Generative Adversarial Networks

Dougal J. Sutherland
Gatsby, UCL → TTIC → UBC

(from `thispersondoesnotexist.com`)

MLCC 2019

Generative models

- Start with a bunch of examples: $X_1, \ldots, X_n \sim \mathbb{P}$
- Want a model for the data: $\mathbb{Q} \approx \mathbb{P}$

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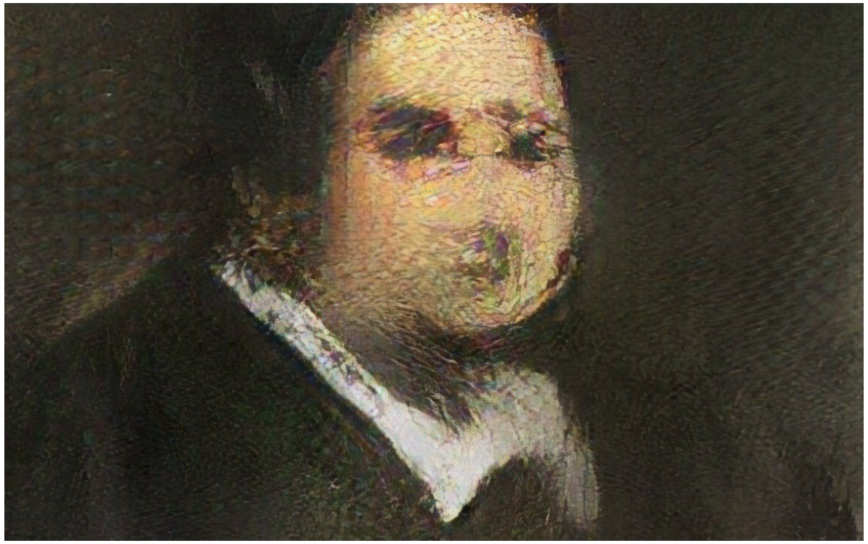
Why produce samples?



Is artificial intelligence set to become art's next medium?

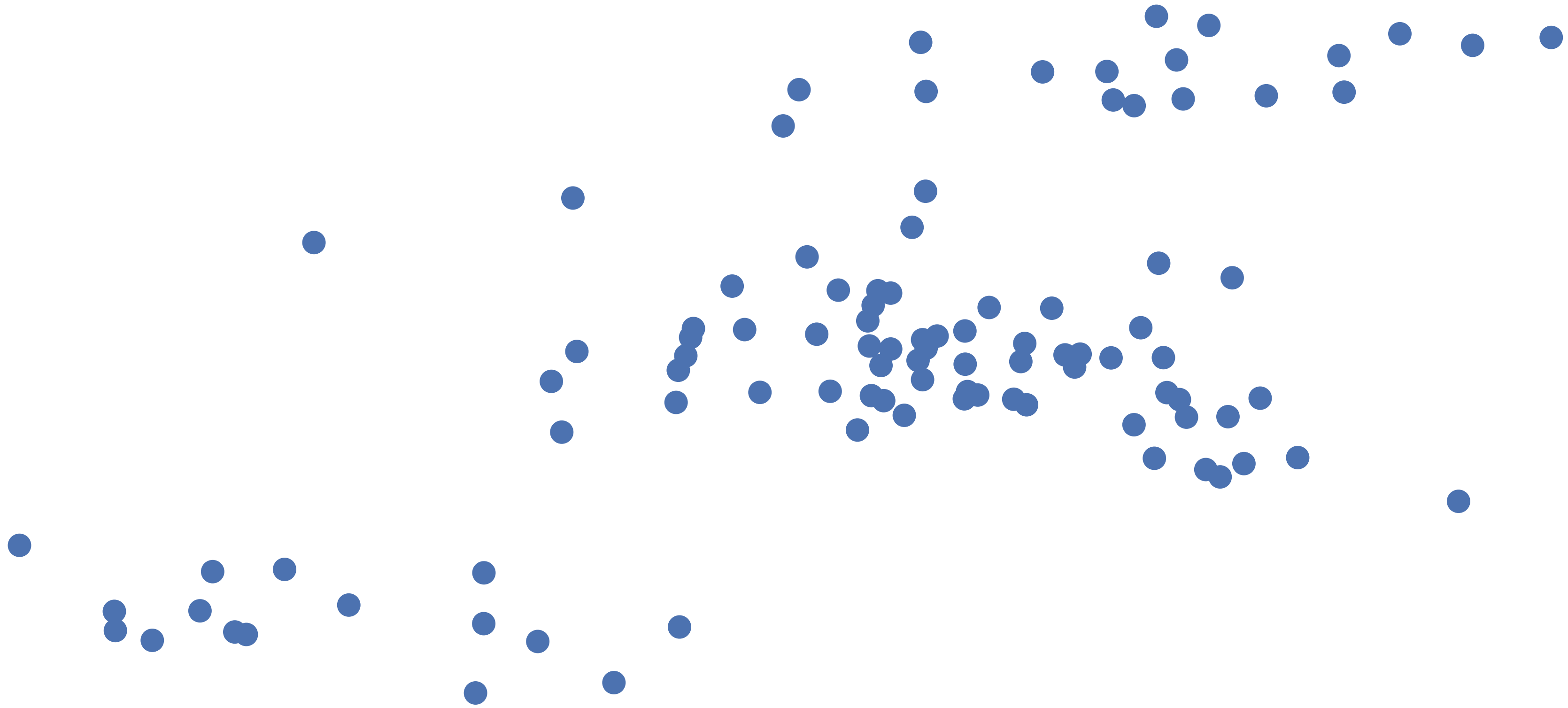
AI artwork sells for $432,500 — nearly 45 times its high estimate — as Christie's becomes the first auction house to offer a work of art created by an algorithm

The portrait in its gilt frame depicts a portly gentleman, possibly French and — to judge by his dark frockcoat and plain white collar — a man of the church. The work appears unfinished: the facial features are somewhat indistinct and there are blank areas of canvas. Oddly, the whole composition is displaced slightly to the north-west. A label on the wall states that the sitter is a man named Edmond Belamy, but the giveaway clue as to the origins of the work is the artist's signature at the bottom right. In cursive Gallic script it reads:

$$\min_G \max_D \mathbb{E}_x[\log(D(x))] + \mathbb{E}_z[\log(1 - D(G(z)))]$$

Image © Obvious

Generative models: a traditional way



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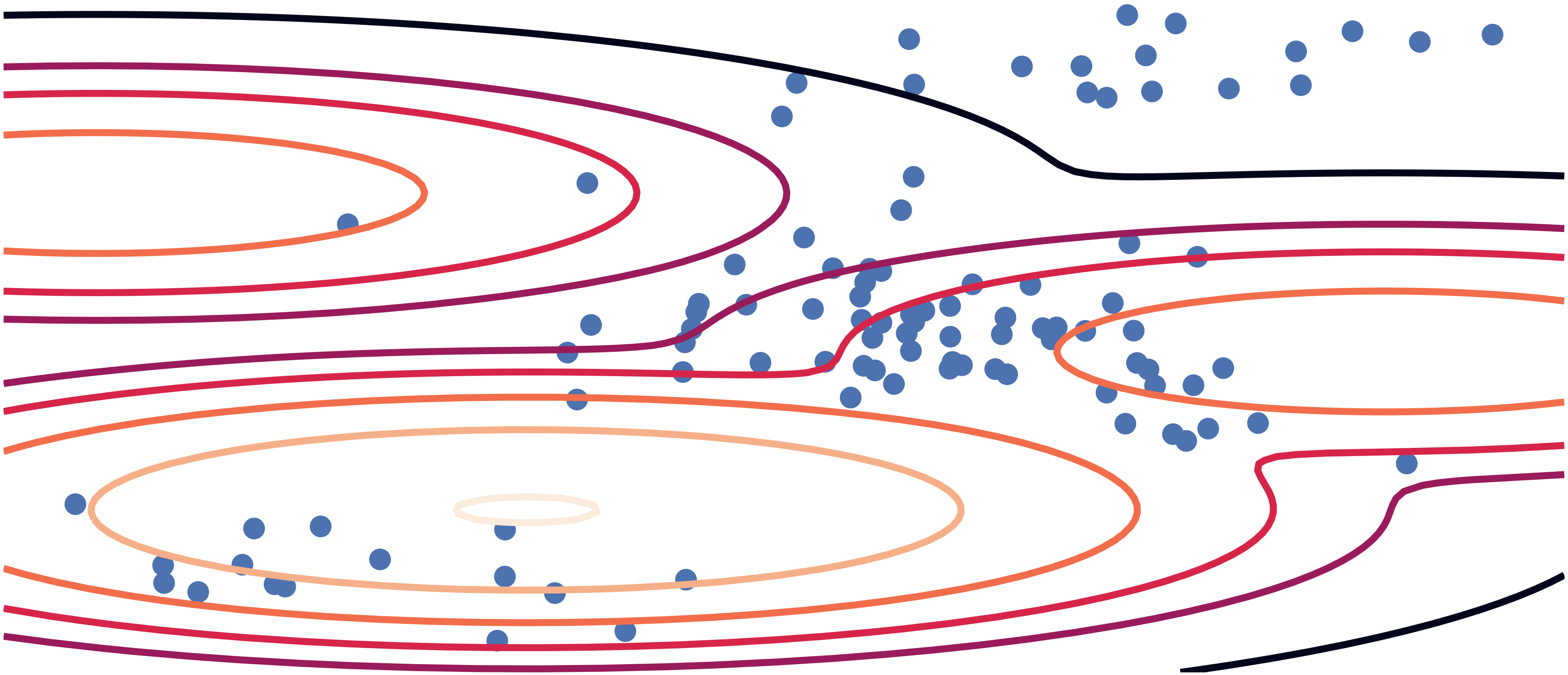

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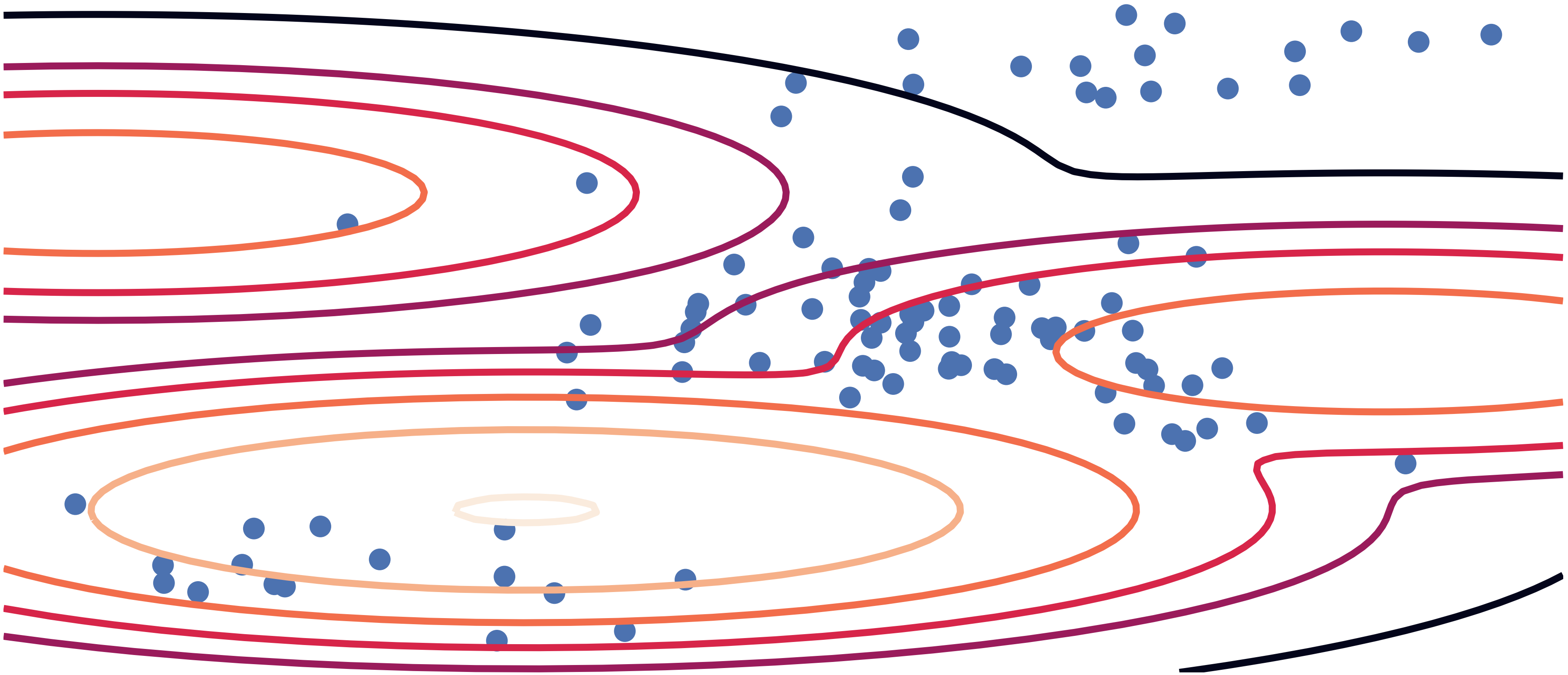

- Maximum likelihood: $\max_\theta \mathbb{E}_{X\sim\mathbb{P}}[\log q_\theta(X)]$

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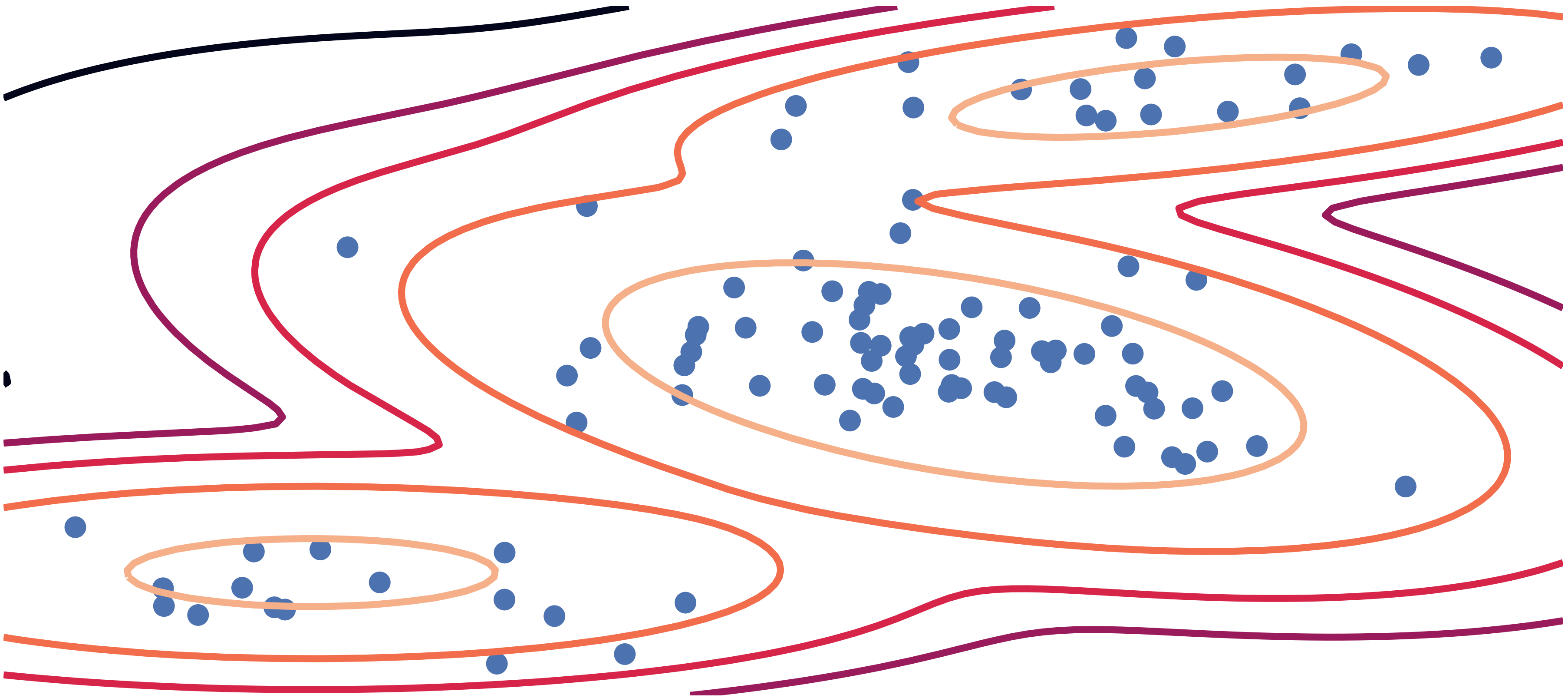

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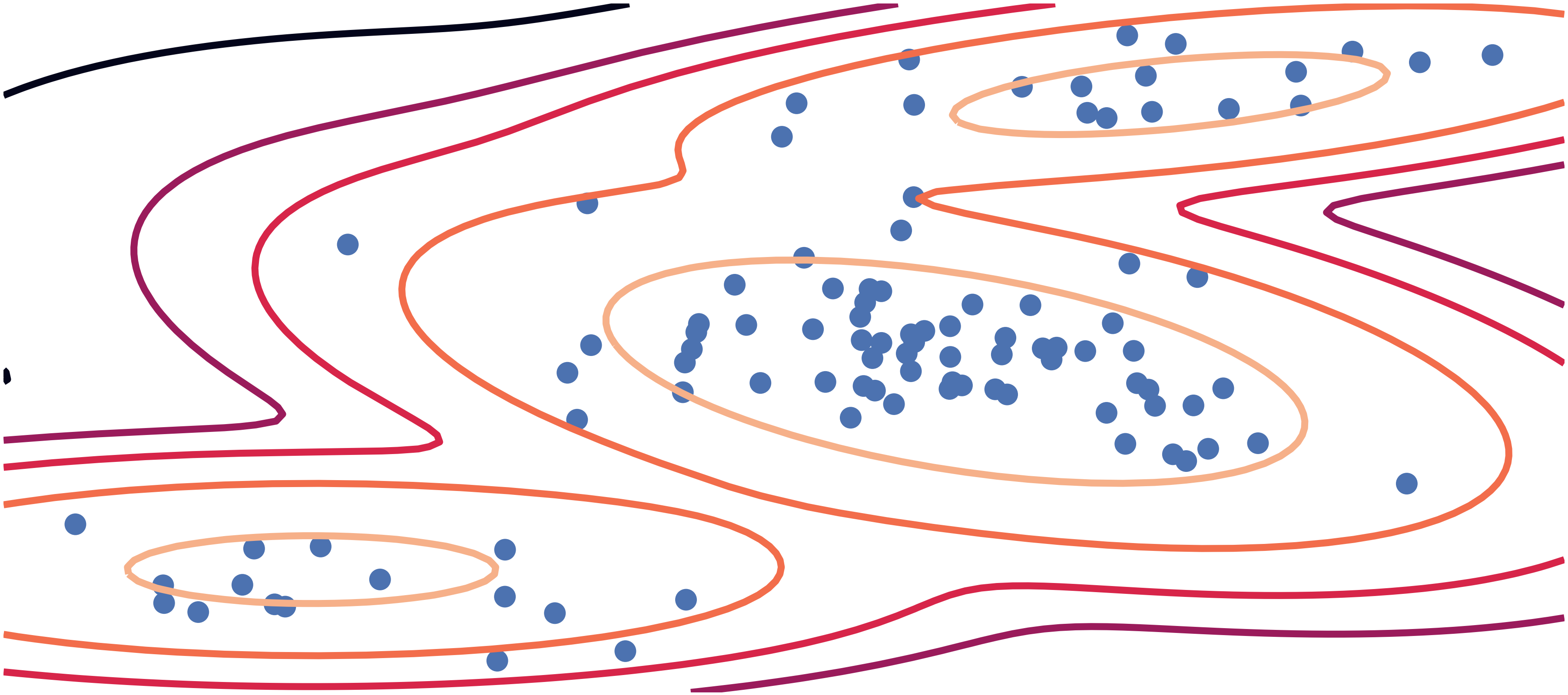
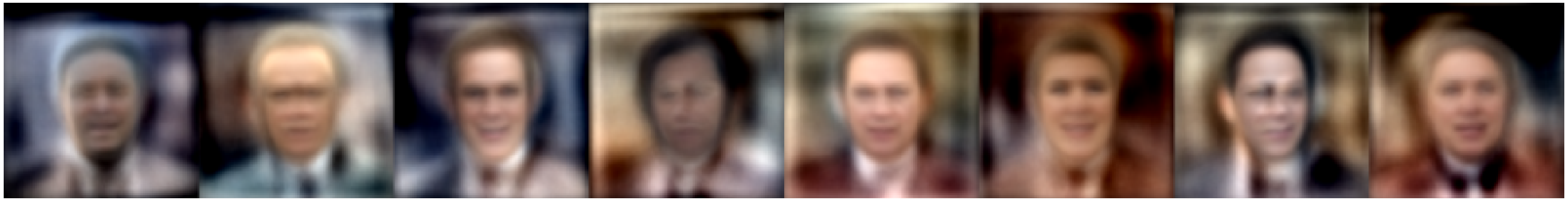


- Maximum likelihood: $\max_\theta \mathbb{E}_{X\sim\mathbb{P}}[\log q_\theta(X)]$
- Equivalent: $\min_\theta \mathrm{KL}(\mathbb{P}\|\mathbb{Q}_\theta) = \min_\theta \int p(x) \log \frac{p(x)}{q_\theta(x)} \mathrm{d}x$

Traditional models for images

- 1987-style generative model of faces (Eigenface via Alex Egg)



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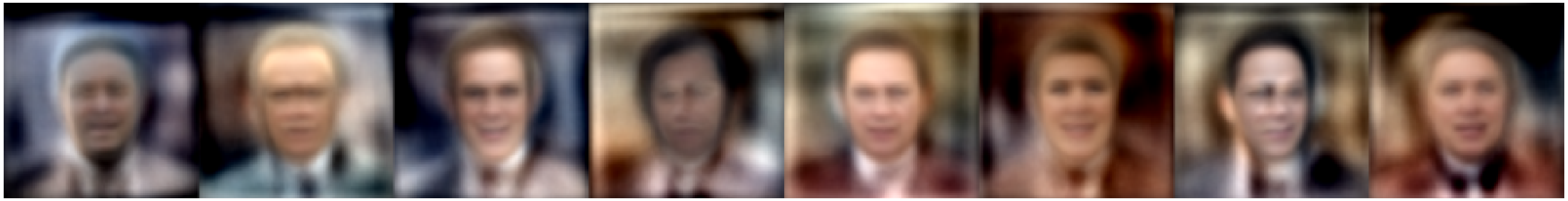

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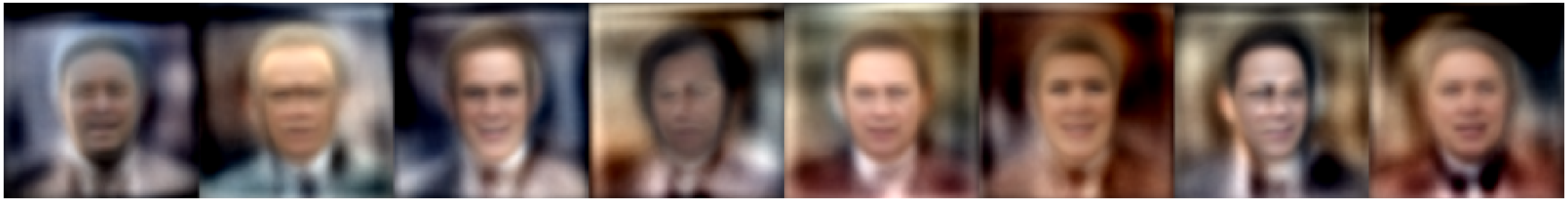

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- Usually based on Gaussian noise $\approx L_2$ loss

A hard case for traditional approaches

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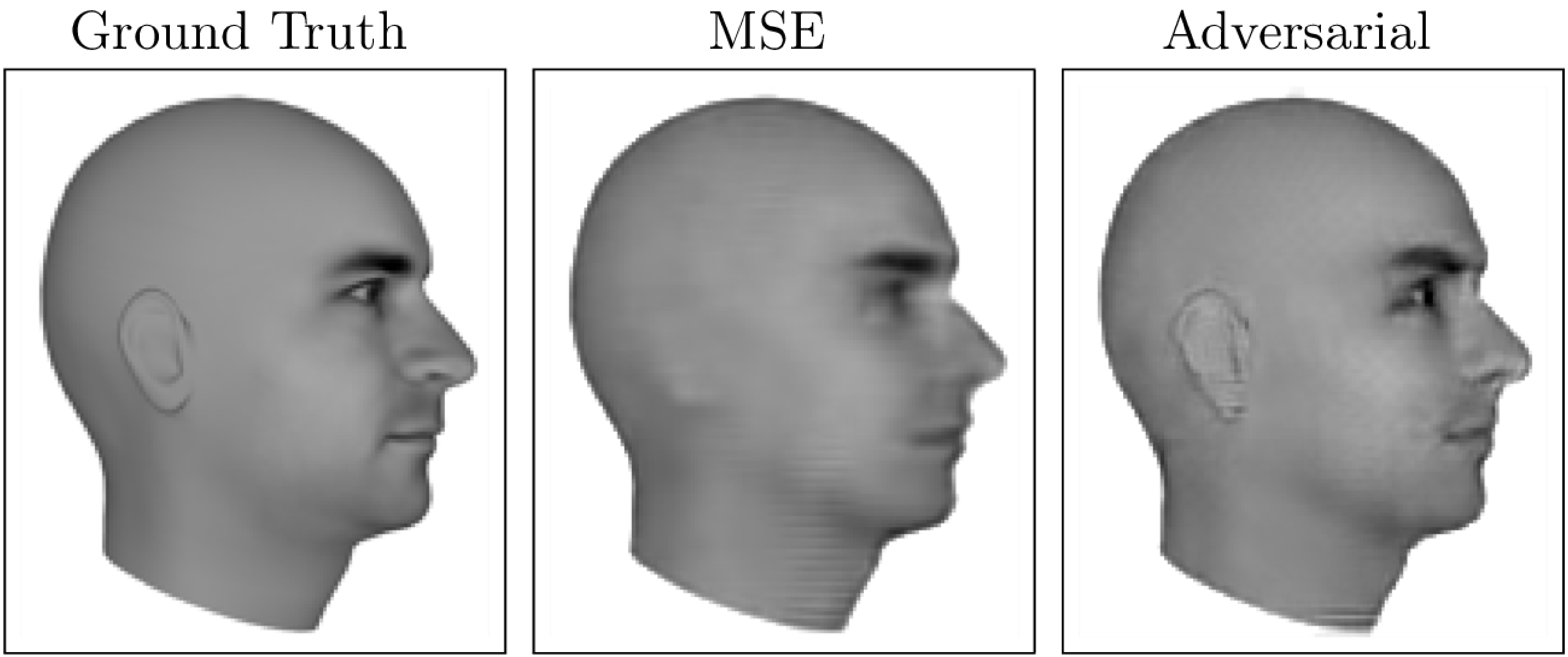
Next-frame video prediction



[Lotter+ 2016]

Trick a discriminator [Goodfellow+ NeurIPS-14]

Generator ($\mathbb{Q}_\theta$)

Discriminator

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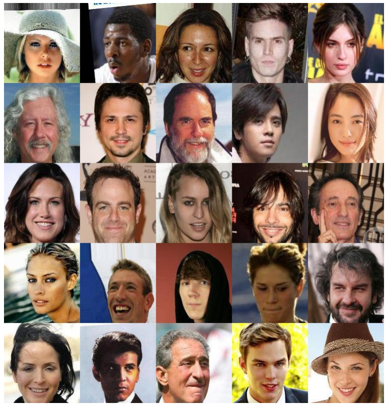

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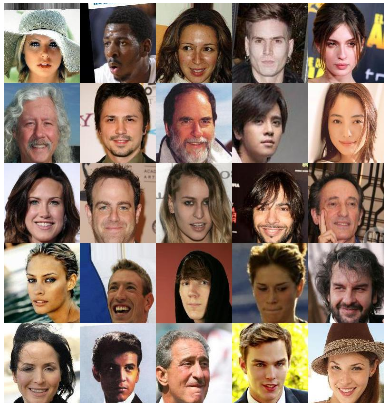

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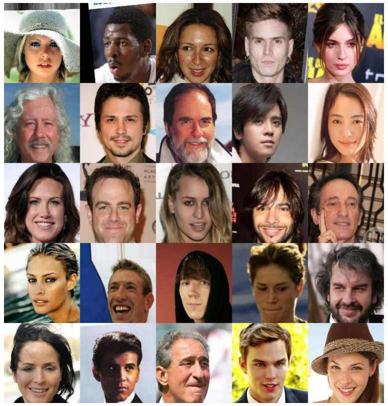

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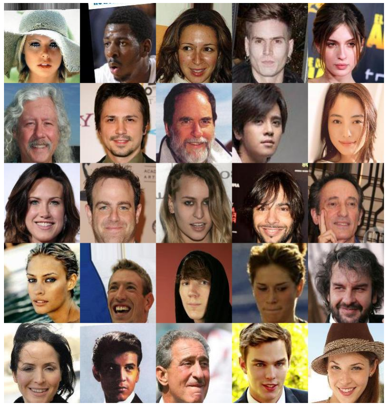

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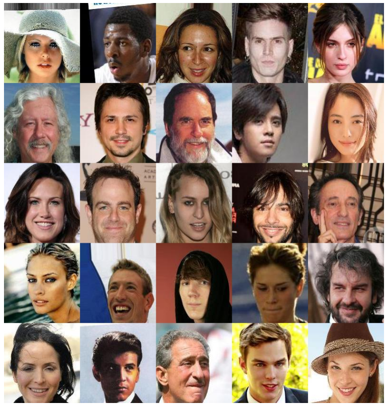

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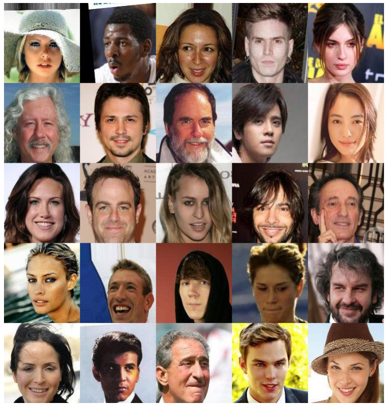

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Is this real? 

Umm... $\mathrm{Pr}(\mathrm{real}) = 0.48$

Aside: deep learning in one slide

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$$\max(x, 0) \qquad \frac{1}{1+e^{-x}} \qquad \frac{e^x - e^{-x}}{e^x + e^{-x}} \qquad \cdots$$

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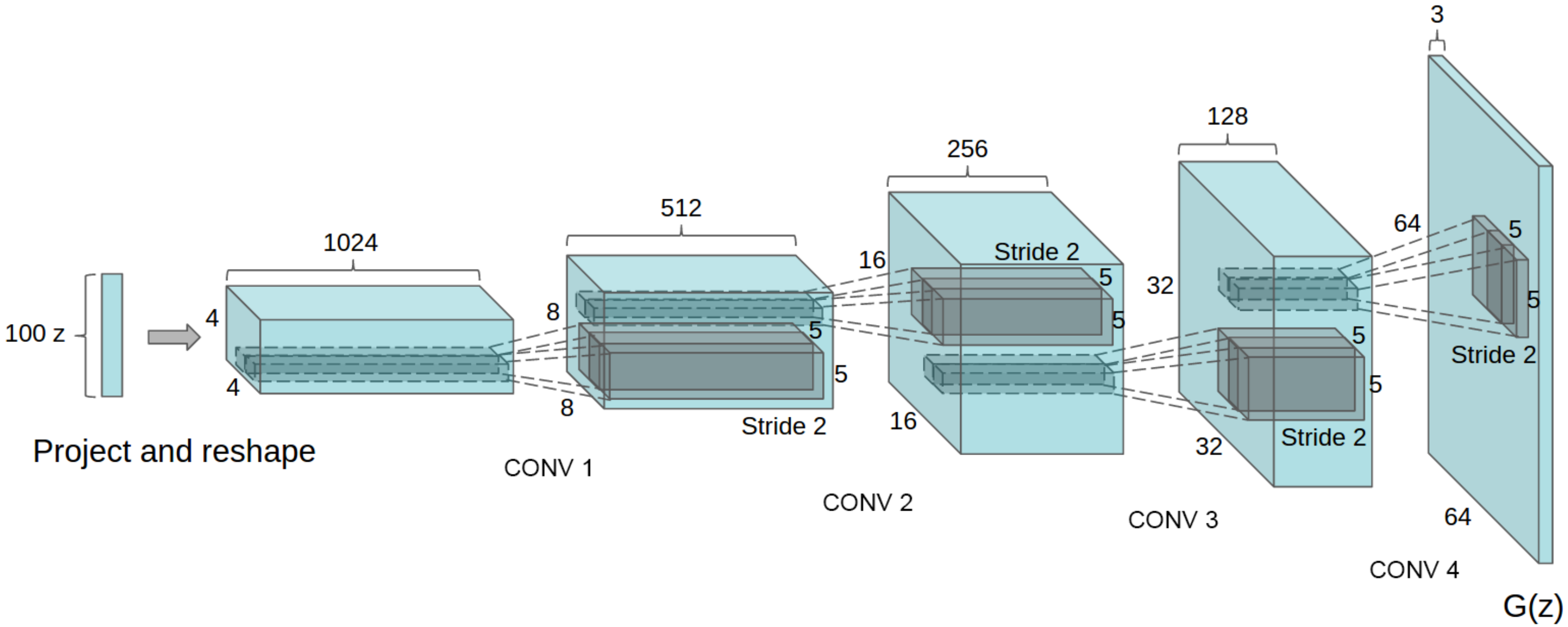
- Optimize with gradient descent

Generator networks

- How to specify $\mathbb{Q}_\theta$?



[Radford+ ICLR-16]

- $Z \sim \mathbb{Z} = \text{Uniform}\left([-1,1]^{100}\right)$
- $G_\theta : [-1,1]^{100} \to \mathcal{X},\, G_\theta(Z) \sim \mathbb{Q}_\theta$

GANs in equations

- Tricking the discriminator:

$$\min_{\theta} \max_{\psi} \frac{1}{2} \mathop{\mathbb{E}}_{X \sim \mathbb{P}} [\log D_{\psi}(X)] + \frac{1}{2} \mathop{\mathbb{E}}_{Y \sim \mathbb{Q}_{\theta}} [\log(1 - D_{\psi}(Y))]$$

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- Using the generator network for $\mathbb{Q}_{\theta}$:

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- Can do alternating gradient descent!

Original paper's results [Goodfellow+ NeurIPS-14]

DCGAN results [Radford+ ICLR-16]

Training instability

Running code from [Salimans+ NeurIPS-16]:

Run 1, epoch 1

Training instability

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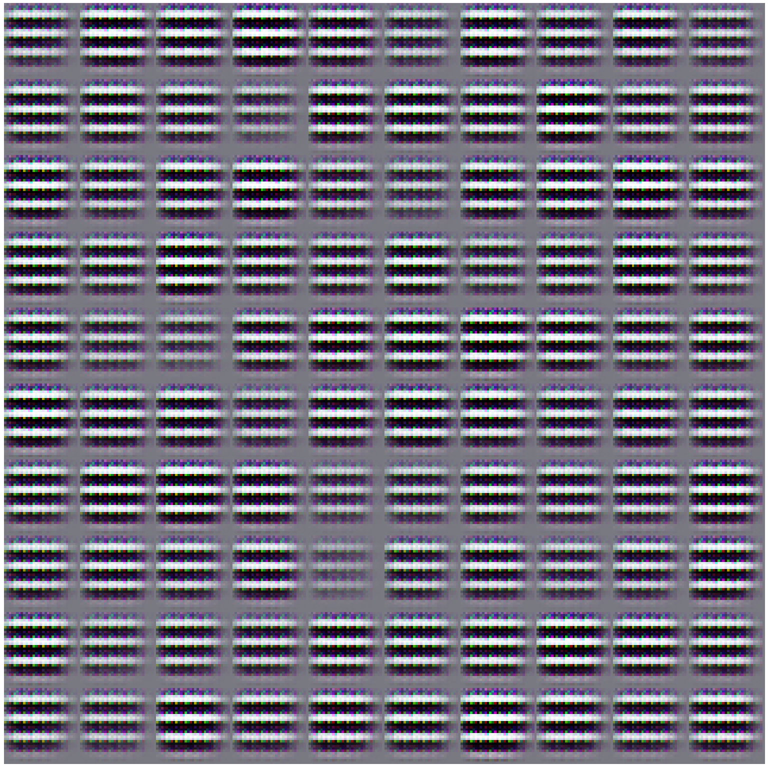

Run 1, epoch 2

Training instability

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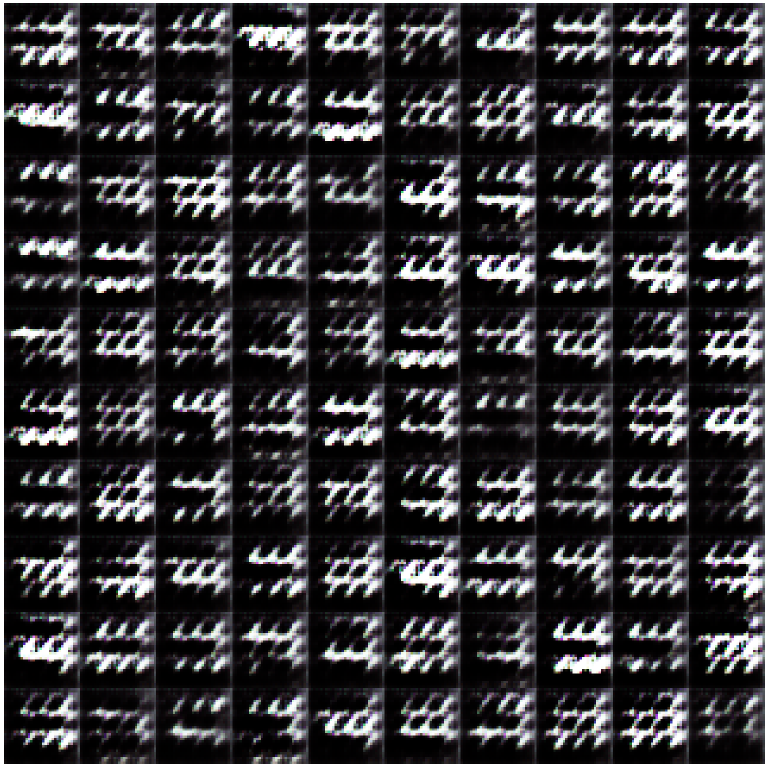
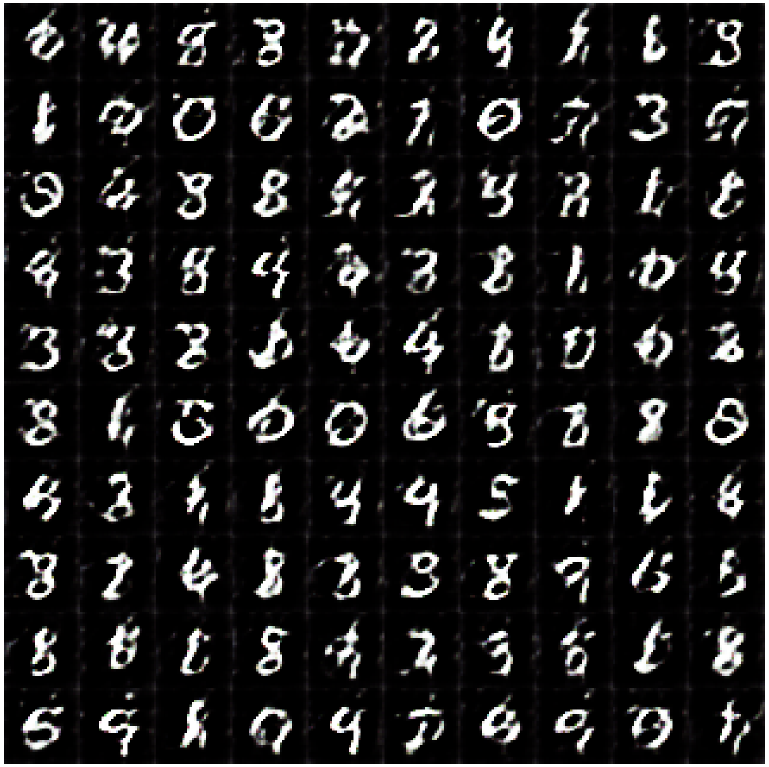


Run 1, epoch 3

Training instability

Running code from [Salimans+ NeurIPS-16]:



Run 1, epoch 4

Training instability

Running code from [Salimans+ NeurIPS-16]:

Run 1, epoch 5

Training instability

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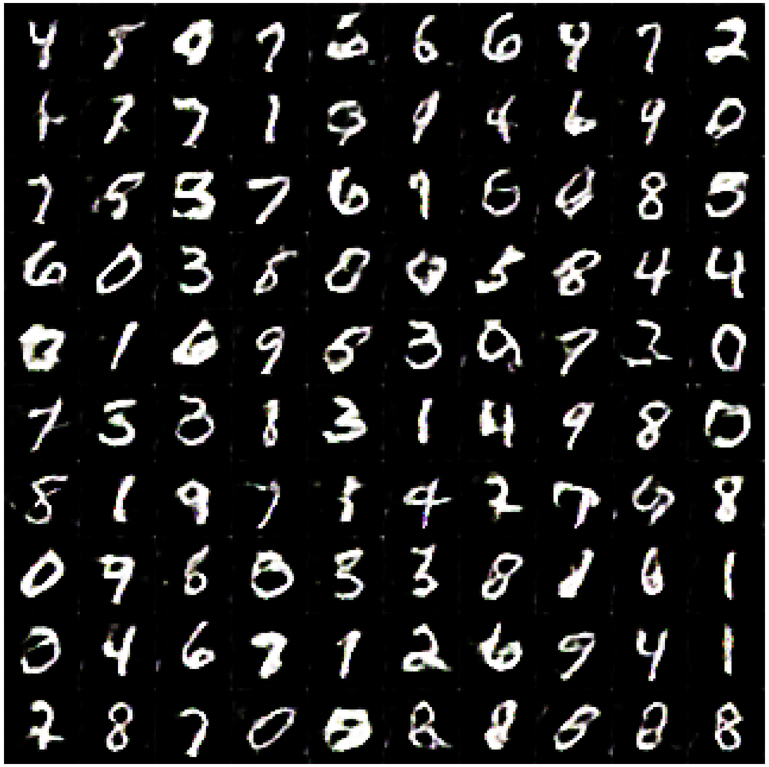
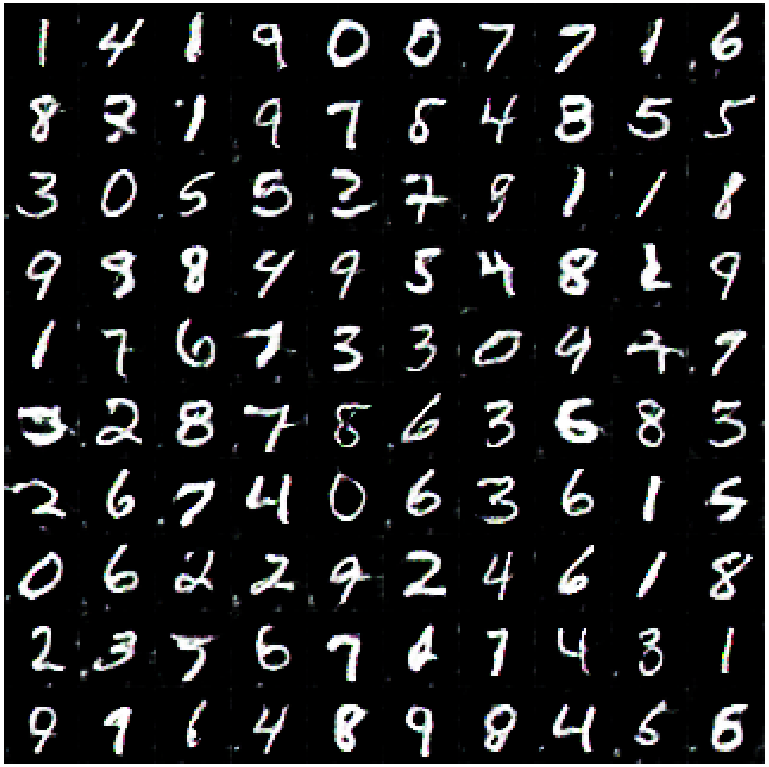


Run 1, epoch 6

Training instability

Running code from [Salimans+ NeurIPS-16]:



Run 1, epoch 11

Training instability

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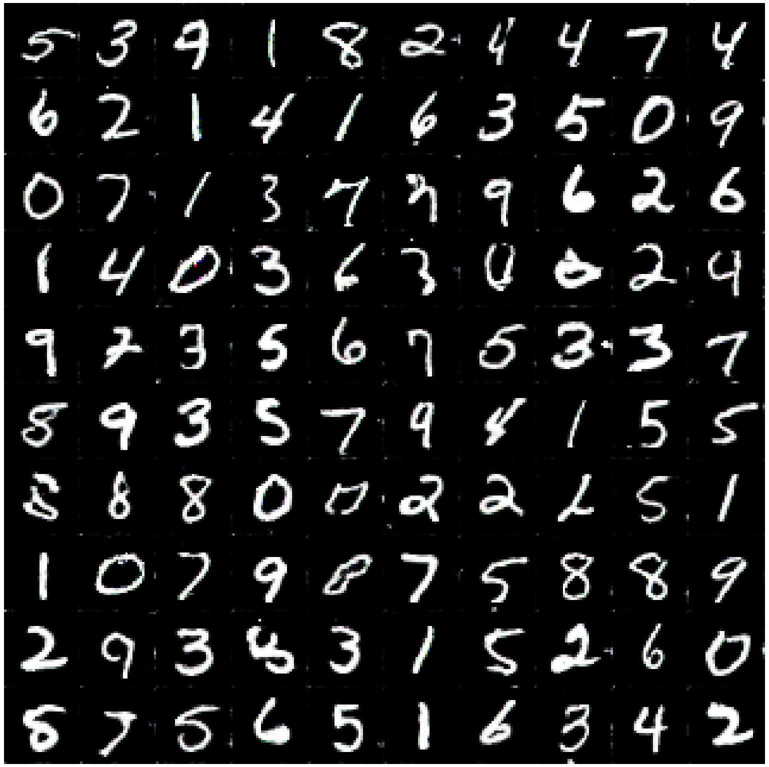

Run 1, epoch 501

Training instability

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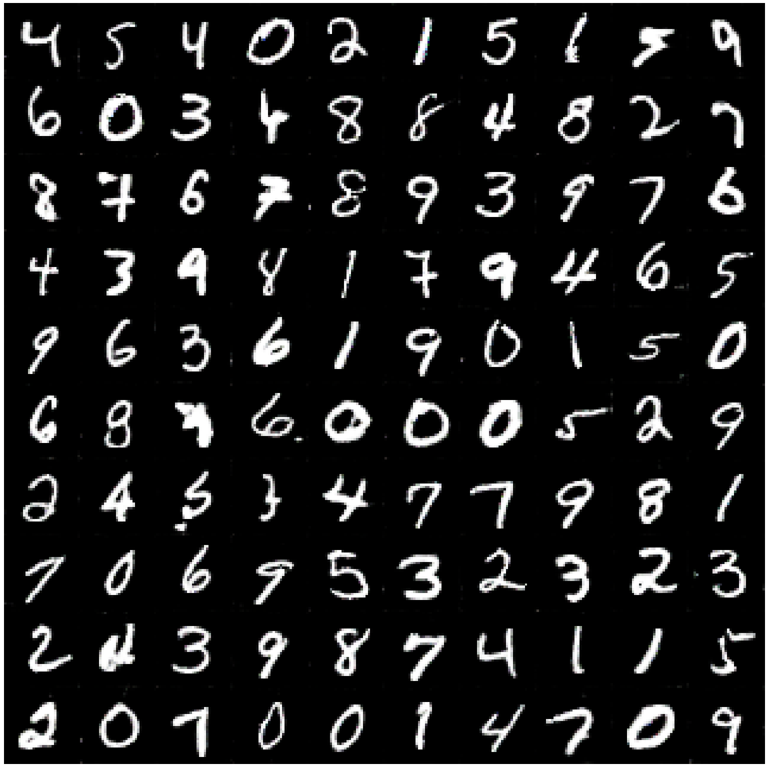

Run 1, epoch 900

Training instability

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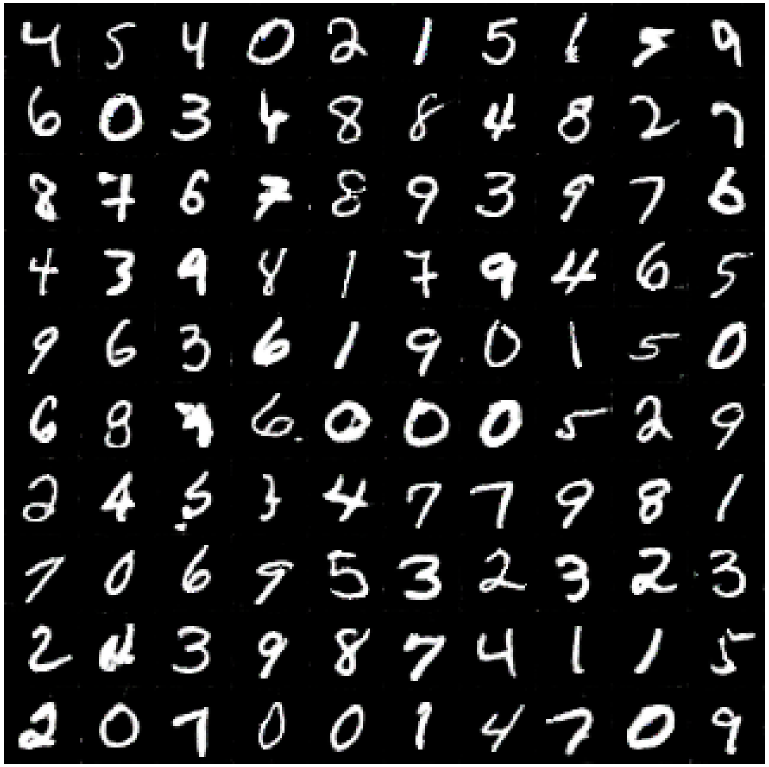

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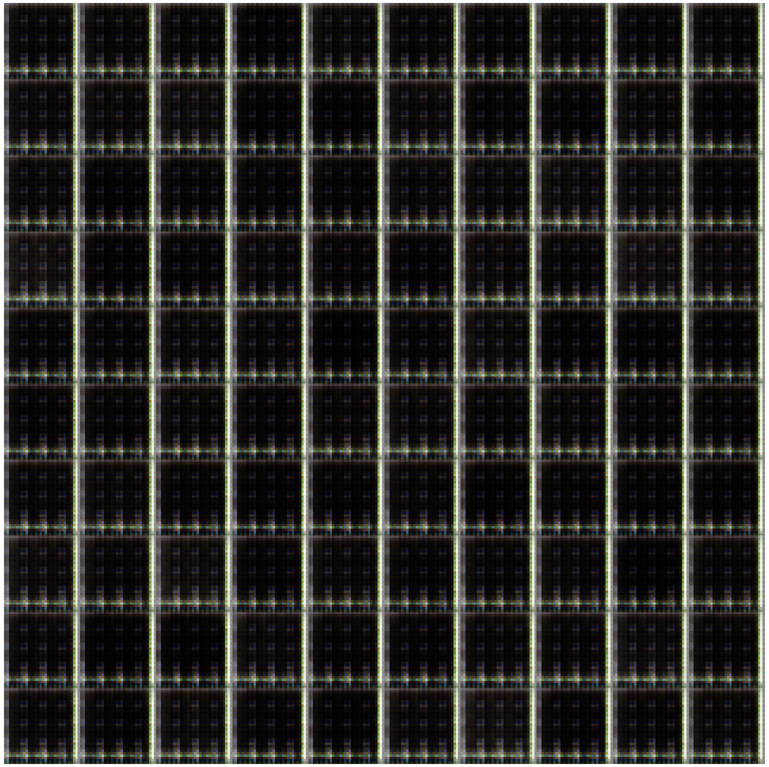
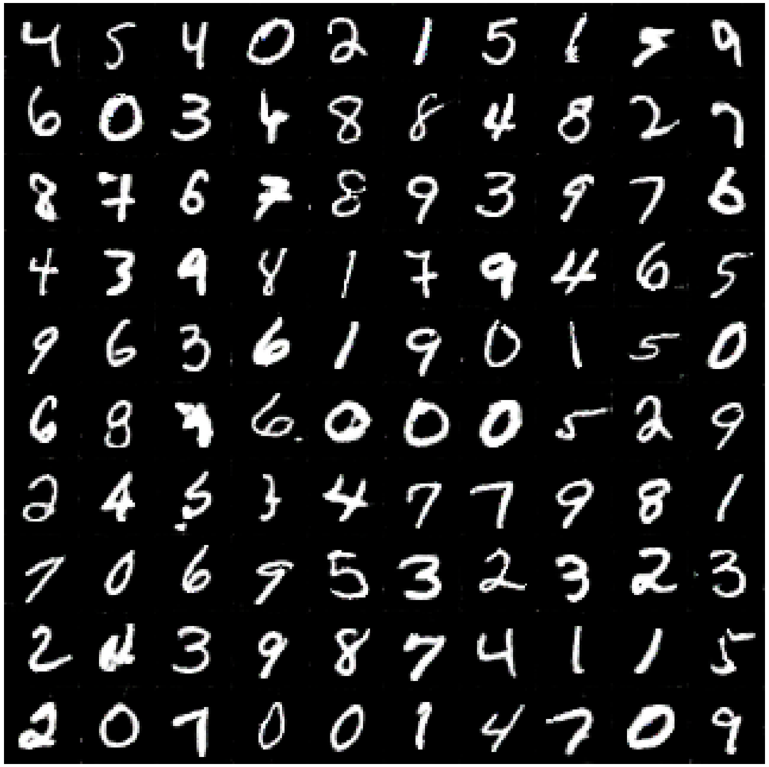


Run 2, epoch 1

Training instability

Running code from [Salimans+ NeurIPS-16]:



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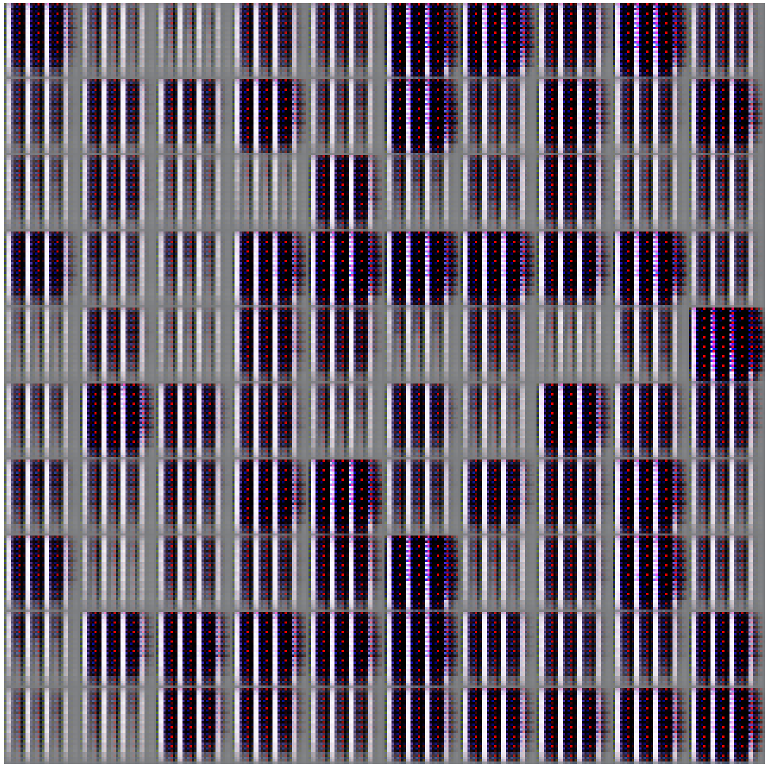

Run 2, epoch 2

Training instability

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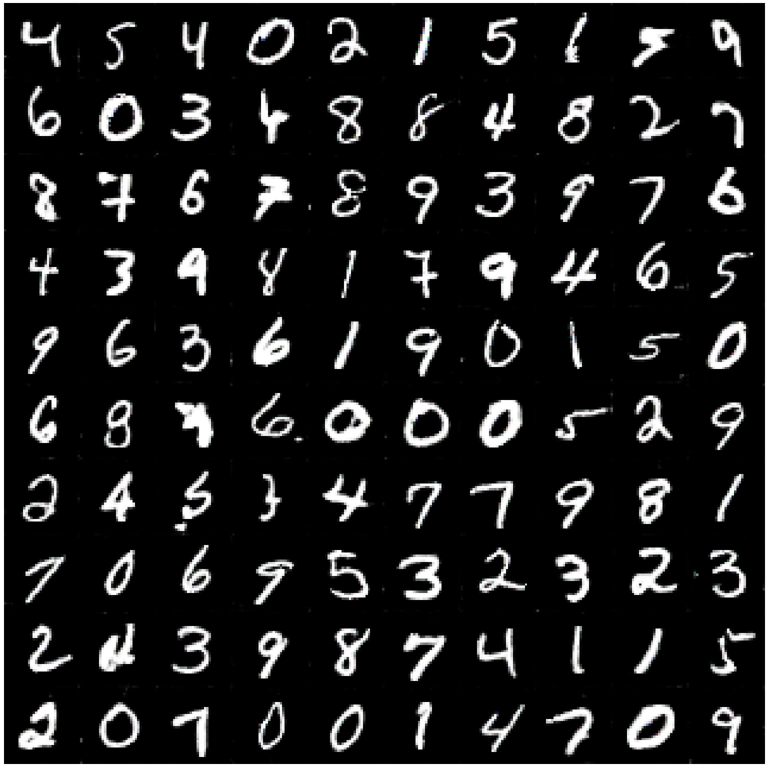

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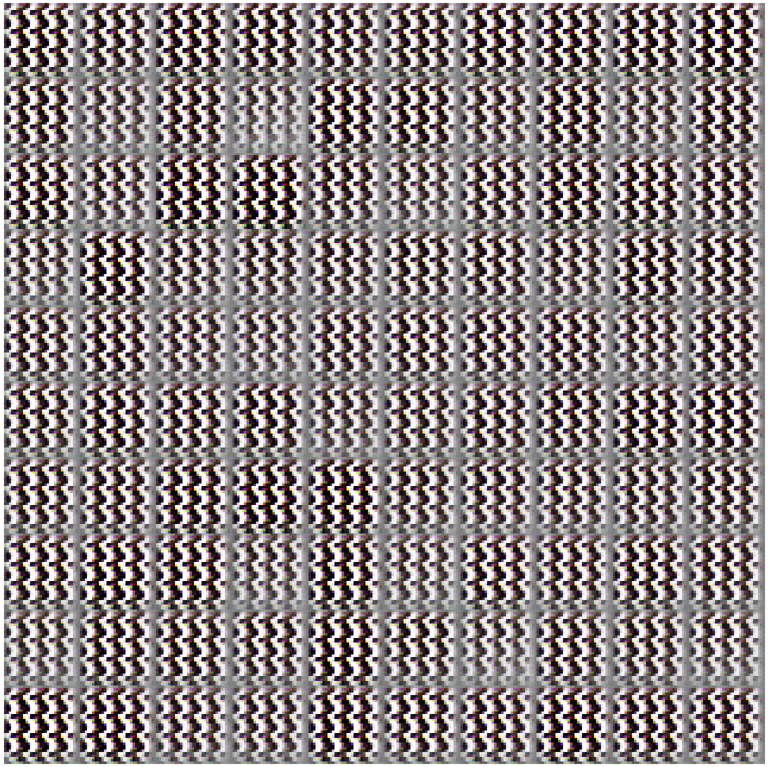

Run 2, epoch 3

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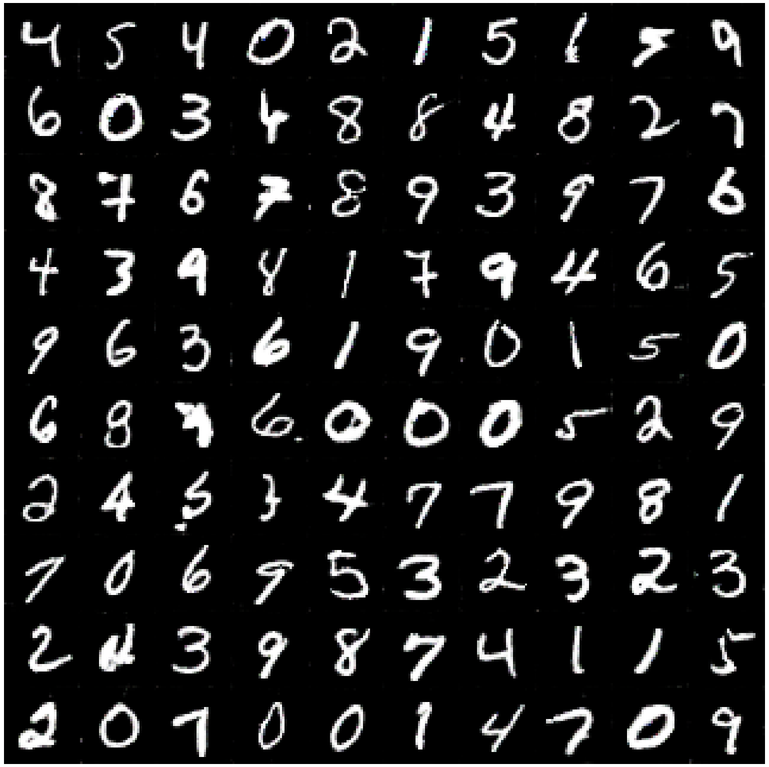

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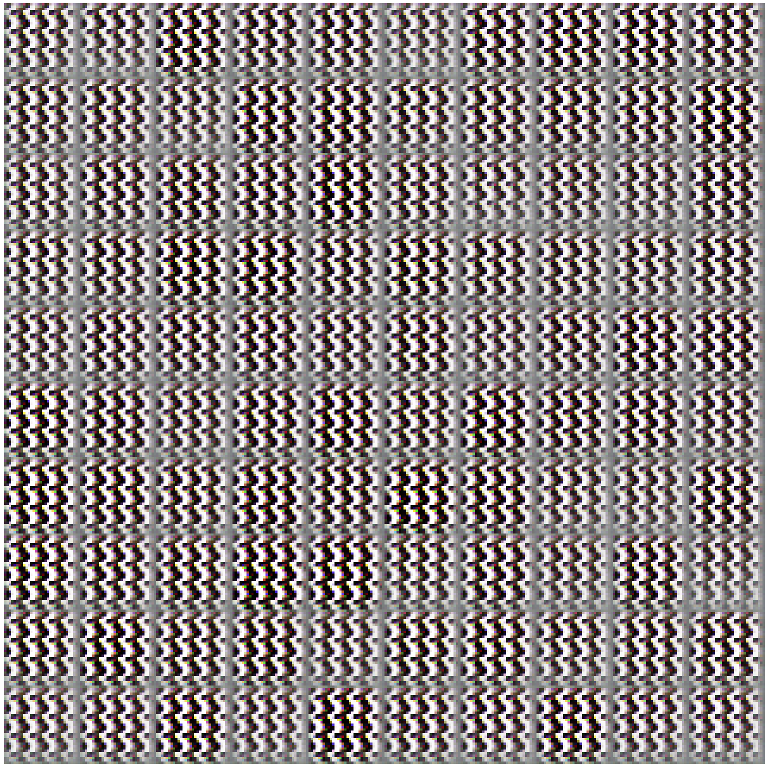

Run 2, epoch 4

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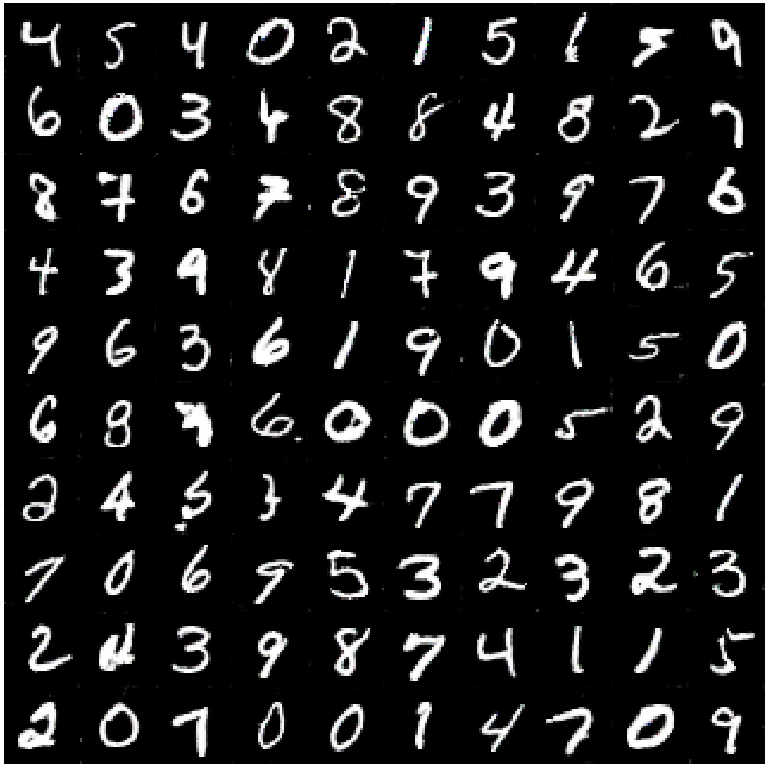

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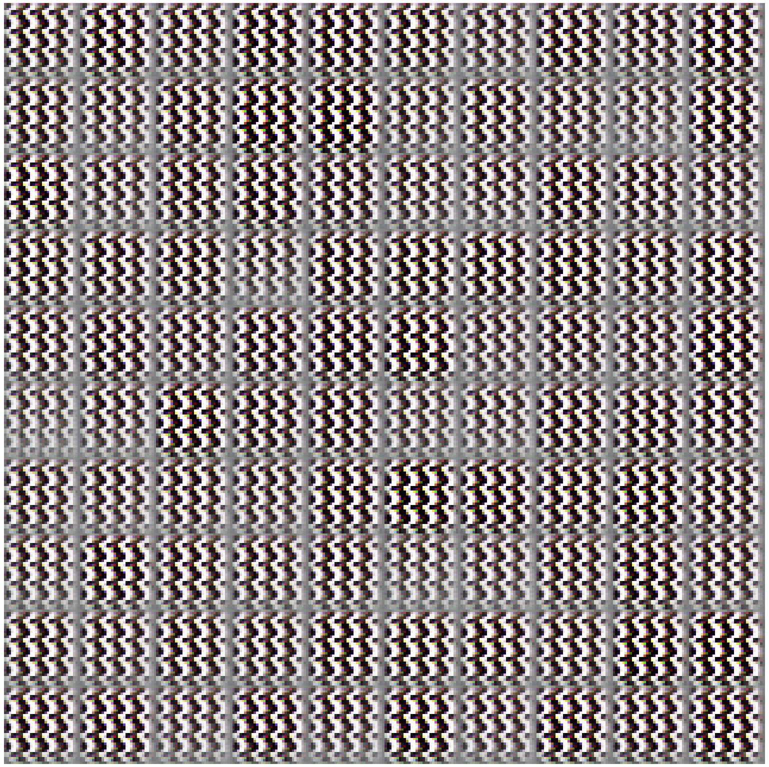

Run 2, epoch 5

One view: distances between distributions

- What happens when D_ψ is at its optimum?

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- If distributions have densities, $D^*_\psi(x) = \frac{p(x)}{p(x)+q_\theta(x)}$

One view: distances between distributions

- What happens when D_ψ is at its optimum?
- If distributions have densities, $D^*_\psi(x) = \frac{p(x)}{p(x)+q_\theta(x)}$
- If D_ψ stays optimal throughout, θ tries to minimize

$$\frac{1}{2} \mathop{\mathbb{E}}_{X\sim\mathbb{P}}\left[\log \frac{p(X)}{p(X)+q_\theta(X)}\right] + \frac{1}{2} \mathop{\mathbb{E}}_{Y\sim\mathbb{Q}_\theta}\left[\log \frac{q_\theta(X)}{p(X)+q_\theta(X)}\right]$$

which is
$\mathrm{JS}(\mathbb{P}, \mathbb{Q}_\theta) - \log 2$

Jensen-Shannon divergence

$$\begin{aligned}\mathrm{JS}(\mathbb{P}, \mathbb{Q}_\theta) = \frac{1}{2} \int p(x) \log \frac{p(x)}{\frac{1}{2}p(x) + \frac{1}{2}q_\theta(x)} \mathrm{d}x \\ + \frac{1}{2} \int q_\theta(x) \log \frac{q_\theta(x)}{\frac{1}{2}p(x) + \frac{1}{2}q_\theta(x)} \mathrm{d}x\end{aligned}$$

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$$
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&\quad + \frac{1}{2}\int q_\theta(x)\log\frac{q_\theta(x)}{\frac{1}{2}p(x)+\frac{1}{2}q_\theta(x)}\mathrm{d}x \\
&= \frac{1}{2}\mathrm{KL}\left(\mathbb{P}\,\middle\|\,\frac{\mathbb{P}+\mathbb{Q}_\theta}{2}\right) + \frac{1}{2}\mathrm{KL}\left(\mathbb{Q}_\theta\,\middle\|\,\frac{\mathbb{P}+\mathbb{Q}_\theta}{2}\right)
\end{aligned}
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&+ \frac{1}{2}\int q_\theta(x)\log\frac{q_\theta(x)}{\frac{1}{2}p(x)+\frac{1}{2}q_\theta(x)}\mathrm{d}x \\
&= \frac{1}{2}\mathrm{KL}\left(\mathbb{P}\,\middle\|\,\frac{\mathbb{P}+\mathbb{Q}_\theta}{2}\right)+\frac{1}{2}\mathrm{KL}\left(\mathbb{Q}_\theta\,\middle\|\,\frac{\mathbb{P}+\mathbb{Q}_\theta}{2}\right) \\
&= \mathrm{H}\left[\frac{\mathbb{P}+\mathbb{Q}_\theta}{2}\right]-\frac{\mathrm{H}[\mathbb{P}]+\mathrm{H}[\mathbb{Q}_\theta]}{2}
\end{aligned}$$

JS with disjoint support [Arjovsky/Bottou ICLR-17]

$$\mathrm{JS}(\mathbb{P}, \mathbb{Q}_\theta) = \frac{1}{2}\int p(x)\log\frac{p(x)}{\frac{1}{2}p(x)+\frac{1}{2}q_\theta(x)}\mathrm{d}x$$
$$+\frac{1}{2}\int q_\theta(x)\log\frac{q_\theta(x)}{\frac{1}{2}p(x)+\frac{1}{2}q_\theta(x)}\mathrm{d}x$$

- If $\mathbb{P}$ and $\mathbb{Q}_\theta$ have (almost) disjoint support

$$\frac{1}{2}\int p(x)\log\frac{p(x)}{\frac{1}{2}p(x)}\mathrm{d}x$$

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so $\mathrm{JS}(\mathbb{P}, \mathbb{Q}_\theta) = \log 2$

Discriminator point of view

Generator ($\mathbb{Q}_\theta$)

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Is this real?

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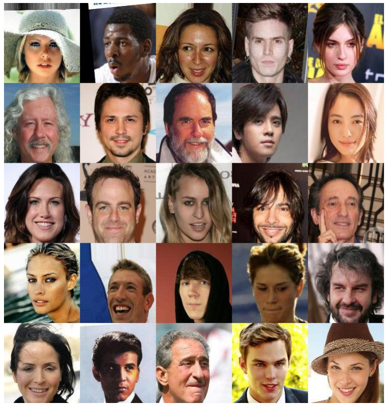

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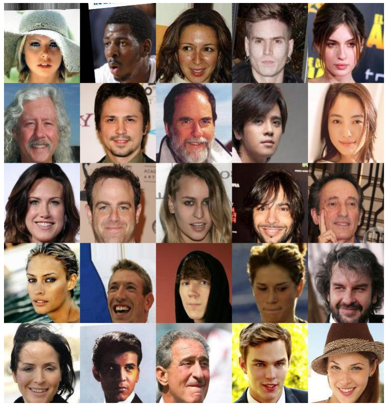

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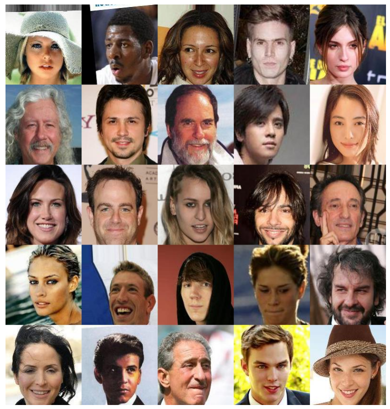

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:(I don't know how to do any better...

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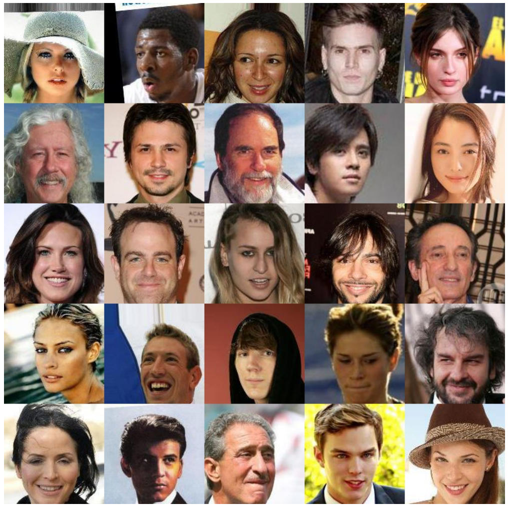
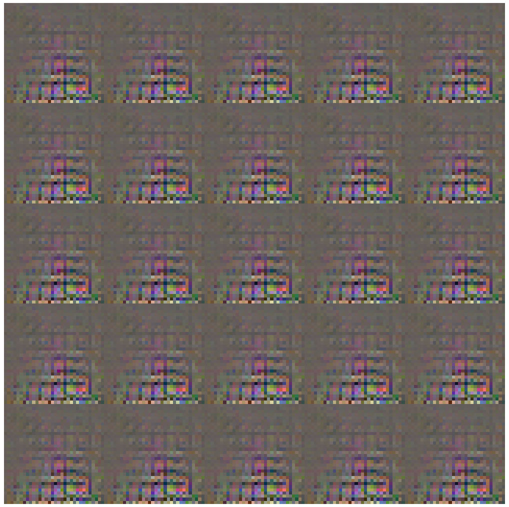
$\mathbb{P}$: 

$\mathbb{Q}_\theta$: 

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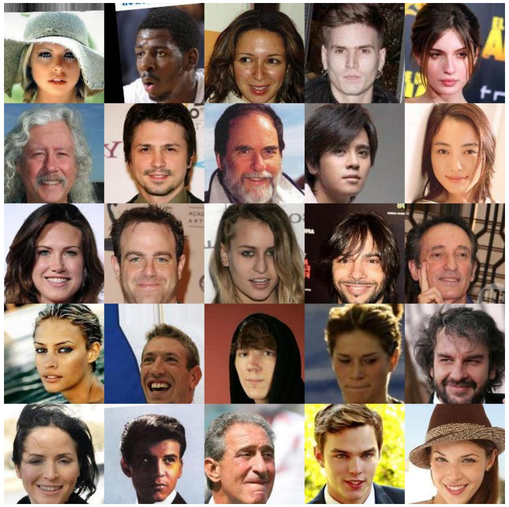
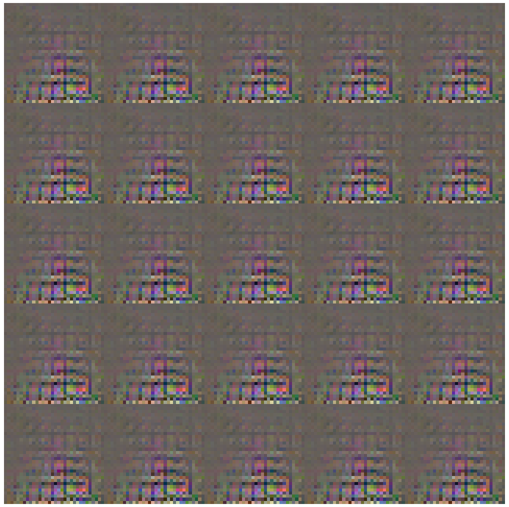
$\mathbb{P}$: 

$\mathbb{Q}_\theta$: 

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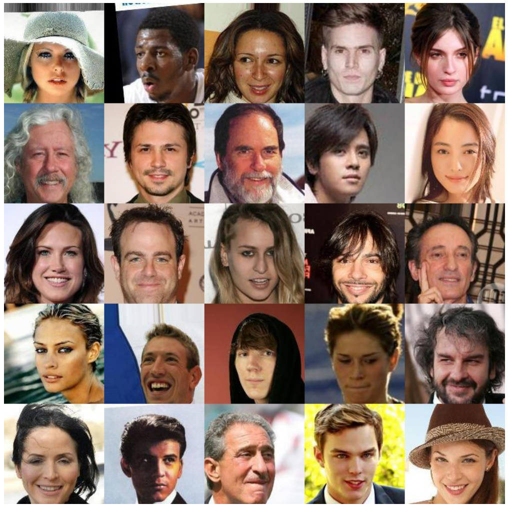
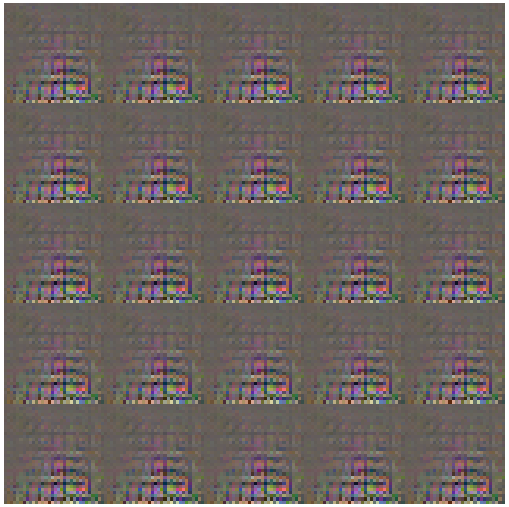
$\mathbb{P}$: 

$\mathbb{Q}_\theta$: 

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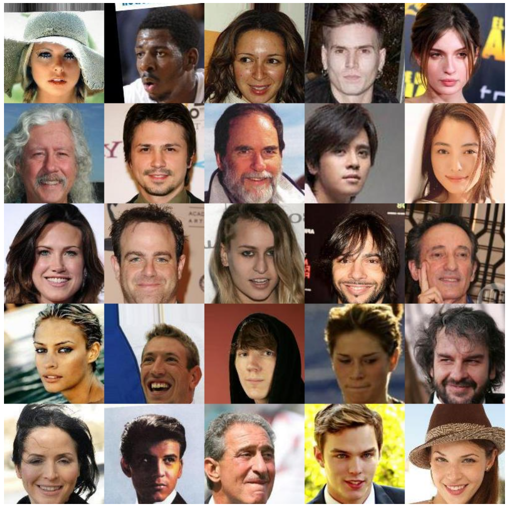
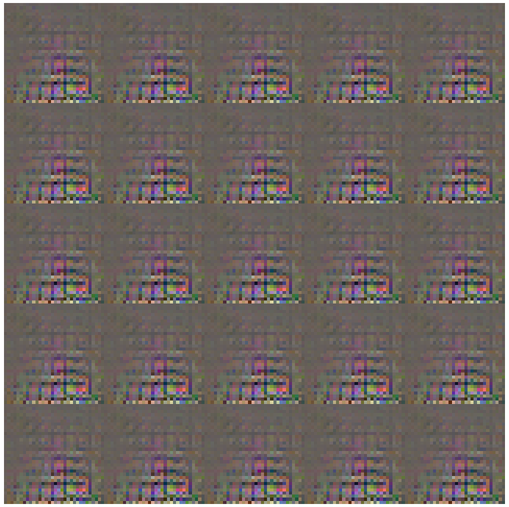
$\mathbb{P}$: 

$\mathbb{Q}_\theta$: 

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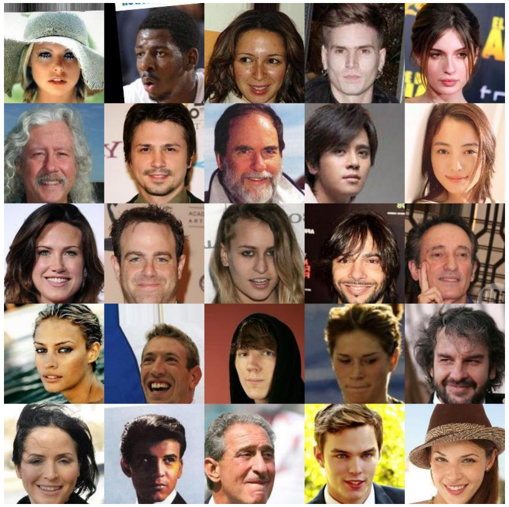

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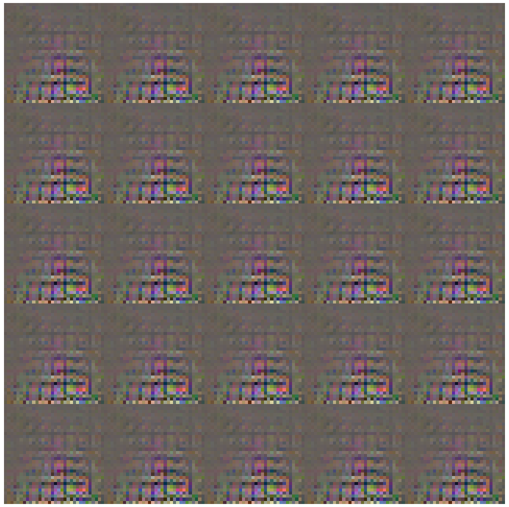

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- No chance that they'd align at init, so $\mathrm{JS}(\mathbb{P}, \mathbb{Q}_\theta) = \log 2$

A heuristic partial workaround

- Original GANs almost never use the minimax game

$$\min_{\theta} \max_{\psi} \frac{1}{2} \mathop{\mathbb{E}}_{X \sim \mathbb{P}} [\log D_\psi(X)] + \frac{1}{2} \mathop{\mathbb{E}}_{Y \sim \mathbb{Q}_\theta} [\log(1 - D_\psi(Y))]$$

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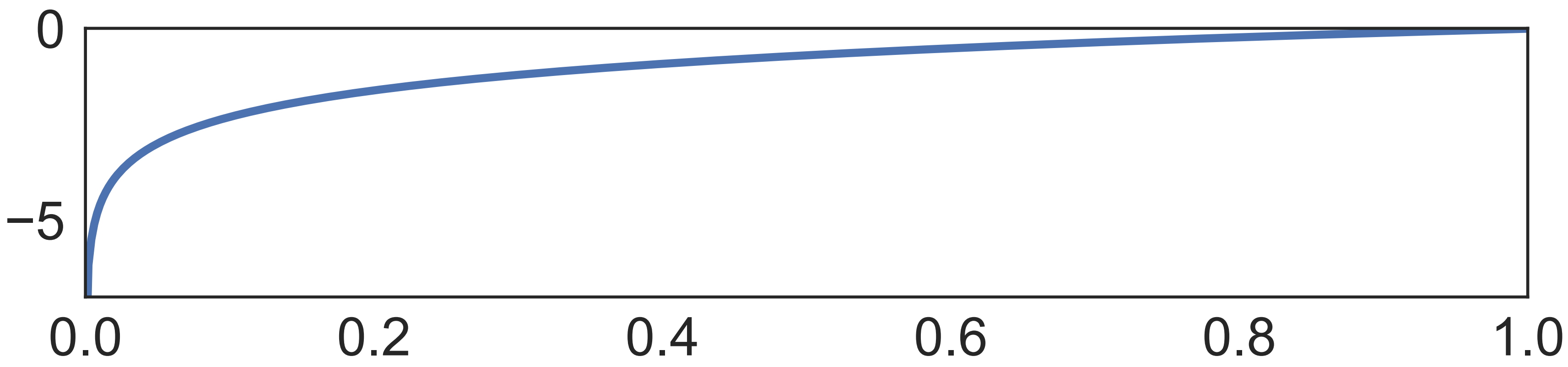

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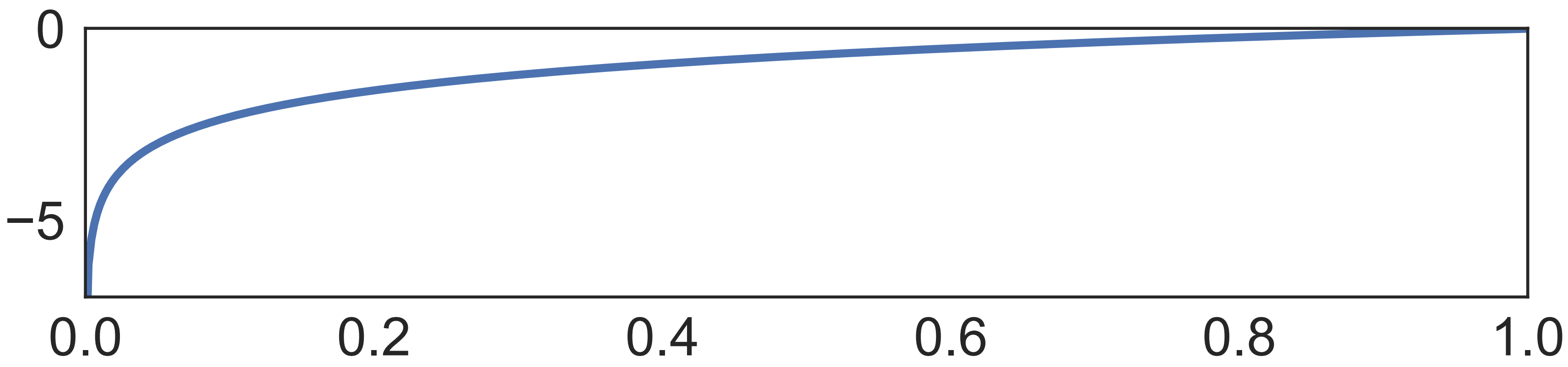

- When D_ψ is near-perfect, makes it unstable instead of stuck

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$$\mathcal{W}(\mathbb{P}, \mathbb{Q}) = \sup_{f:\|f\|_{\mathrm{Lip}} \leq 1} \mathop{\mathbb{E}}_{X \sim \mathbb{P}}[f(X)] - \mathop{\mathbb{E}}_{Y \sim \mathbb{Q}}[f(Y)]$$

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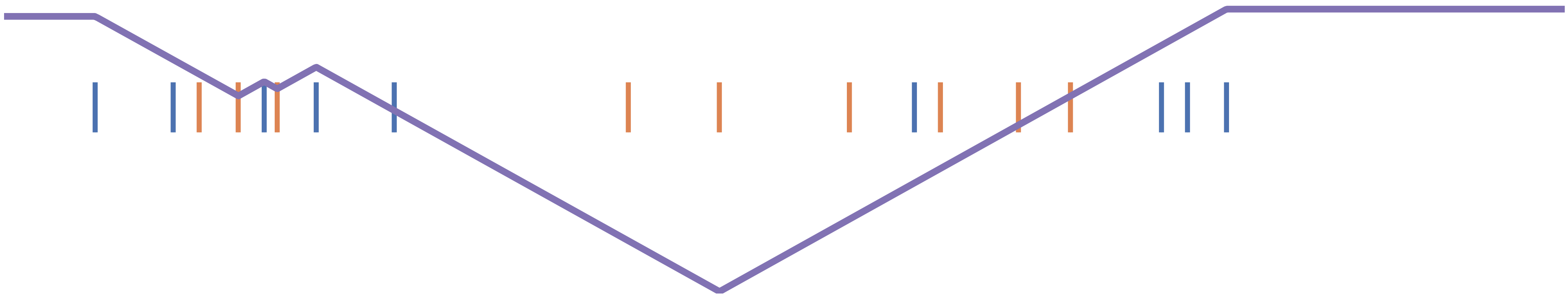

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- Specifically: $\tilde{X} = \theta X + (1-\theta)Y, \theta \sim \mathrm{Uniform}([0,1])$

Solution 2: add noise

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Solution 3: Spectral normalization [Miyato+ ICLR-18]

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- Spectral normalization: $f_\ell = \sigma\left(\frac{1}{\|W_\ell\|_2} W_\ell f_{\ell-1}(x) + b_\ell\right)$
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New samples [Mescheder+ ICML-18]

How to evaluate?

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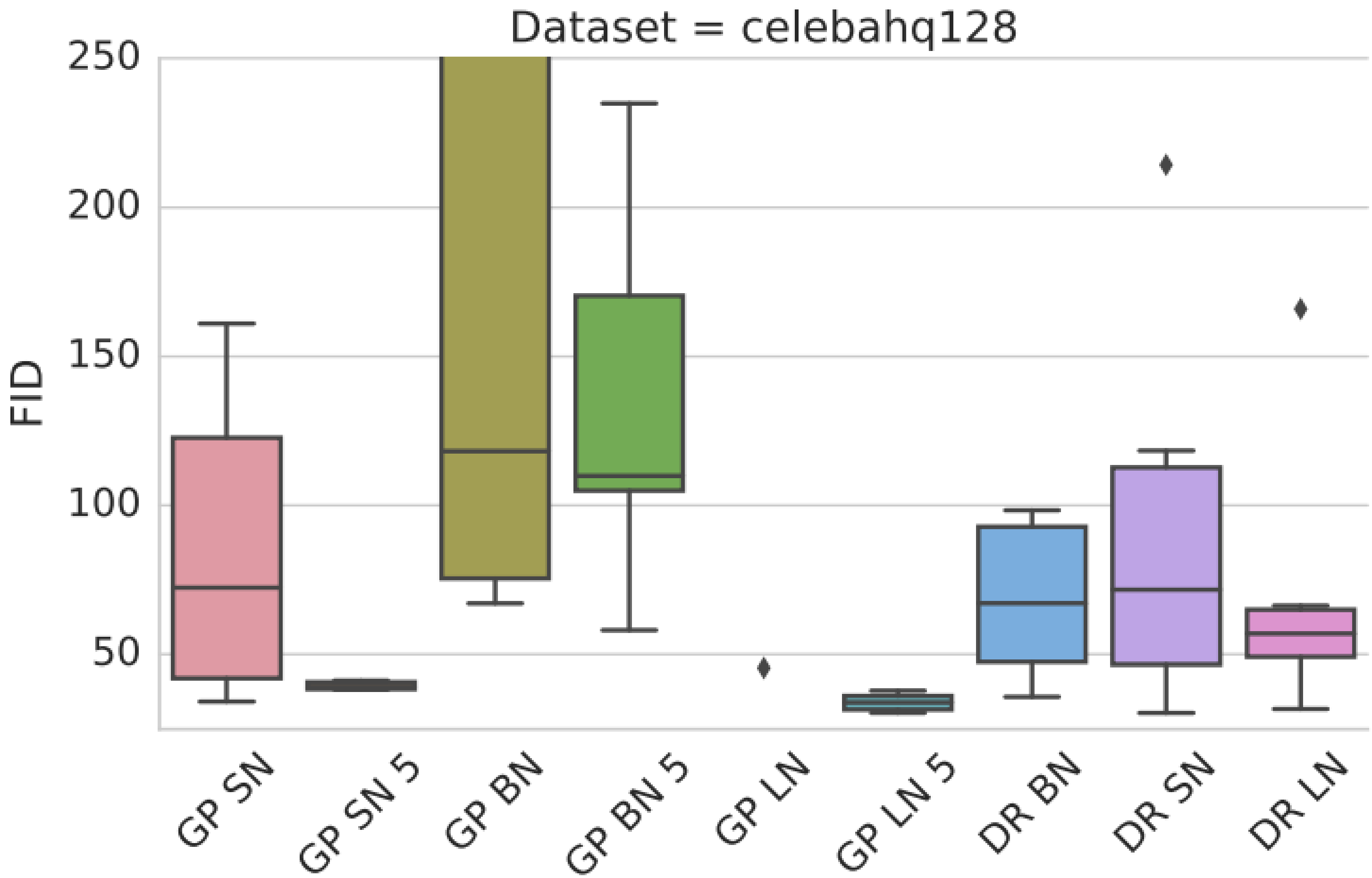
    - Similar distance with unbiased, ~normal estimator!

Comparing approaches [Kurach+ ICML-19]



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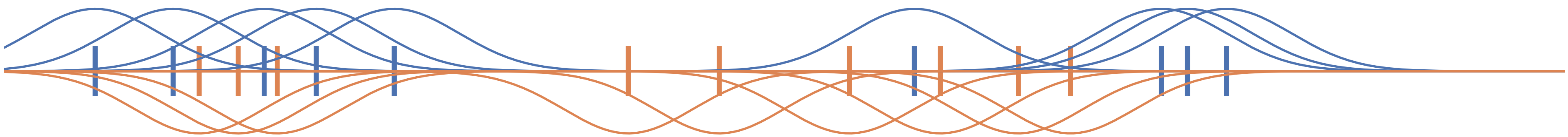

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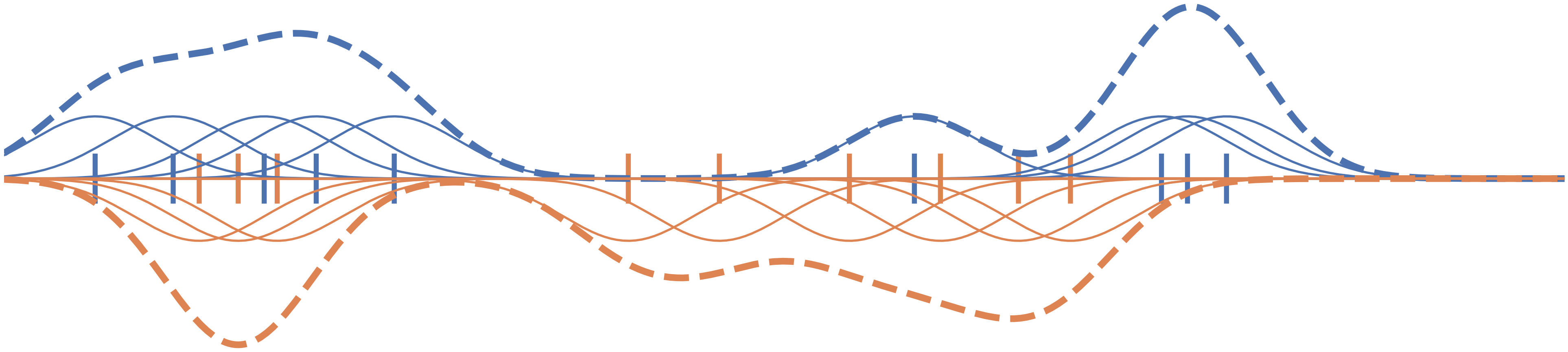

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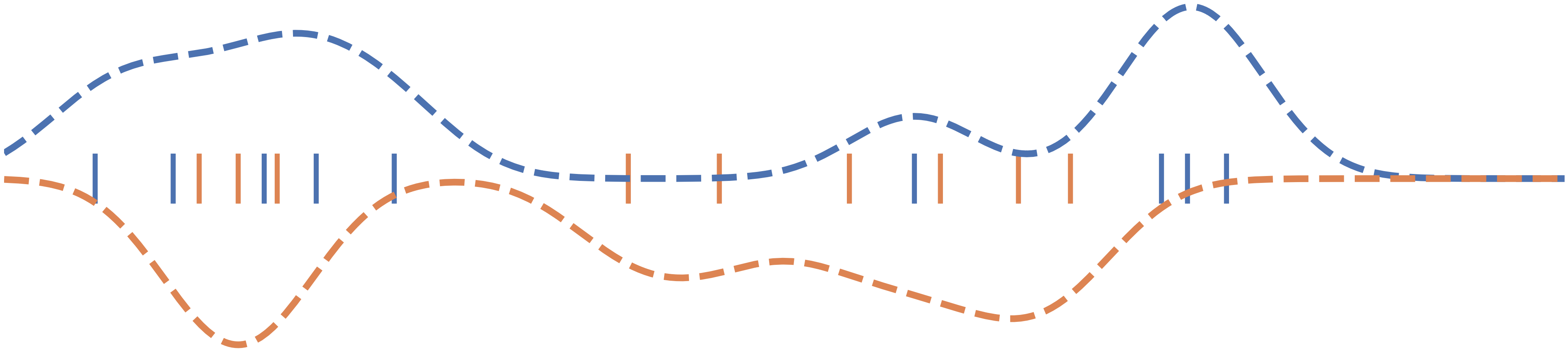

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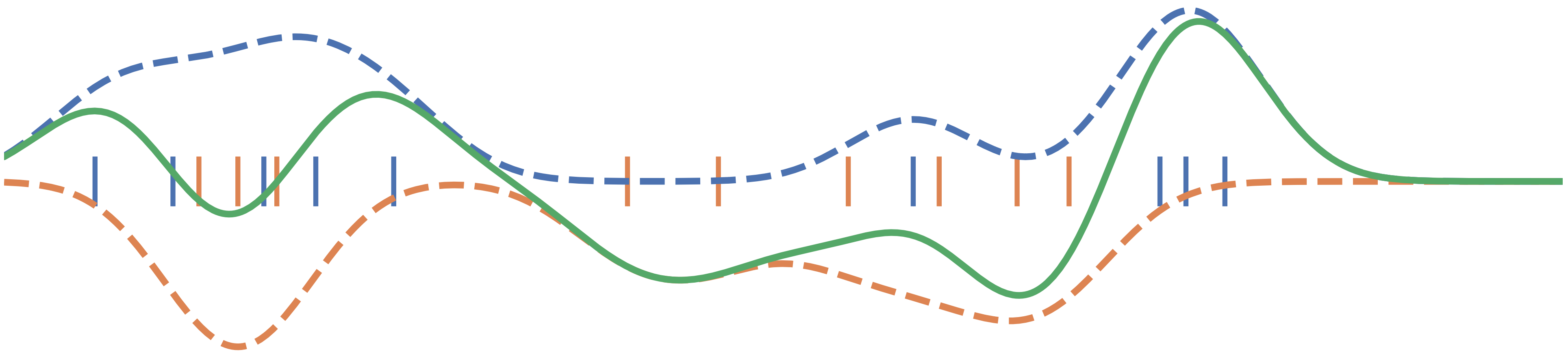

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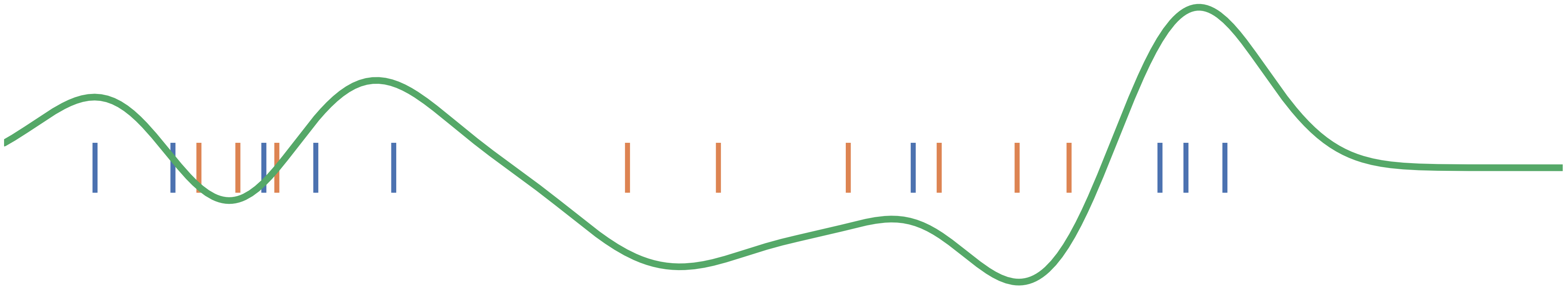

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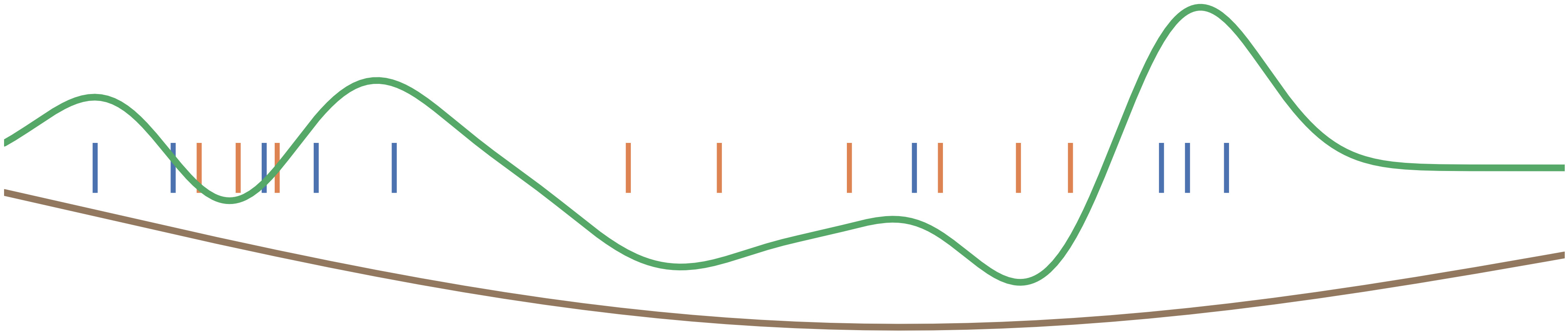

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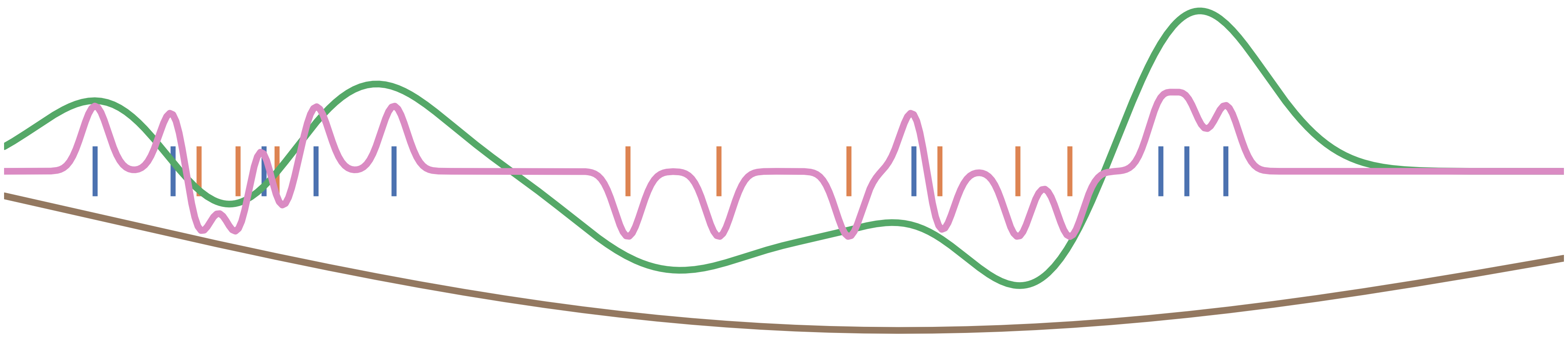

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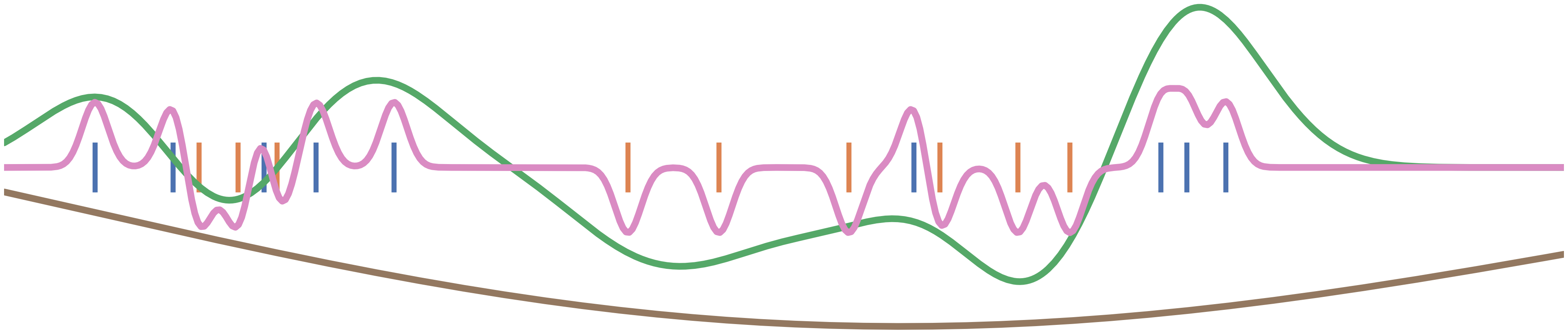
Optimal f *analytically*: $f^*(t) \propto \mathbb{E}_{X \sim \mathbb{P}}\, k(t, X) - \mathbb{E}_{Y \sim \mathbb{Q}}\, k(t, Y)$



Estimating MMD

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	1.0	0.2	0.6
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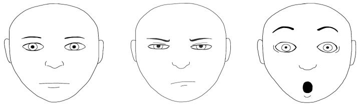
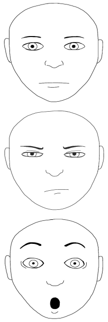

	1.0	0.8	0.7
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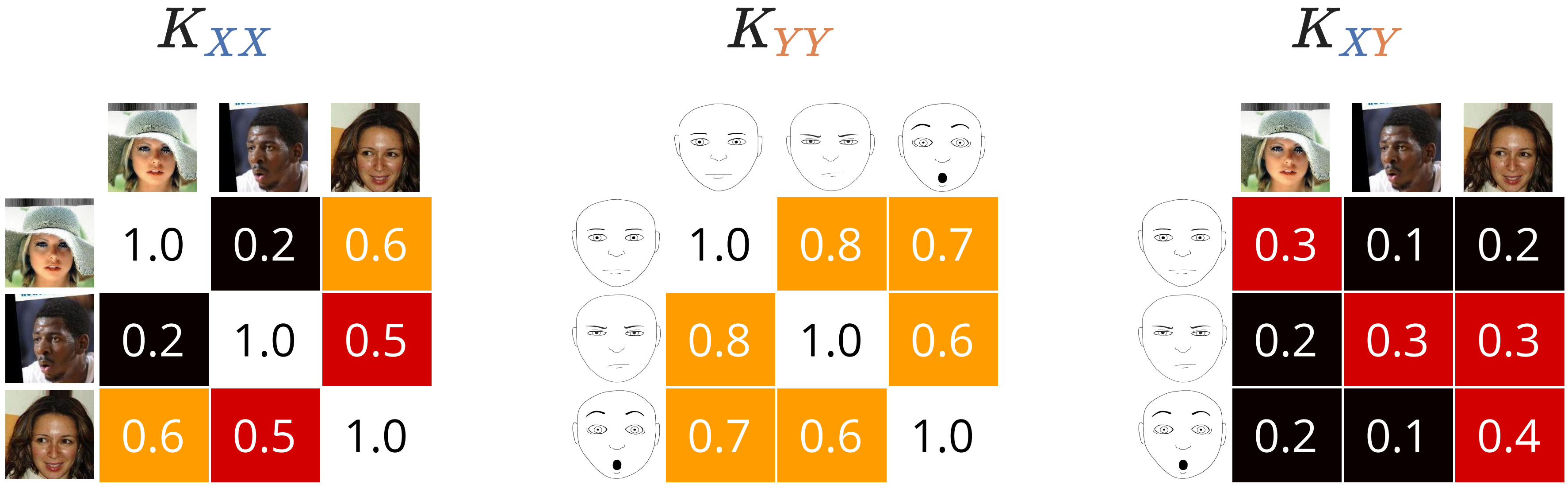

MMD models [Li+ ICML-15, Dziugaite+ UAI-15]

- No need for a discriminator – just minimize $\widehat{\mathrm{MMD}}_k$!
- Continuous loss

Critic

Generator ($\mathbb{Q}_\theta$)

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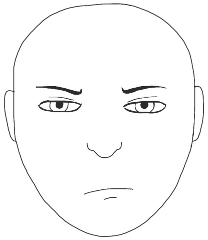

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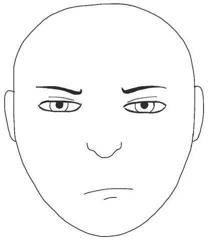

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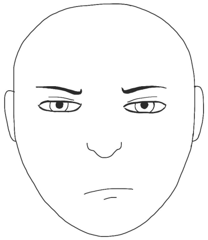

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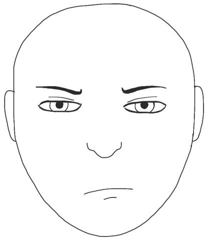

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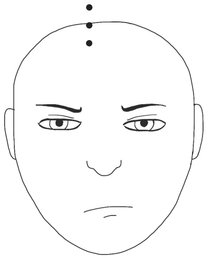

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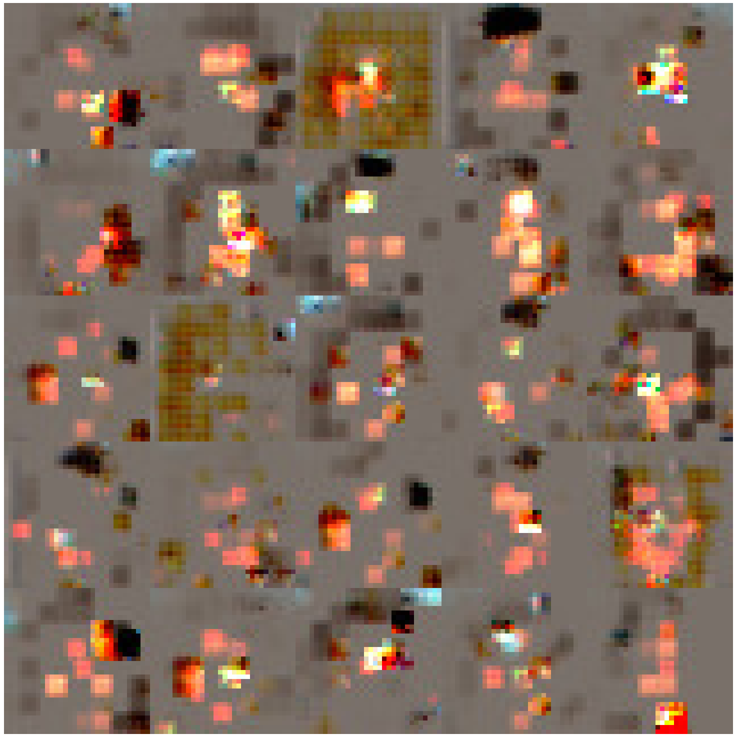

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MMD loss with a smarter kernel

$$k(x, y) = k_{\text{top}}(\phi(x), \phi(y))$$

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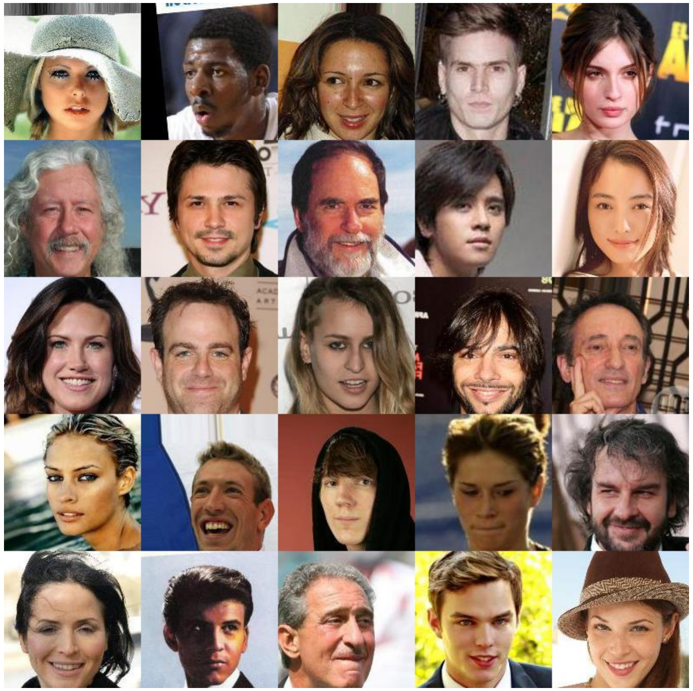

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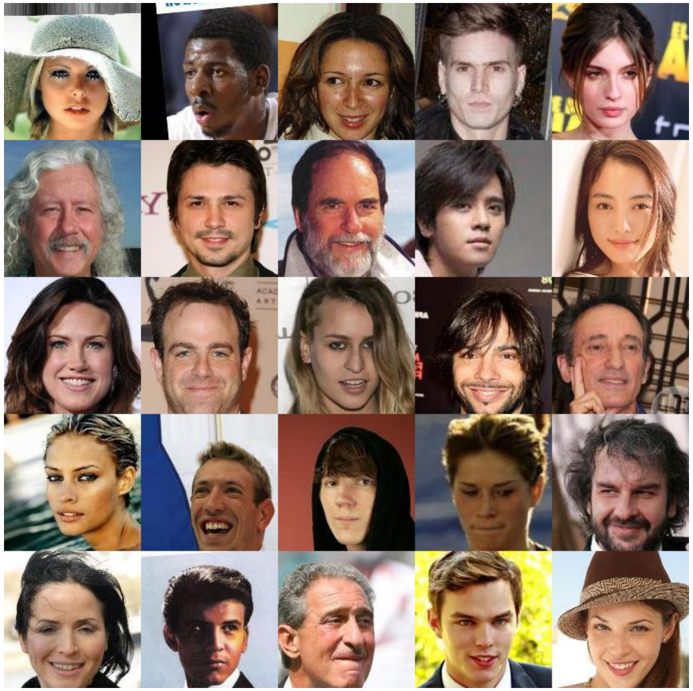

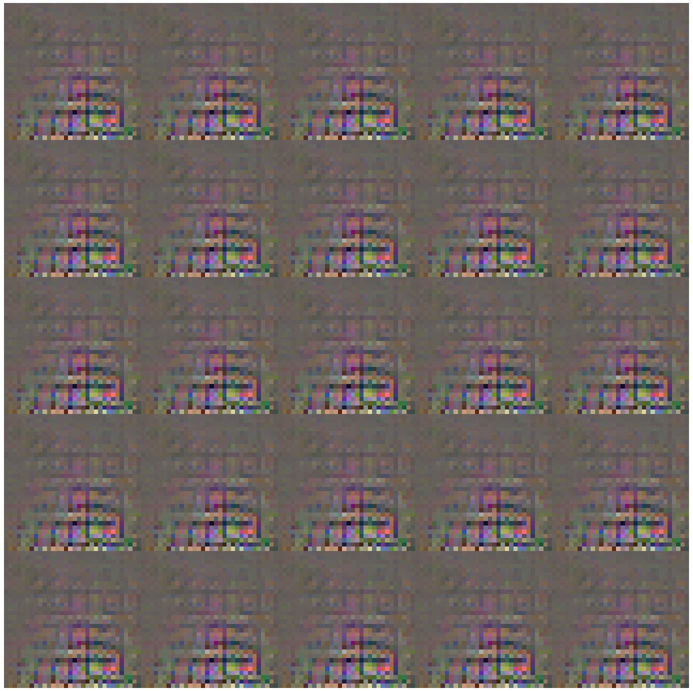

$\mathbb{P}$ $\mathbb{Q}_\theta$

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- ϕ :
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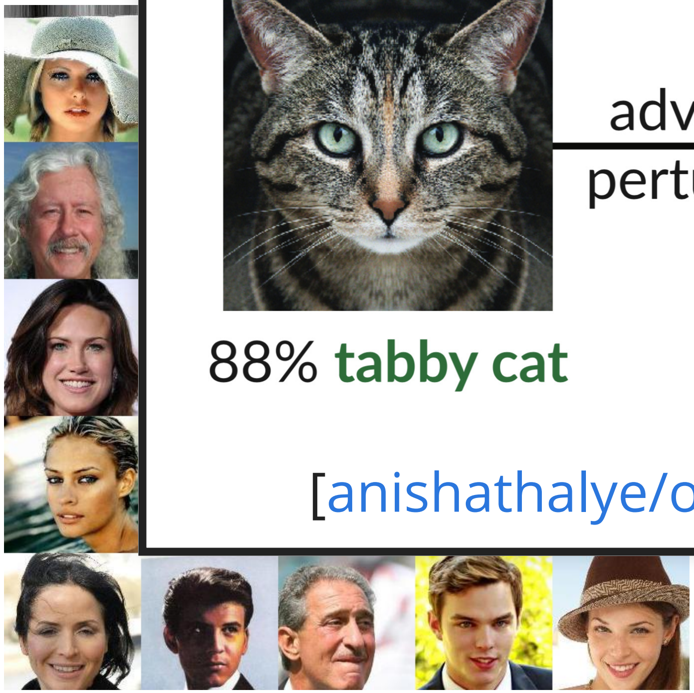

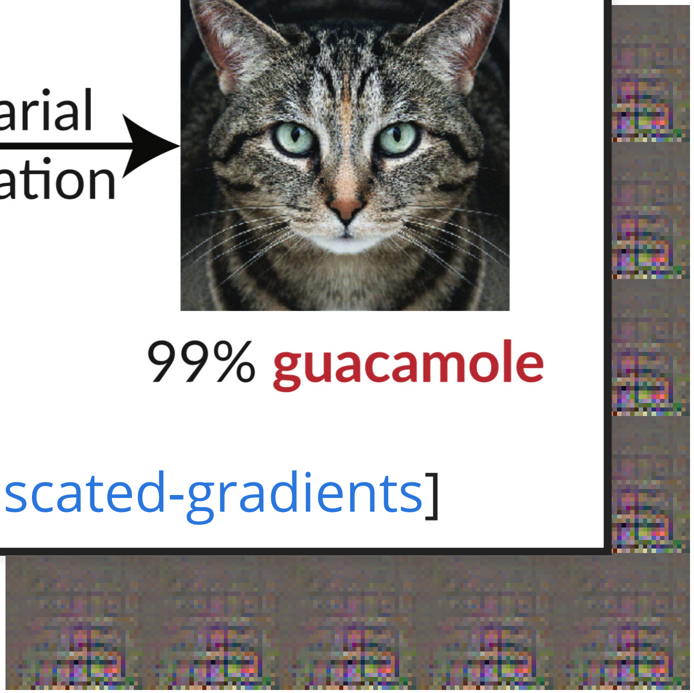

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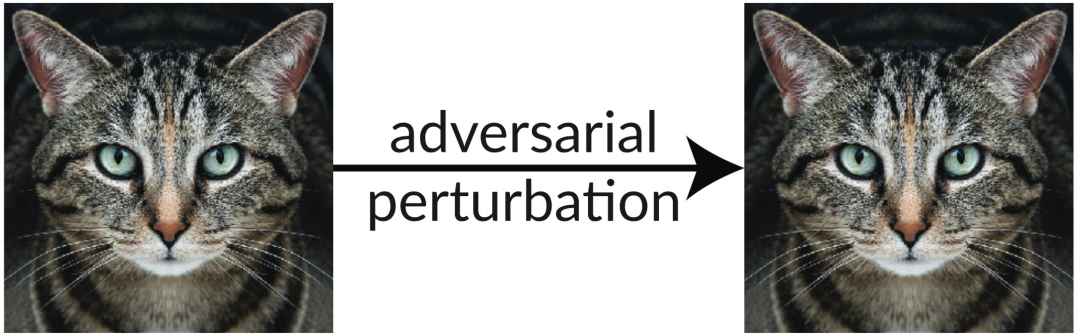
We just got adversarial examples!



88% tabby cat 99% guacamole

[anishathalye/obfuscated-gradients]

Optimized MMD: MMD GANs [Li+ NeurIPS-17]

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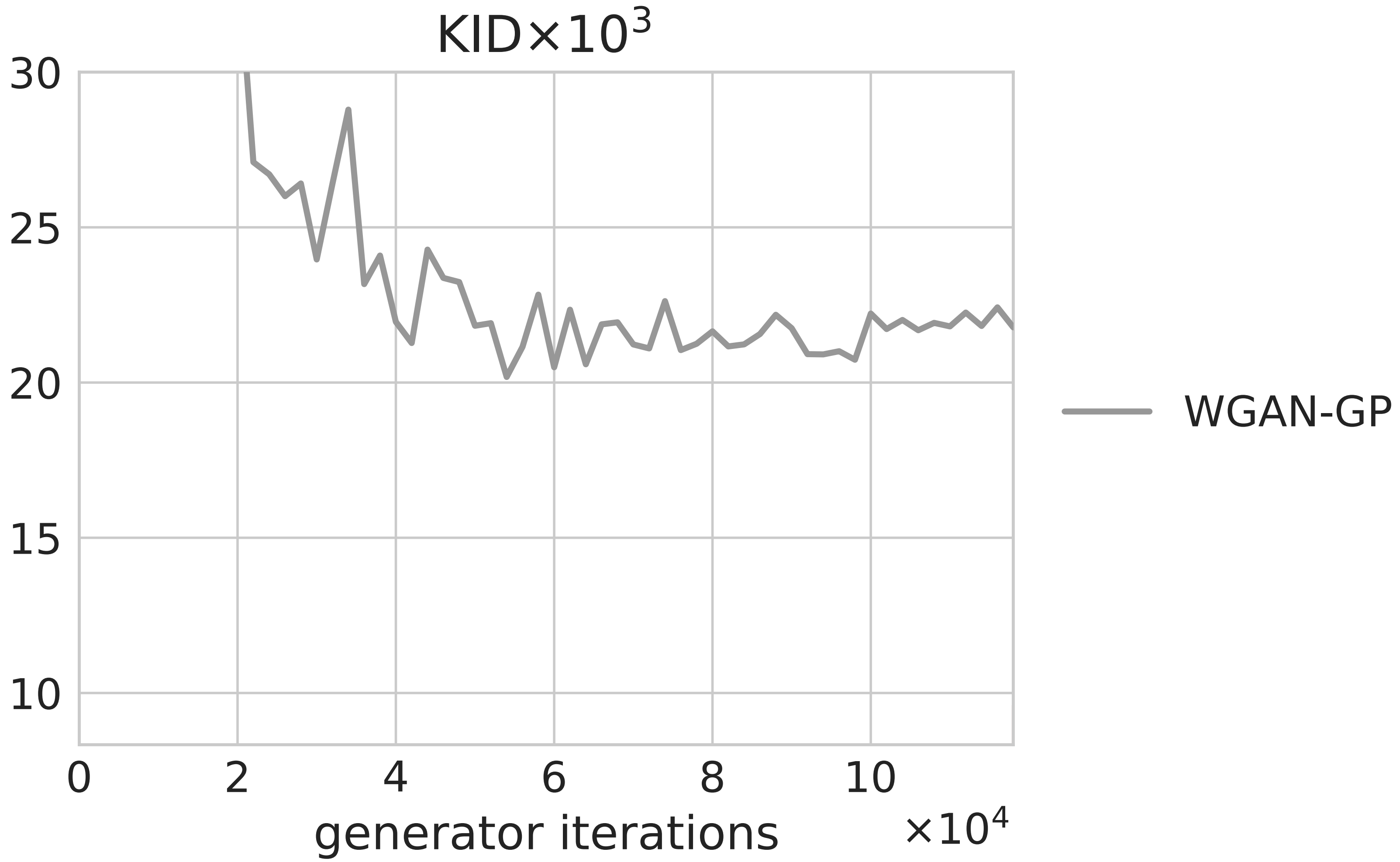
- Scaled MMD GANs [Arbel+ NeurIPS-18]
  correct $\mathcal{D}_{\text{MMD}}$ with a gradient penalty to make it continuous

Why MMD GANs?

- "Easy parts" of the optimization done *in closed form*



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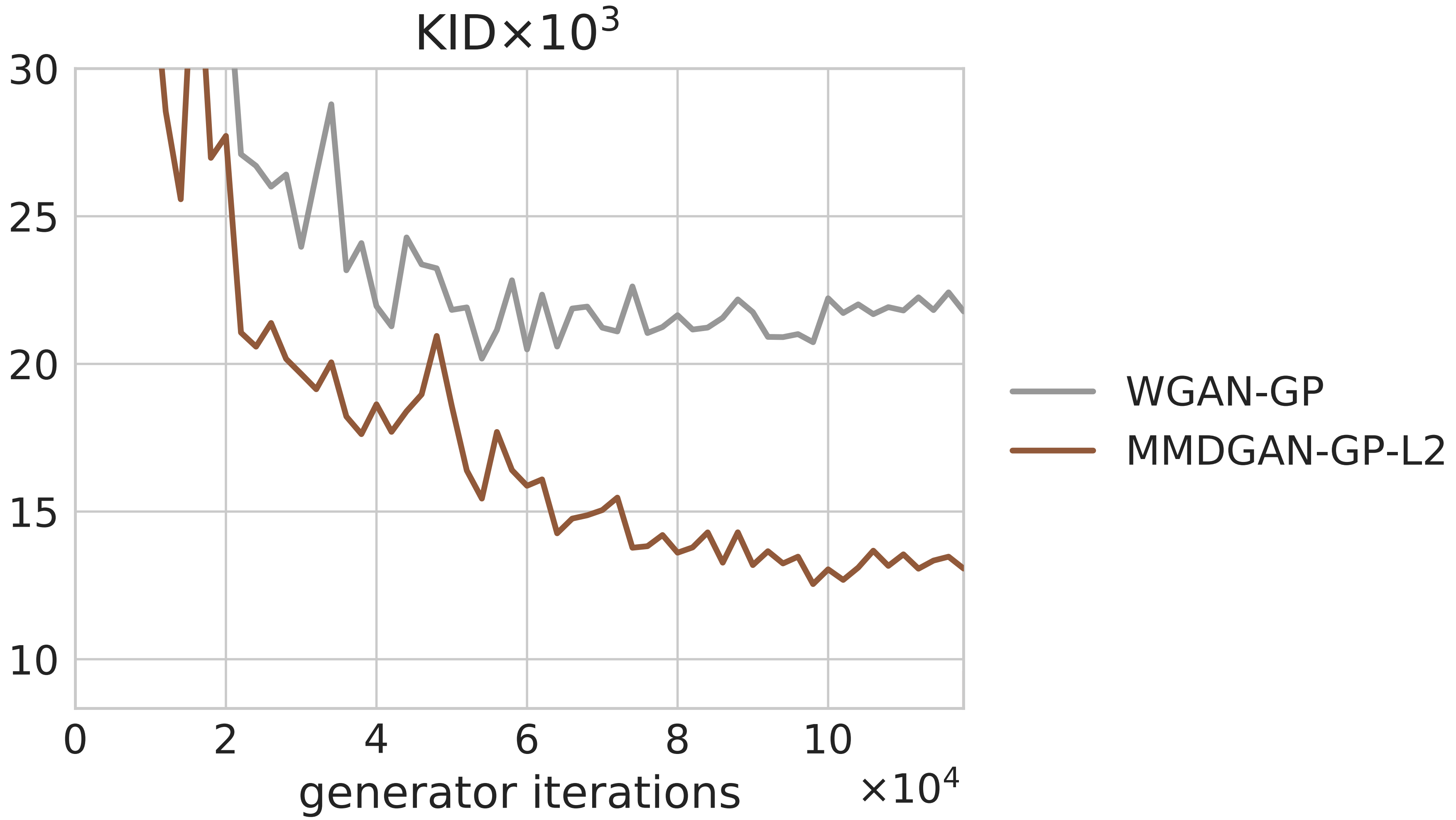

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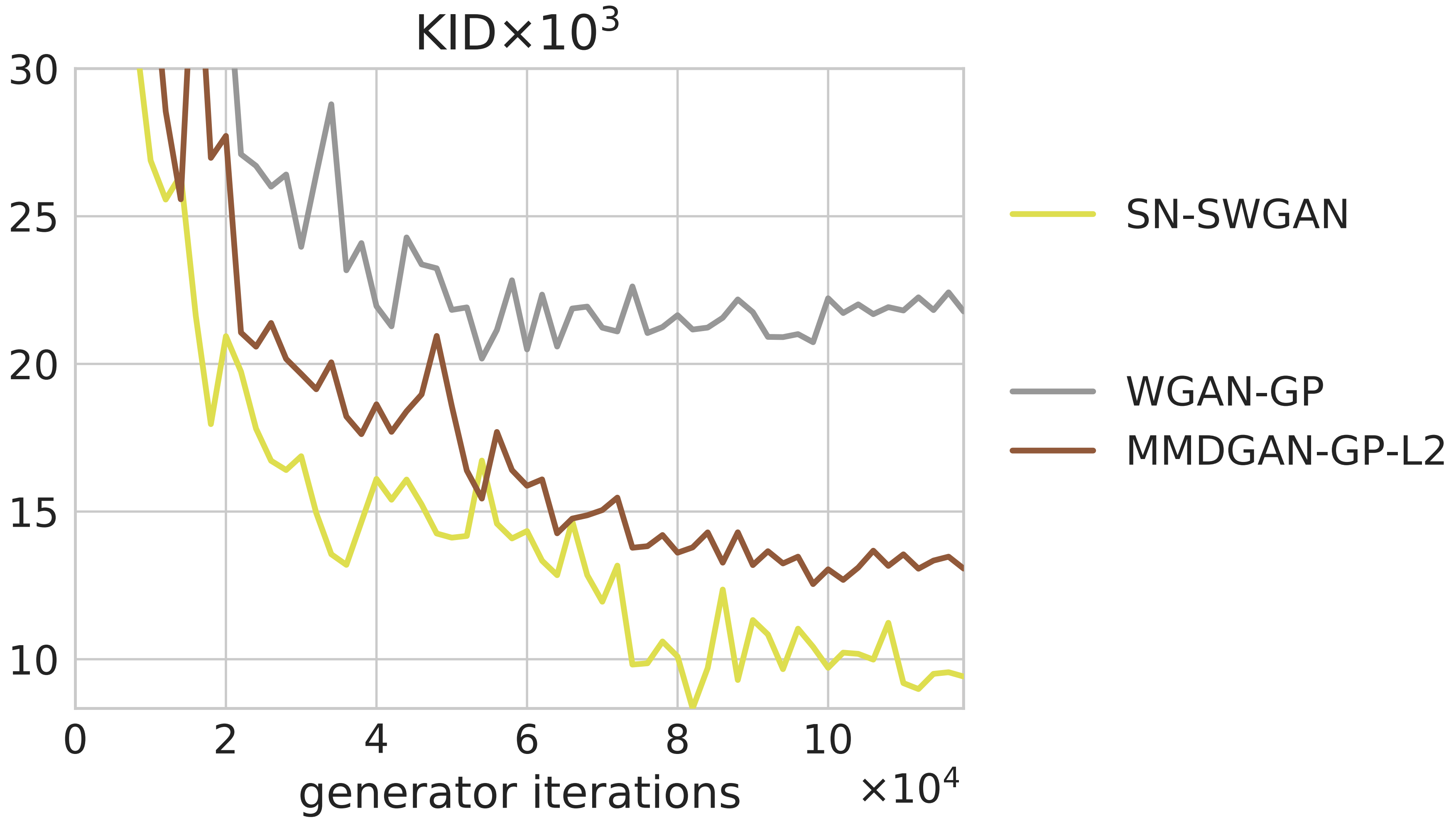

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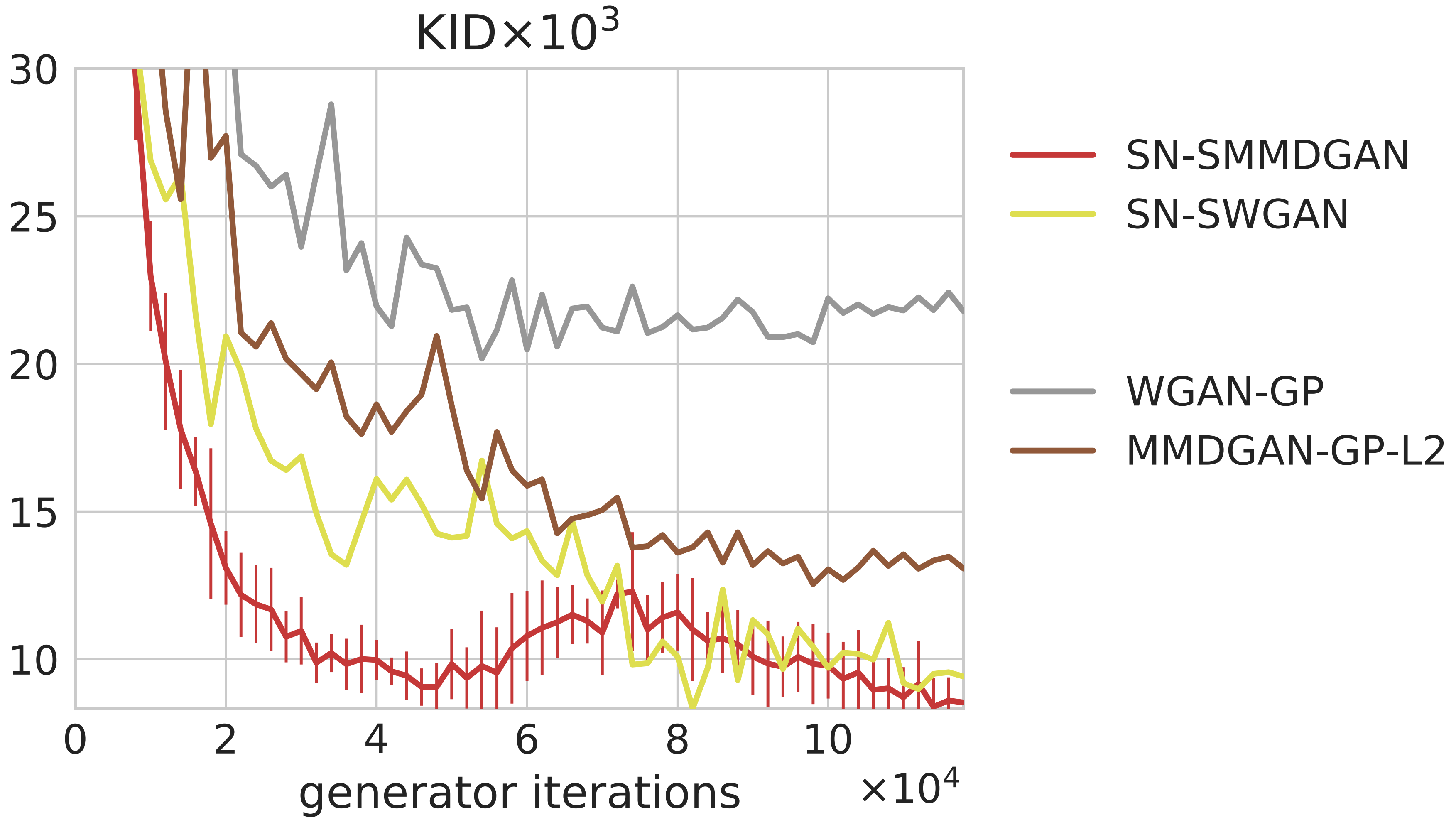

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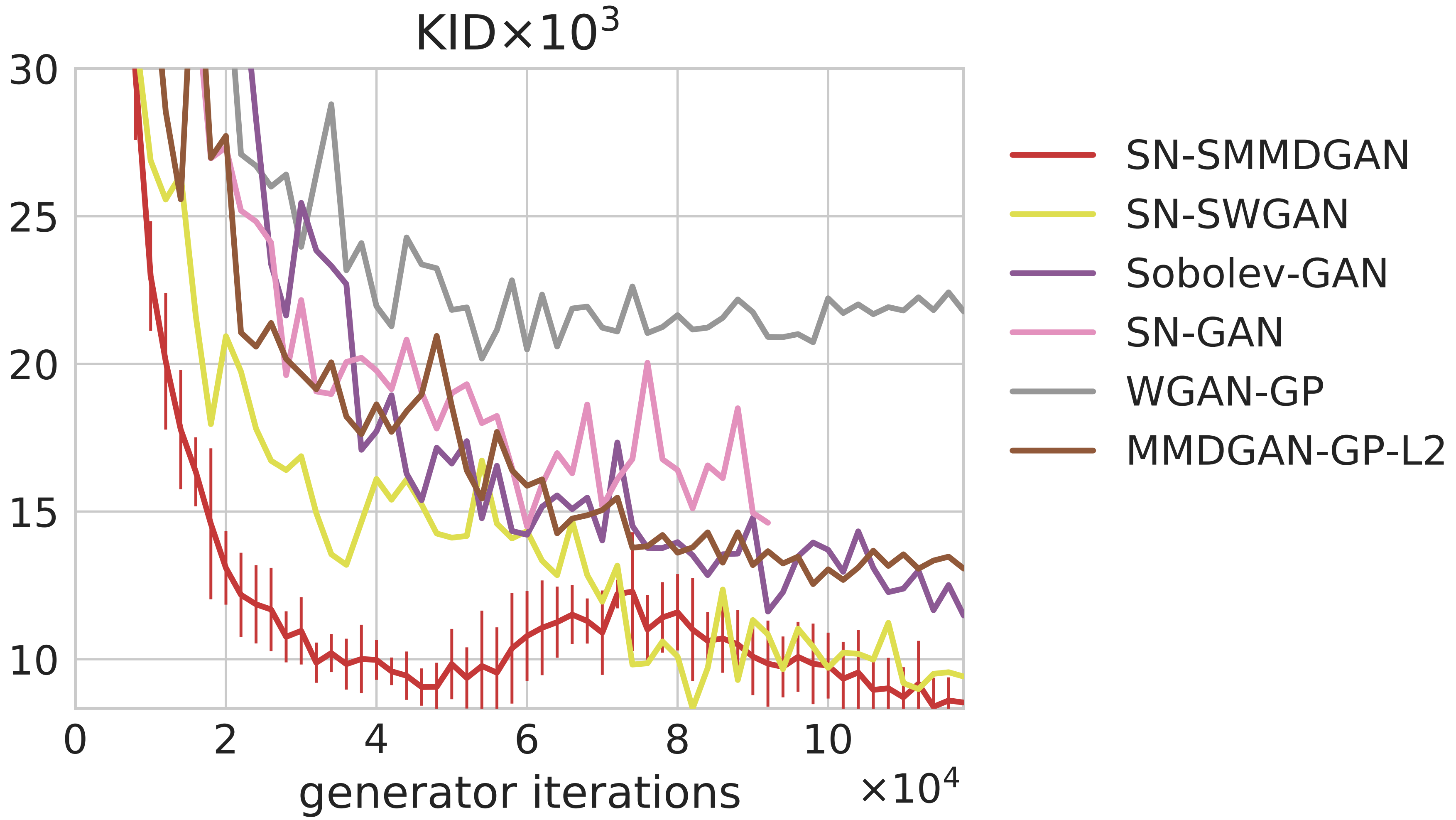
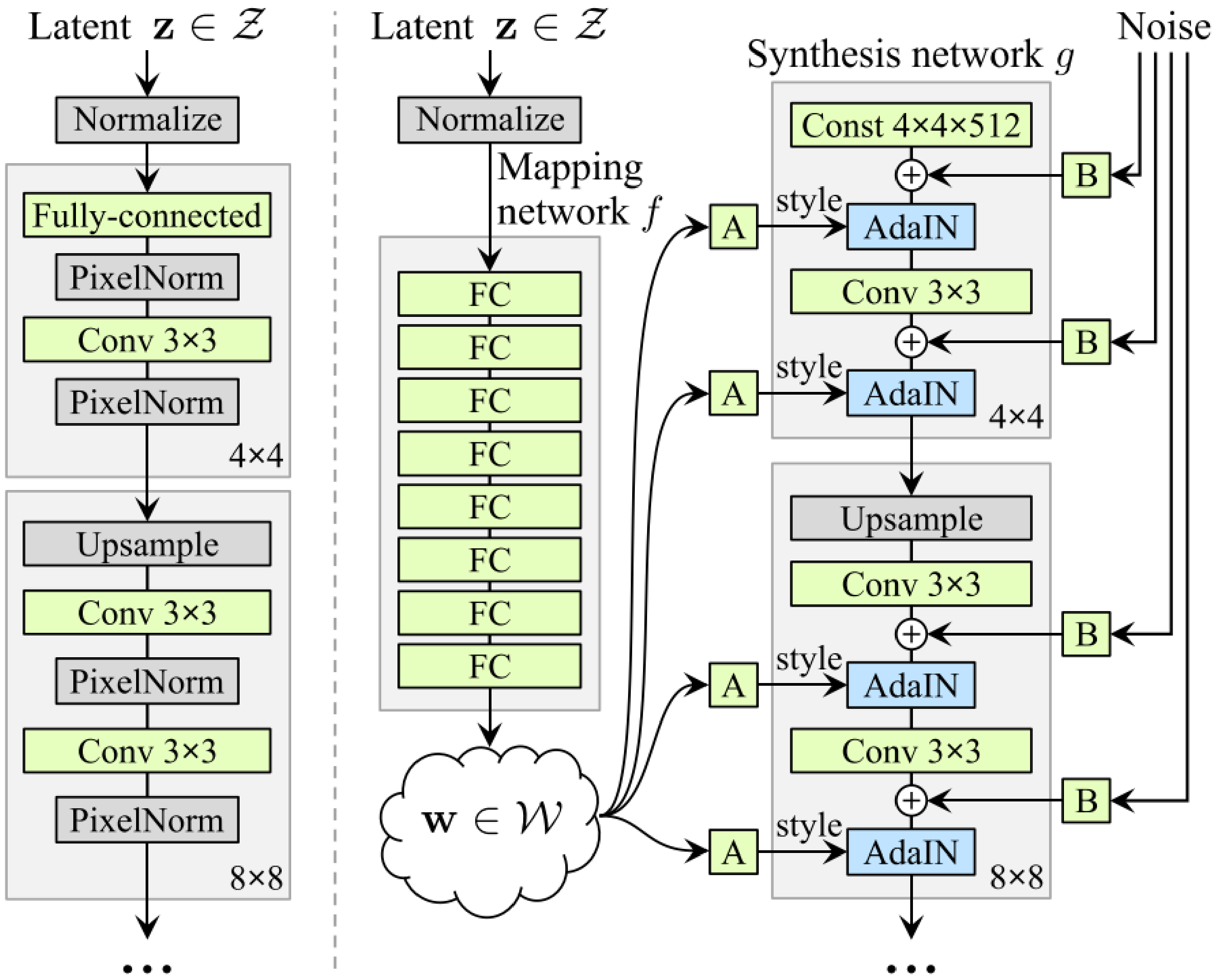


StyleGANs [Karras+ 2018]



(a) Traditional

(b) Style-based generator

StyleGAN: latent structure

StyleGAN: local noise

(a) Generated image (b) Stochastic variation (c) Standard deviation

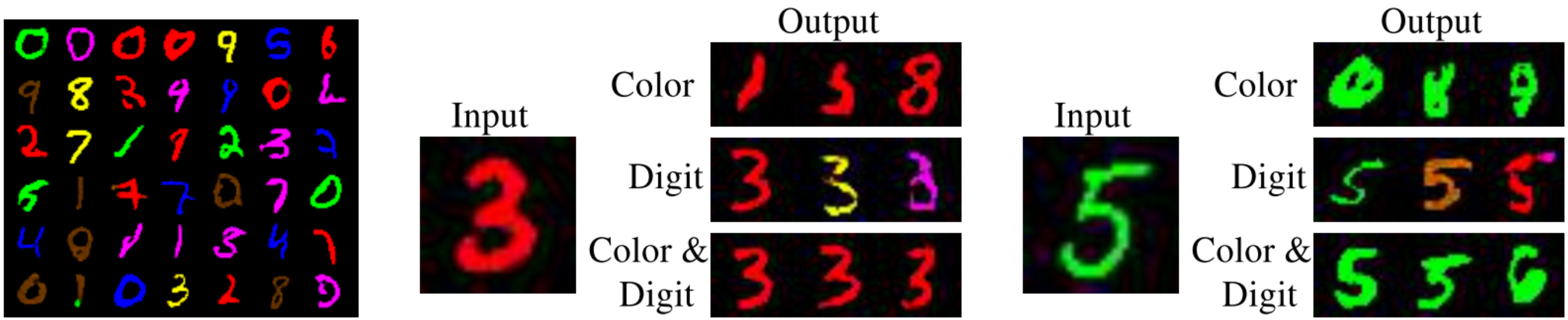
StyleGANs on a different domain [@roadrunning01]

▪

Finding samples you want [Jitkrittum+ ICML-19]

If we want to find "more samples like $\{X\}$":

$$\min_{\{Z_1,\ldots,Z_n\}} \widehat{\mathrm{MMD}}_k^2\left(\{X_i\}_{i=1}^m, \{G_\theta(Z_i)\}_{i=1}^n\right)$$



(a) Samples from DCGAN (b) Input: digit 3 in red (c) Input: digit 5 in green

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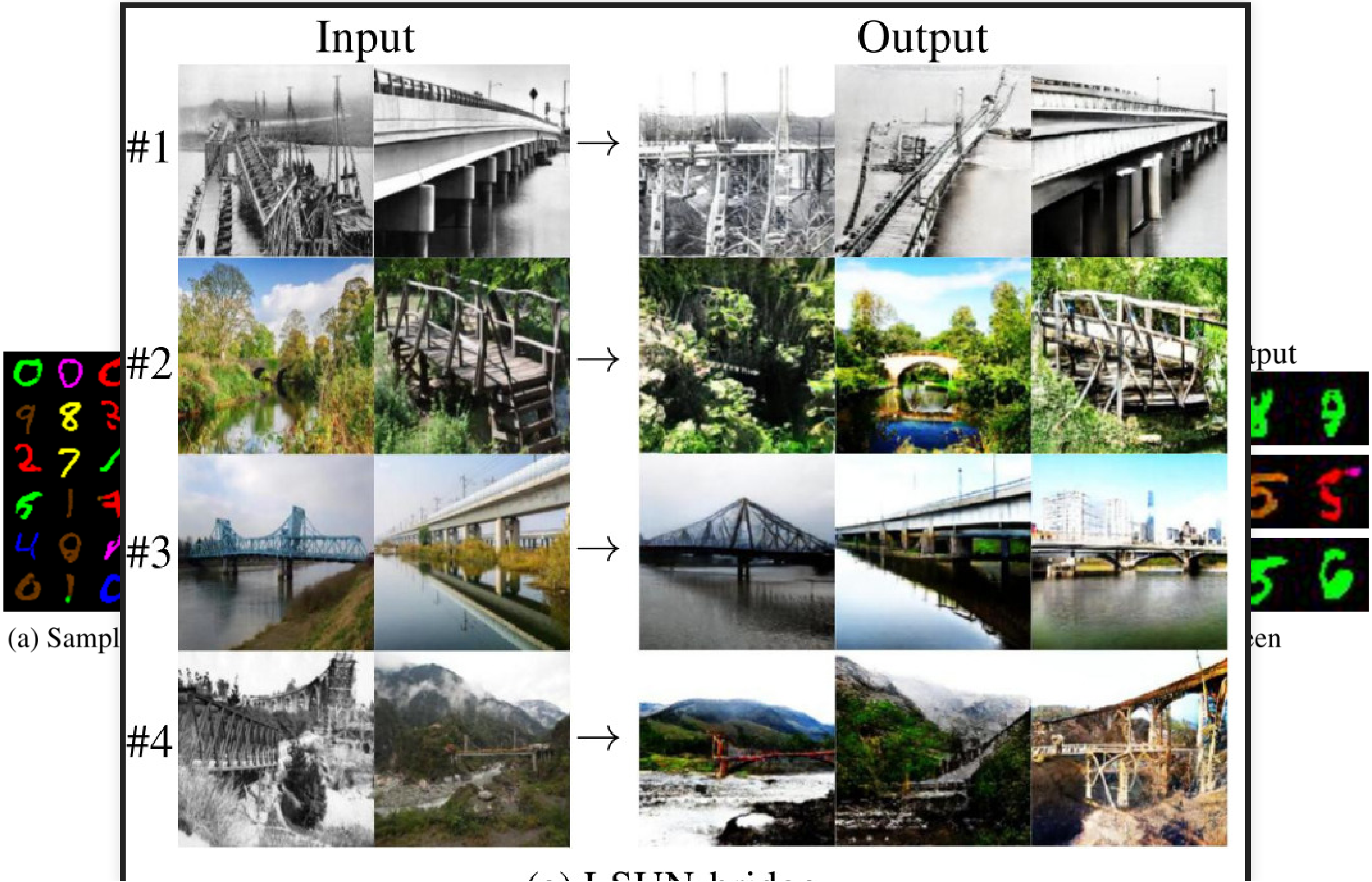

Conditional GANs and BigGAN

- Conditional GANs: [Mirza+ 2014]
  - Just add a class label as input to G_θ and D_ψ
- BigGAN [Brock+ ICLR-19]: a bunch of tricks to make it huge

Image-to-image translation [Isola+ CVPR-17]

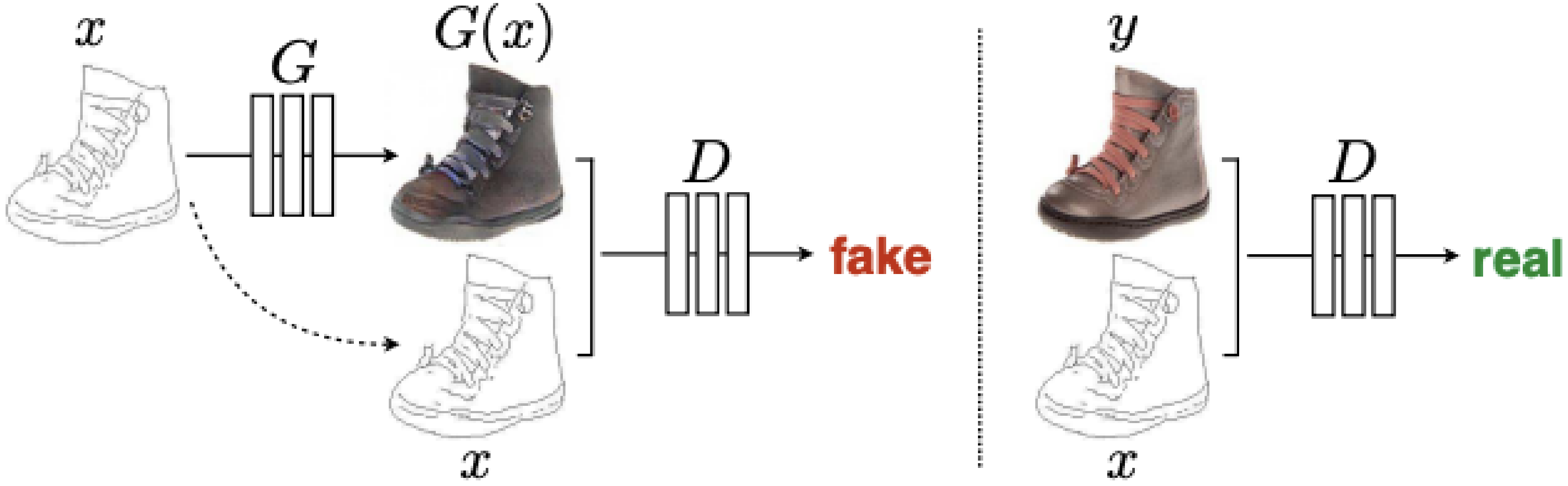

Figure 2: Training a conditional GAN to map edges→photo. The discriminator, D, learns to classify between fake (synthesized by the generator) and real {edge, photo} tuples. The generator, G, learns to fool the discriminator. Unlike an unconditional GAN, both the generator and discriminator observe the input edge map.

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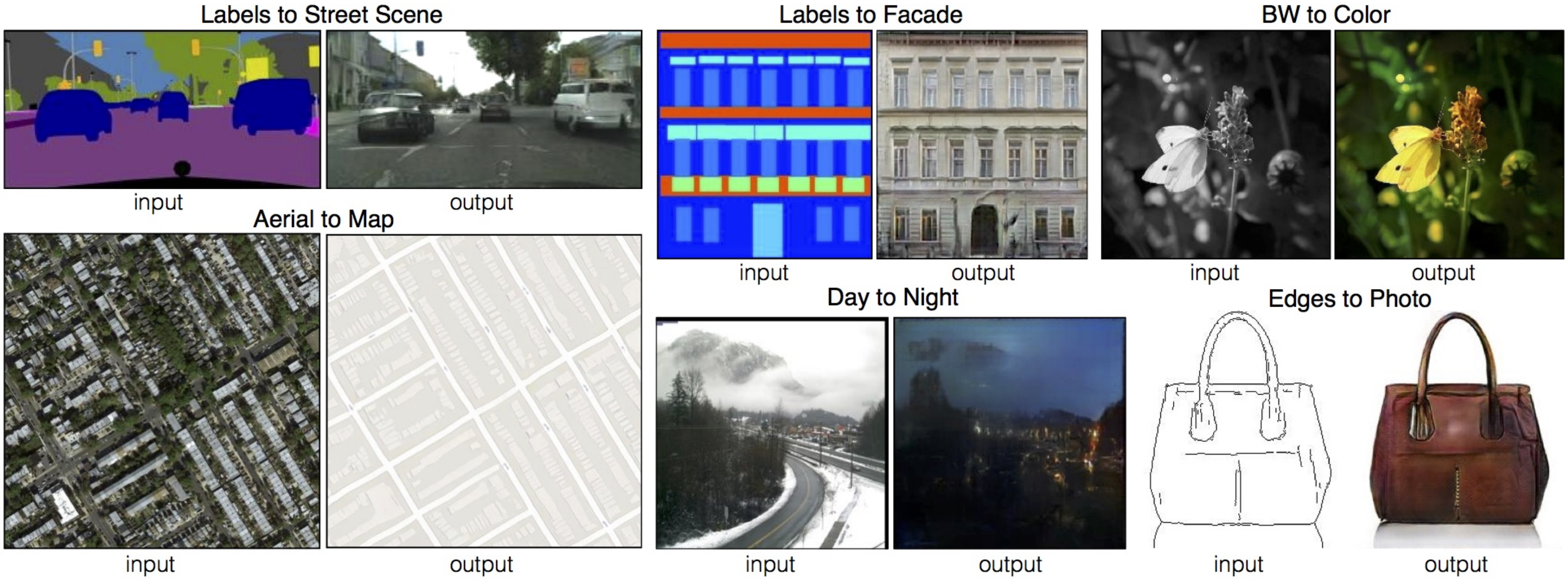
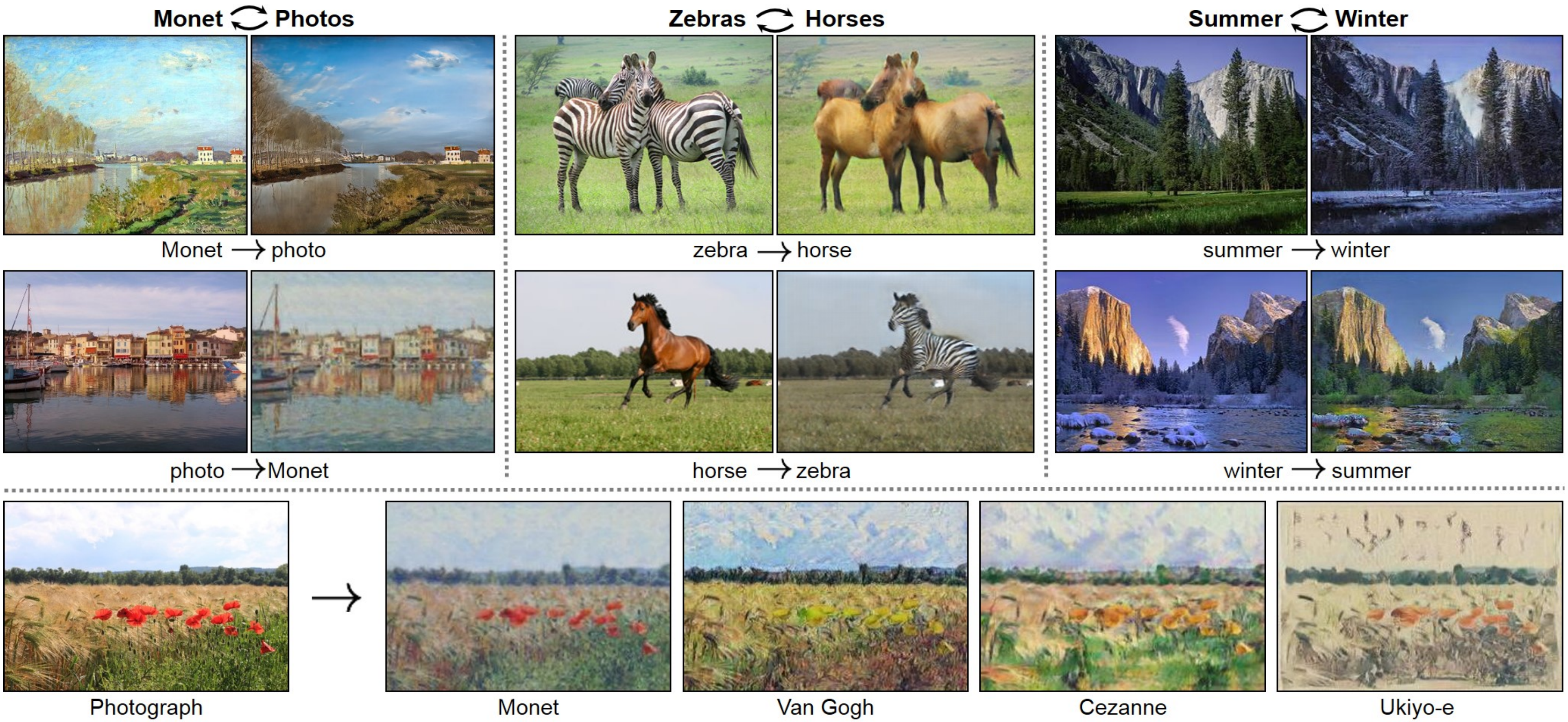


CycleGAN [Zhu+ ICCV-17]



Pose-to-image translation [Chan+ 2018]

▪

DeepFakes

Use your new knowledge for good!

Slides (including links to papers) are online:

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