Generative Adversarial Network

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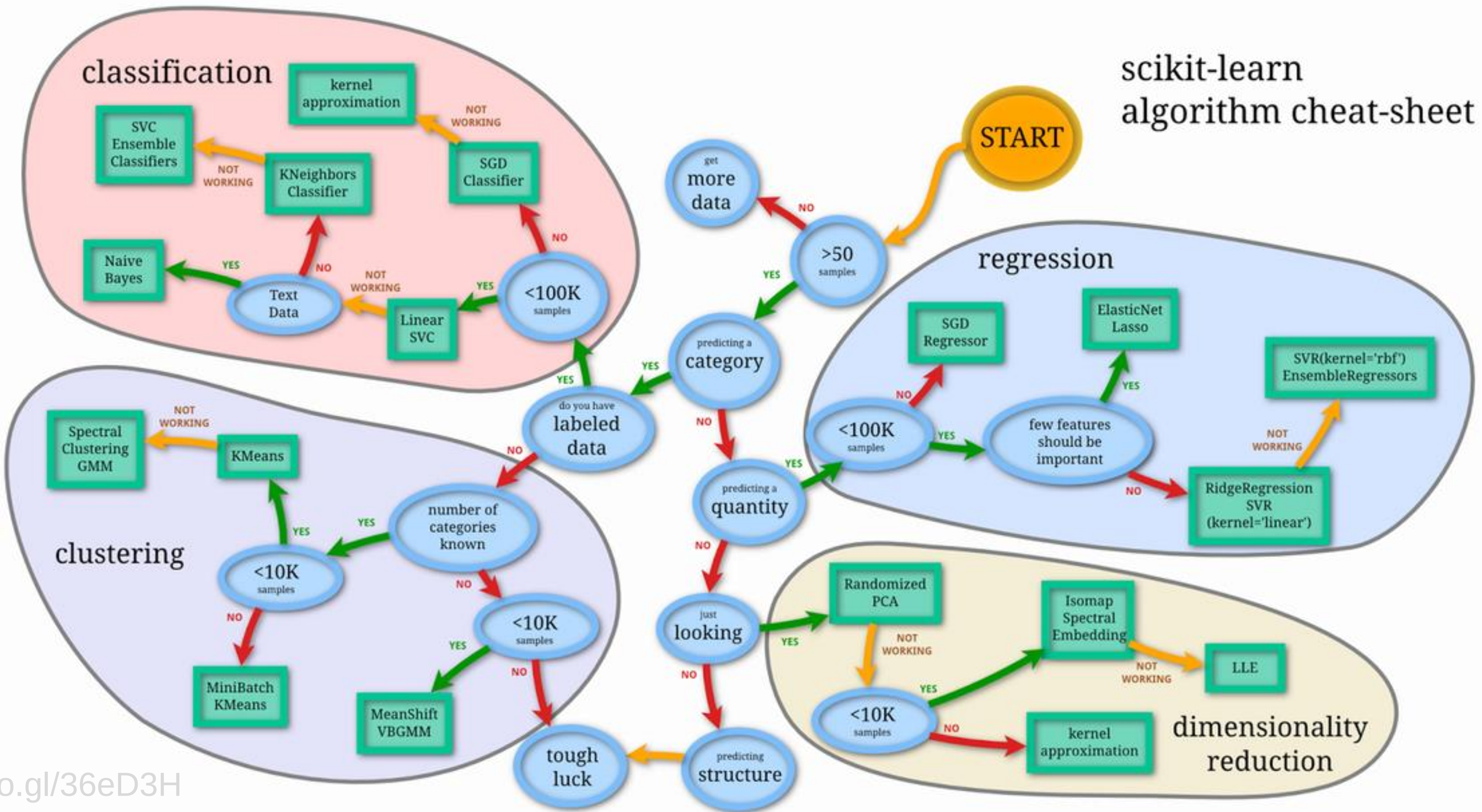
فهرست مطالب

- بخش اول
  - مقدمه
  - مدل‌های پارامتری و غیر پارامتری
  - بررسی تخمین‌گر ماکزیمم likelihood
  - تولید داده؟!
    - AE
    - VAE کلیات
- بخش دوم
  - مروری برمفاهیم به صورت مقایسه
  - دورنمایی از آمار پژوهش های GAN
  - اپلیکیشن های مختلف GAN

مقدمه...



https://goo.gl/36eD3H

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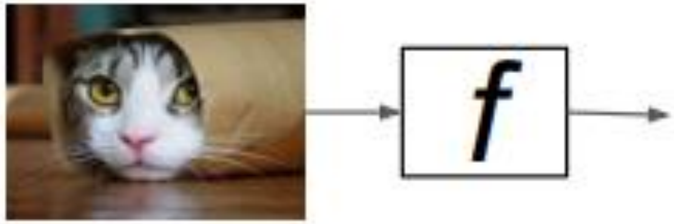
مقدمه...

- یادگیری بانظارت (Supervised learning)

$f : y = f(x)$

x : داده

y : برچسب



گربه

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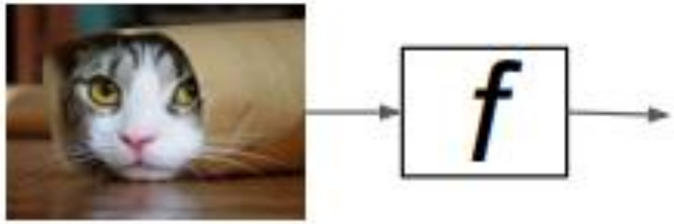


گربه : ۰.۹

سگ : ۰.٤

موش : ۰.۶

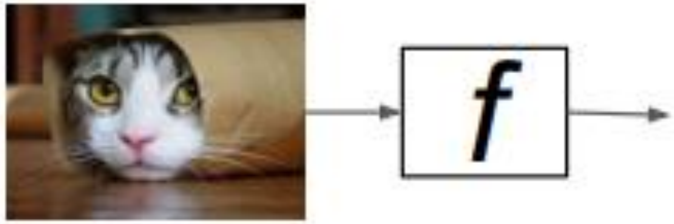
مقدمه...

f : $y = f(x)$

x : داده

y : برچسب

- یادگیری بانظارت (Supervised learning)



گربه : ۰.۹

سگ : ۰.٤

موش : ۰.۶

– y : label, x : data, z : latent, θ : learnable parameter

Optimal

$$\theta^* = \arg\max_{\theta} P(Y \mid X; \theta)$$

get θ when P is maximum   probability   given   parameterized by

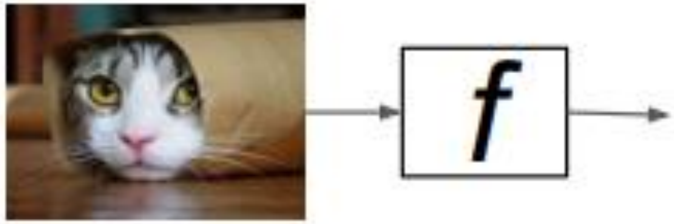
مقدمه...

- یادگیری بانظارت (Supervised learning)

f : ***y = f(x)***

x : داده

y : برچسب



گربه : ۰.۹

سگ : ۰.٤

موش : ۰.۶

– y : label, x : data, z : latent, θ^*: fixed optimal parameter

Optimal label prediction

$$y^* = \arg\max_y P(Y \mid X; \theta^*)$$

get y when P is maximum — probability — given — parameterized by

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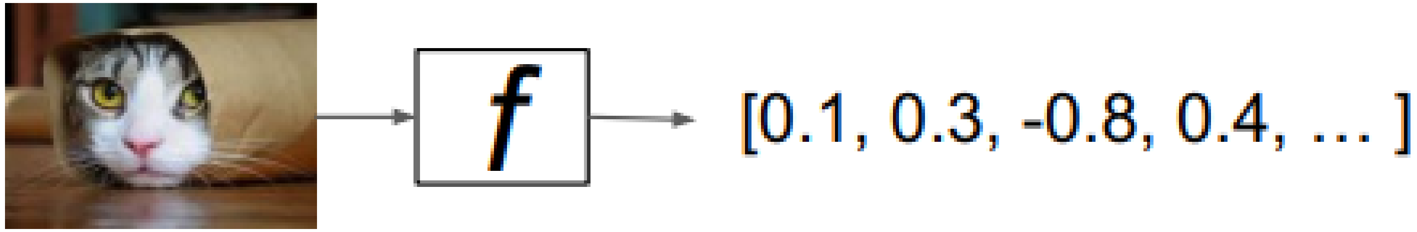
مقدمه...

- یادگیری بدون نظارت(UnSupervised learning)

f : *z = f(x)*

x : داده

z : latent



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مقدمه...

- یادگیری بدون نظارت(UnSupervised learning)

f : $z = f(x)$

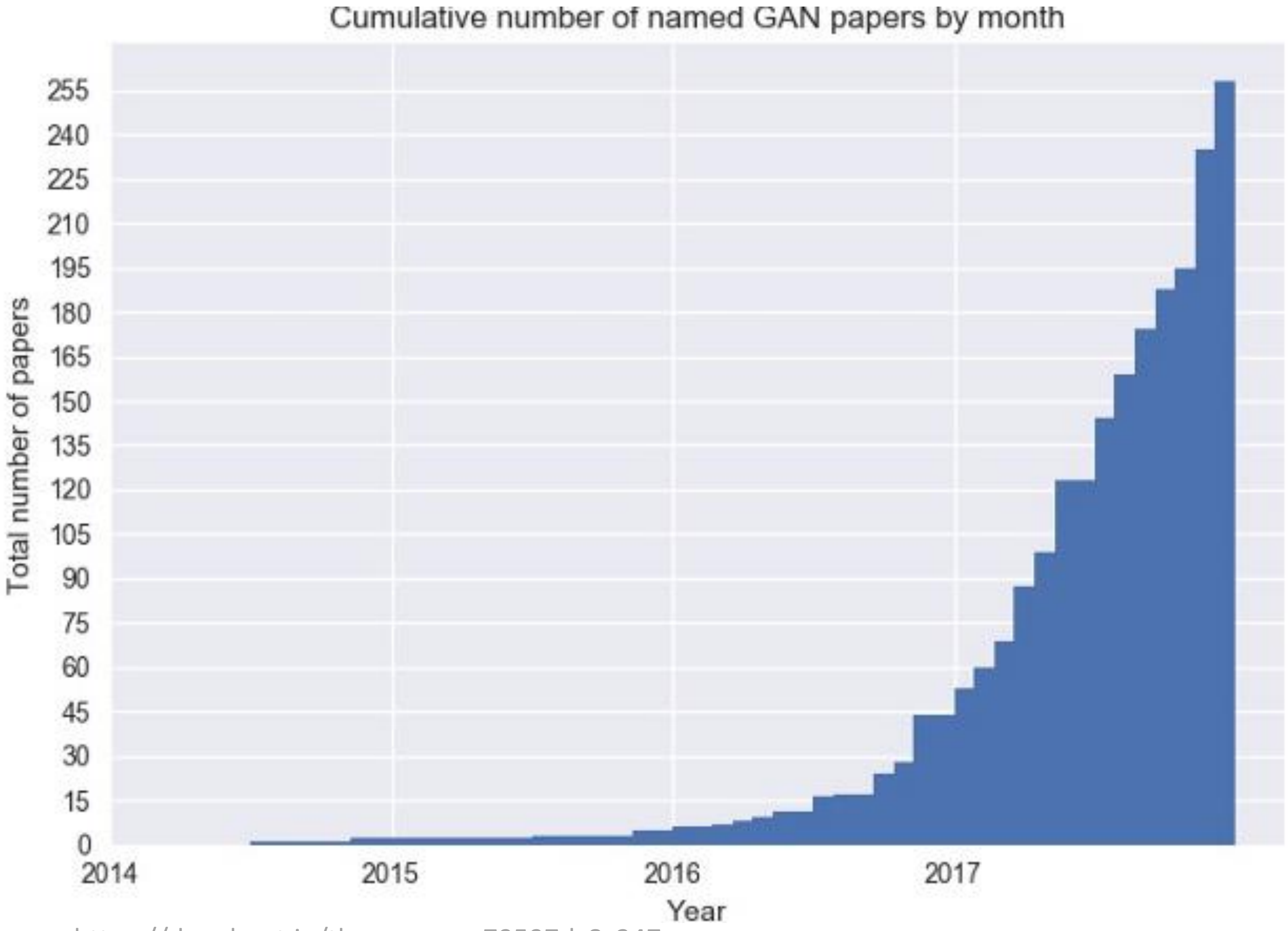
x : داده

z : latent

$\rightarrow \boxed{f} \rightarrow [0.1, 0.3, -0.8, 0.4, \ldots]$

✓ معیار شباهت ...

روندگسترش پژوهش‌های مبتنی بر GAN



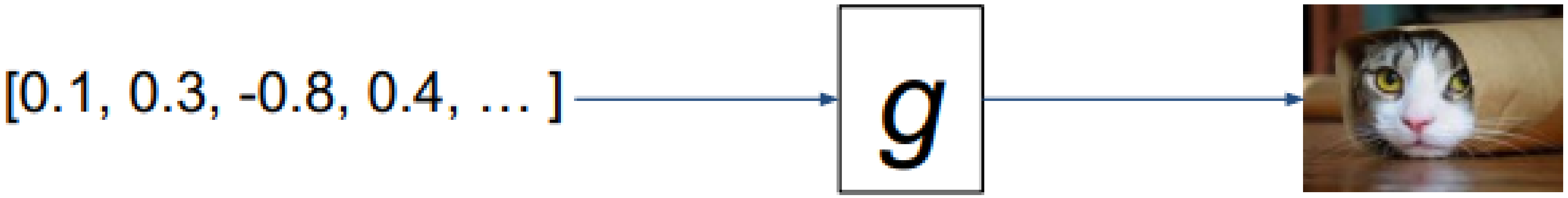
https://deephunt.in/the-gan-zoo-79597dc8c347

مدل‌های مولد

G : ***x = g(z)***

x : داده

z : latent

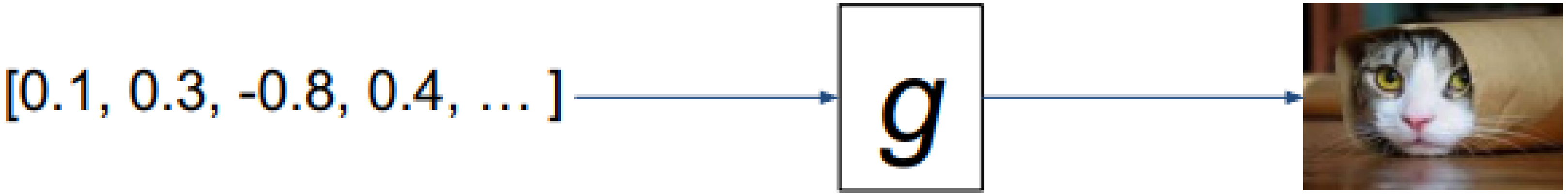


مدل‌های مولد

G : $x = g(z)$

x : داده

z : latent



بدون نظارت	مدل‌های مولد
$z = f(x)$	$x = g(z)$
$P(z\|x)$	$P(x\|z)$
Encoder	*Decoder (Generator)*

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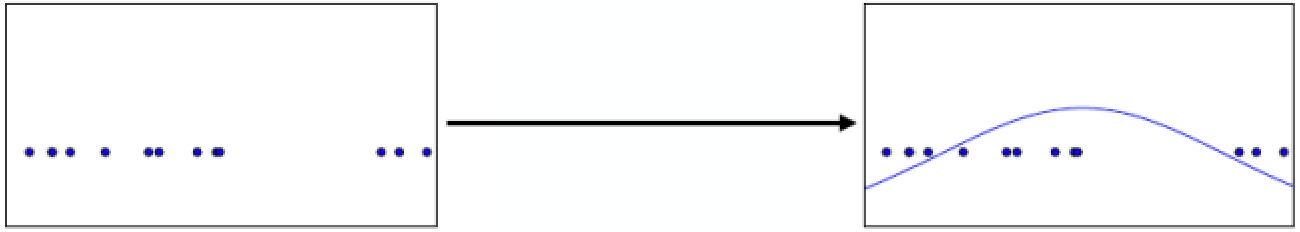
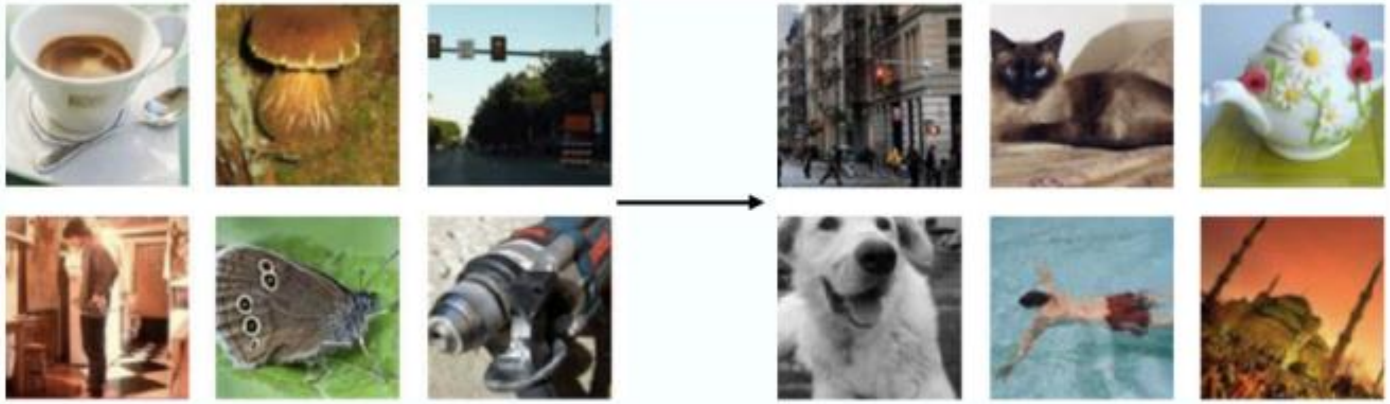
مدل‌های مولد

- مبتنی بر تخمین توزیع



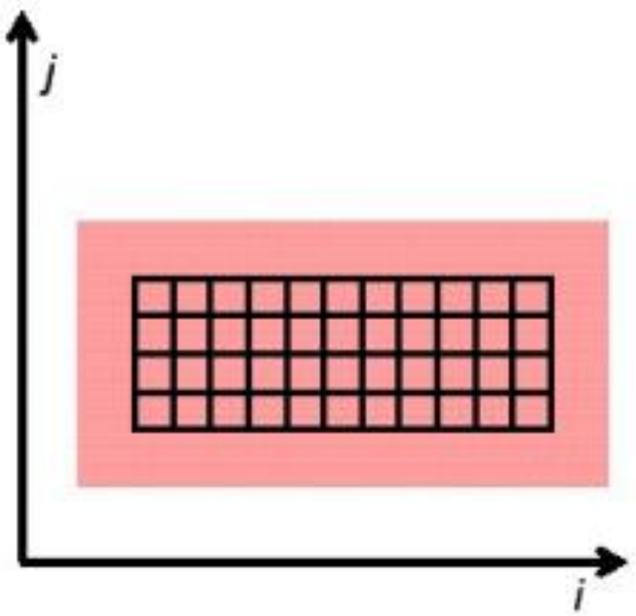
- مبتنی بر تولید نمونه



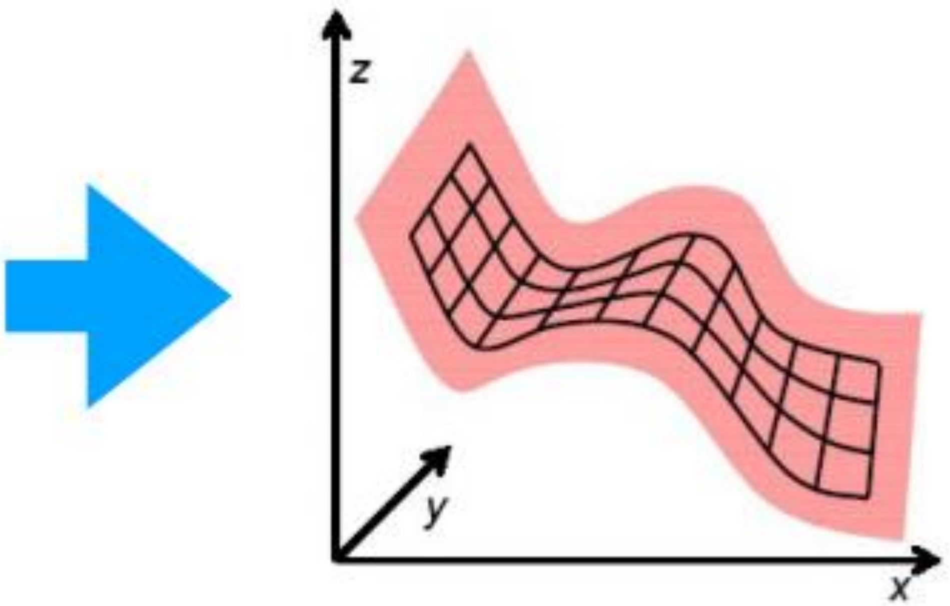
نمونه‌های آموزشی نمونه‌های تولیدی

Goodfellow 2016
https://arxiv.org/pdf/1701.00160.pdf

فضای یادگیری و داده؟!



فضای نهان
Latent space



فضای داده‌ای
Data space

NVIDIA
https://goo.gl/XZVmCt

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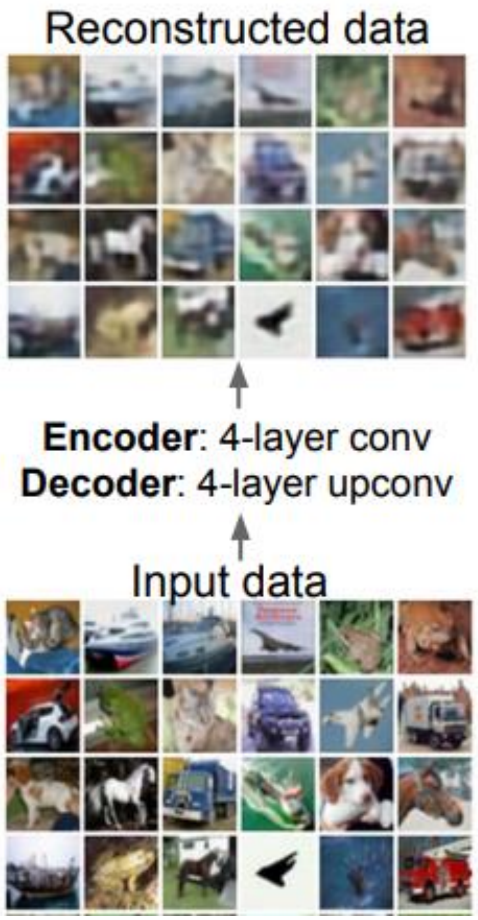
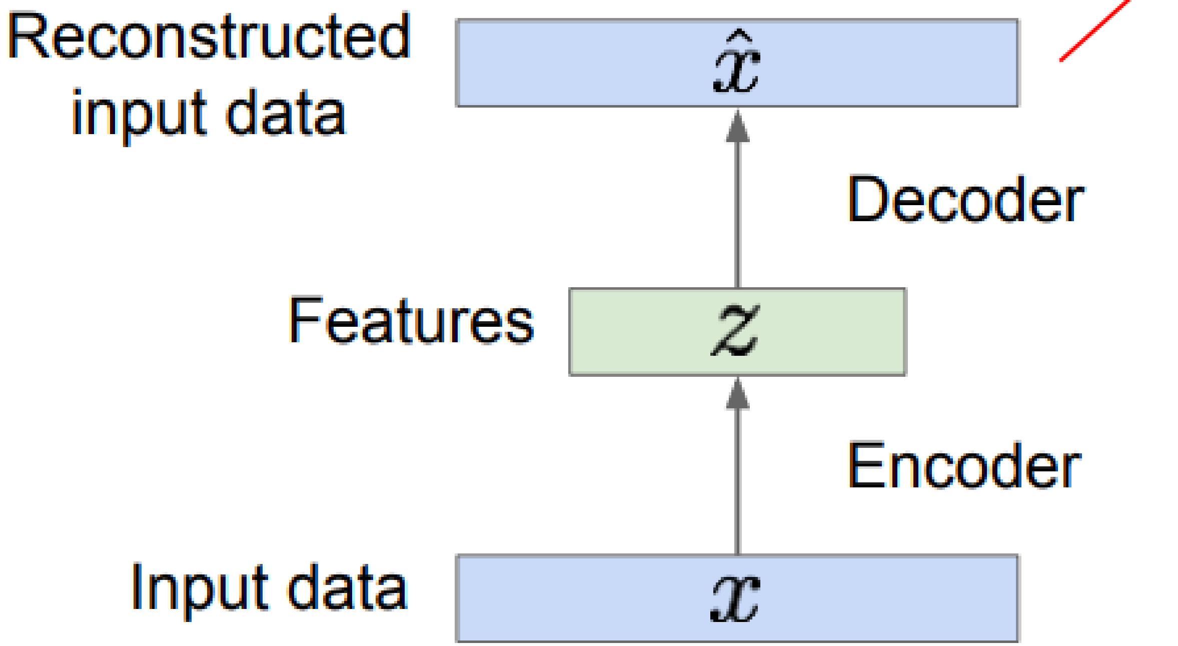
خودرمزکننده (AutoEncoder)





Originally: Linear + nonlinearity (sigmoid)
Later: Deep, fully-connected
Later: ReLU CNN (upconv)

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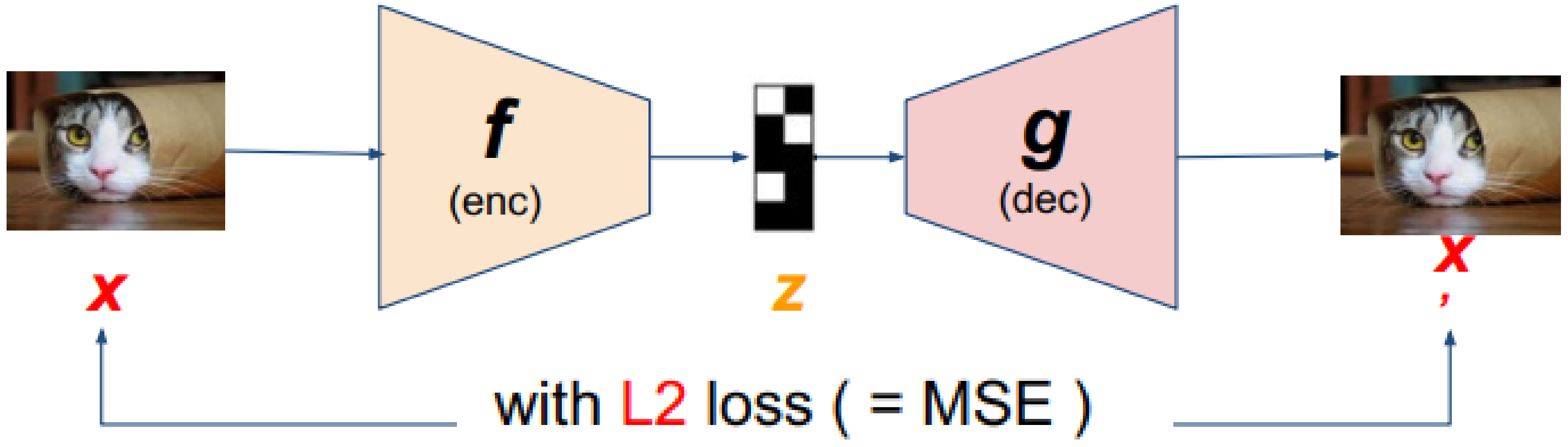
خودرمزکننده (AutoEncoder)



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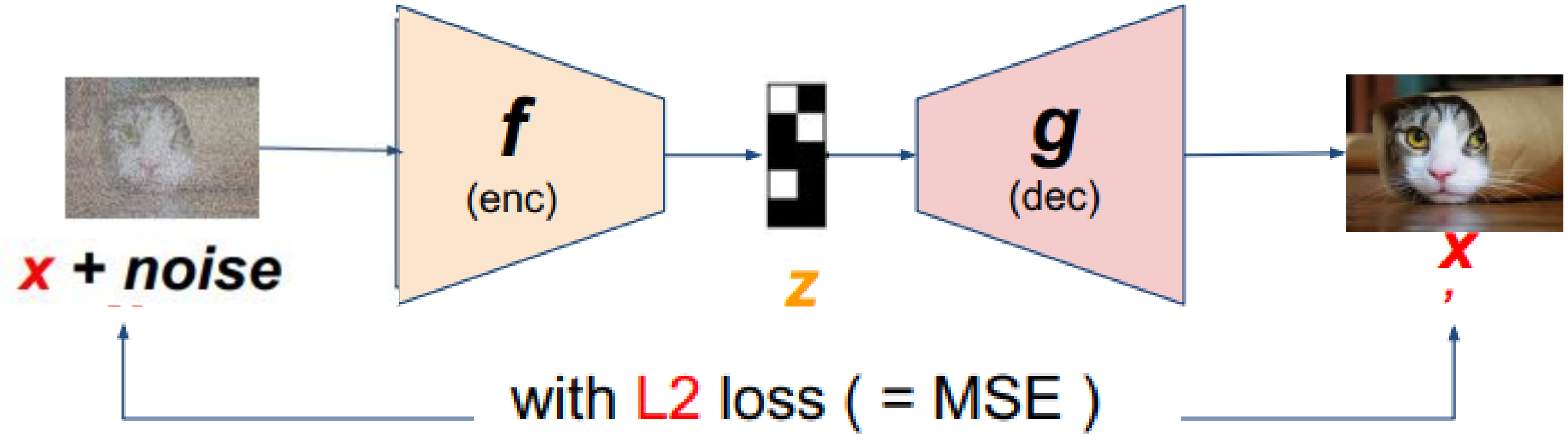
خودرمزکننده (AutoEncoder)



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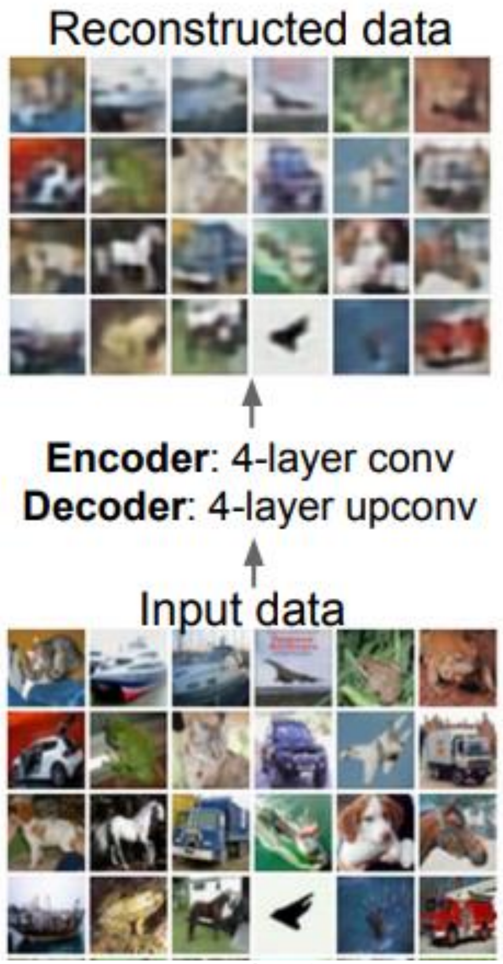
خودرمزکننده (AutoEncoder)



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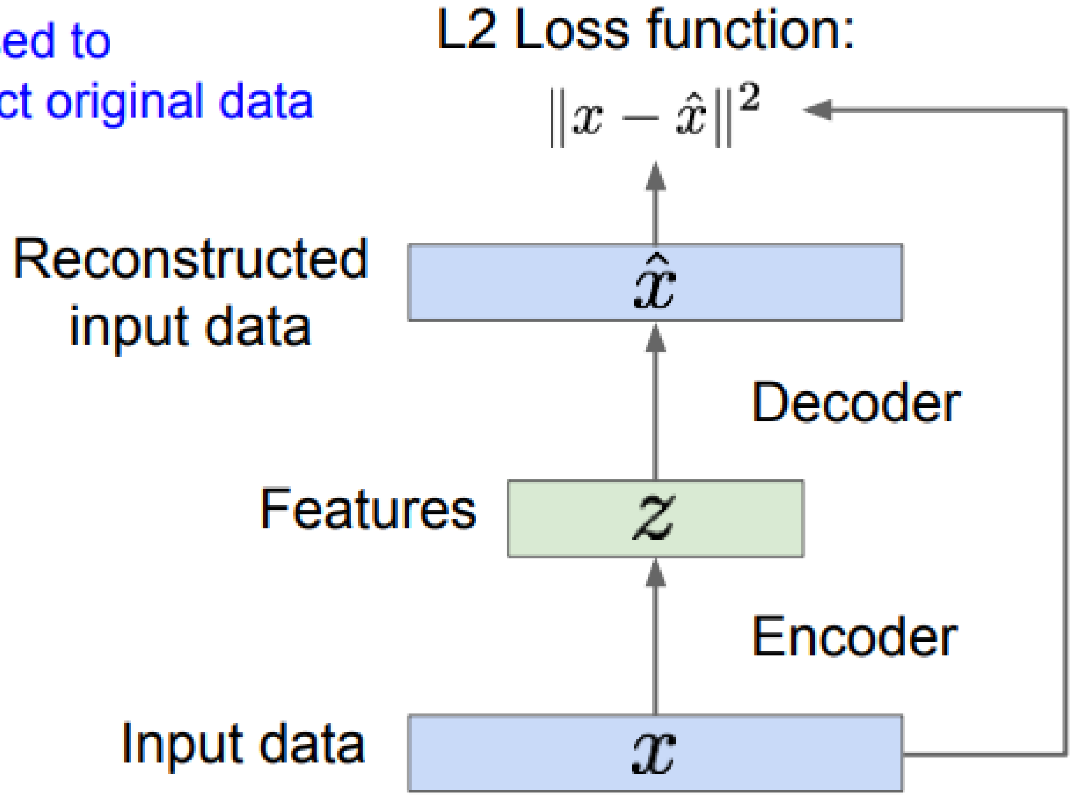
Train such that features can be used to reconstruct original data

Doesn't use labels!



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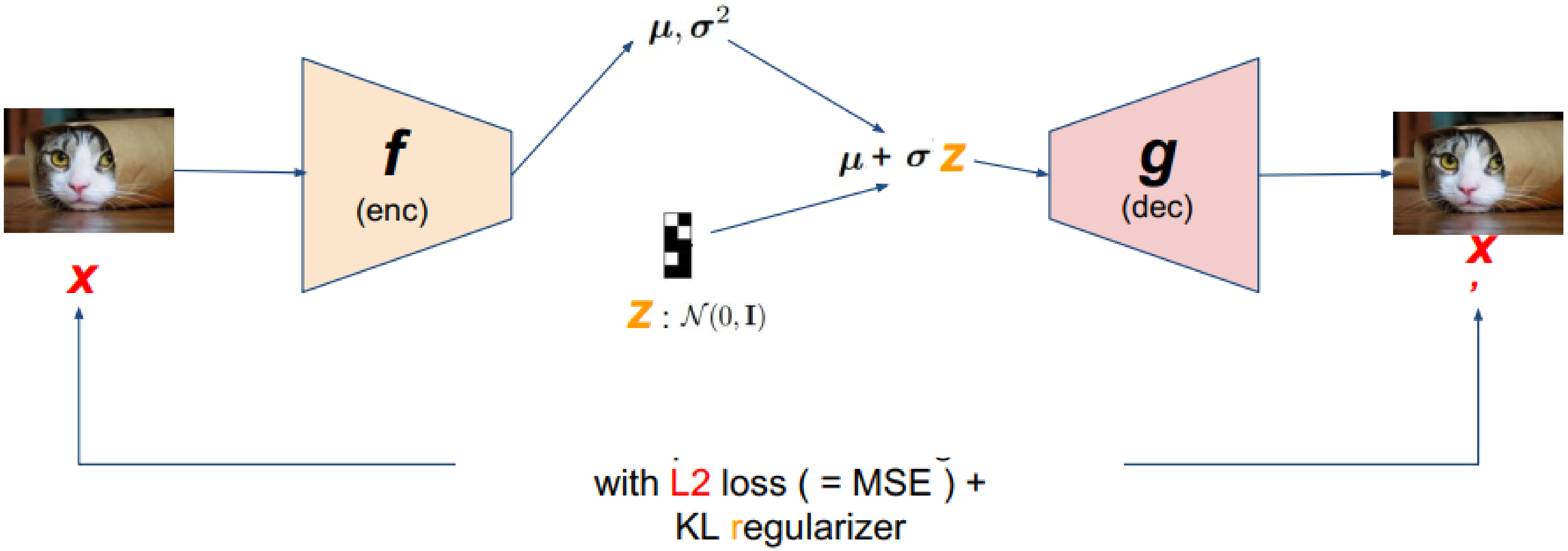
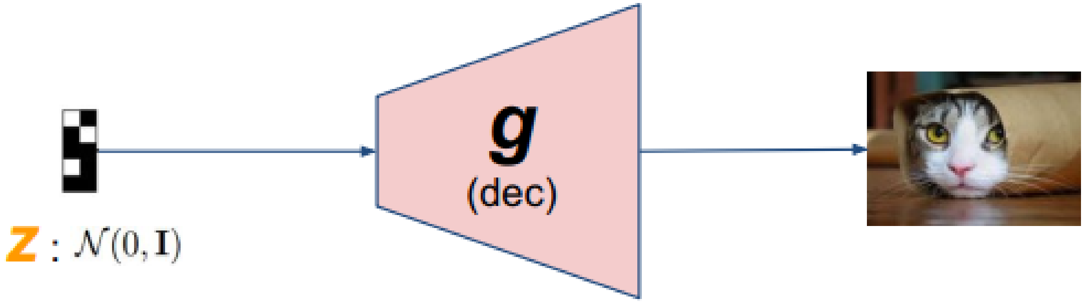
VAE (Variational Autoencoders)



VAE (Variational Autoencoders)



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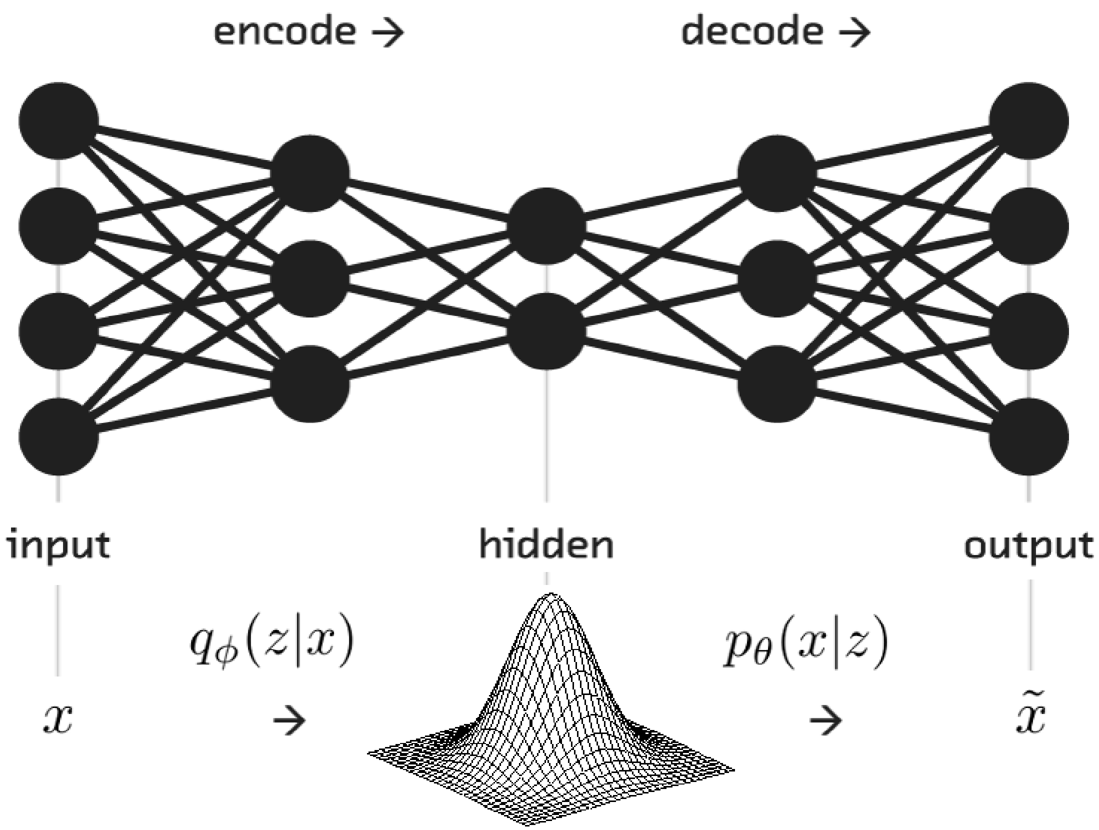
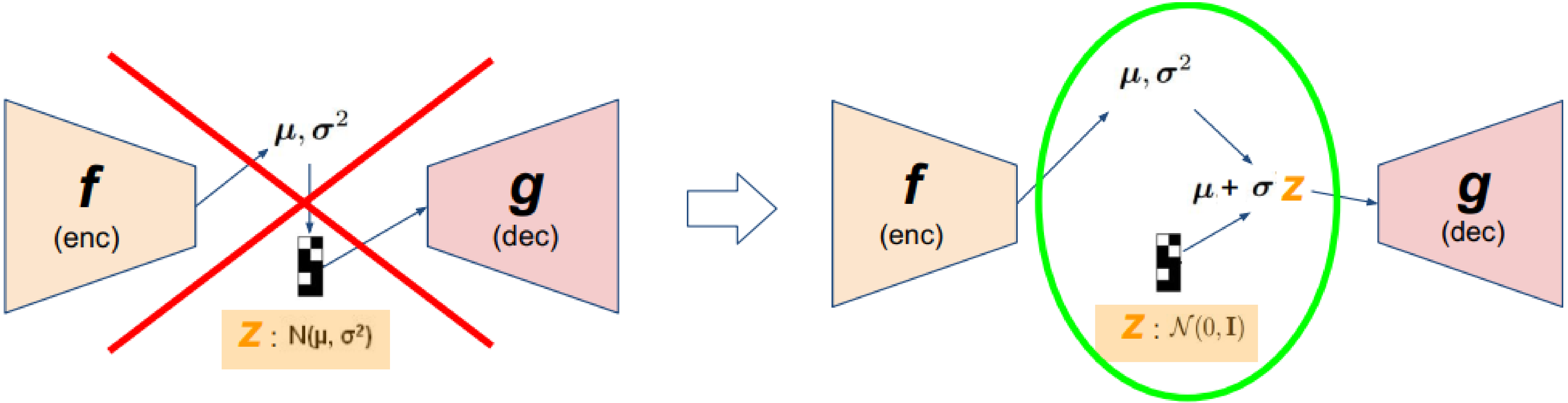
VAE (Variational Autoencoders)



https://goo.gl/Jd3sQb

VAE (Variational Autoencoders)



https://goo.gl/Jd3sQb

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VAE (Variational Autoencoders)

32x32 CIFAR-10

Labeled Faces in the Wild

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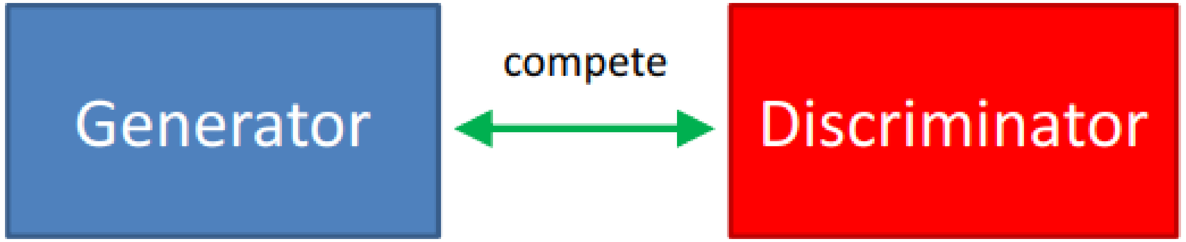
Generative Adversarial Network

- Ian Goodfellow et al, "Generative Adversarial Networks", 2014.



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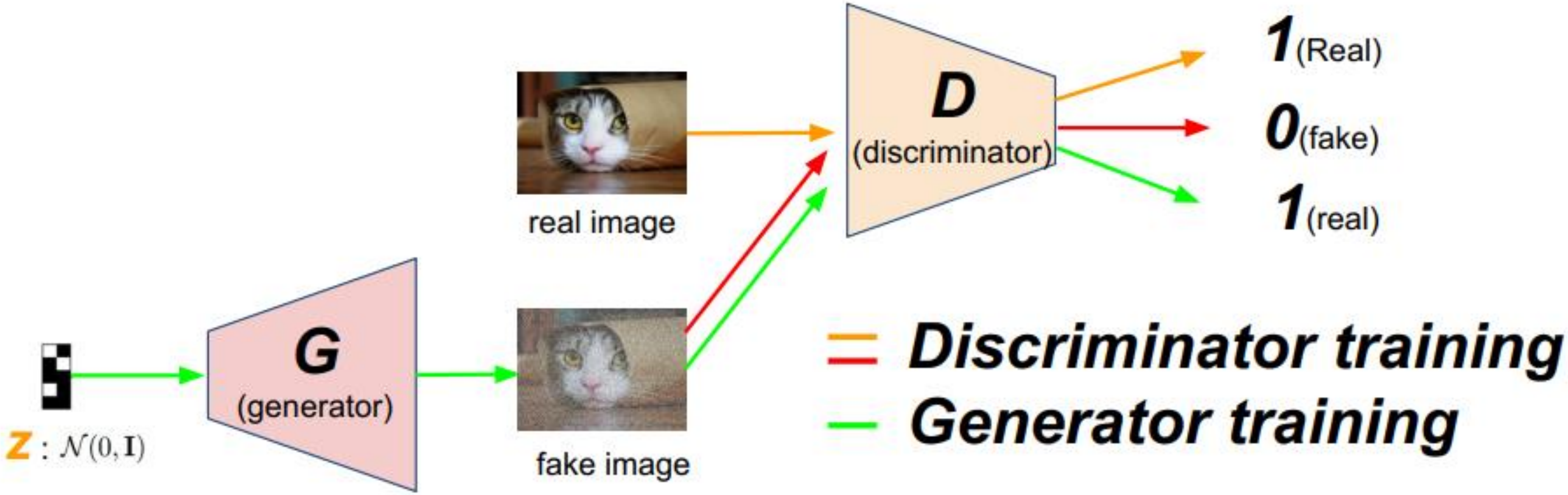
Generative Adversarial Network



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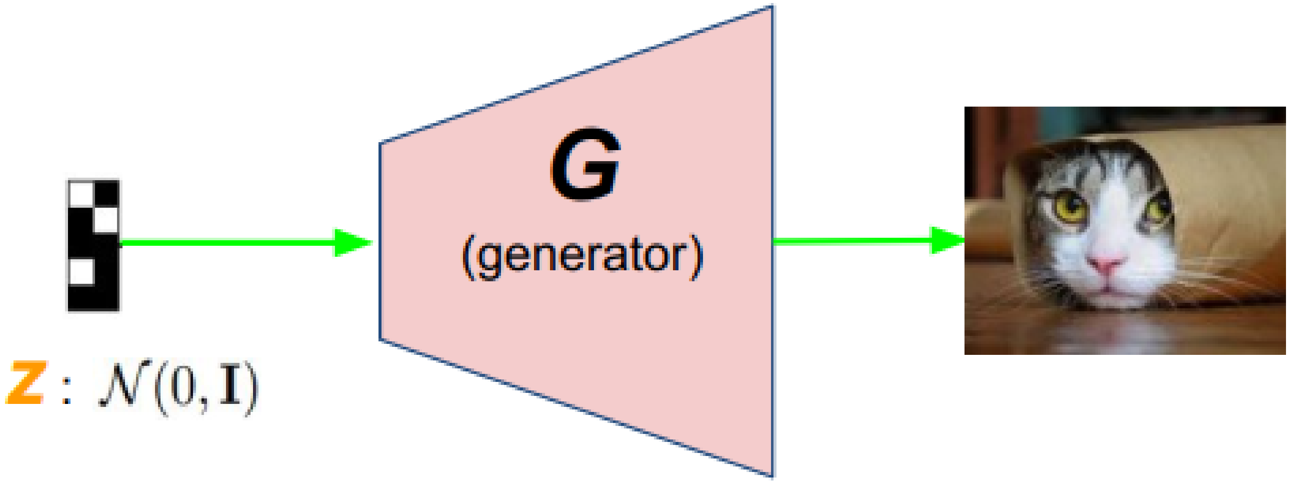

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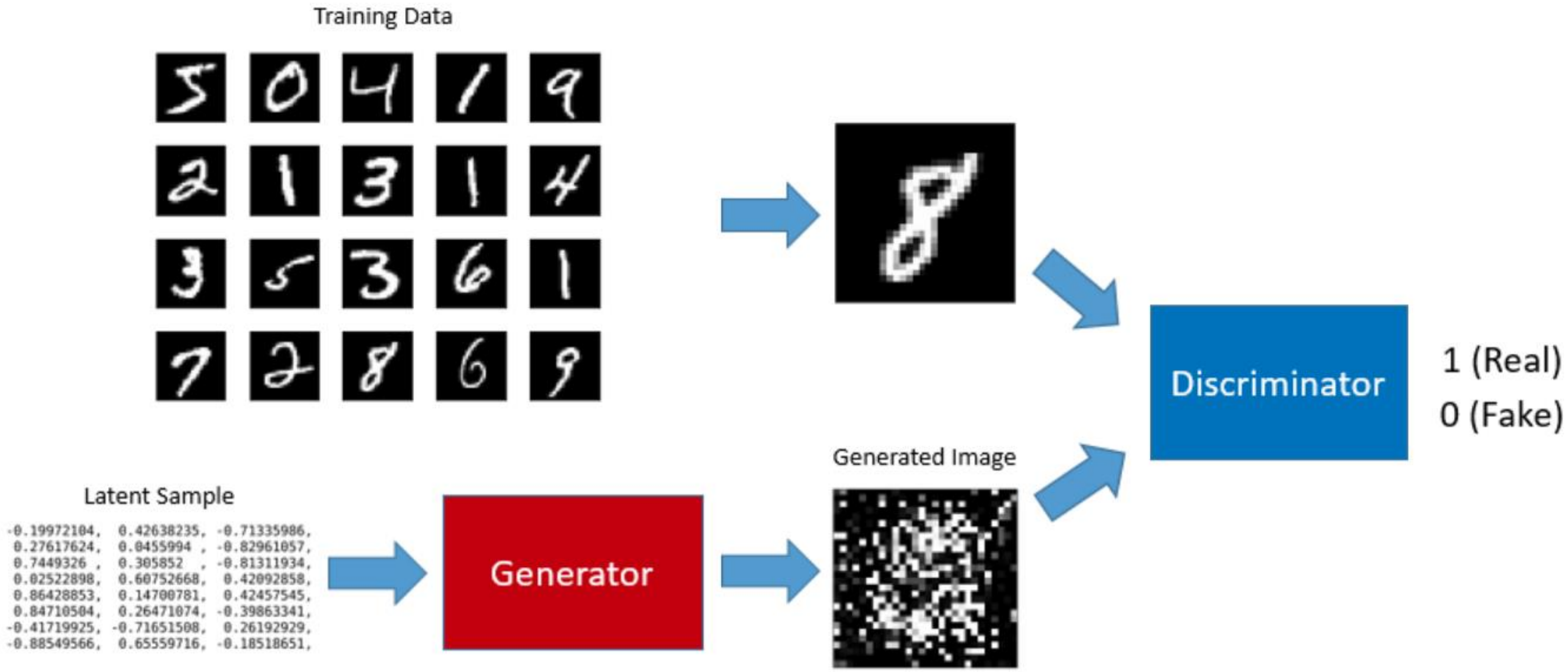
Generative Adversarial Network



https://goo.gl/8AH4bj

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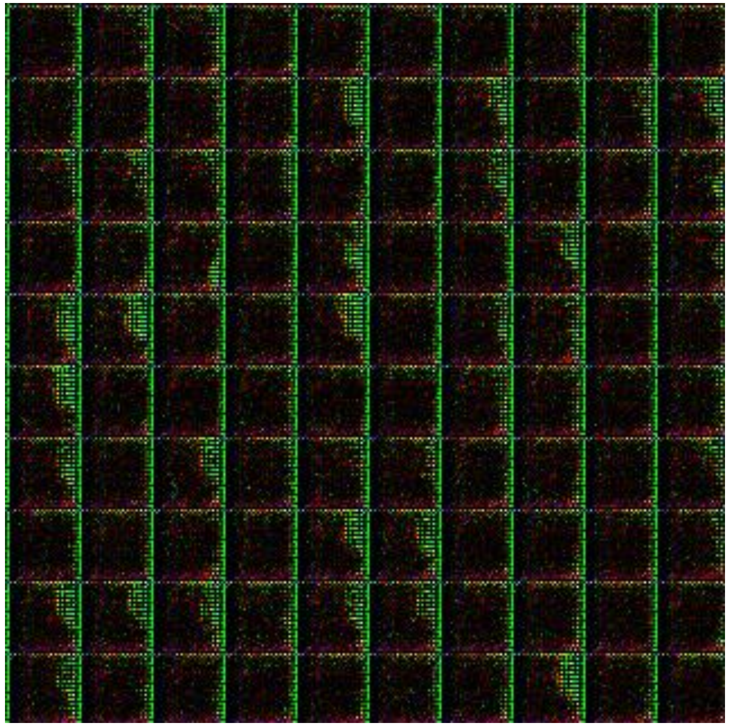
Generative Adversarial Network

VAE

learning to generate images (log time)



GAN

learning to generate images (linear time)

https://blog.openai.com/generative-models/

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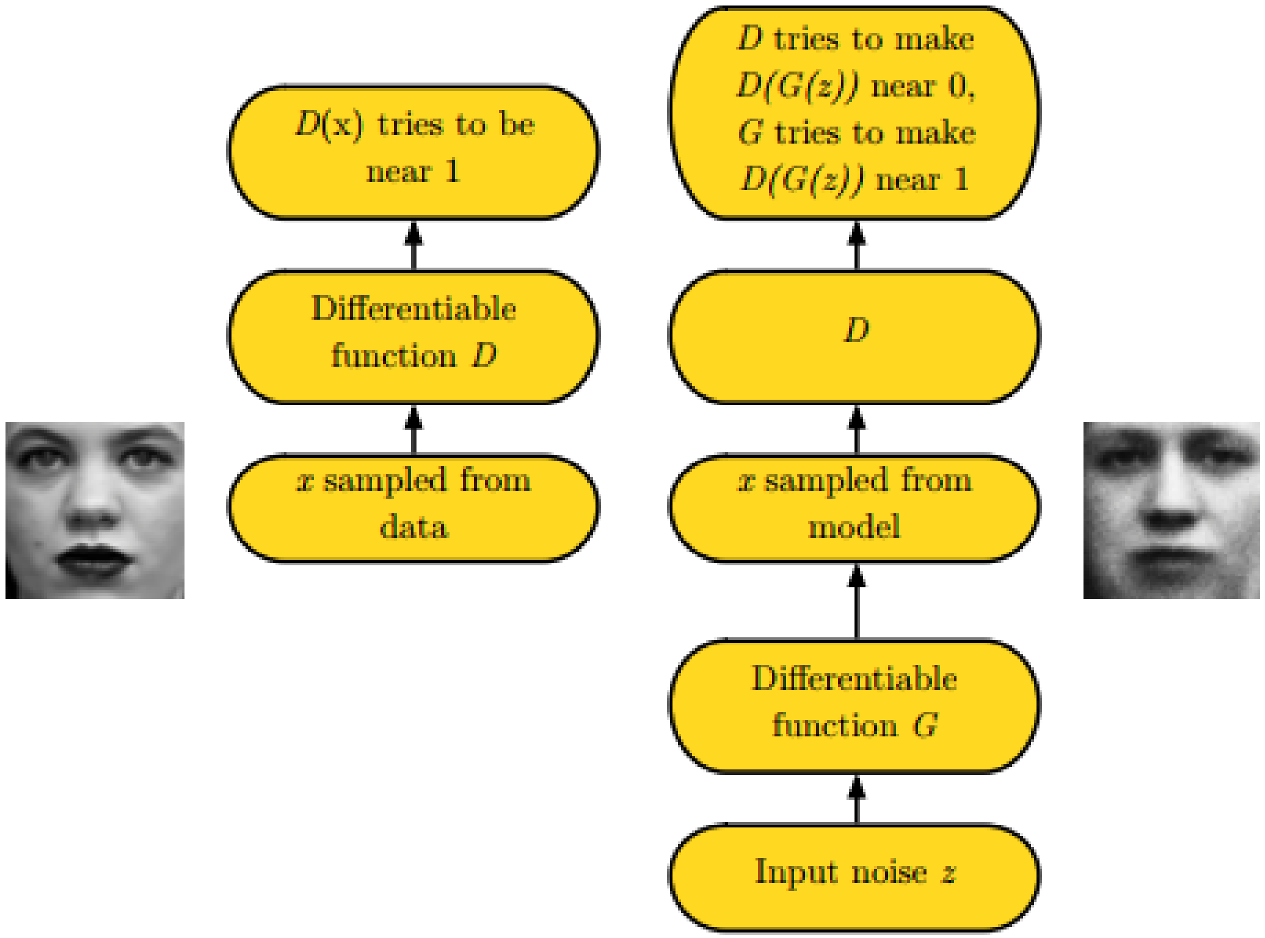
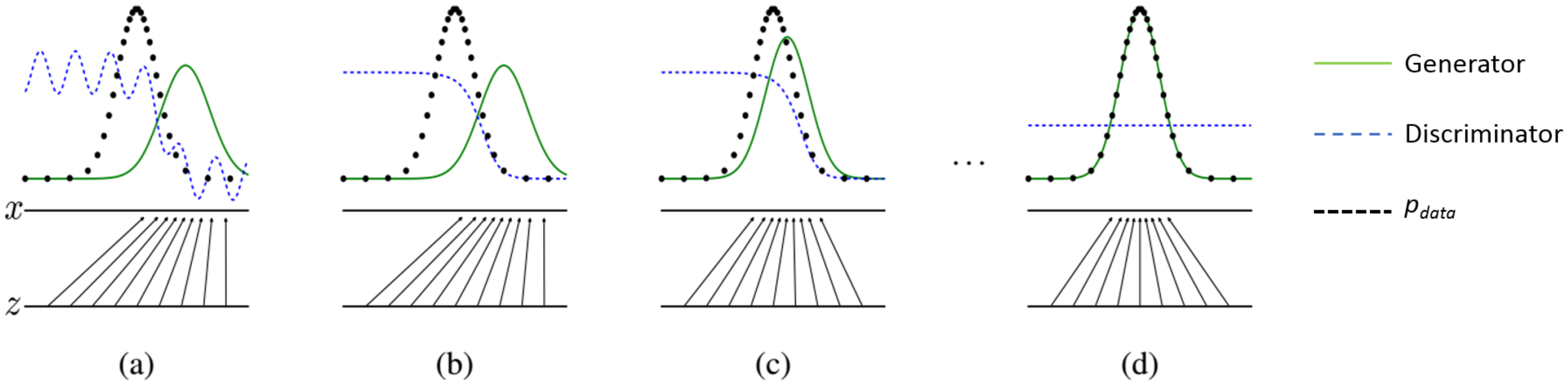
Generative Adversarial Network

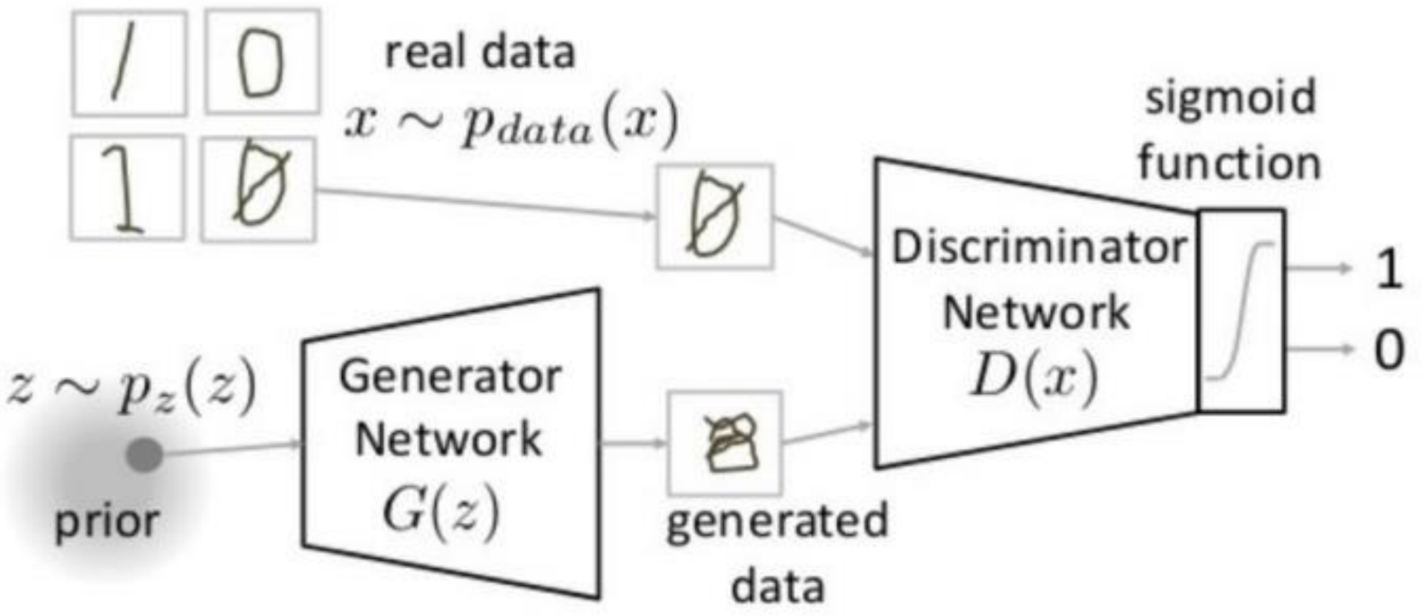


Generative Adversarial Network



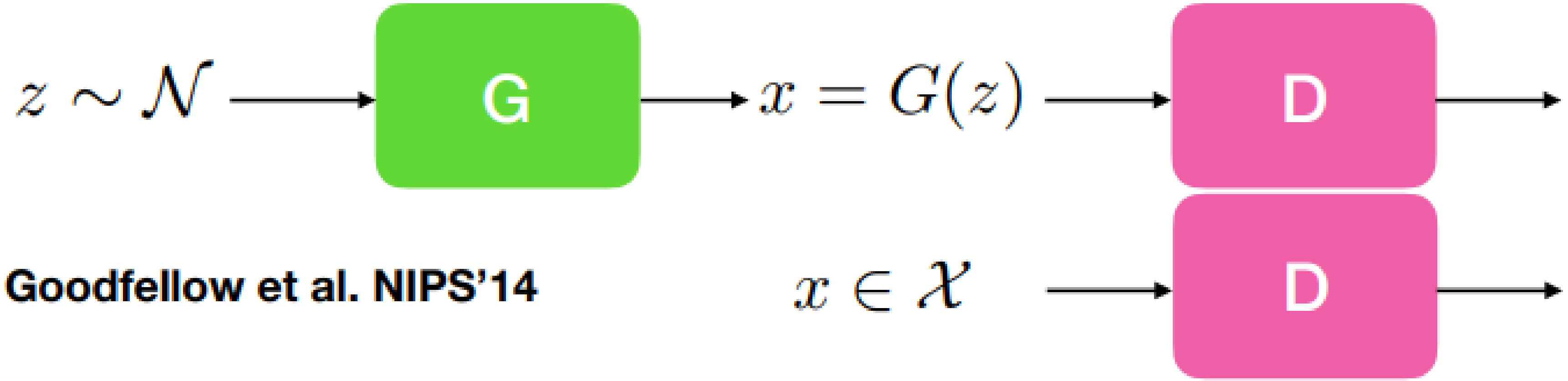
Goodfellow *et al.* 2014
https://arxiv.org/pdf/1406.2661

Generative Adversarial Network



"Introductory Guide to Generative Adversarial Networks (GANs)." *Analytics Vidhya*, June 15, 2017.

Generative Adversarial Network



Goodfellow et al. NIPS'14

$$\max_{G} E_{z \sim p_{\mathcal{N}}} [\log D(G(z))]$$

$$\max_{D} E_{x \sim p_{\mathcal{X}}} [\log D(X)] + E_{z \sim p_{\mathcal{N}}} [\log(1 - D(G(z)))]$$

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Generative Adversarial Network

Value of — Expectation — prob. of D(real) — prob. of D(fake)

$$\min_{G} \max_{D} V(D, G) = \mathbb{E}_{\boldsymbol{x} \sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z} \sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]$$

Minimize G — Maximize D — x is sampled from real data — z is sampled from N(0, I) — fake

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Generative Adversarial Network

$$\max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]$$

Maximize prob. of D(real)

Minimize prob. of D(fake)

BCE(binary cross entropy) with label 1 for real, 0 for fake.

(Practically, **CE** will be OK. or more plausible.)

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Generative Adversarial Network

$$\min_G V(D,G) = \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))] \simeq \boxed{\max_G \mathbb{E}_{z \sim p_z(z)}[\log(D(G(z)))]}$$

Maximize prob. of D(fake)

BCE(binary cross entropy) with label 1 for fake.

(Practically, **CE** will be OK. or more plausible.)

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Generative Adversarial Network

$$D_G^*(\boldsymbol{x}) = \frac{p_{data}(\boldsymbol{x})}{p_{data}(\boldsymbol{x}) + p_g(\boldsymbol{x})} \longrightarrow 0.5$$

$$\begin{aligned}
C(G) =& \max_D V(G, D) \\
=& \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}}[\log D_G^*(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}}[\log(1 - D_G^*(G(\boldsymbol{z})))] \\
=& \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}}[\log D_G^*(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{x}\sim p_g}[\log(1 - D_G^*(\boldsymbol{x}))] \\
=& \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}}\left[\log \frac{p_{\text{data}}(\boldsymbol{x})}{P_{\text{data}}(\boldsymbol{x}) + p_g(\boldsymbol{x})}\right] + \mathbb{E}_{\boldsymbol{x}\sim p_g}\left[\log \frac{p_g(\boldsymbol{x})}{p_{\text{data}}(\boldsymbol{x}) + p_g(\boldsymbol{x})}\right]
\end{aligned}$$

$$C(G) = -\log(4) + \underbrace{KL\left(p_{\text{data}} \middle\| \frac{p_{\text{data}} + p_g}{2}\right) + KL\left(p_g \middle\| \frac{p_{\text{data}} + p_g}{2}\right)}_{2 \cdot JSD\left(p_{\text{data}} \| p_g\right)}$$

Jansen-Shannon divergence

Thank you!

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