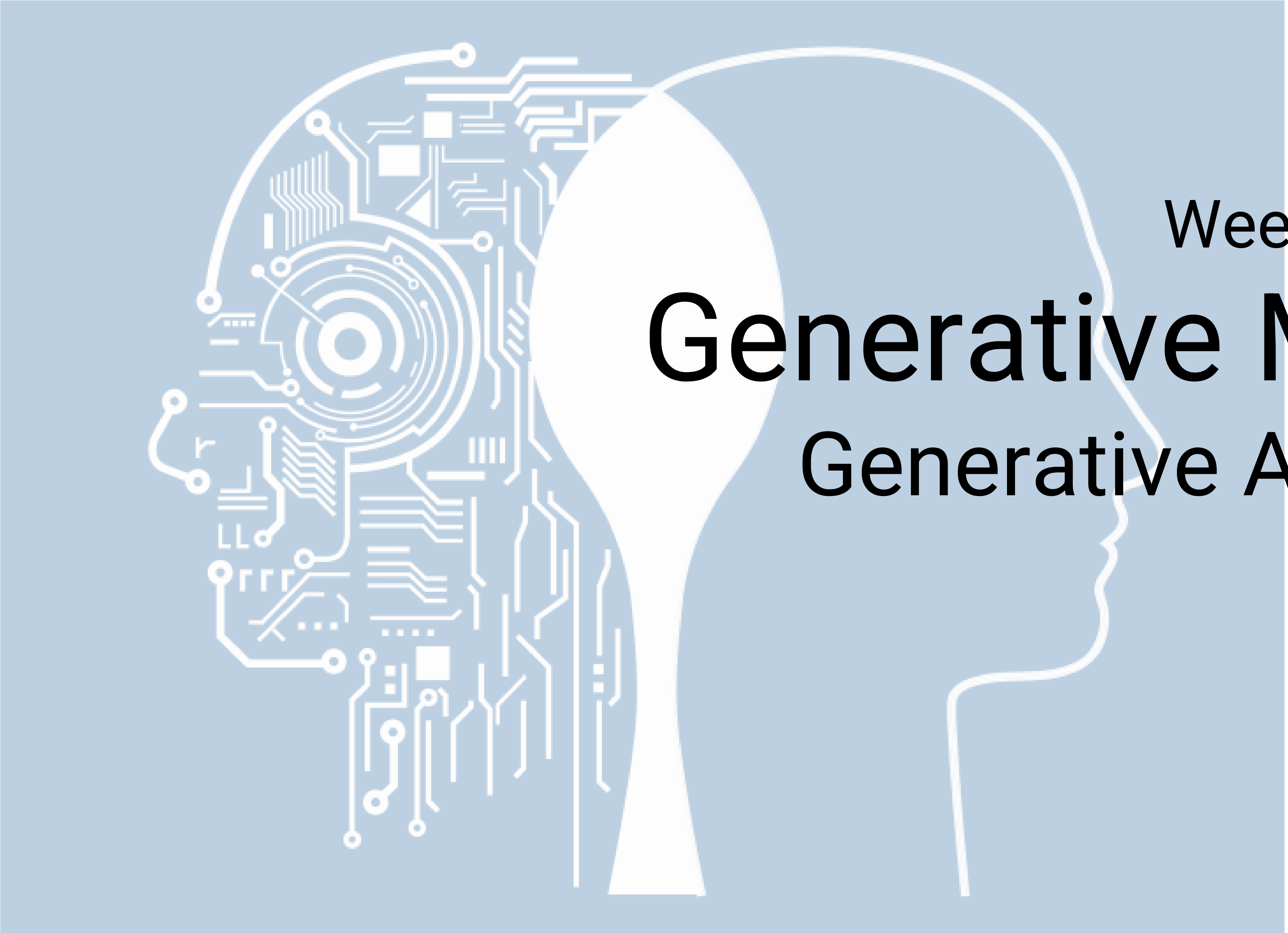
Class core values

1. Be **respect**ful to yourself and others
2. Be **confident** and believe in yourself
3. Always do your **best**
4. Be **cooperative**
5. Be **creative**
6. Have **fun**
7. Be **patient** with yourself while you learn
8. Don’t be shy to **ask “stupid” questions**
9. Be **inclusive** and **accepting**



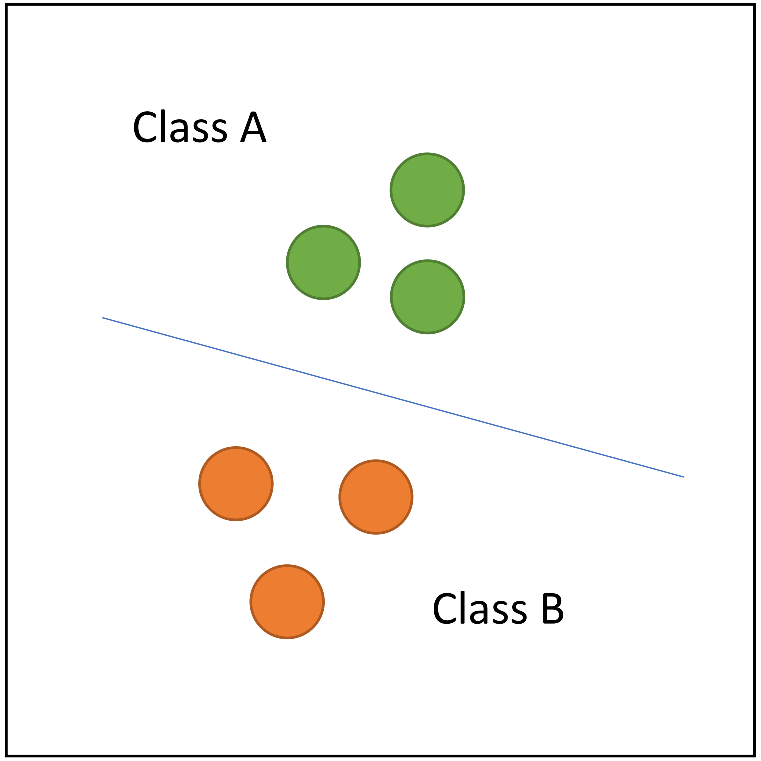
Week 8, Lecture 2

Generative Models:

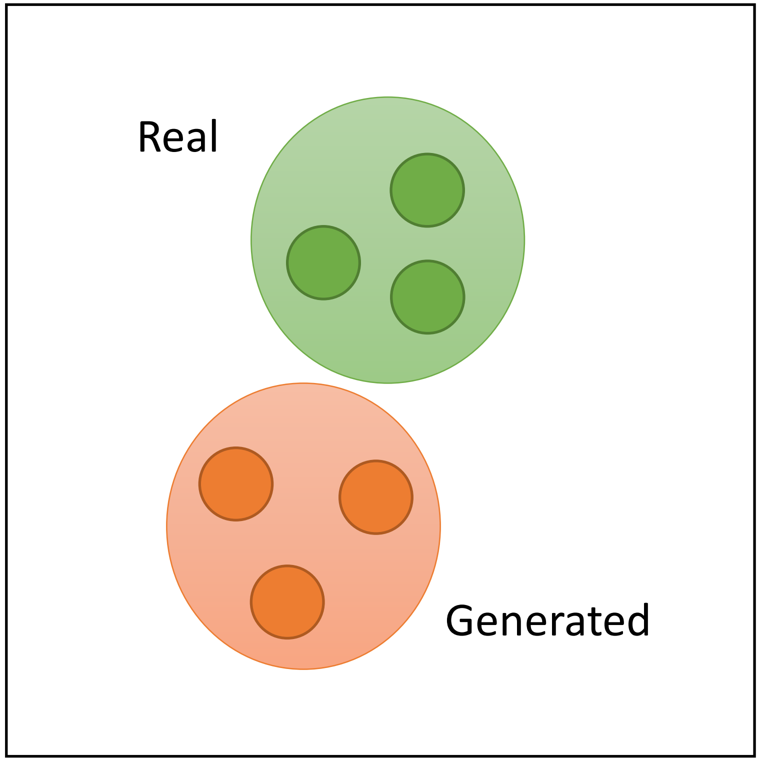
Generative Adversarial Networks

Discriminative and generative models

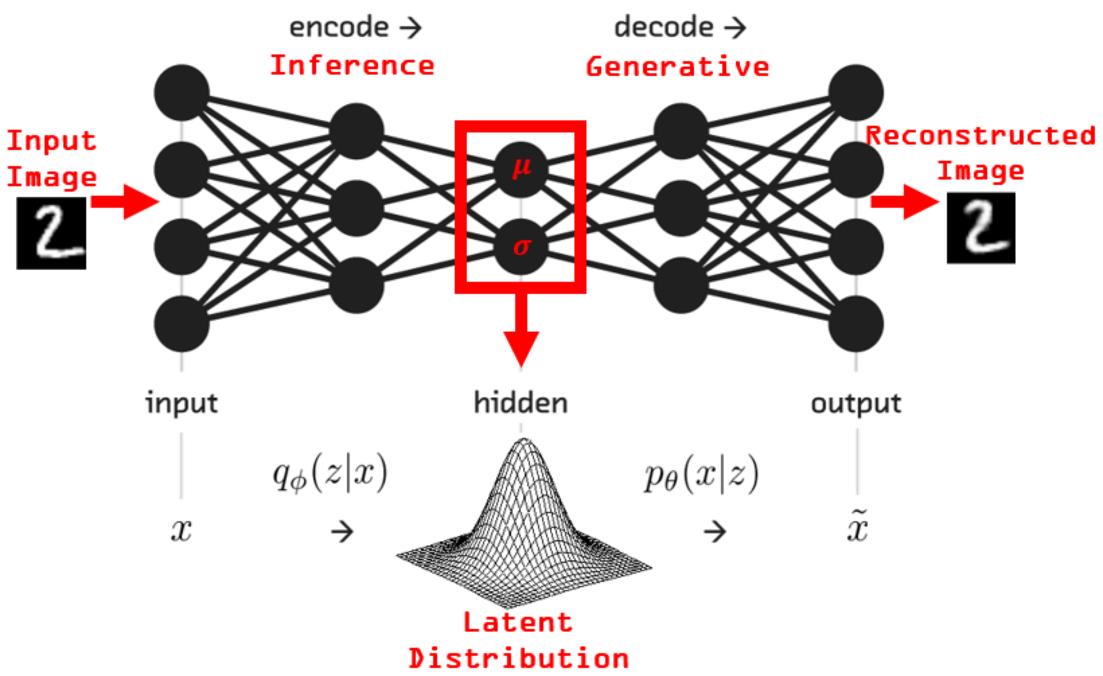
Discriminative

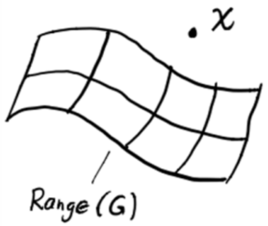


Generative



VAEs and explicit density





$$p(z|x) = \frac{p(x|z)\,p(z)}{p(x)}$$

$$p(x) = \int p(x|z)\,p(z)\,dz$$

Problem: intractable

Estimate

Functions (e.g., Gaussians)

$$q_x(z) \equiv \mathcal{N}(g(x), h(x)) \qquad g \in G \qquad h \in H$$

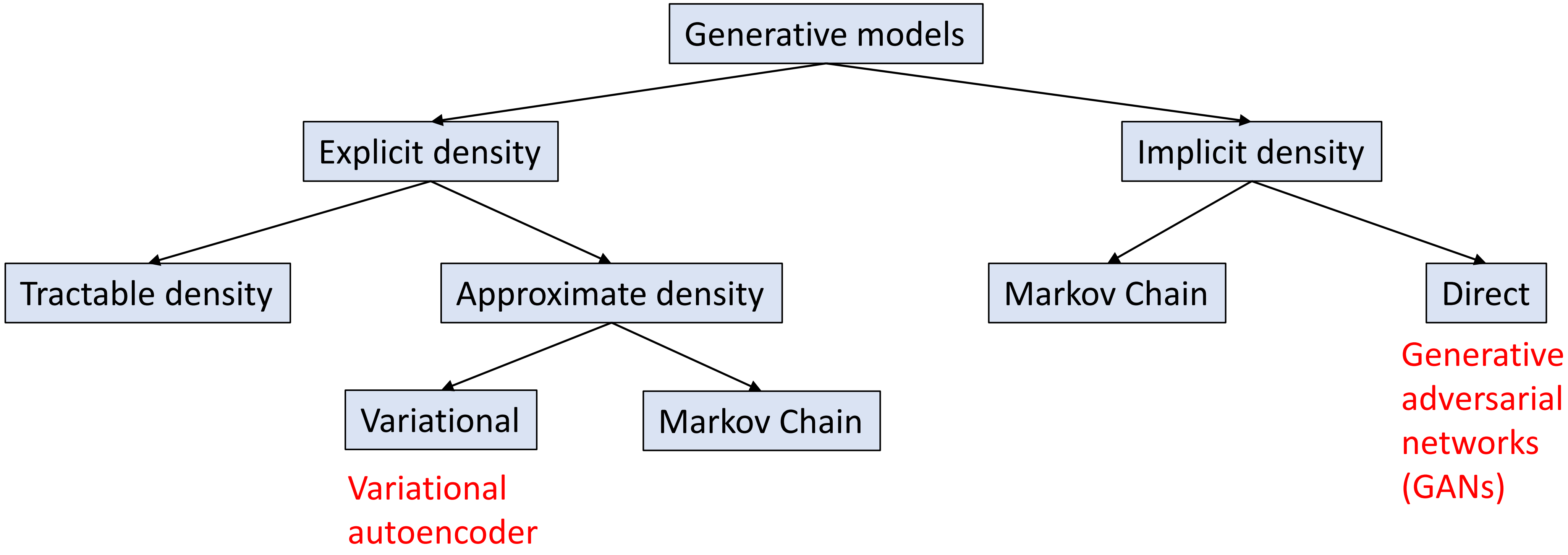
Solution: tractable

Optimizing lower bound of probability distribution

$$\begin{aligned}
(g^*, h^*) &= \underset{(g,h)\in G\times H}{\arg\min}\ KL(q_x(z), p(z|x)) \\
&= \underset{(g,h)\in G\times H}{\arg\min} \left(\mathbb{E}_{z\sim q_x}(\log q_x(z)) - \mathbb{E}_{z\sim q_x}\left(\log \frac{p(x|z)p(z)}{p(x)}\right)\right) \\
&= \underset{(g,h)\in G\times H}{\arg\min} \left(\mathbb{E}_{z\sim q_x}(\log q_x(z)) - \mathbb{E}_{z\sim q_x}(\log p(z)) - \mathbb{E}_{z\sim q_x}(\log p(x|z)) + \mathbb{E}_{z\sim q_x}(\log p(x))\right) \\
&= \underset{(g,h)\in G\times H}{\arg\max} \left(\mathbb{E}_{z\sim q_x}(\log p(x|z)) - KL(q_x(z), p(z))\right) \\
&= \underset{(g,h)\in G\times H}{\arg\max} \left(\mathbb{E}_{z\sim q_x}\left(-\frac{||x - f(z)||^2}{2c}\right) - KL(q_x(z), p(z))\right)
\end{aligned}$$

Image from [NEU CS7150: VAEs]

Taxonomy of generative models



What you can do with GANs

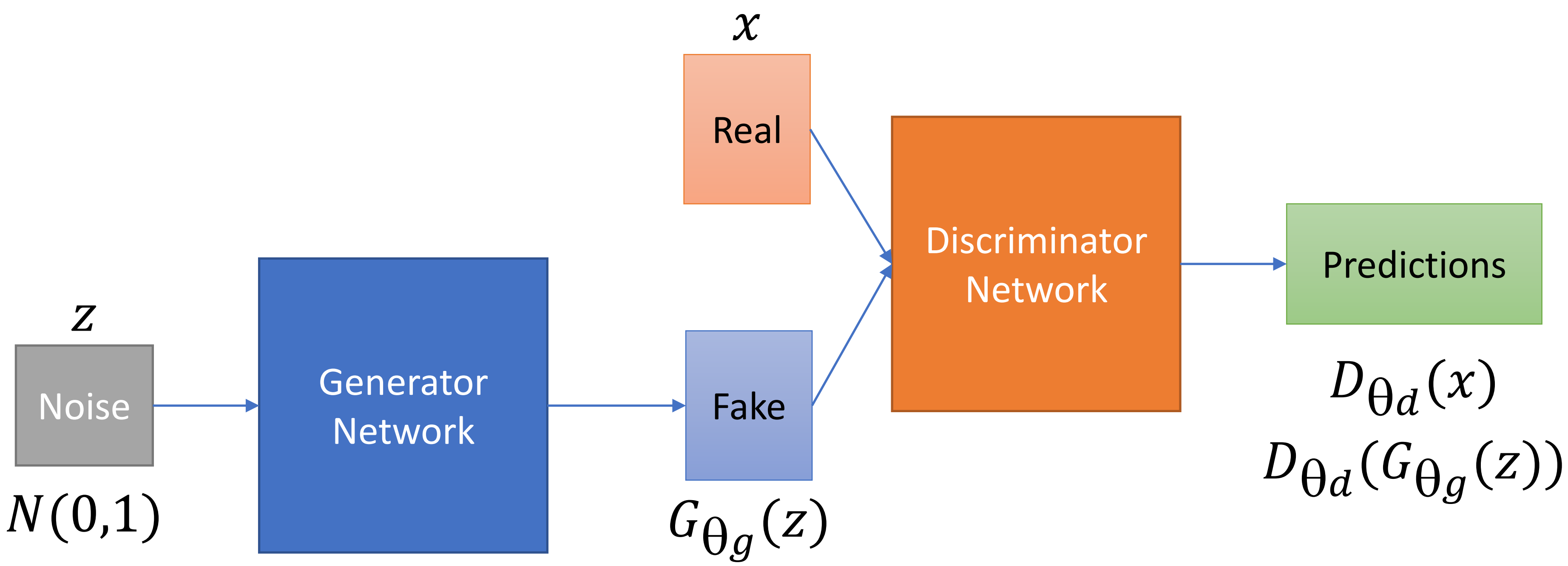



https://thispersondoesnotexist.com/image

What you can do with GANs

https://thispersondoesnotexist.com/image

Generative adversarial networks



Idea behind GANs

Evolutionary arms race

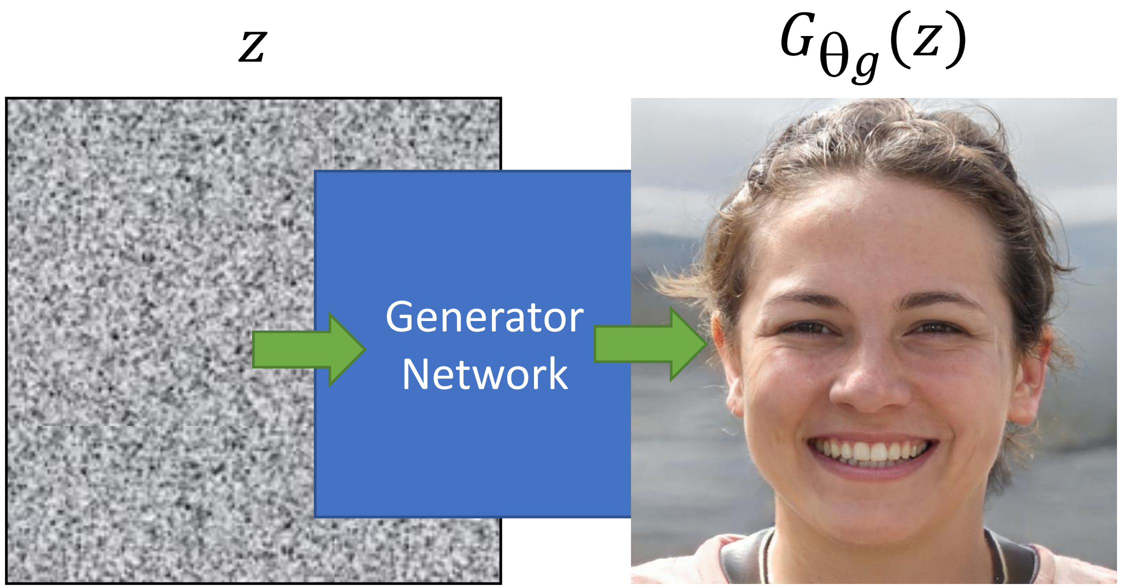
Image from [What Is the Evolutionary Arms Race?]

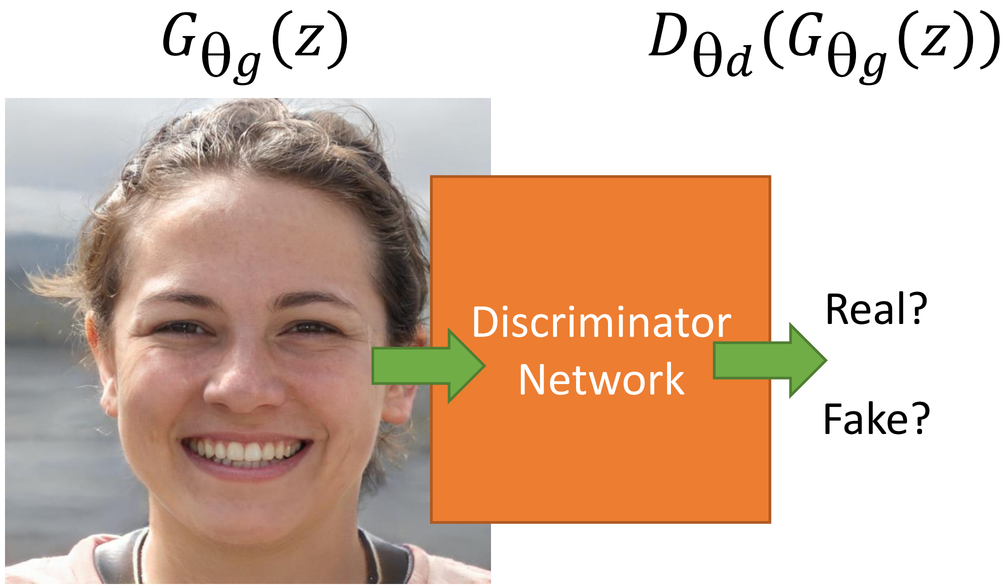
Idea behind GANs

Evolutionary arms race

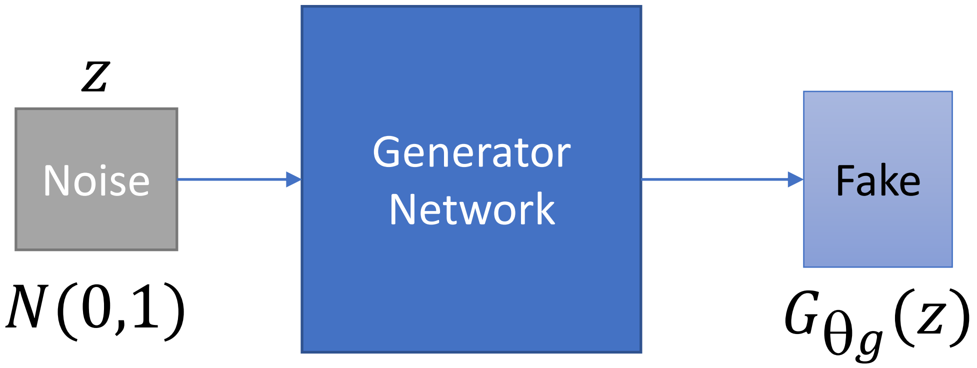
Image from [What Is the Evolutionary Arms Race?](#) [Coevolution and Evolutionary Arms Races](#)

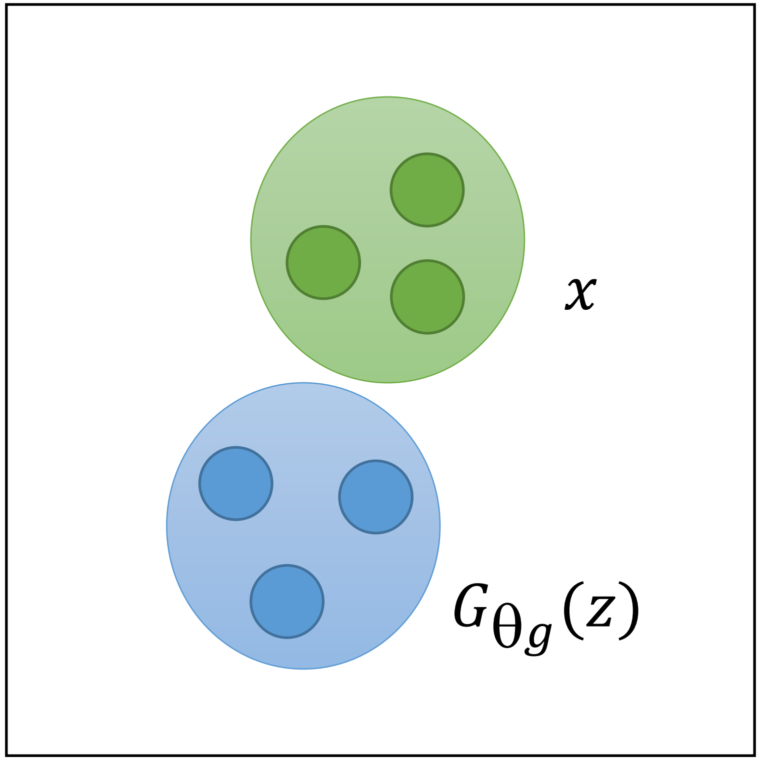
Generator vs discriminator





Generator



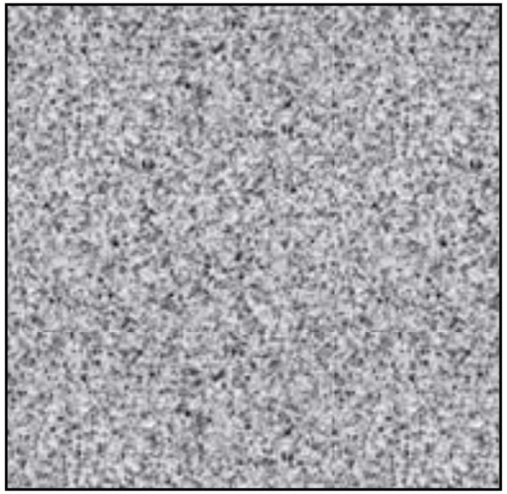


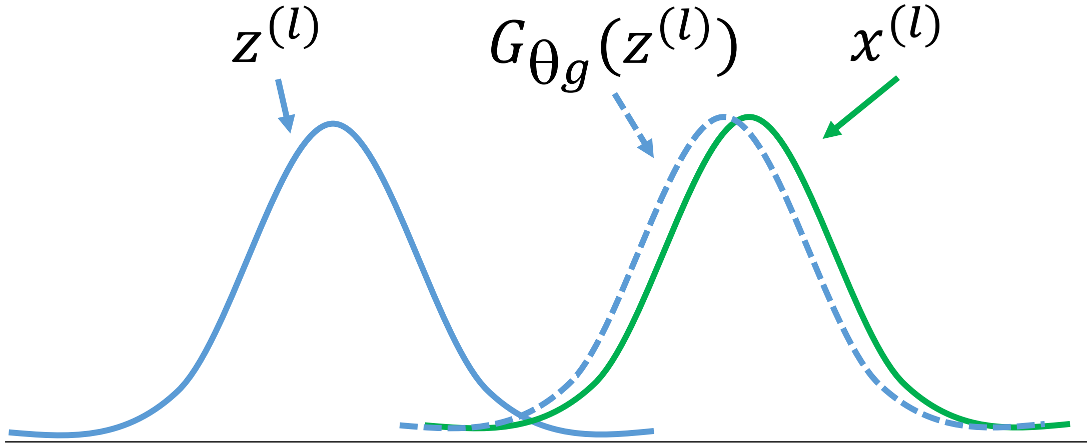
Random noise as input

$N(0,1)$

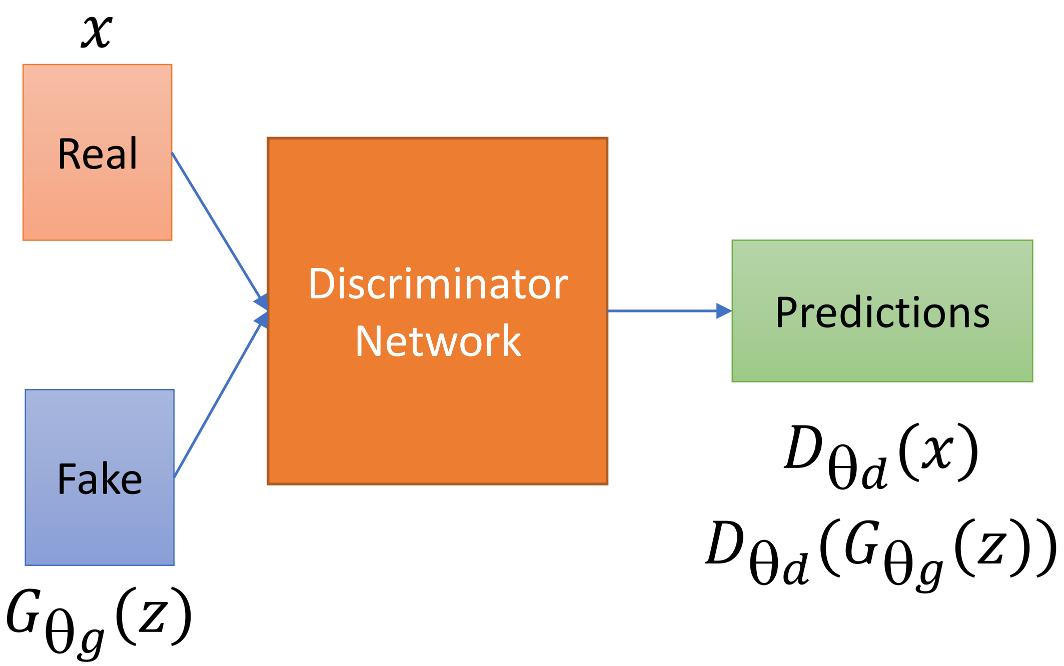
z
0.916767
0.862388
0.972409
0.258342
0.836252
0.969561
0.502568
0.634358
0.360669
0.567881
0.248232
0.464164
0.385207
0.592359
0.320633
0.549819
0.087568
0.369488
0.103373
.
.
.

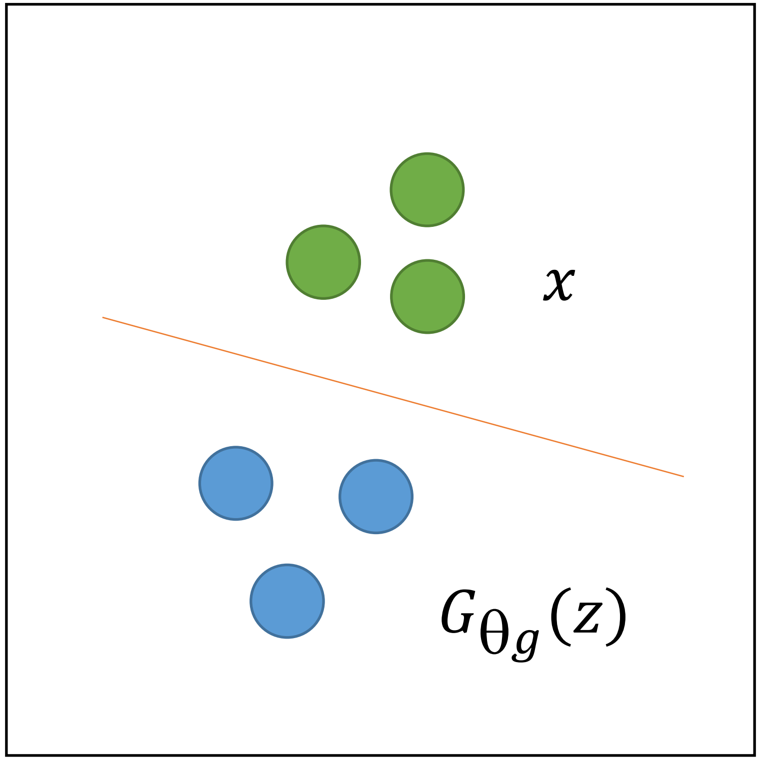
$\xrightarrow{\text{reshape}}$





Discriminator





Real vs fake

Real vs fake

x

$D_{\theta_d}(x)$ Real ✓ Fake ✗

$G_{\theta_g}(z)$

$D_{\theta_d}(G_{\theta_g}(z))$ Real ✗ Fake ✓

Real vs fake

x

$D_{\theta_d}(x)$ Real ✓ Fake ✗

$G_{\theta_g}(z)$

$G_{\theta_g}(z)$ Real ✓ Fake ✗

Objective function

$$\min_{\theta_g}\max_{\theta_d}\left[\mathbb{E}_{x\sim p_{data}}\log \underbrace{D_{\theta_d}(x)}_{\text{Discriminator output for real data x}} + \mathbb{E}_{z\sim p(z)}\log(1-\underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\text{Discriminator output for generated fake data G(z)}})\right]$$

Image from Stanford CS231

Objective function

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log \underbrace{D_{\theta_d}(x)}_{\text{Discriminator output for real data x}} + \mathbb{E}_{z \sim p(z)} \log(1 - \underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\text{Discriminator output for generated fake data G(z)}}) \right]$$

Alternate between:

1. **Gradient ascent** on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

Image from Stanford CS231

Objective function

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log \underbrace{D_{\theta_d}(x)}_{\text{Discriminator output for real data x}} + \mathbb{E}_{z \sim p(z)} \log(1 - \underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\text{Discriminator output for generated fake data G(z)}}) \right]$$

Alternate between:

1. **Gradient ascent** on discriminator

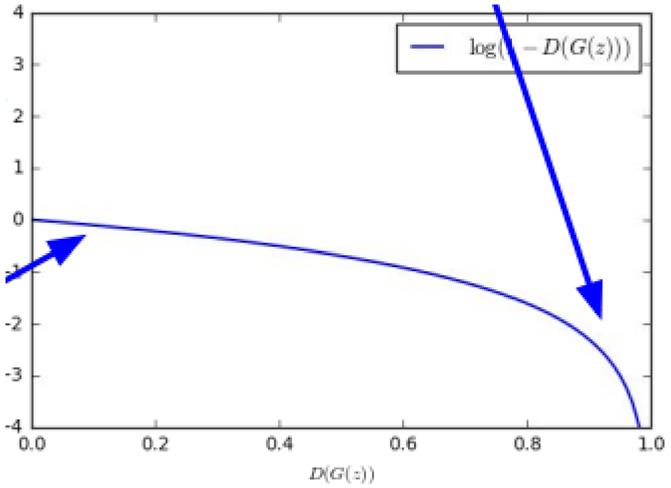
$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

2. **Gradient descent** on generator

$$\min_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

Minimize likelihood of discriminator being **right**

Generator performance is high



Generator performance is low

Image from Stanford CS231

Objective function

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log \underbrace{D_{\theta_d}(x)}_{\text{Discriminator output for real data x}} + \mathbb{E}_{z \sim p(z)} \log(1 - \underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\text{Discriminator output for generated fake data G(z)}}) \right]$$

Alternate between:

1. **Gradient ascent** on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

2. **Instead: Gradient ascent** on generator, different objective

$$\max_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(D_{\theta_d}(G_{\theta_g}(z)))$$

Maximize likelihood of discriminator being **wrong**

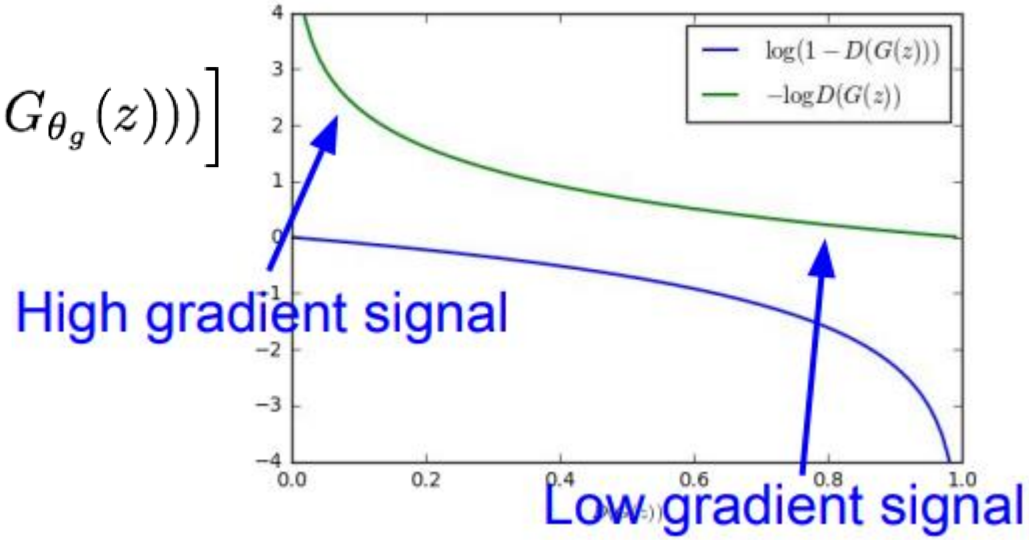
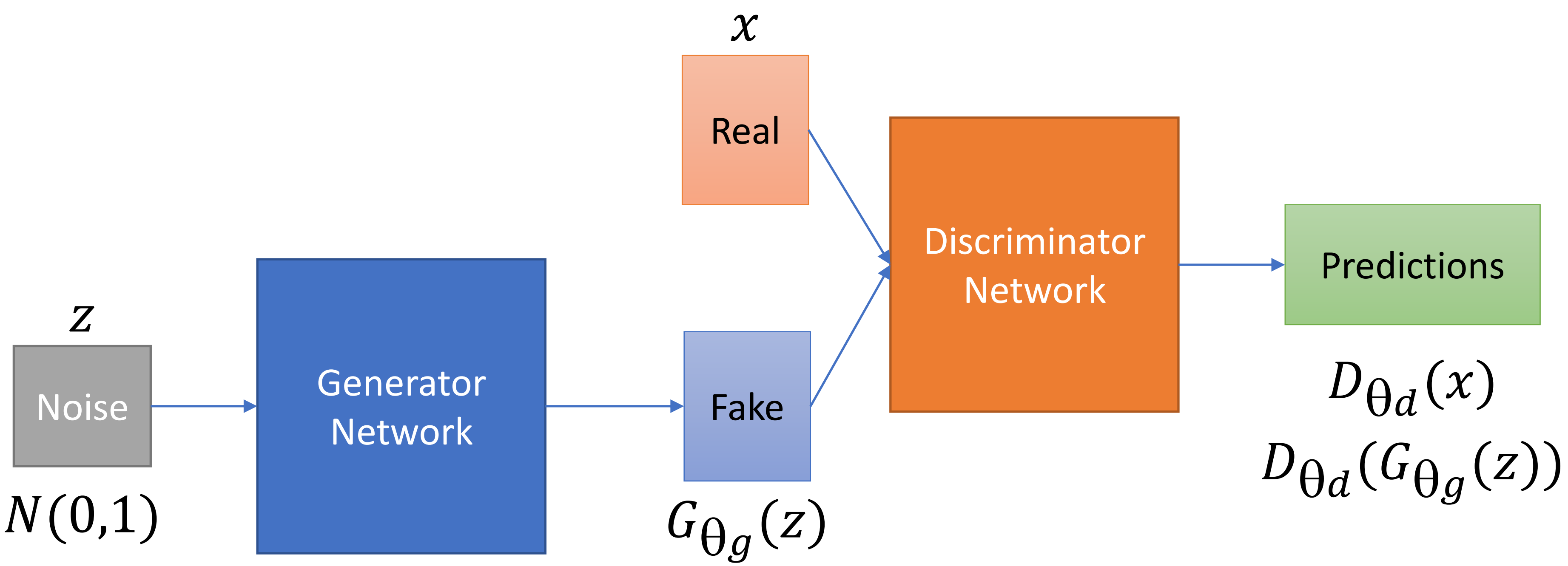


Image from Stanford CS231

Difficulties with training GANs



Challenging to train two separate networks. Can be unstable.
Once trained, produced great outputs

Latent space tricks: Interpolation

$z^{(1)}$

0.916767
0.862388
0.972409
0.258342
0.836252
0.969561
0.502568
0.634358
0.360669
0.567881
0.248232
0.464164
0.385207
0.592359
0.320633
0.549819
0.087568
0.369488
0.103373
.
.
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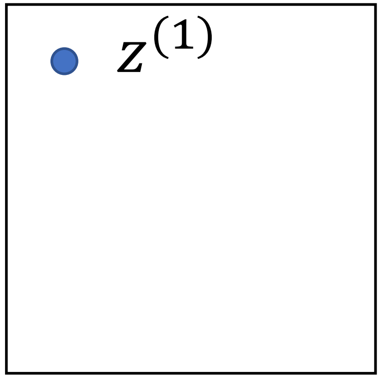

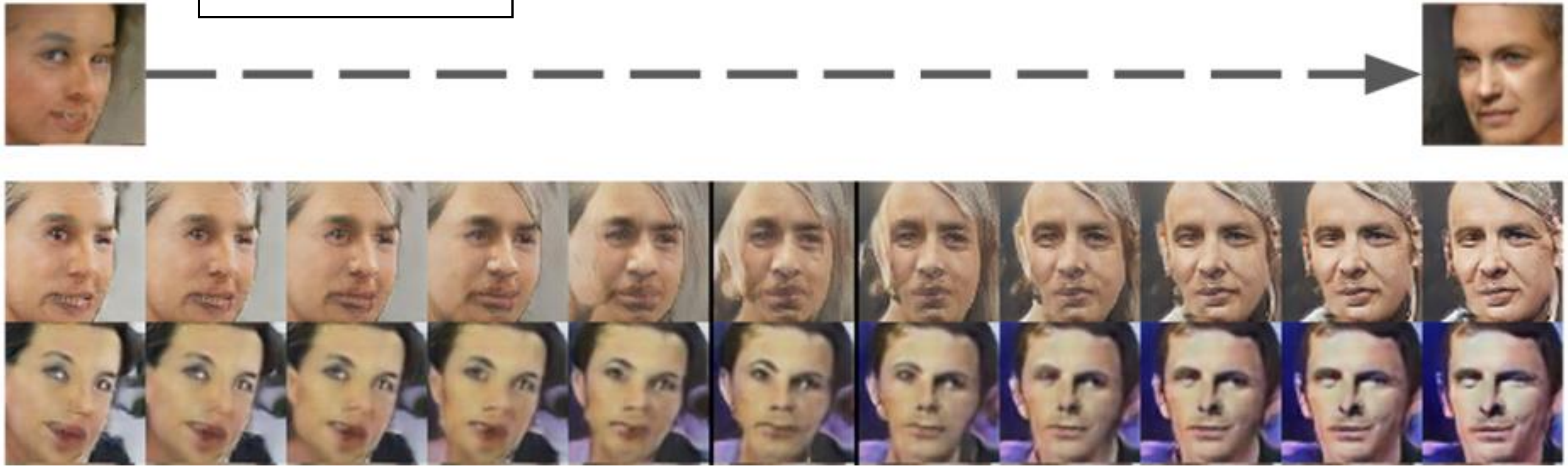

Image from [Radford et al., ICLR 2016]()

Latent space tricks: Interpolation

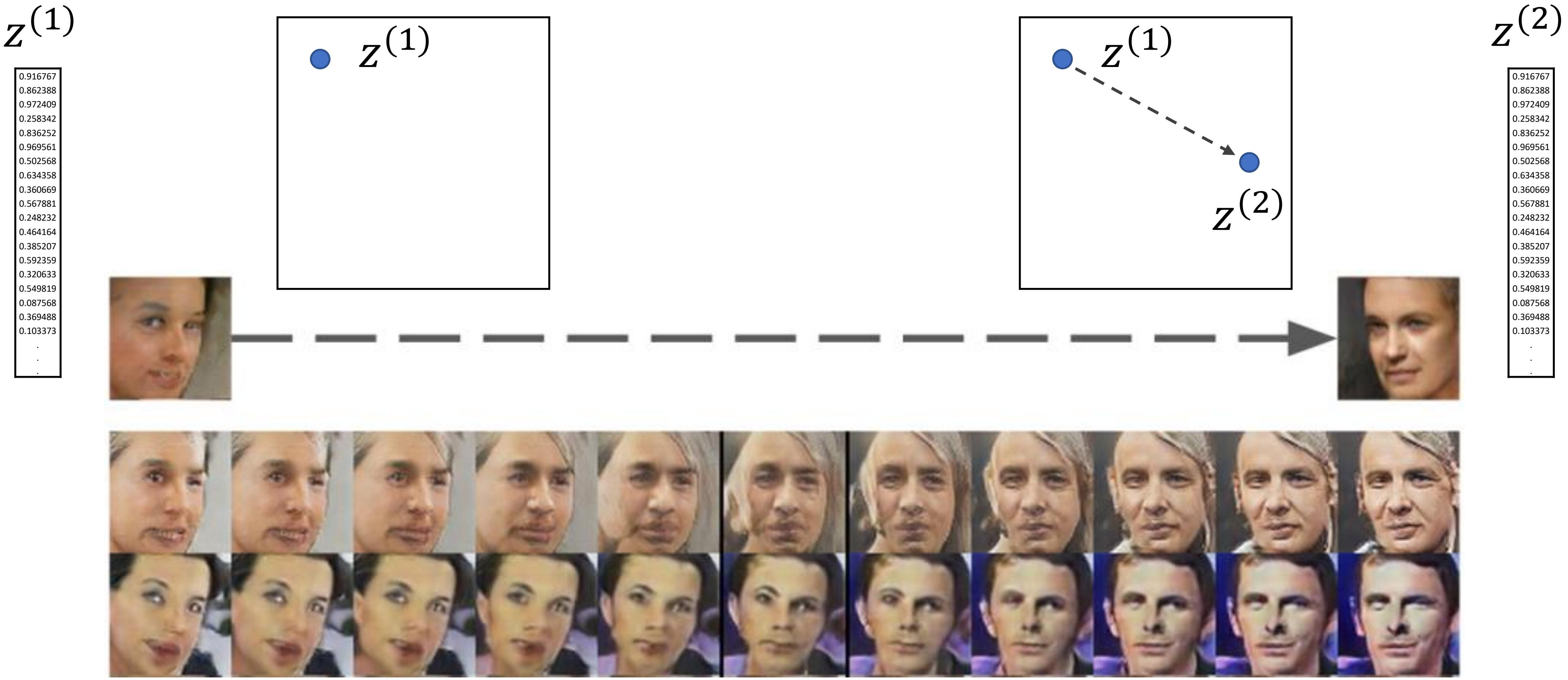

Image from Radford et al., ICLR 2016

Latent space tricks: Vector math

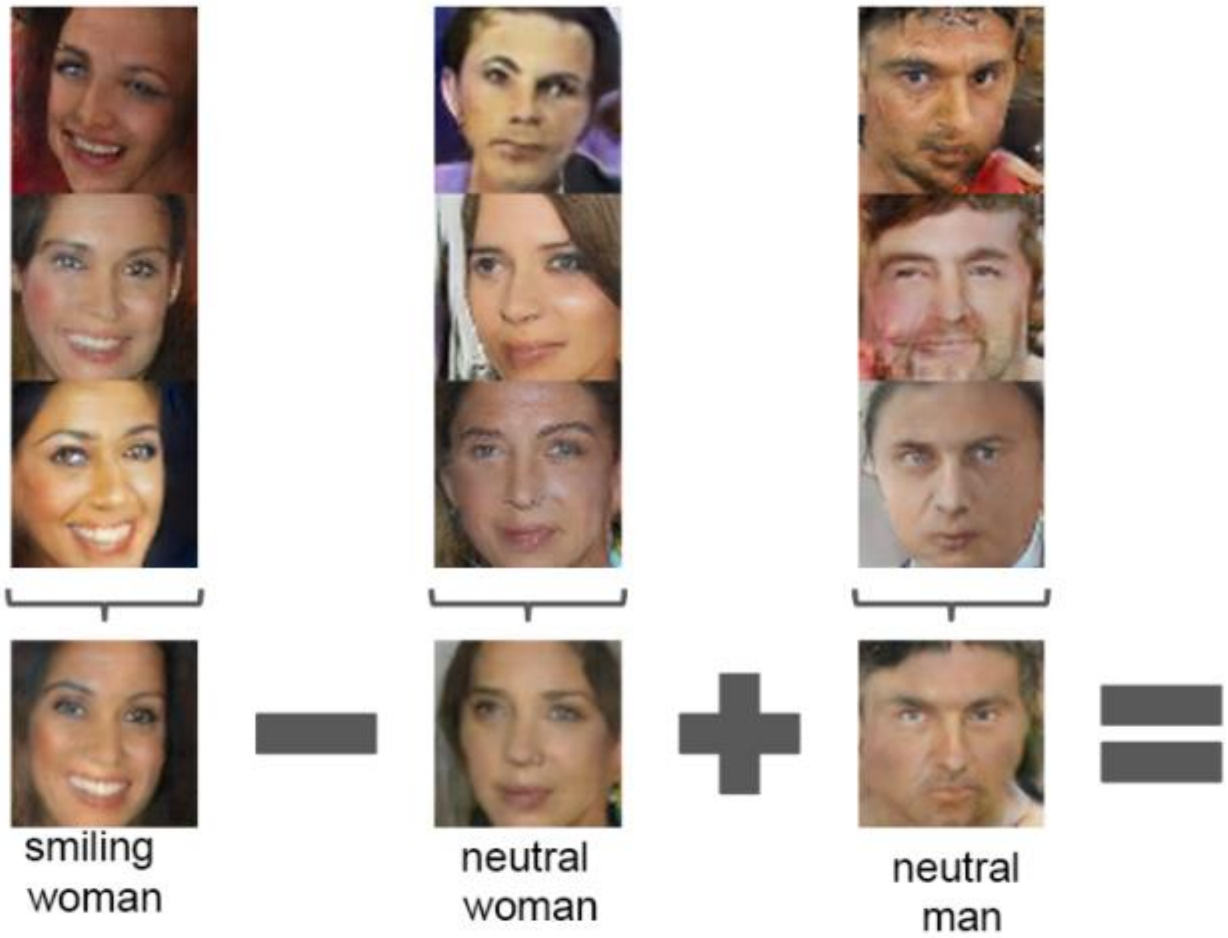

Image from Radford et al., ICLR 2016

Latent space tricks: Vector math

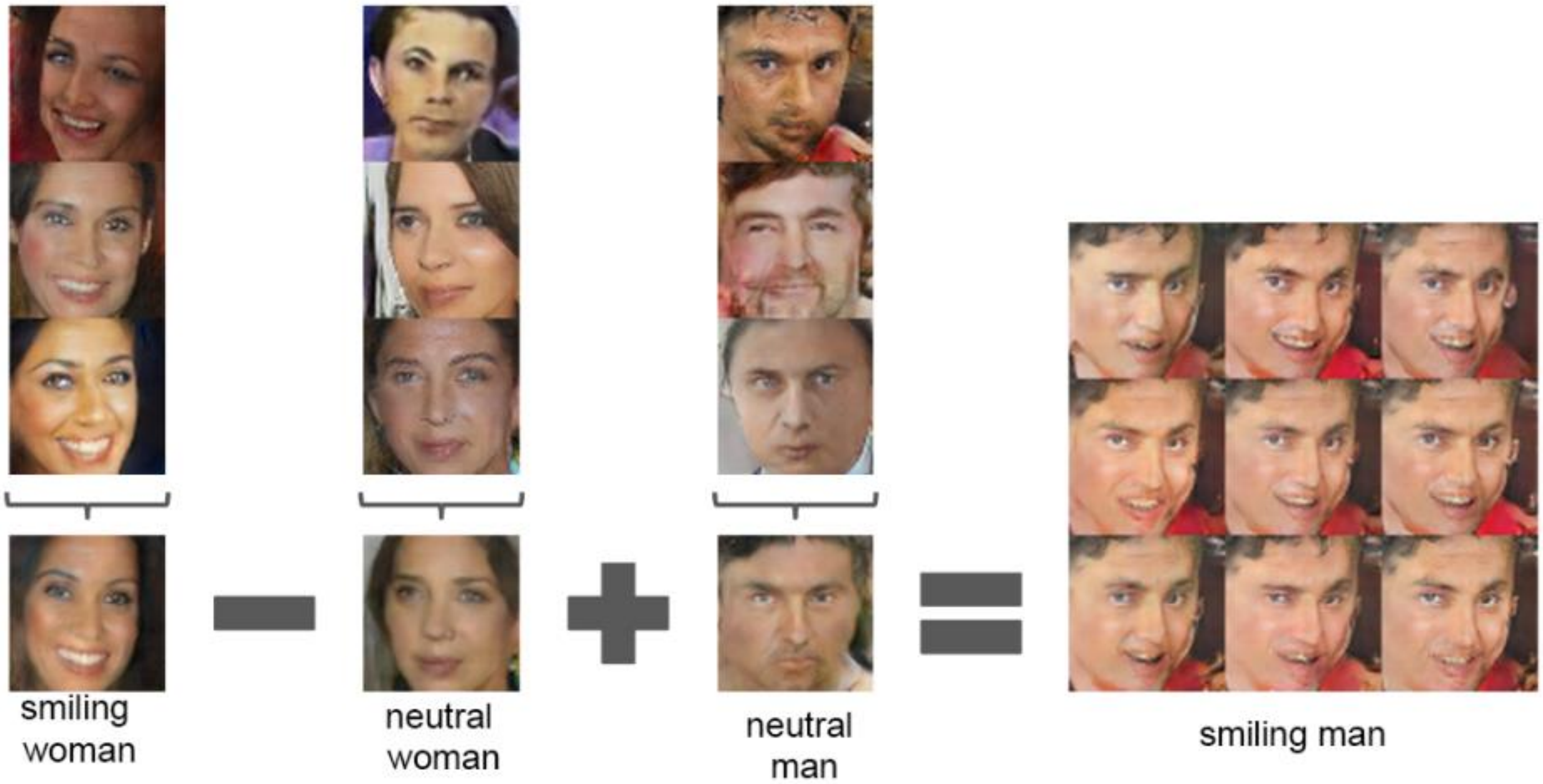

Image from [Radford et al., ICLR 2016]

Latent space tricks: Vector math

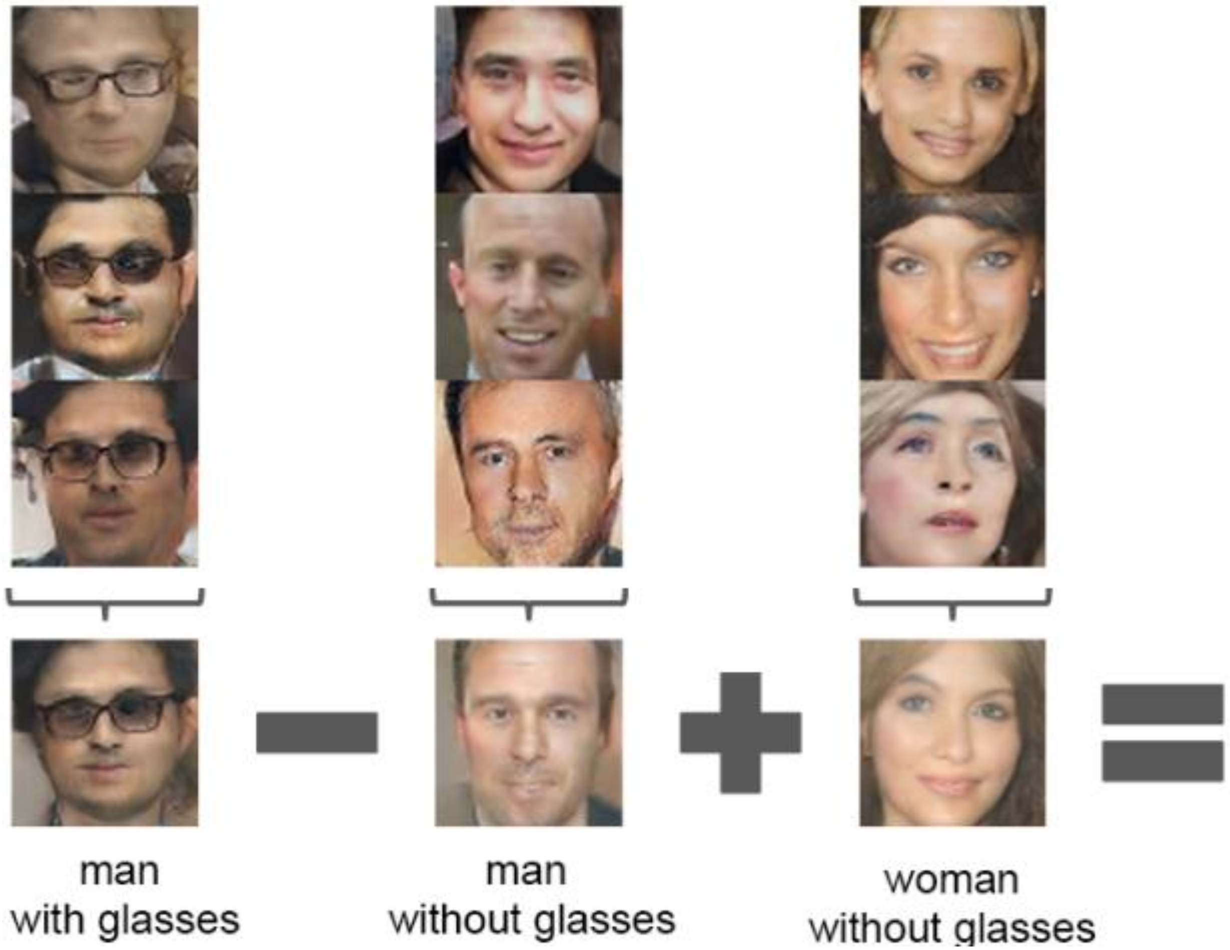

Image from [Radford et al., ICLR 2016]

Latent space tricks: Vector math

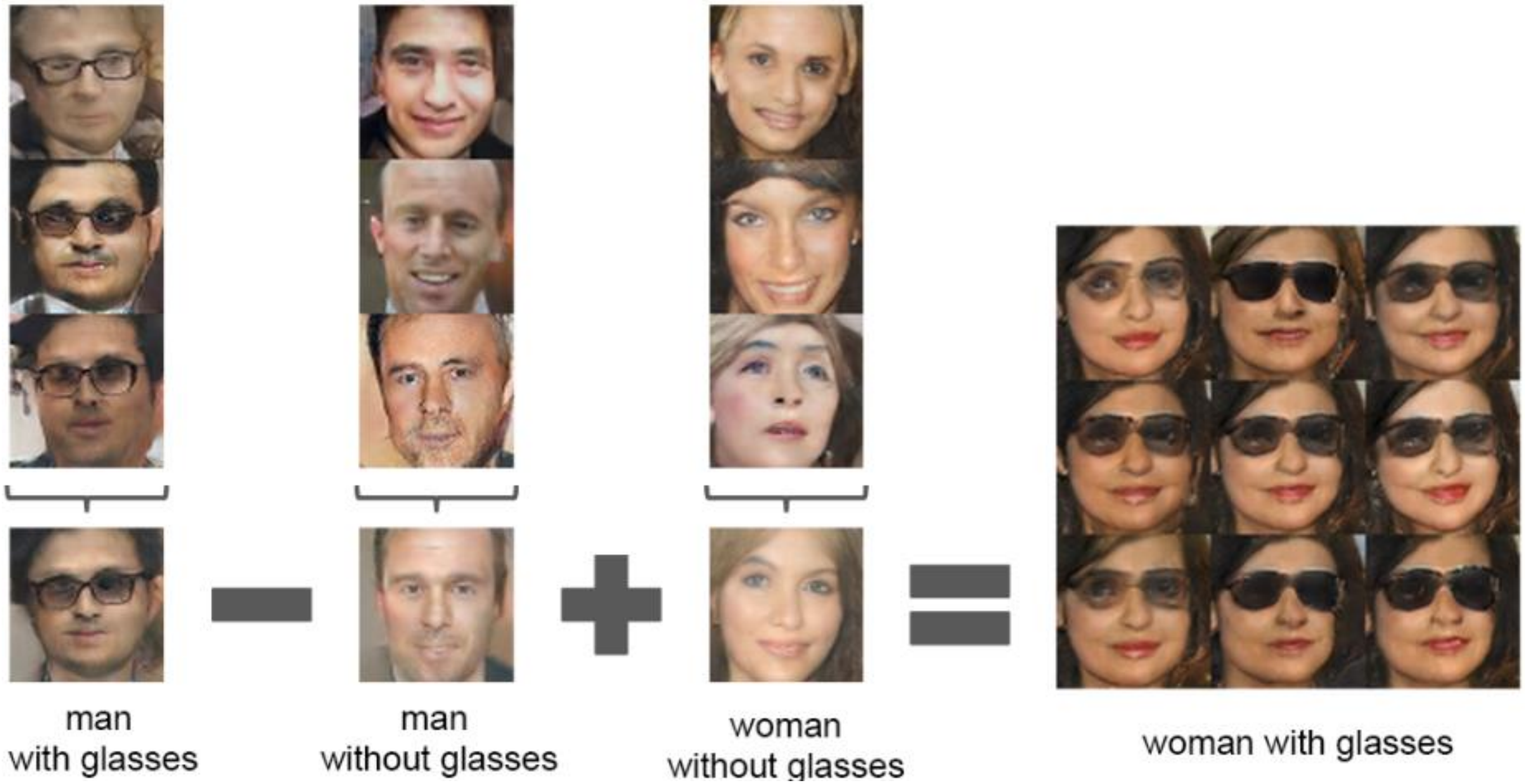

Image from [Radford et al., ICLR 2016]

Comparison with VAEs

- VAE
  - Optimize variational lower bound of likelihood
  - Training generally straightforward
  - Results are generally not as good*
- GAN
  - Game-theoretic approach
  - Training is difficult
  - Results are generally better*

*for image generation

GAN Zoo

- 3D-ED-GAN - Shape Inpainting using 3D Generative Adversarial Network and Recurrent Convolutional Networks
- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling (github)
- 3D-IWGAN - Improved Adversarial Systems for 3D Object Generation and Reconstruction (github)
- 3D-PhysNet - 3D-PhysNet: Learning the Intuitive Physics of Non-Rigid Object Deformations
- 3D-RecGAN - 3D Object Reconstruction from a Single Depth View with Adversarial Learning (github)
- ABC-GAN - ABC-GAN: Adaptive Blur and Control for improved training stability of Generative Adversarial Networks (github)
- ABC-GAN - GANs for LIFE: Generative Adversarial Networks for Likelihood Free Inference
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- acGAN - Face Aging With Conditional Generative Adversarial Networks
- ACGAN - Coverless Information Hiding Based on Generative adversarial networks
- acGAN - On-line Adaptative Curriculum Learning for GANs
- ACtuAL - ACtuAL: Actor-Critic Under Adversarial Learning
- AdaGAN - AdaGAN: Boosting Generative Models
- Adaptive GAN - Customizing an Adversarial Example Generator with Class-Conditional GANs
- AdvEntuRe - AdvEntuRe: Adversarial Training for Textual Entailment with Knowledge-Guided Examples
- AdvGAN - Generating adversarial examples with adversarial networks
- AE-GAN - AE-GAN: adversarial eliminating with GAN
- AE-OT - Latent Space Optimal Transport for Generative Models
- AEGAN - Learning Inverse Mapping by Autoencoder based Generative Adversarial Nets
- AF-DCGAN - AF-DCGAN: Amplitude Feature Deep Convolutional GAN for Fingerprint Construction in Indoor Localization System
- AffGAN - Amortised MAP Inference for Image Super-resolution
- AIM - Generating Informative and Diverse Conversational Responses via Adversarial Information Maximization
- AL-CGAN - Learning to Generate Images of Outdoor Scenes from Attributes and Semantic Layouts
- ALI - Adversarially Learned Inference (github)
- AlignGAN - AlignGAN: Learning to Align Cross-Domain Images with Conditional Generative Adversarial Networks
- AlphaGAN - AlphaGAN: Generative adversarial networks for natural image matting

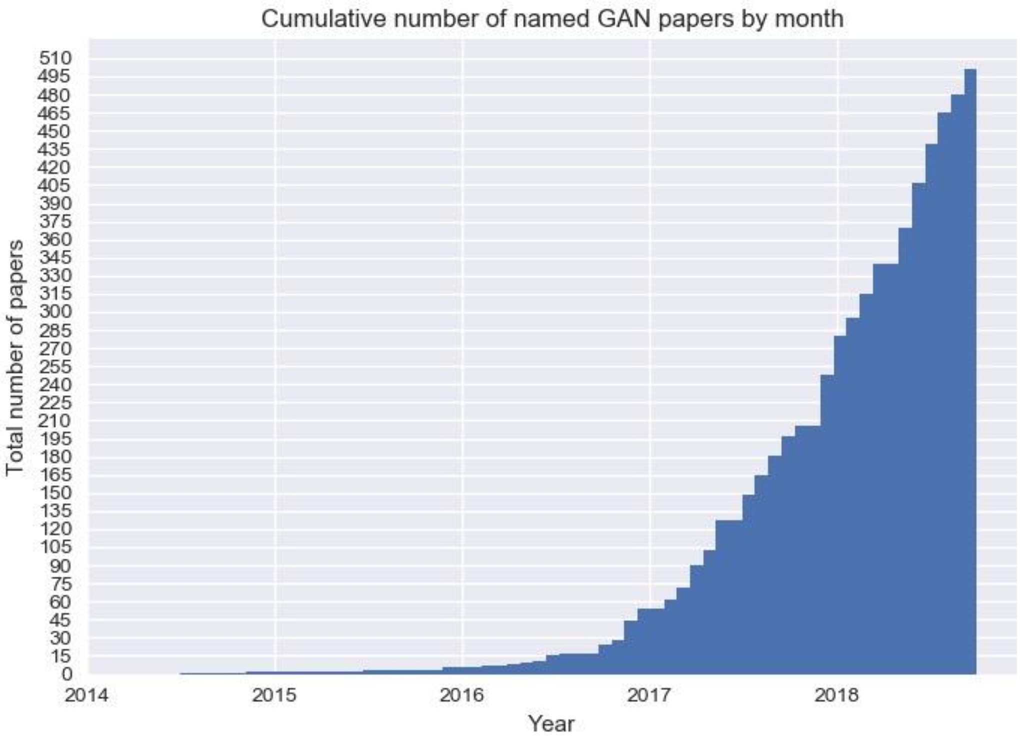

Image from GAN Zoo

VAE-GAN

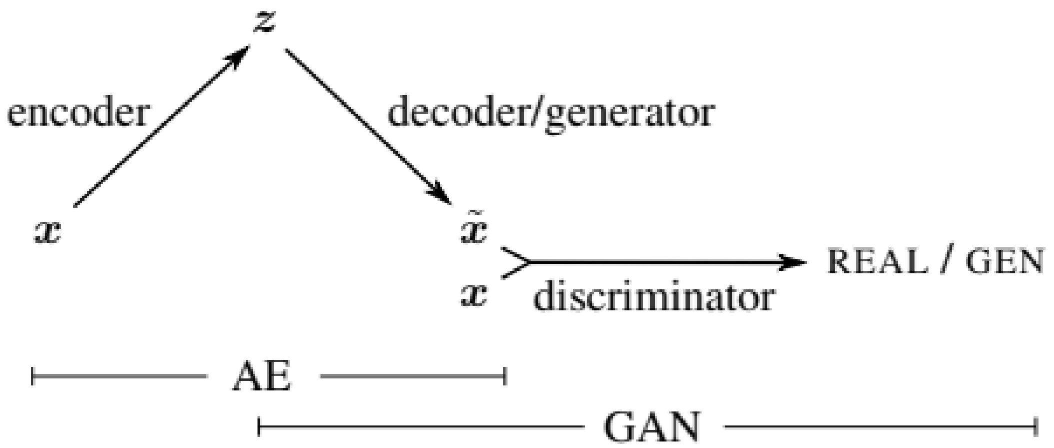

Figure 1. Overview of our network. We combine a VAE with a GAN by collapsing the decoder and the generator into one.

Image from Larson et al., ICML 2016

Generating proteins using GANs

MutaGAN

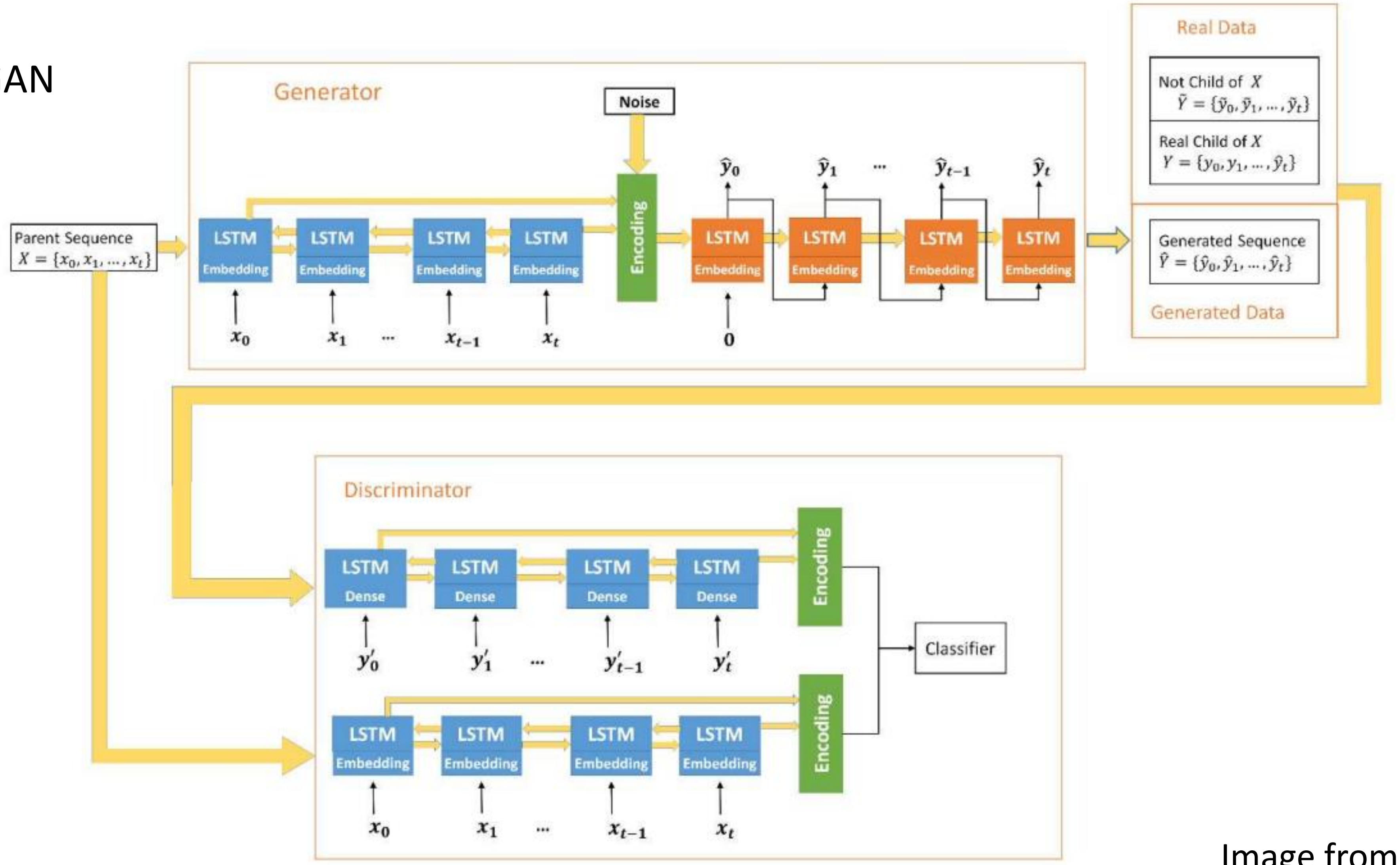

Image from Berman et al., 2020

Generating proteins using GANs

MutaGAN

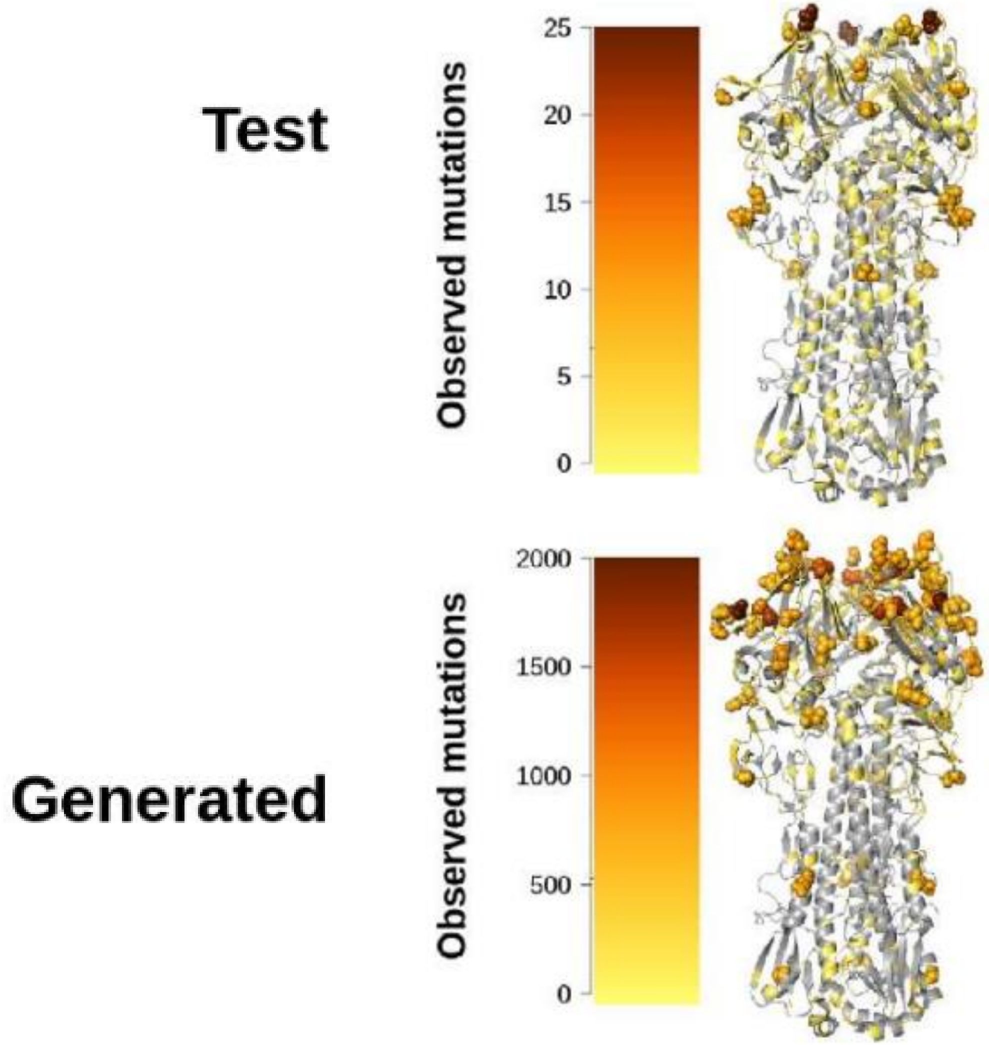

Image from [Berman et al., 2020]