Fast Fréchet Inception Distance

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Paper URL

Slides URL

Today (45 minutes):

1. Comparing Generative Models

2. Metrics

3. Fast Fréchet Inception Distance

4. What is it Good For? ♬

Comparing Generative Models

Which one is better?

"Real"

$$x_1, \ldots, x_n \sim P_{\text{real}}$$

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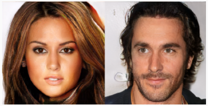
$x_1^{(1)}, \dots, x_n^{(1)} \sim P_{G_1}$



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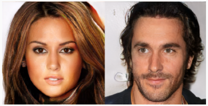
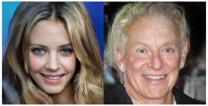


“Fake 2”

$x_1^{(2)}, \dots, x_n^{(2)} \sim P_{G_2}$



Desiderata

1. Fast

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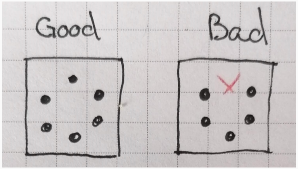

1. Fast
2. Diversity

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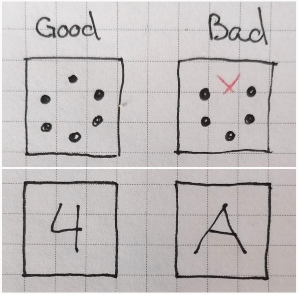
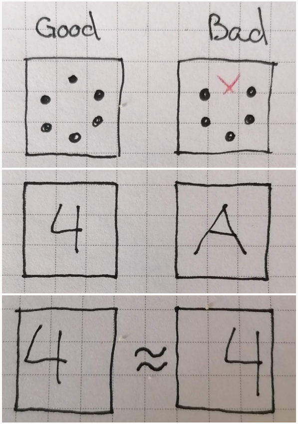


Desiderata

1. Fast
2. Diversity
3. Classifiable
4. Translation invariant



Metrics

First Idea: Inception Score [1]

[1] Salimans, T., Goodfellow, I., Zaremba, W., Cheung, V., Radford, A. and Chen, X., 2016. Improved techniques for training gans. arXiv preprint arXiv:1606.03498.

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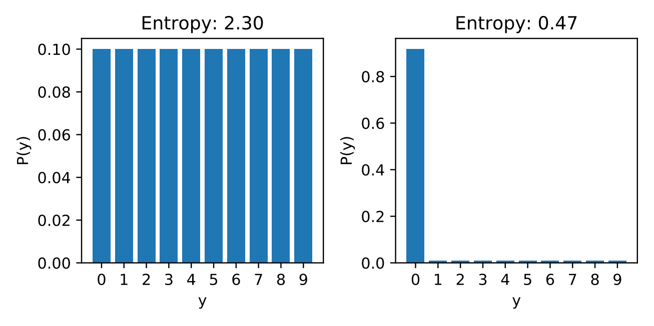

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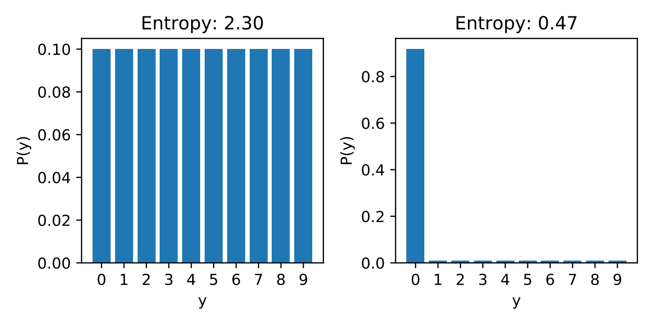

Inception Score

Correlates with human judgement but doesn't take P_d into account!

Second Idea: Fréchet Inception Distance [2]

[2] Heusel, M., Ramsauer, H., Unterthiner, T., Nessler, B. and Hochreiter, S., 2017. Gans trained by a two time-scale update rule converge to a local nash equilibrium. arXiv preprint arXiv:1706.08500.

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Today this is state-of-the-art.

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```
Q, V ← SchurDecompose(A) ;        /* QVQᵀ = A */
U ← TriangSqrt(V) ;               /* V = U² */
C ← QUQᵀ ;                        /* C = √(Σ_r Σ_f) */
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4 **return** $\mathrm{Tr}[C]$;

Line [1-3] each takes cubic time!

Fast Fréchet Inception Distance

Idea 3: Don't compute $\mathrm{Tr}\left[\sqrt{\Sigma_r \Sigma_f}\right]$, use *eigenvalues* instead.[3]

[3] Mathiasen, A. and Hvilshøj, F., 2020. Fast Fréchet Inception Distance. arXiv preprint arXiv:2009.14075.

Lemmas

Lemma 1
$\mathrm{Tr}[\sqrt{A}] = \sum_i |\sqrt{\lambda_i(A)}|$. [4]

[4] There are some nuances here, please refer to paper for full details.

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Lemma 2
Computing eigenvalues of $d \times d$ matrix A takes $\mathcal{O}(d^3)$ time. (similar time to compute $\sqrt{A}$)

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Lemma 3
The nonzero eigenvalues of AB are equal to those of BA, as long as the products are square. [5]

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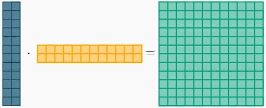

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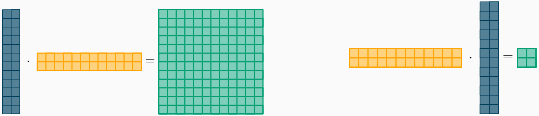

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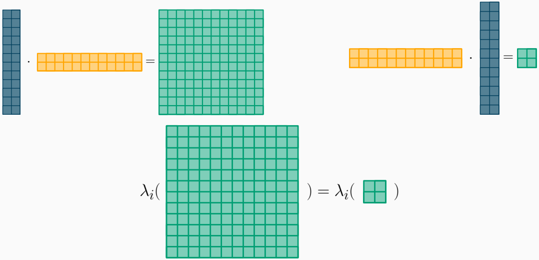

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Fast Fréchet Inception Distance

High level idea: *Construct "small" matric M such that $\lambda_i(M)$ satisfy $\sum_i |\sqrt{\lambda_i(M)}| = \mathrm{Tr}[\sqrt{\Sigma_r \Sigma_f}]$. When M is sufficiently small, computing eigenvalues will be faster than computing $\sqrt{\Sigma_r \Sigma_f}$ explicitly.*

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Finally due to Lemma 1:

$$\mathrm{Tr}\left[\sqrt{\Sigma_r \Sigma_f}\right] = \sum_{i=1}^{m-1} \left|\sqrt{\lambda_i(C_f^{\mathsf{T}} \Sigma_r C_f)}\right| \tag{8}$$

Overall, we get runningtime

$$\mathrm{FID} = \underbrace{\|\mu_r - \mu_f\|_2^2}_{\mathcal{O}(d)} + \underbrace{\mathrm{Tr}[\Sigma_r + \Sigma_f]}_{\mathcal{O}(d)} - 2\sum_{i=1}^{m-1} |\underbrace{\sqrt{\lambda_i(C_f^T \Sigma_r C_f)}}_{\mathcal{O}(d^2 m + m^3)}| \quad (9)$$

What is it Good For? 🎵

The Greater Perspective

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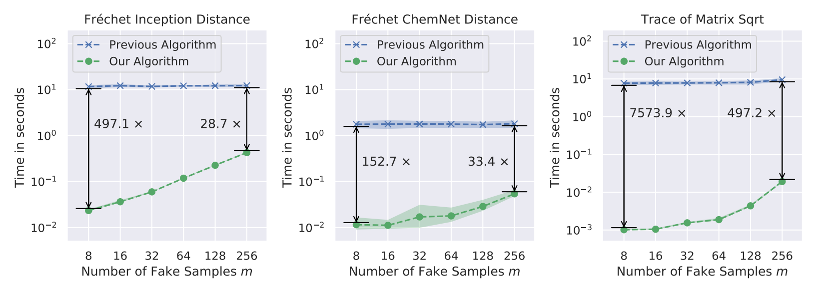
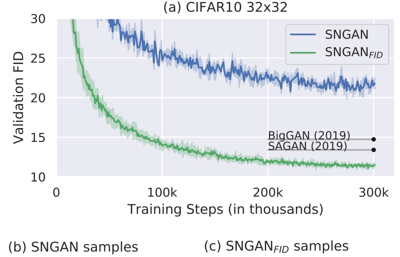
Let's use FID for optimizations!

Performance



Minimizing FID



GAN

GAN_{FID}

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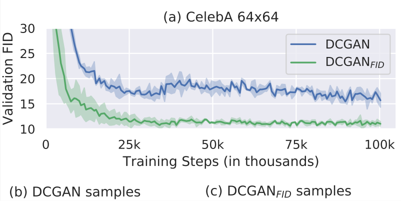

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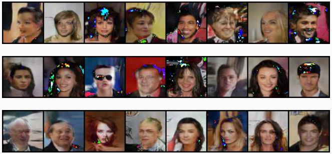

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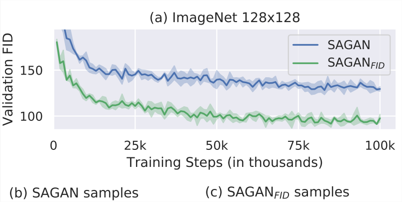

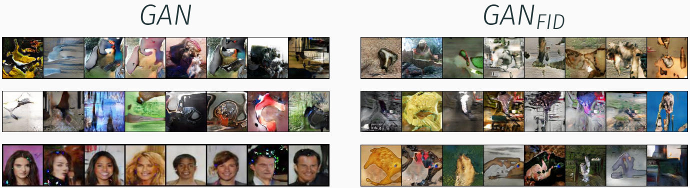

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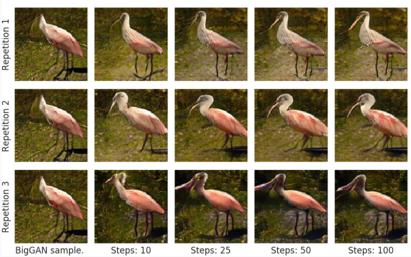

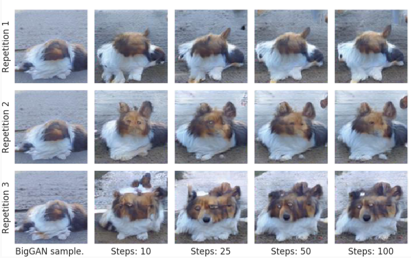

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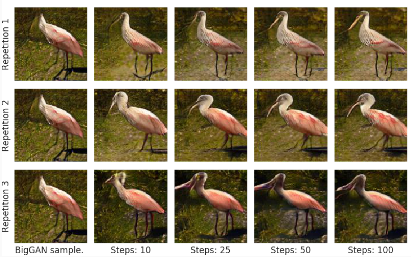

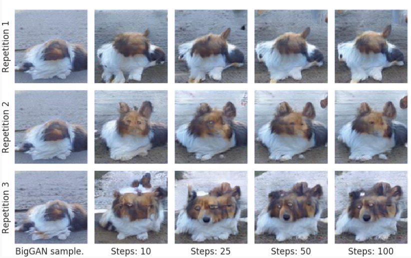

$$\underbrace{\left\|\mu_r - \mu_f\right\|_2^2}_{\text{mean difference}} + \underbrace{\mathrm{Tr}\left[\Sigma_r\right] + \mathrm{Tr}\left[\Sigma_f\right] - 2\mathrm{Tr}\left[\sqrt{\Sigma_r \Sigma_f}\right]}_{\text{covariance difference}} \tag{10}$$