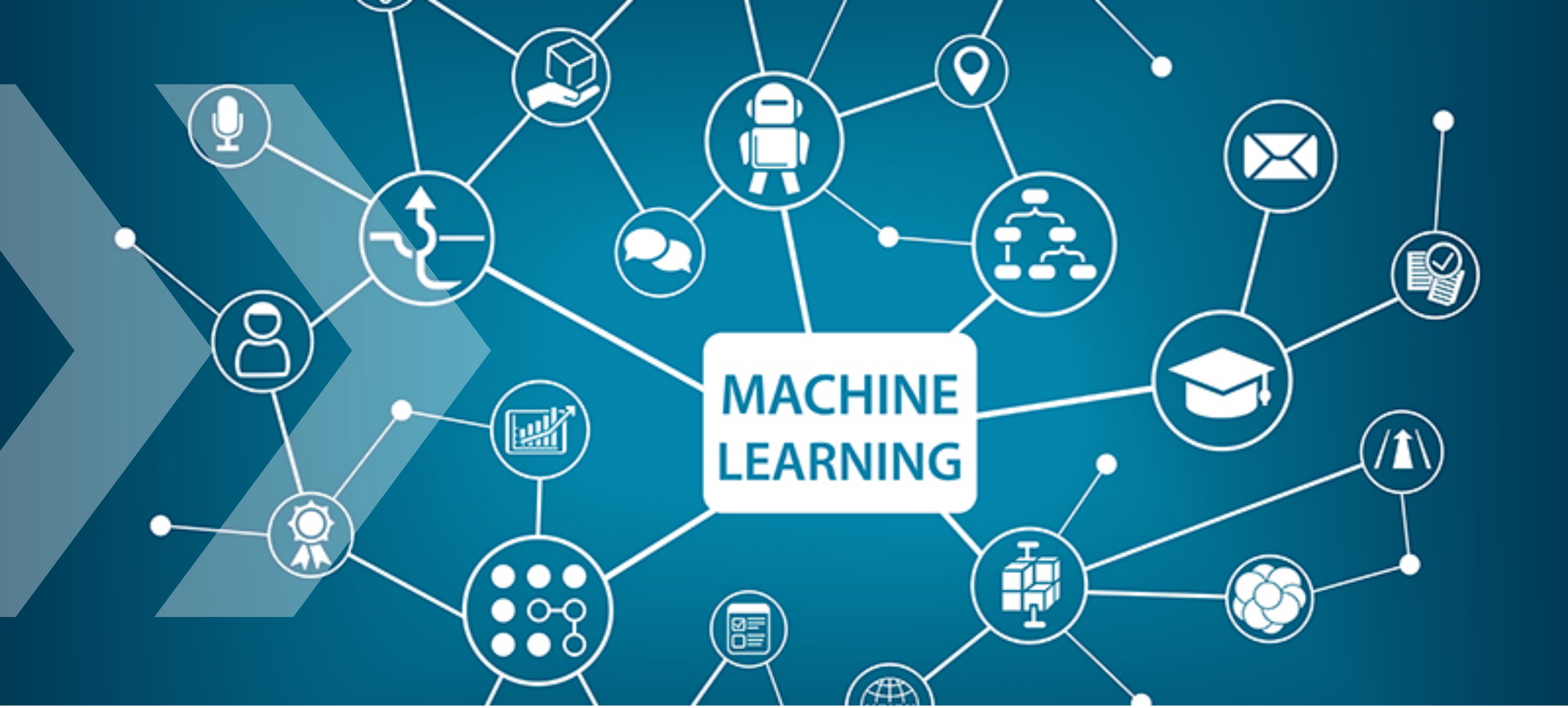

CS489/698: Intro to ML

Lecture 15: Generative Adversarial Networks

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Outline

- Motivation
- Formulation
- Optimization
- Advanced

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Generative Models

- Given training data from p_{data}

- Generate new samples from p_{model}

- Want $p_{model} \sim p_{data}$

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The "Obvious" Approach

- Use training data to estimate density $p_{model} \sim p_{data}$
  - Which algorithm?

- Then sample from p_{model}

- What might go wrong?
  - Estimating density is hard, very hard…
  - Sampling from high-d density is hard, very hard…

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Why Generative Models?

- If we can generate, we must know the objects so well!
  - Feature extraction; pre-training

- Semi-supervised learning

- Planning

- And the cool applications

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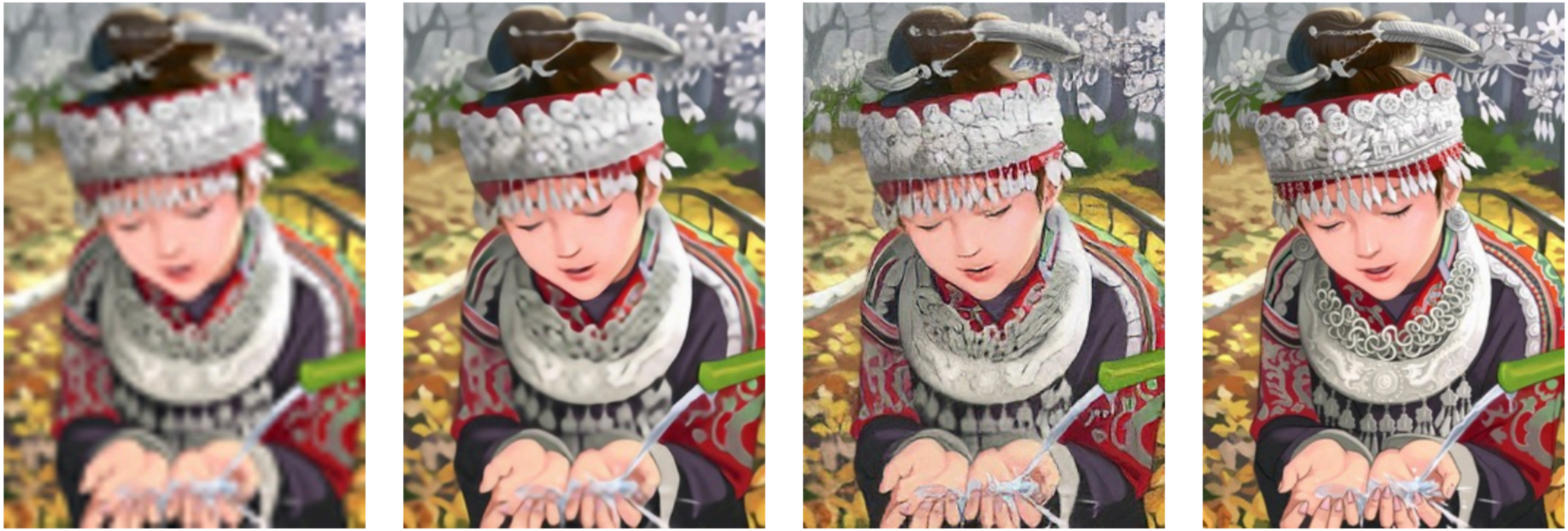
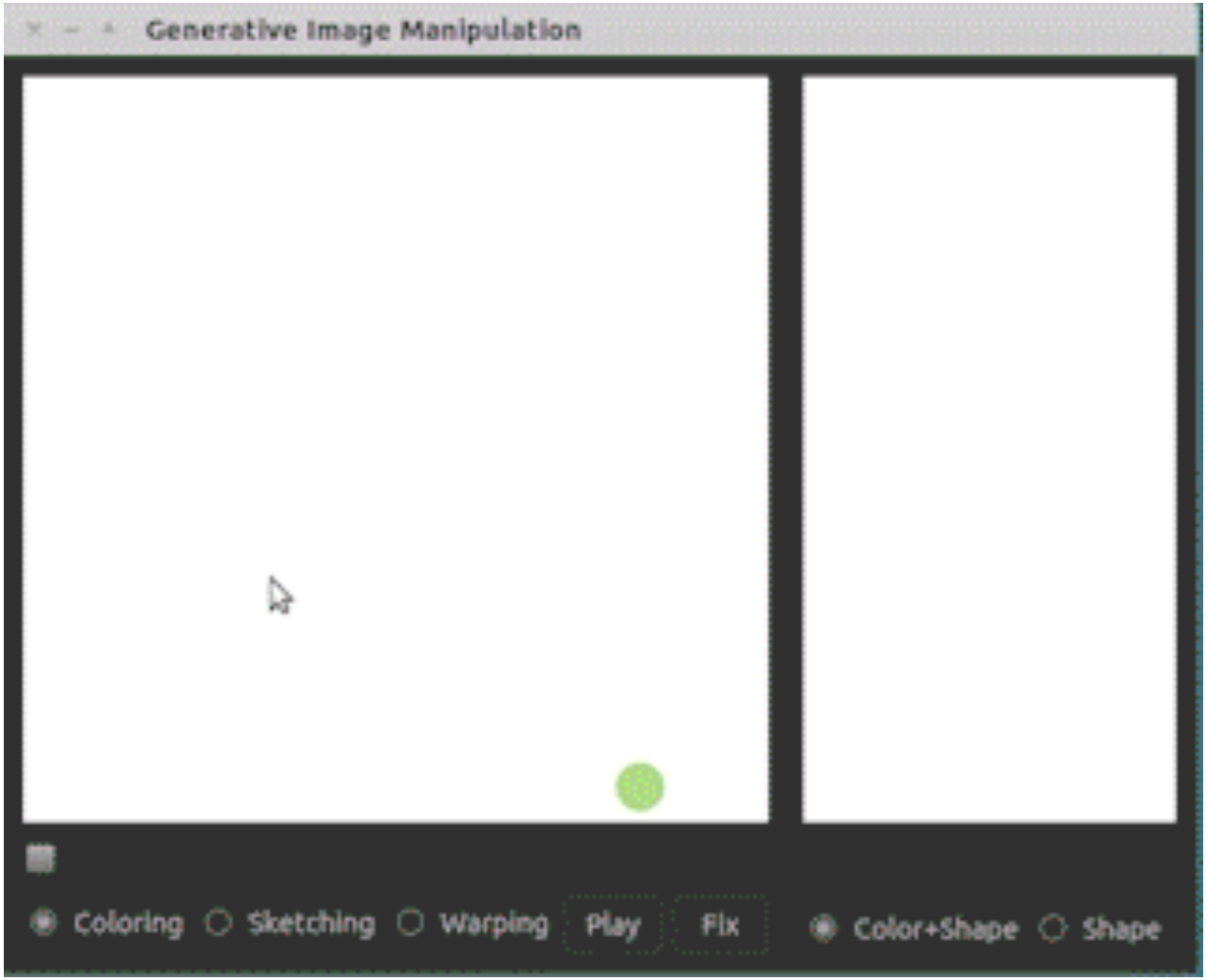
Image Super-Resolution (Ledig et al, CVPR'17)

bicubic (21.59dB/0.6423) | SRResNet (23.53dB/0.7832) | SRGAN (21.15dB/0.6868) | original



Interactive Image Generation
(Zhu et al, ECCV'16)



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Neural photo editing (Brock et al, ICLR'17)

Image to Image Translation
(Isola et al, CVPR'17)

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Generative Adversarial Networks
(Goodfellow et al, NIPS'14)

- A generator proposes samples
- A discriminator examines samples
  - Accept if sample "resembles" training data
  - Reject otherwise
- How can generator "fool" discriminator?

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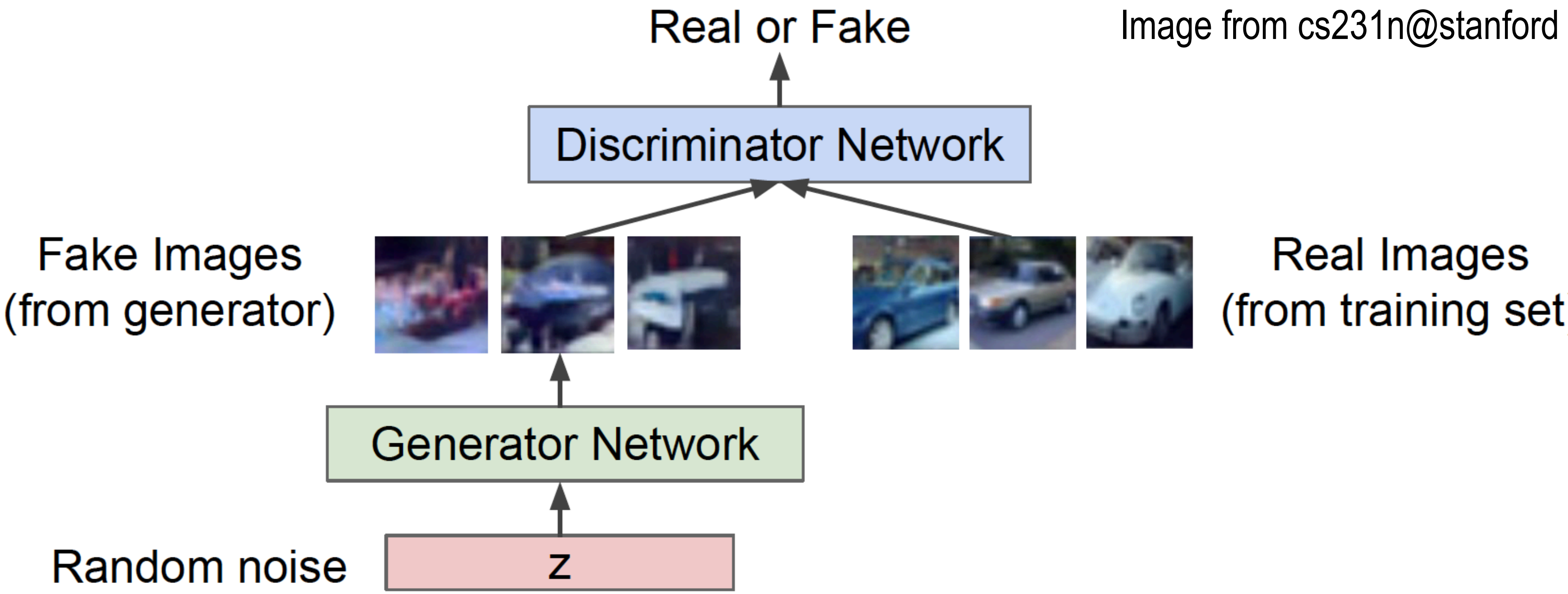
Key Idea

Image from cs231n@stanford



- No density estimation
- Directly generate image from random noise!

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Minimax Game

$$\min_G \max_D \; \mathbf{E}_{x\sim p_{\text{data}}}[\log D(x)] + \mathbf{E}_{z\sim p_z}[\log(1 - D(G(z)))]$$

- D(x): probability of x coming from same distribution as training data
- Discriminator D: max prob of training data and min prob of generated sample
- Generator G: max prob of generated sample (fool discriminator)
- Zero-sum game: your loss is my gain

Why Would It Work?

$$\min_G \max_D \ \mathbf{E}_{x\sim p_{\text{data}}}[\log D(x)] + \mathbf{E}_{z\sim p_z}[\log(1 - D(G(z)))]$$

change of variable

$$\min_G \max_D \ \mathbf{E}_{x\sim p_{\text{data}}}[\log D(x)] + \mathbf{E}_{x\sim p_{\text{model}}}[\log(1 - D(x))]$$

- Fix G, when is D optimal?
  - $D(x) = p_{\text{data}}(x) / [p_{\text{data}}(x) + p_{\text{model}}(x)]$

$$\boxed{\min_G \mathsf{JS}(p_{\text{data}} \| p_{\text{model}})}$$

- Plug in optimal D, when is G optimal?
  - $p_{\text{model}} = p_{\text{data}}$

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Minimax Theorem

$$\min_G \max_D \; \mathbf{E}_{x\sim p_{\text{data}}}[\log D(x)] + \mathbf{E}_{x\sim p_{\text{model}}}[\log(1 - D(x))]$$

$$\Updownarrow$$

$$\max_D \min_G \; \mathbf{E}_{x\sim p_{\text{data}}}[\log D(x)] + \mathbf{E}_{x\sim p_{\text{model}}}[\log(1 - D(x))]$$

- Fix D, when is G optimal?
  - collapsing on modes of D
- Plug in optimal G, when is D optimal?
  - D(x) = 1/2

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Representing D and G

- So far assumed D and G can be arbitrarily "smart"

- In practice, $D(x) = D(x; \theta_d)$ and $G(z; \theta_g)$
  - Each is a DCNN, with θ being the weights

    Deep CNN

- Run SGD to find best θ_d and θ_g

Algorithm (Goodfellow et al, NIPS'14)

for number of training iterations **do**

  for k steps **do**

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
  - Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right].$$

  end for

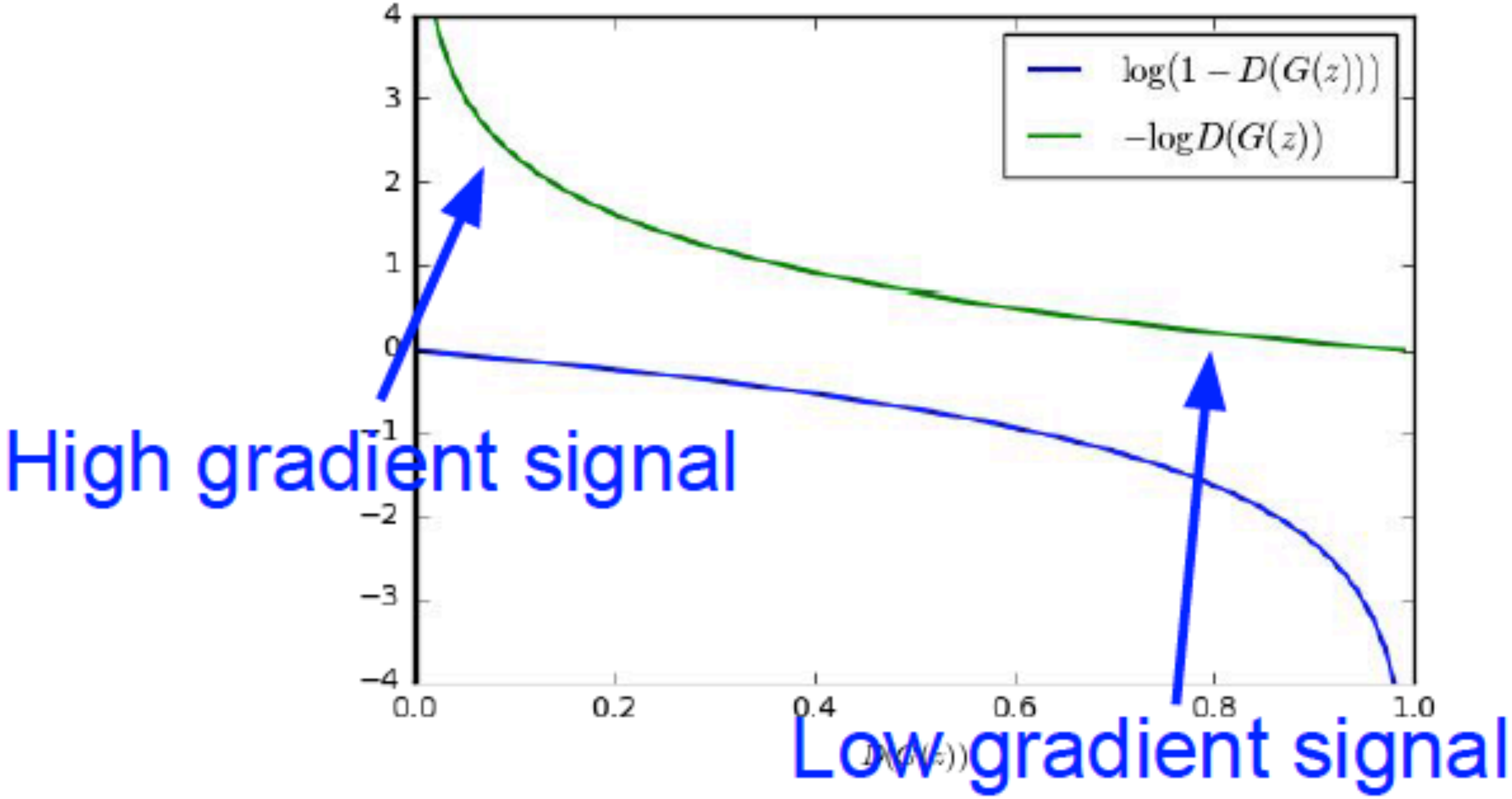
- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

Trick for Saturating Gradient

Image from cs231n@stanford



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In practice

$$\boxed{\max_D \mathbf{E}_{x\sim p_{\text{data}}}[\log D(x)] + \mathbf{E}_{x\sim p_{\text{model}}}[\log(1 - D(x))]}$$

$$\cancel{\min_G \mathbf{E}_{x\sim p_{\text{model}}}[\log(1 - D(x))]}$$

$$\boxed{\min_G \mathbf{E}_{x\sim p_{\text{model}}}[-\log D(x)]}$$

$$\min_G \max_D \mathbf{E}_{x\sim p_{\text{data}}}[\log D(x)] + \mathbf{E}_{x\sim p_{\text{model}}}[-\log D(x)]$$

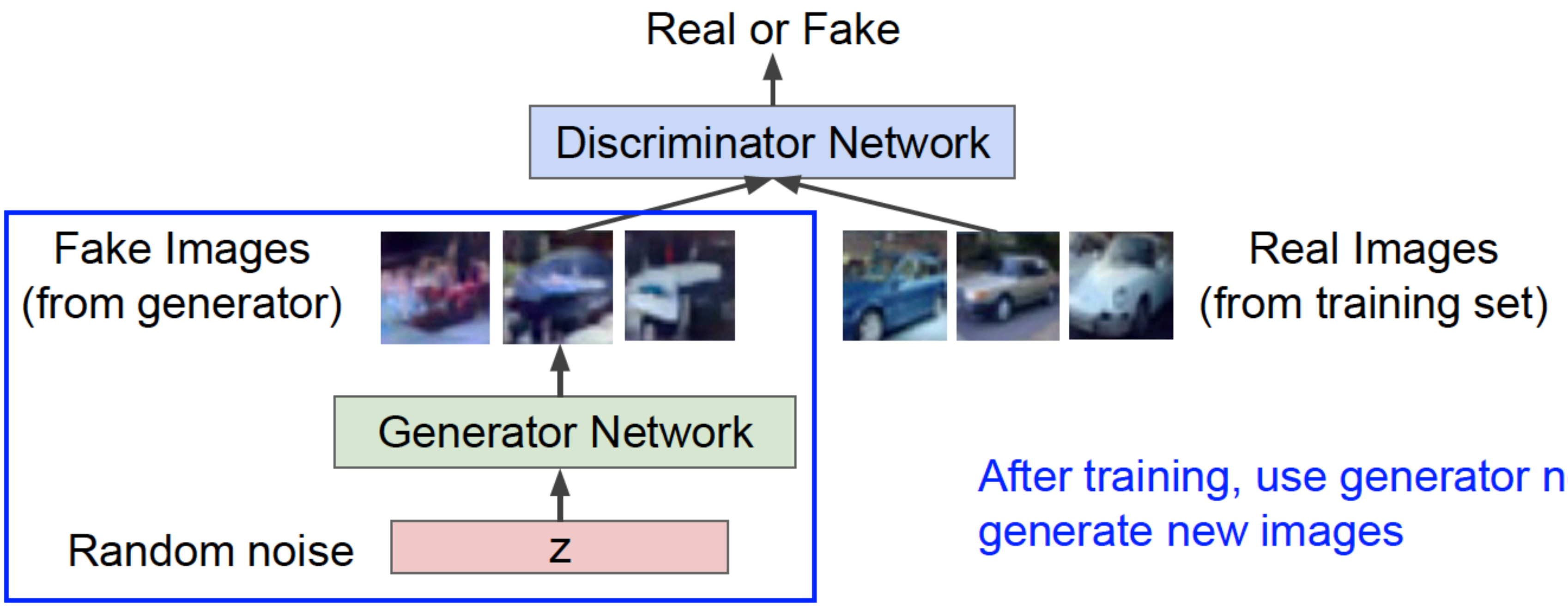
Fix G, what is the optimal D? Plug in optimal D, what is the optimal G?

$$\max_D \min_G \mathbf{E}_{x\sim p_{\text{data}}}[\log D(x)] + \mathbf{E}_{x\sim p_{\text{model}}}[-\log D(x)]$$

Fix D, what is the optimal G? Plug in optimal G, what is the optimal D?

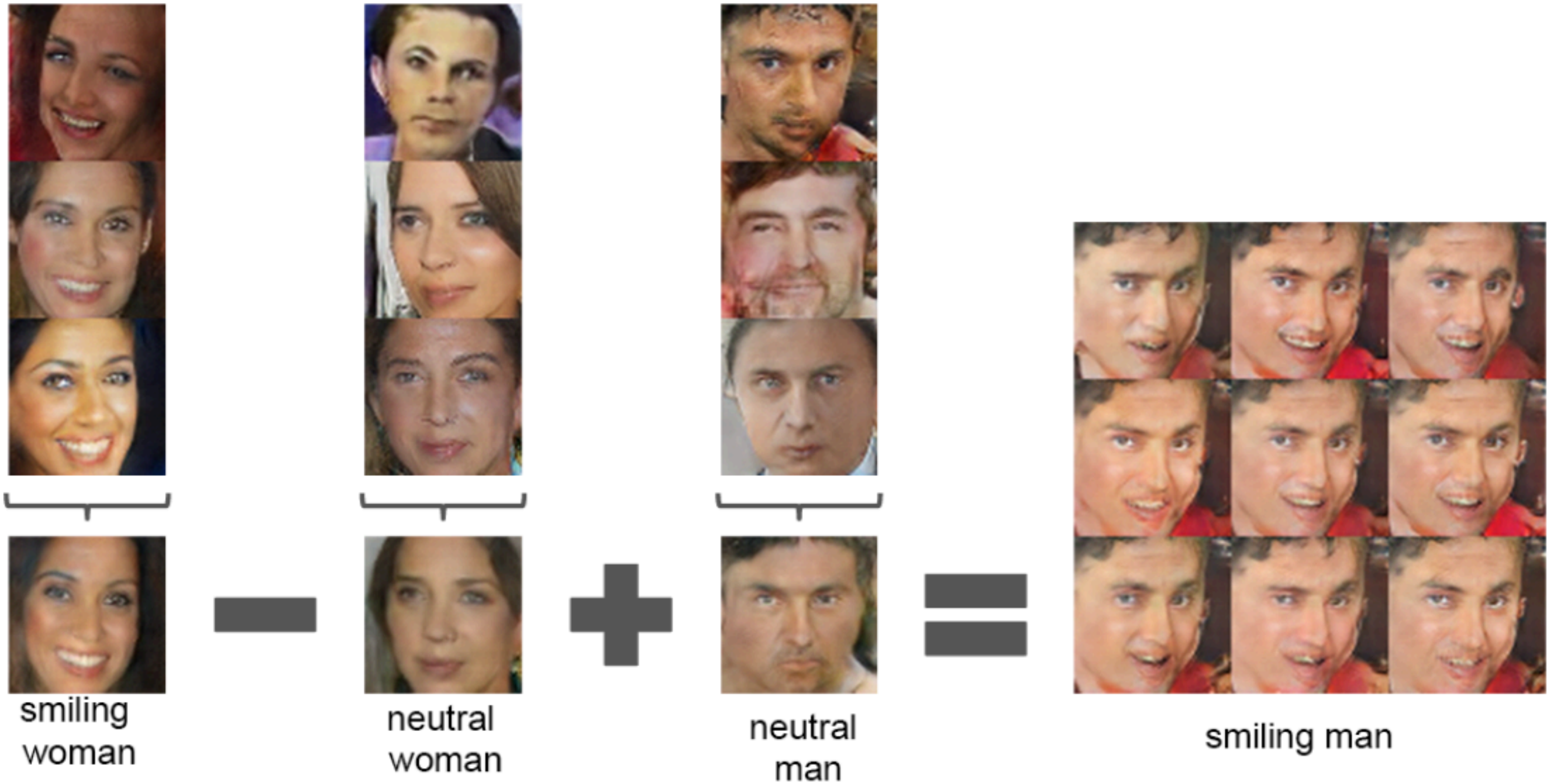
Testing

Image from cs231n@stanford

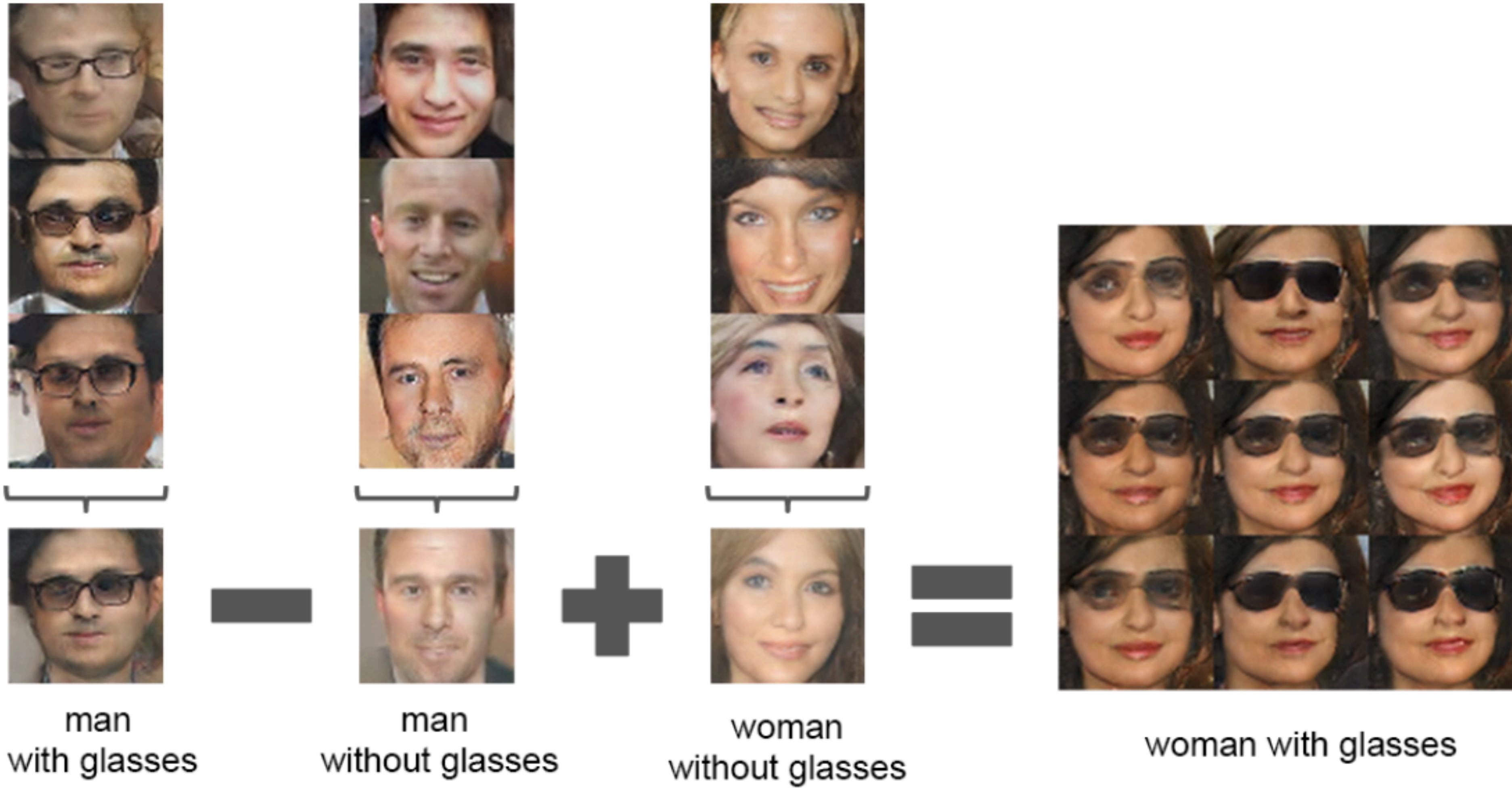


After training, use generator network to generate new images

More Intriguing Examples
(Radford et al, ICLR'16)



More Intriguing Examples cont’
(Radford et al, ICLR’16)



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Wasserstein GAN (Arjovsky et al, ICML'17)

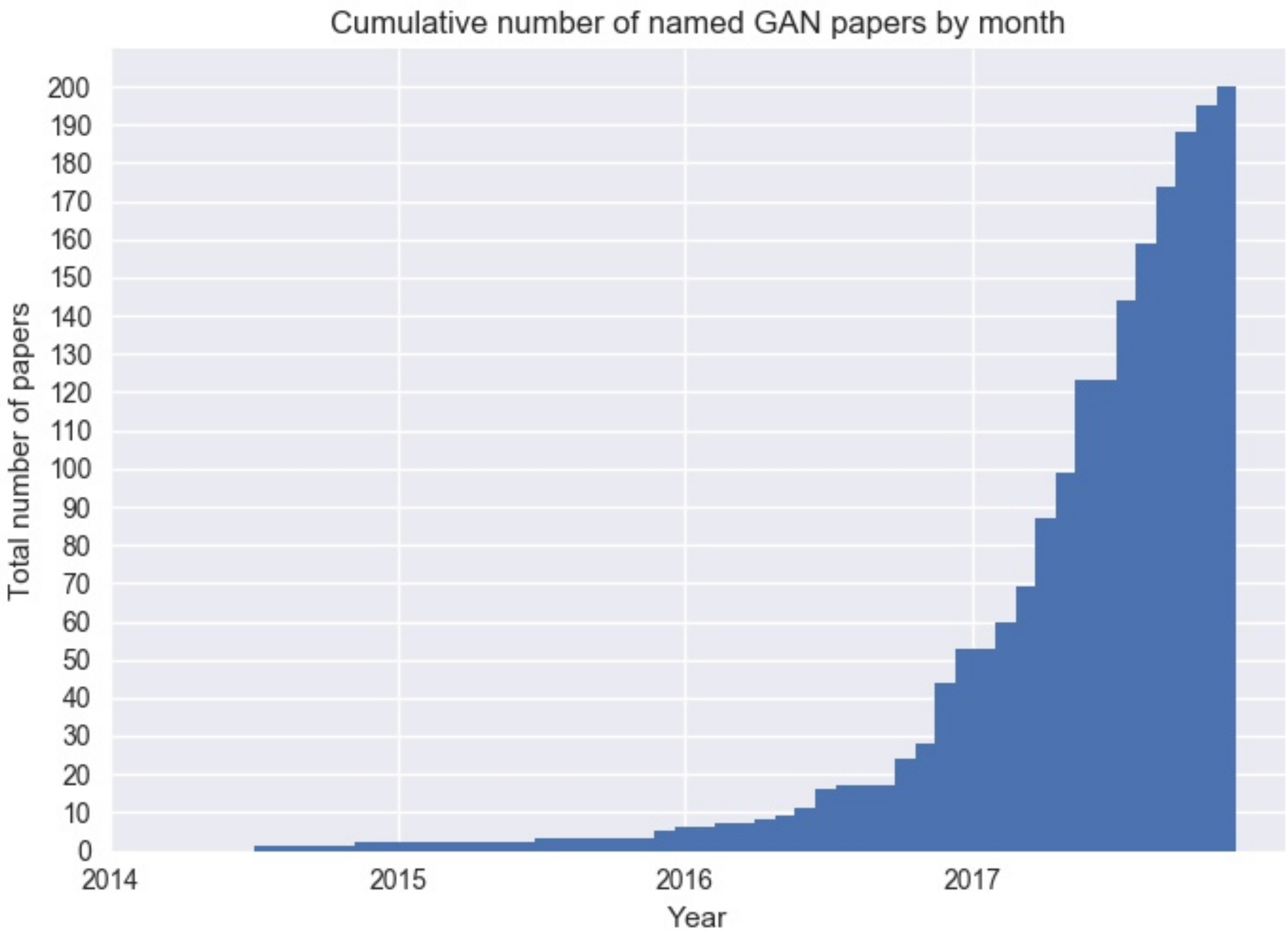
- GAN objective
  - Could be discontinuous

$$\boxed{\min_G \mathsf{JS}(p_{\mathrm{data}} \| p_{\mathrm{model}})}$$

- Better objective
  - Much better behaved
  - Connection to kernels

$$\boxed{\min_G \mathsf{W}(p_{\mathrm{data}}, p_{\mathrm{model}})}$$

The GAN Zoo (https://github.com/hindupuravinash/the-gan-zoo)



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Questions?

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