Captions*. Version 1.0. url https://github.com/JD-P/simulacra-aesthetic-captions. Stability AI, 2022.

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Already Training on Curated/Filtered Data 2/2

JourneyDB Dataset[a]

[a] P. Junting et al. "JourneyDB: A Benchmark for Generative Image Understanding". In: *NeurIPS* (2023).

- Midjourney[a]: text-to-image model
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[a] Midjourney. https://www.midjourney.com/home/. Version 5.2. Accessed: 2023-09-09. 2023.

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Remarks

- No access to pairwise comparisons
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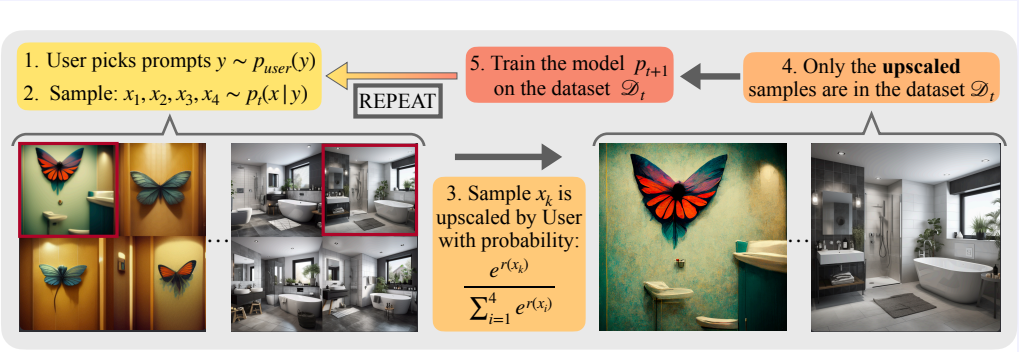
A Simple Curation Model 1/2



A Simple Curation Model $2/2$

Curation Model

- Suppose the existence of a reward model r
  $\hookrightarrow$ score $r(x)$ to each sample x
- $$\text{Sample } \tilde{\mathbf{x}}_1 \sim p_t, \ldots, \tilde{\mathbf{x}}_K \sim p_t \text{ , } i.i.d.$$
- $$\text{Pick } \hat{\mathbf{x}} \sim \mathcal{BT}(\tilde{\mathbf{x}}_1, \ldots, \tilde{\mathbf{x}}_K) \text{ , } i.e.,$$
$$\mathbb{P}(\hat{\mathbf{x}} = \tilde{\mathbf{x}}_k | \tilde{\mathbf{x}}_1, \ldots, \tilde{\mathbf{x}}_K) = \frac{e^{r(\tilde{\mathbf{x}}_k)}}{\sum_{j=1}^{K} e^{r(\tilde{\mathbf{x}}_j)}} \text{ , } 1 \leq k \leq K$$

Iterative Retraining

$$p_{t+1} = \arg\max_{p \in \mathcal{P}} \mathbb{E}_{x \sim \hat{p}_{\text{data}}} \Big[\log p(x) \Big] + \lambda \cdot \mathbb{E}_{\substack{\tilde{\mathbf{x}}_1, \ldots, \tilde{\mathbf{x}}_K \sim p_t \\ \hat{\mathbf{x}} \sim \mathcal{BT}(\tilde{\mathbf{x}}_1, \ldots, \tilde{\mathbf{x}}_K)}} \Big[\log p(\hat{\mathbf{x}}) \Big]$$

A Simple Curation Model 2/2

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Q: What will happen?

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$$\mathbb{E}_{p_t} \Big[e^{r(x)} \Big] \xrightarrow{t \to \infty} e^{r_*} \quad \text{and} \quad \mathrm{Var}_{p_t} \Big[e^{r(x)} \Big] \xrightarrow{t \to \infty} 0 \ .$$

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- Equivalent to do RLHF if $K \to \infty$
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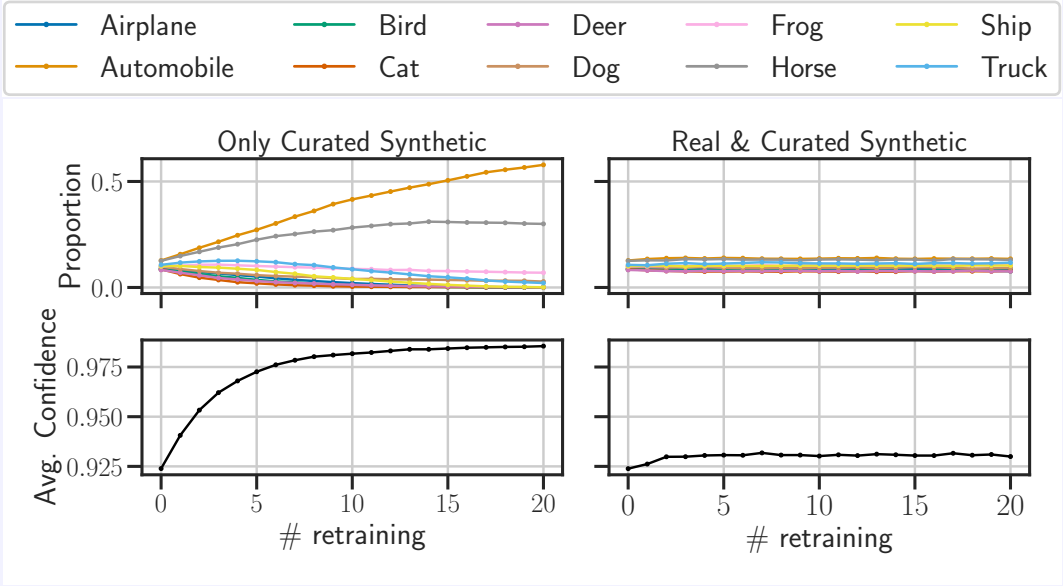

- reward(x) = confidence of a pretrained classifier for the image x
- $\lambda = 1/2$

Conclusion and Future Work

Future Work

- Filtering without Human-Feedback?
  - ↪ Score per sample? Downstream-task specific?

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[a] M. Jiralerspong et al. "Feature Likelihood Score: Evaluating Generalization of Generative Models Using Samples". In: *NeurIPS* (2023).

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Thank You!

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