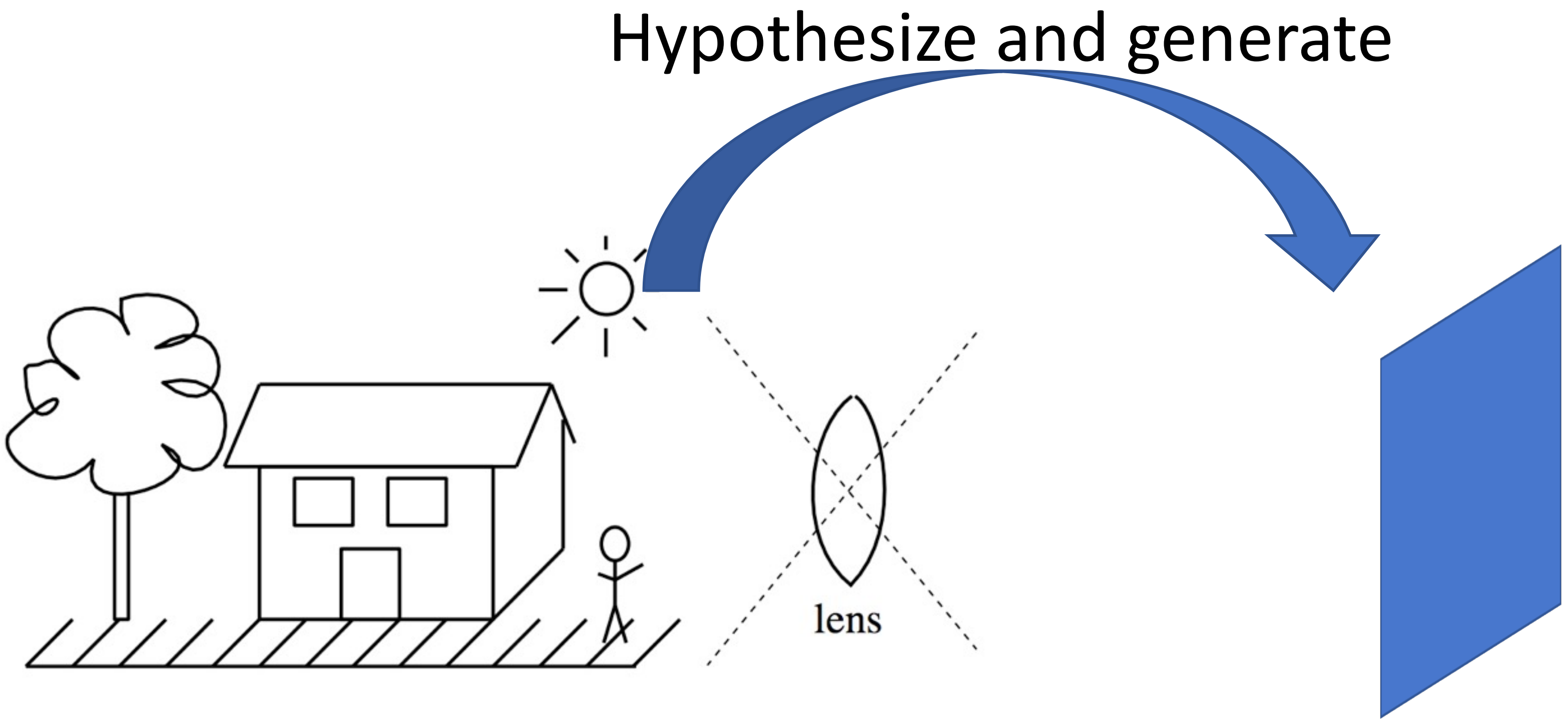
Image Synthesis

Why generative modeling?

- Understanding the visual world
- Generating samples for learning
- Unsupervised learning
- Graphics and image processing
- Art and creativity

Synthesis for understanding - Analysis by synthesis



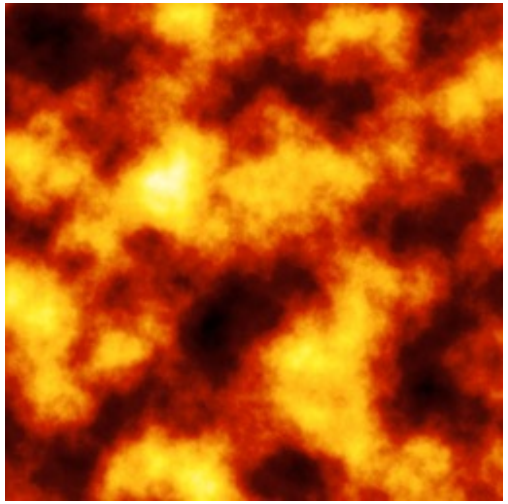
$$P(y \mid x) = \frac{P(x, y)}{P(x)}$$

Slide adapted from Bruno Olshausen

Generating samples for learning

Graphics and image processing

We have been doing generation for a while…



Perlin noise

We have been doing generation for a while…

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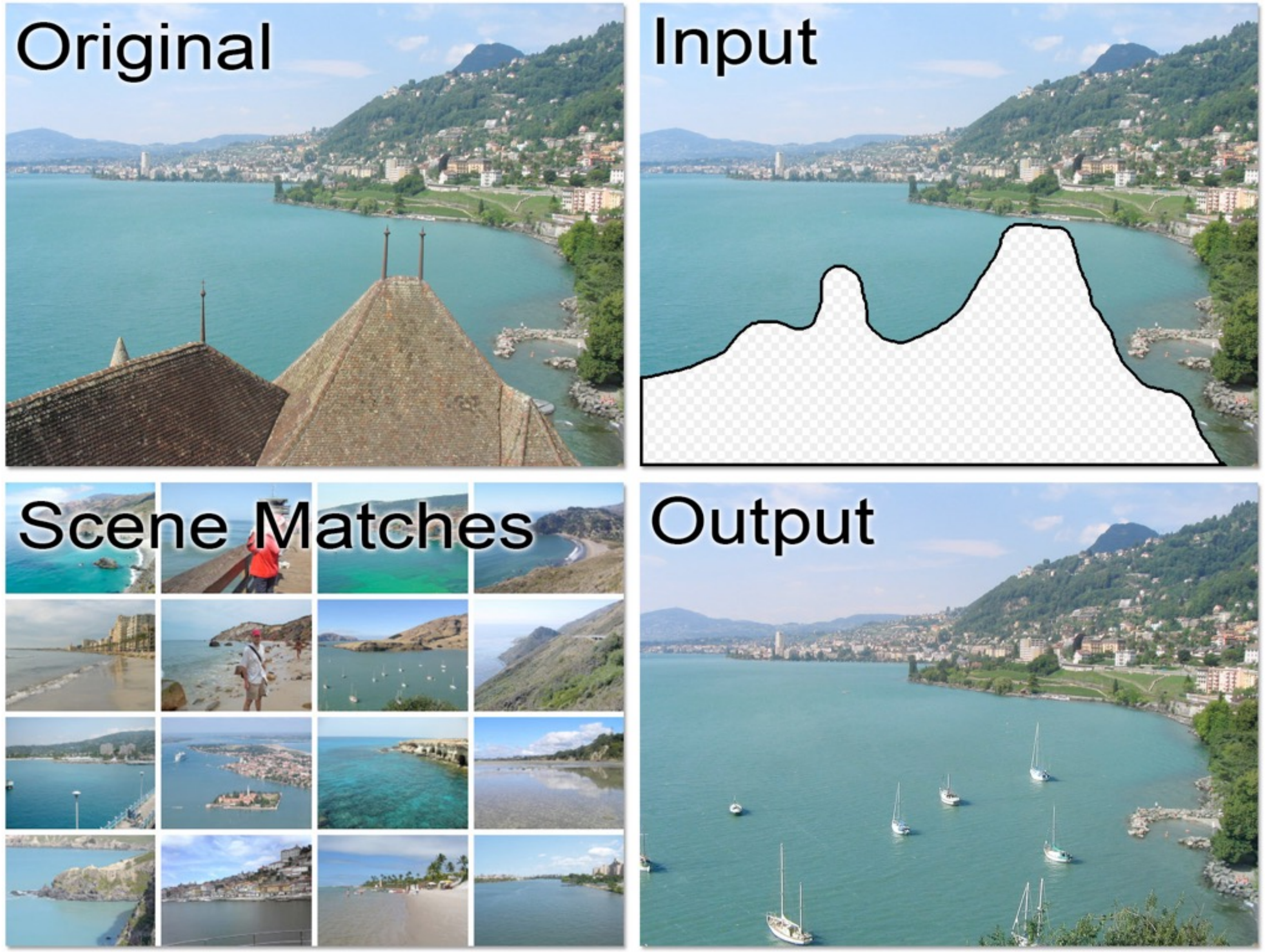
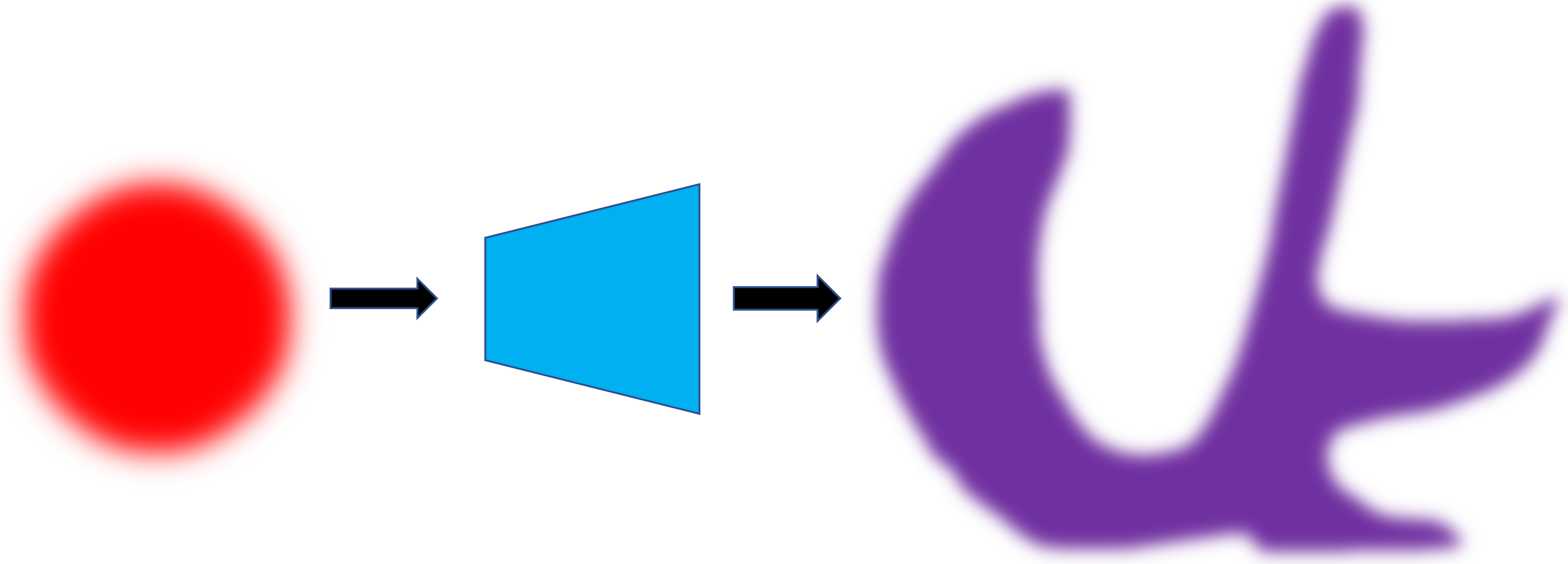


Learning generative models of images

- Standard probabilistic models (e.g. Gaussian)
  - Can be sampled from
  - Cannot capture arbitrary distributions
- Neural networks
  - Can learn to model arbitrary functions
  - Are deterministic
- Key idea 1: neural networks with noise input!

Learning generative models of images

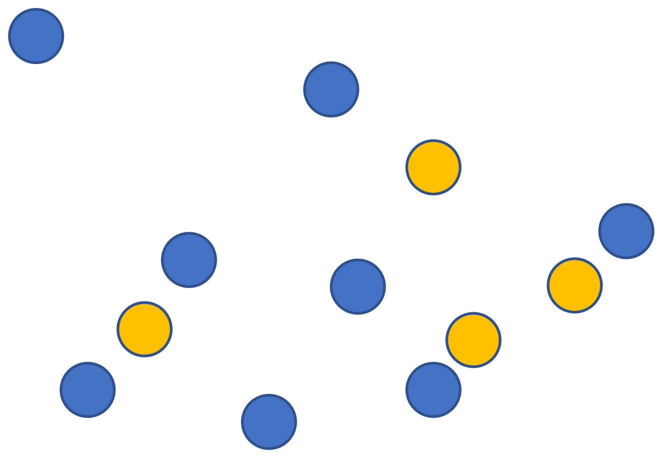


Learning generative models of images

- Two distributions: p_{real} and p_{model}
- Both highly multimodal, high-dimensional
- Only have samples from each distribution
- Want to minimize the difference between the two distributions

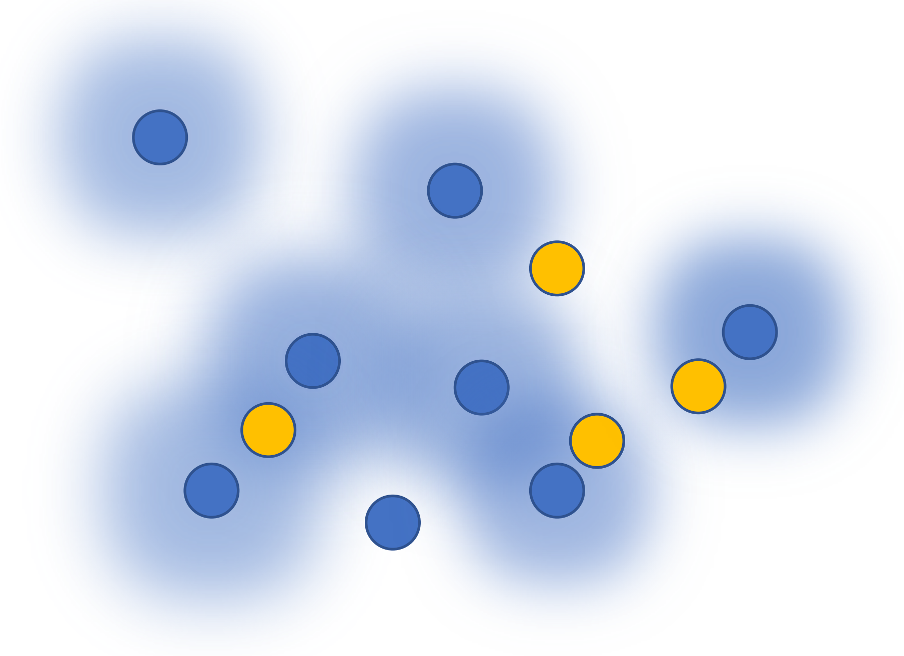
Computing the difference between two distributions

- Idea 1: parzen window estimation



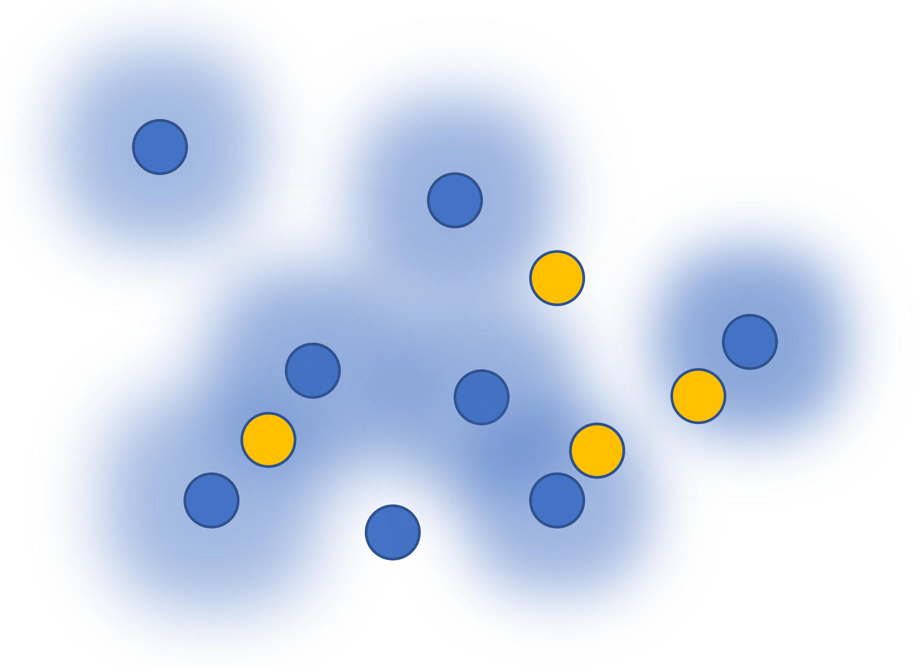
Computing the difference between two distributions

- Idea 1: parzen window estimation
- Plop a Gaussian at each sample to convert samples into a distribution



Computing the difference between two distributions

- Idea 1: parzen window estimation
- Problem: calculating distances an issue in high dimensional spaces
- Need dense sampling

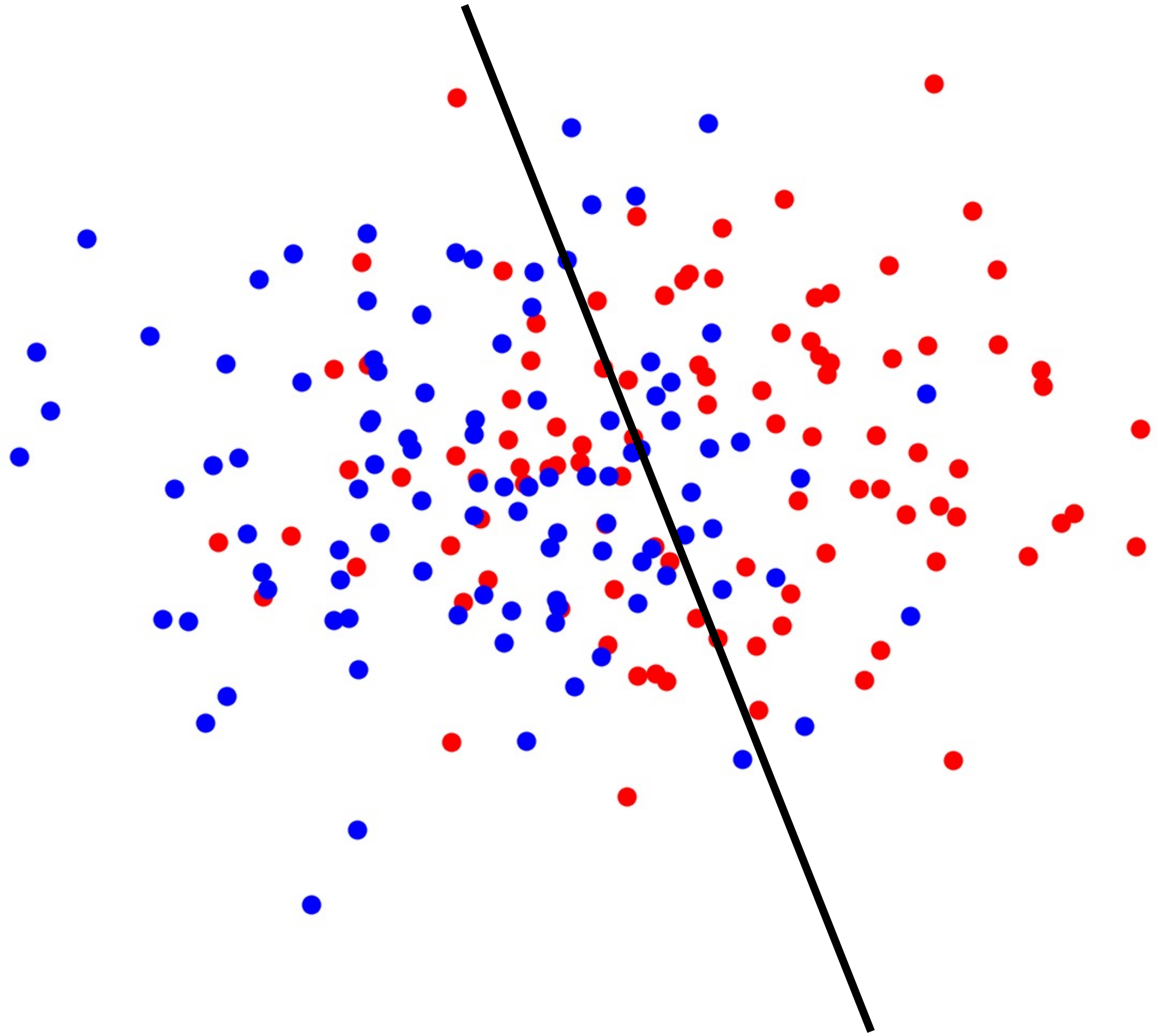


Computing the difference between two distributions

- Idea 1: parzen window estimation
- Problem: calculating distances an issue in high dimensional spaces
- Need dense sampling

The adversary

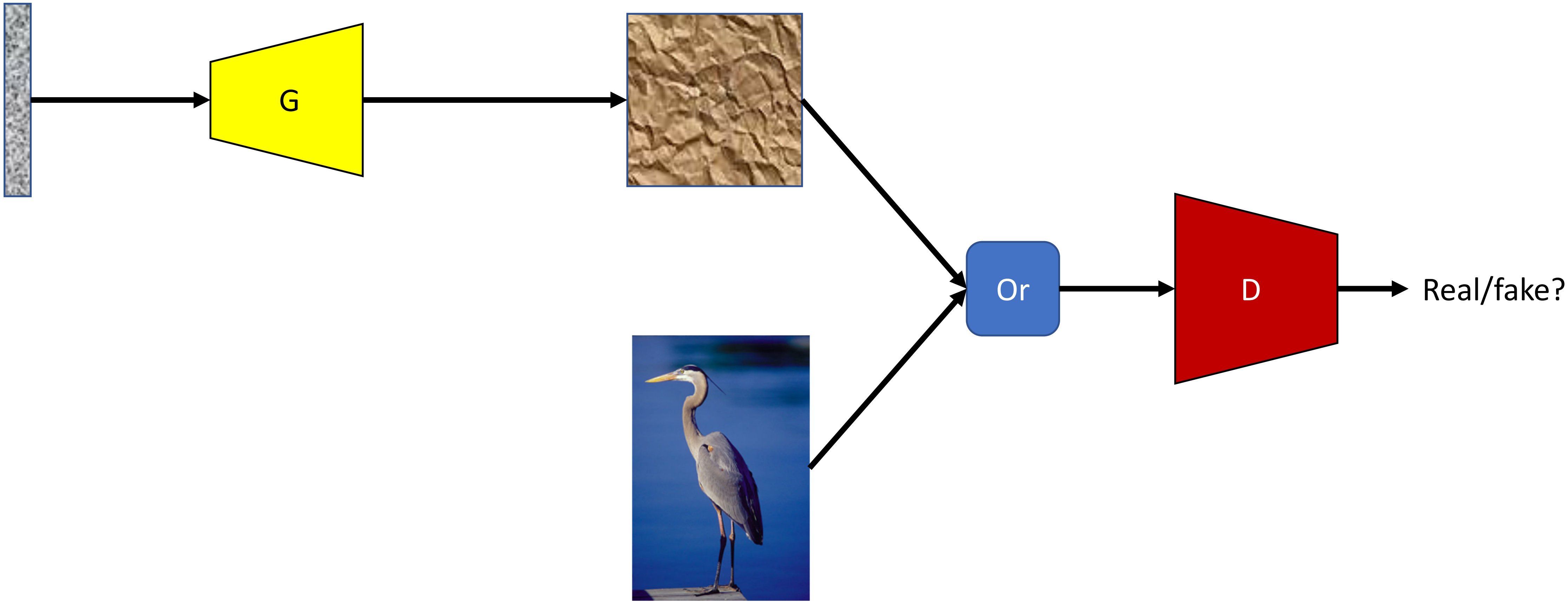
- Train a classifier to see if the distributions are different!



The adversary

- Essentially the same idea as:
  - Maximum mean discrepancy (MMD)
  - $\mathcal{A}$-distance

Generative Adversarial Nets



Generative Adversarial Nets

- Perspective 1: Two player game
  - Discriminator’s job to distinguish model samples from real thing
  - Generator’s job to fool the discriminator

- Perspective 2: Density estimation

$$D(x) = \frac{p_{data}(x)}{p_{model}(x) + p_{data}(x)}$$

  - Discriminator estimates density and tells generator which samples are unlikely
  - Generator learns to sample

Generative Adversarial Nets

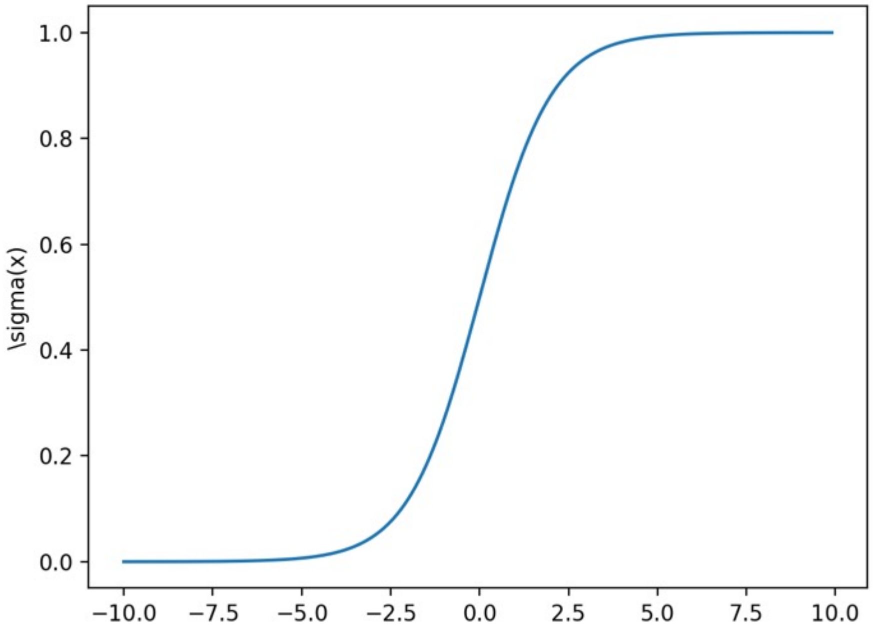
$$\max_G \min_D (-\mathbb{E}_x \log D(x) - \mathbb{E}_z \log(1 - D(G(z))))$$

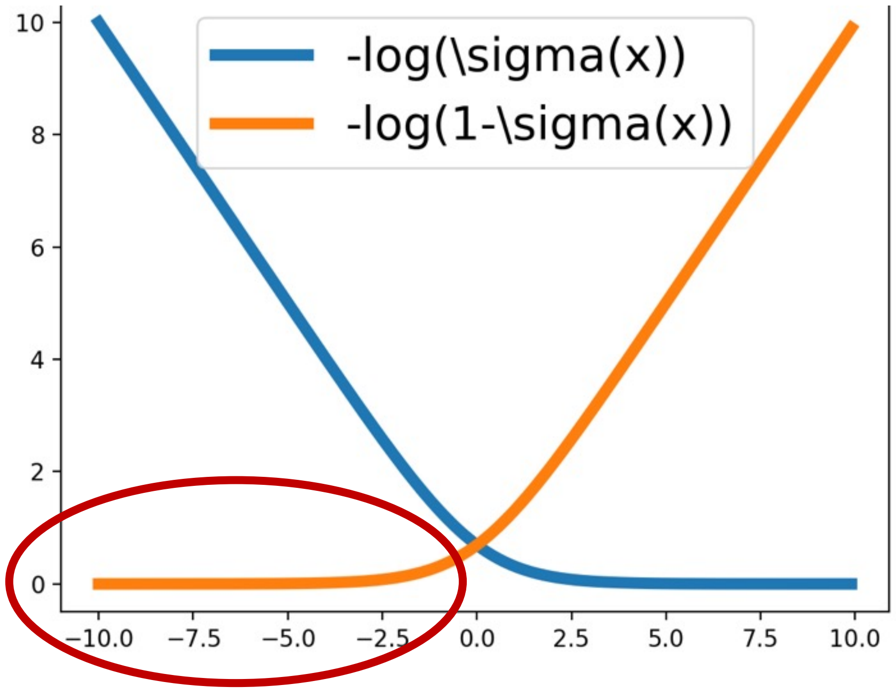
- Training:
- Sample x
- Sample z
- Take step(s) along discriminator
- Take step(s) along generator

Generative Adversarial Nets

$$\max_G \min_D (-\mathbb{E}_x \log D(x) - \mathbb{E}_z \log(1 - D(G(z))))$$

- Usually, discriminator's task is easier
- D(G(z)) often close to 0



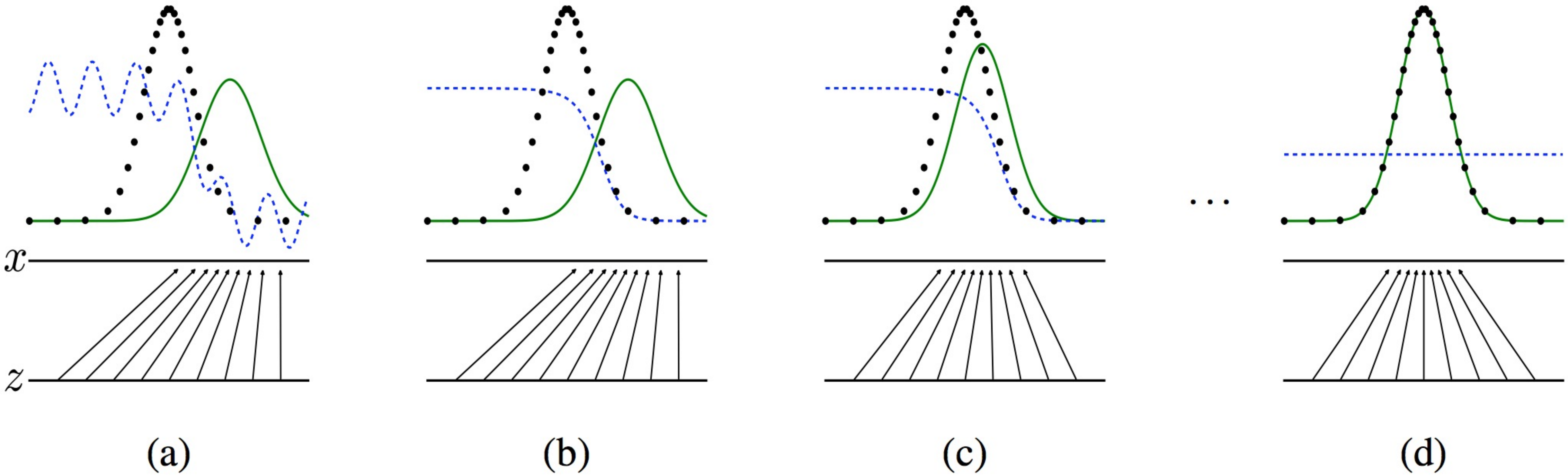


Generative Adversarial Nets

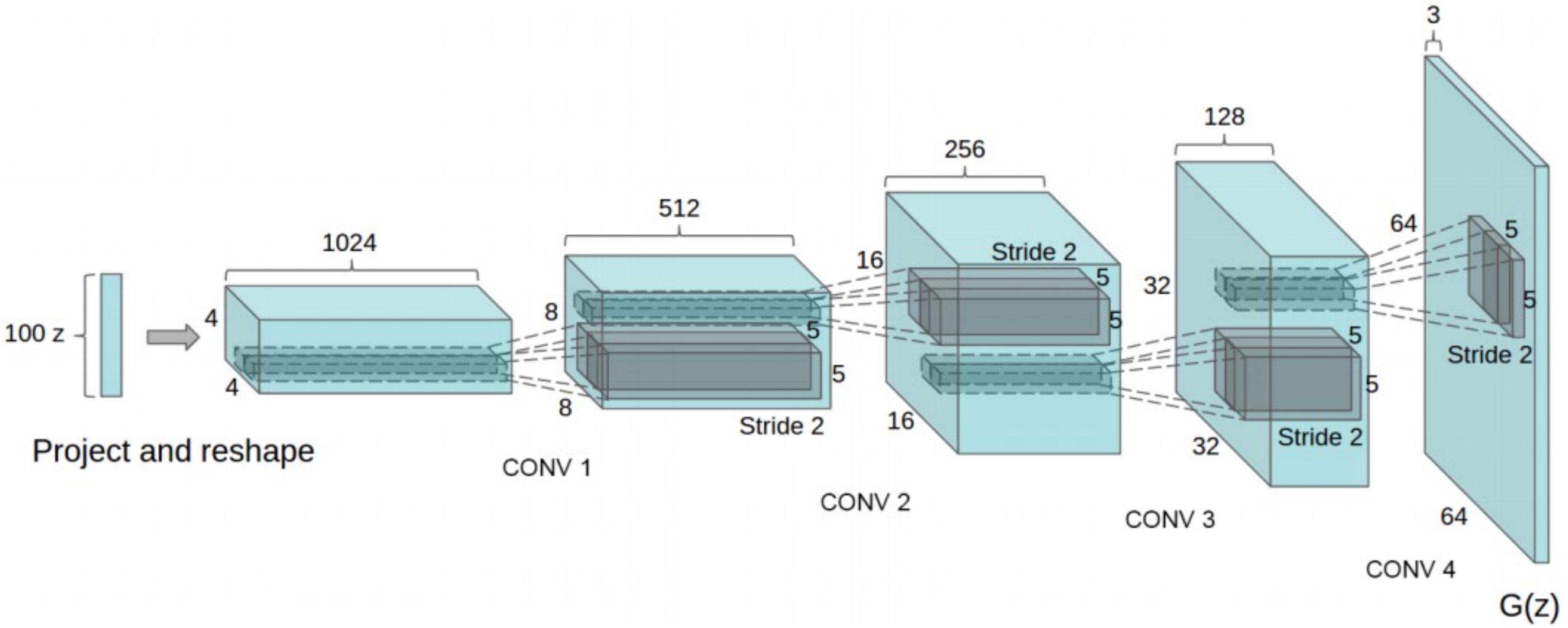
$$J_D(x) = -\mathbb{E}_x \log D(x) - \mathbb{E}_z \log(1 - D(G(z)))$$

$$J_G(x) = -\mathbb{E}_z \log D(G(z))$$

Generative Adversarial Networks (GANs)



Generative adversarial networks



Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." *arXiv preprint arXiv:1511.06434* (2015).

What do GANs generate?

Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." *arXiv preprint arXiv:1511.06434* (2015).

GAN variants

Real-valued discriminator

Gradient penalty

Table 1: Generator and discriminator loss functions. The main difference whether the discriminator outputs a probability (MM GAN, NS GAN, DRAGAN) or its output is unbounded (WGAN, WGAN GP, LS GAN, BEGAN), whether the gradient penalty is present (WGAN GP, DRAGAN) and where is it evaluated. We chose those models based on their popularity.

GAN	Discriminator Loss	Generator Loss
MM GAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{GAN}} = -\mathbb{E}_{x\sim p_d}[\log(D(x))] - \mathbb{E}_{\hat{x}\sim p_g}[\log(1-D(\hat{x}))]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{GAN}} = \mathbb{E}_{\hat{x}\sim p_g}[\log(1-D(\hat{x}))]$
NS GAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{NSGAN}} = -\mathbb{E}_{x\sim p_d}[\log(D(x))] - \mathbb{E}_{\hat{x}\sim p_g}[\log(1-D(\hat{x}))]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{NSGAN}} = -\mathbb{E}_{\hat{x}\sim p_g}[\log(D(\hat{x}))]$
WGAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{WGAN}} = -\mathbb{E}_{x\sim p_d}[D(x)] + \mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{WGAN}} = -\mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})]$
WGAN GP	$\mathcal{L}_{\mathrm{D}}^{\mathrm{WGANGP}} = \mathcal{L}_{\mathrm{D}}^{\mathrm{WGAN}} + \lambda\mathbb{E}_{\hat{x}\sim p_g}[(\|\nabla D(\alpha x + (1-\alpha\hat{x})\|_2 - 1)^2]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{WGANGP}} = -\mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})]$
LS GAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{LSGAN}} = -\mathbb{E}_{x\sim p_d}[(D(x)-1)^2] + \mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})^2]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{LSGAN}} = -\mathbb{E}_{\hat{x}\sim p_g}[(D(\hat{x}-1)^2]$
DRAGAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{DRAGAN}} = \mathcal{L}_{\mathrm{D}}^{\mathrm{GAN}} + \lambda\mathbb{E}_{\hat{x}\sim p_d+\mathcal{N}(0,c)}[(\|\nabla D(\hat{x})\|_2 - 1)^2]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{DRAGAN}} = \mathbb{E}_{\hat{x}\sim p_g}[\log(1-D(\hat{x}))]$
BEGAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{BEGAN}} = \mathbb{E}_{x\sim p_d}[\|x-\mathrm{AE}(x)\|_1] - k_t\mathbb{E}_{\hat{x}\sim p_g}[\|\hat{x}-\mathrm{AE}(\hat{x})\|_1]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{BEGAN}} = \mathbb{E}_{\hat{x}\sim p_g}[\|\hat{x}-\mathrm{AE}(\hat{x})\|_1]$

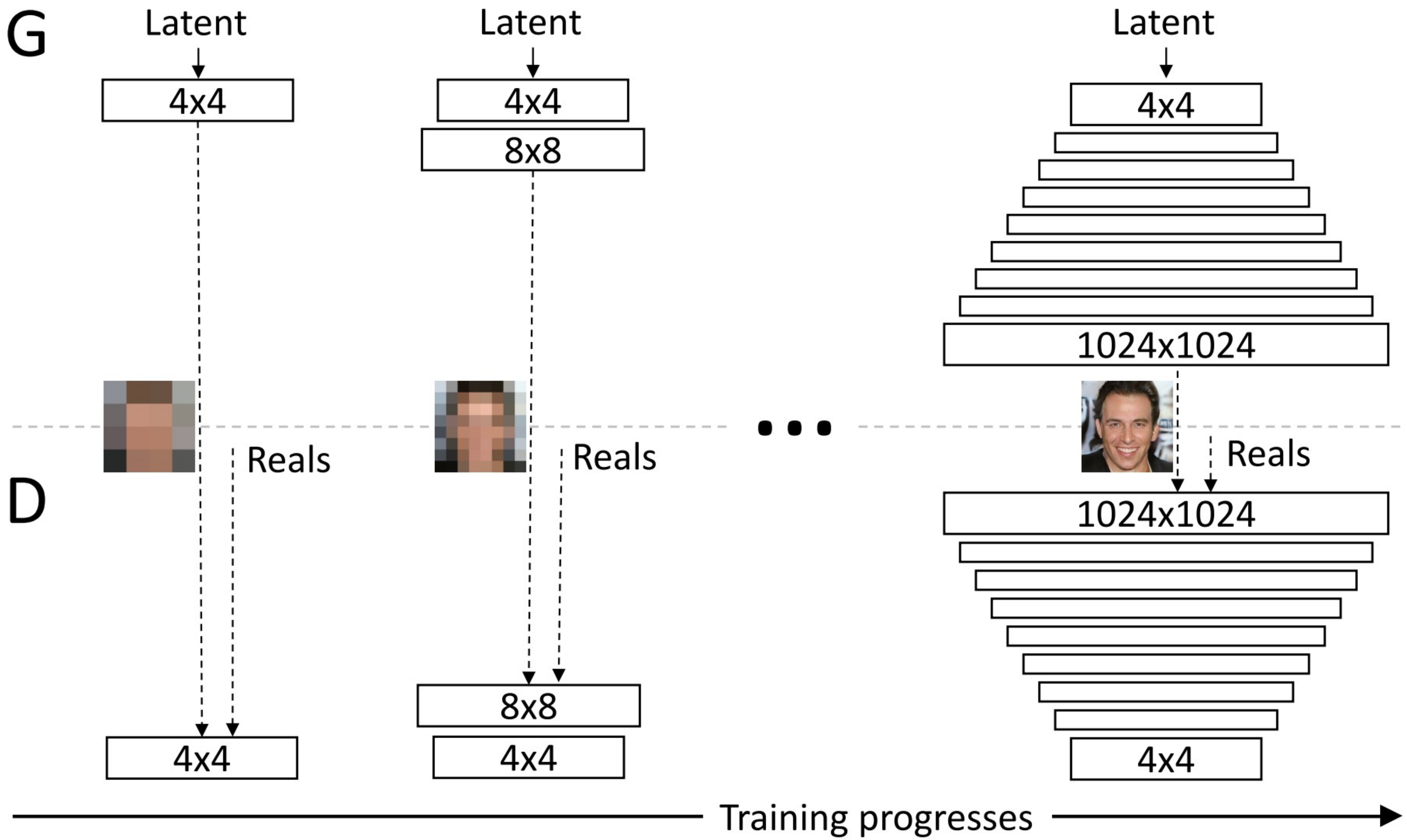
Lucic, Mario, et al. "Are gans created equal? a large-scale study." *arXiv preprint arXiv:1711.10337*(2017).

What do GANs generate?



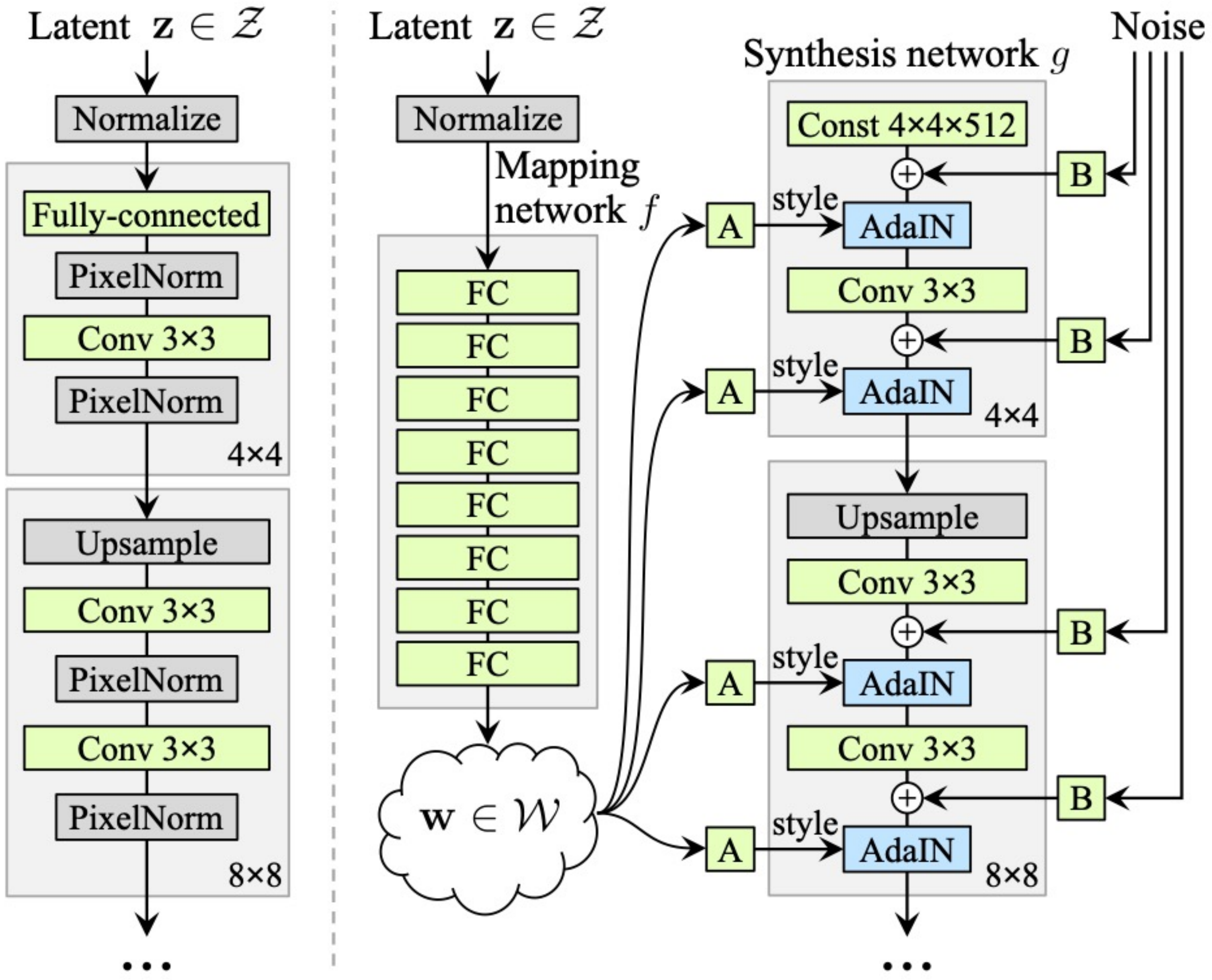
Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." *arXiv preprint arXiv:1511.06434* (2015).

What do GANs generate?



https://arxiv.org/pdf/1710.10196.pdf

New generation architectures



(a) Traditional

(b) Style-based generator

Karras, Tero, Samuli Laine, and Timo Aila. "A style-based generator architecture for generative adversarial networks." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2019.

State-of-the-art generation

State-of-the-art generation

State-of-the-art generation

Some caveats about faces

- Faces are *almost* linear

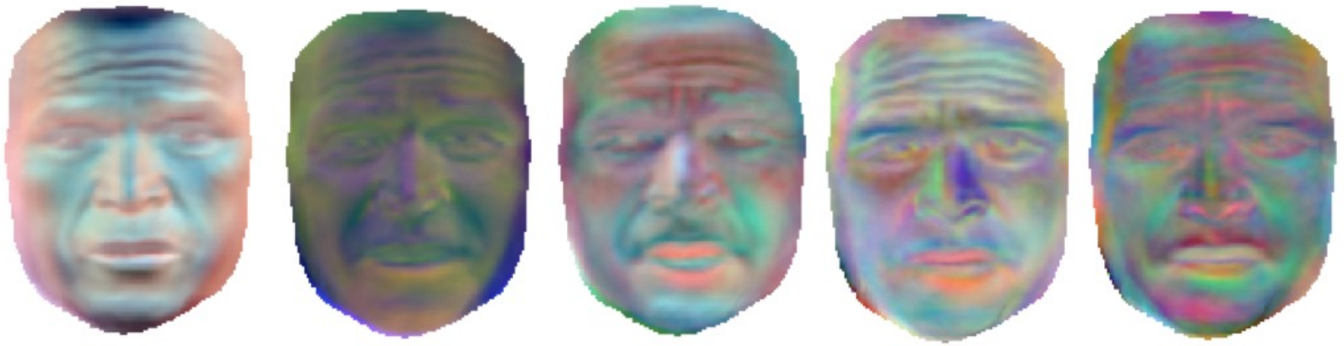
Original face

Reconstruction from 7 principal components

PCA components of faces

- First few basis elements: shading
- Next basis elements: identity + expression

Basis images 1-4 model the shading



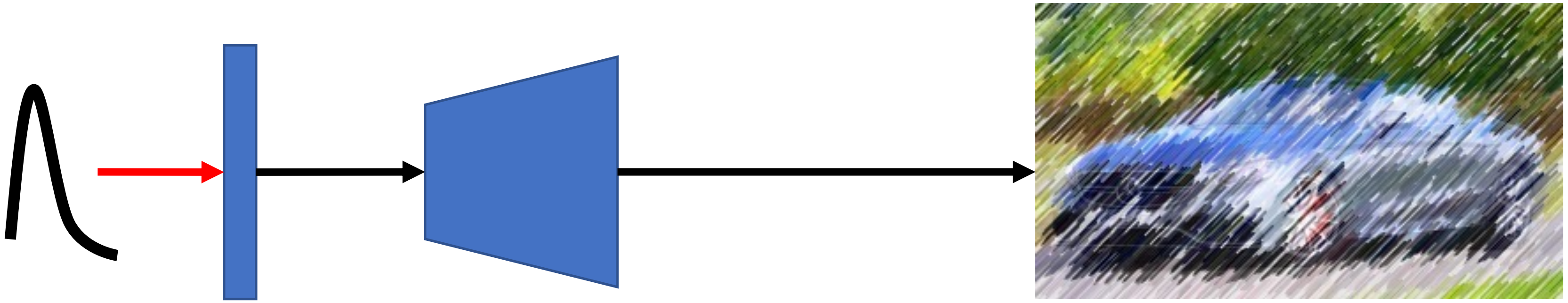
Rest of the basis images (five representatives are shown) model the facial expression

https://grail.cs.washington.edu/cflow/

Variational Autoencoders

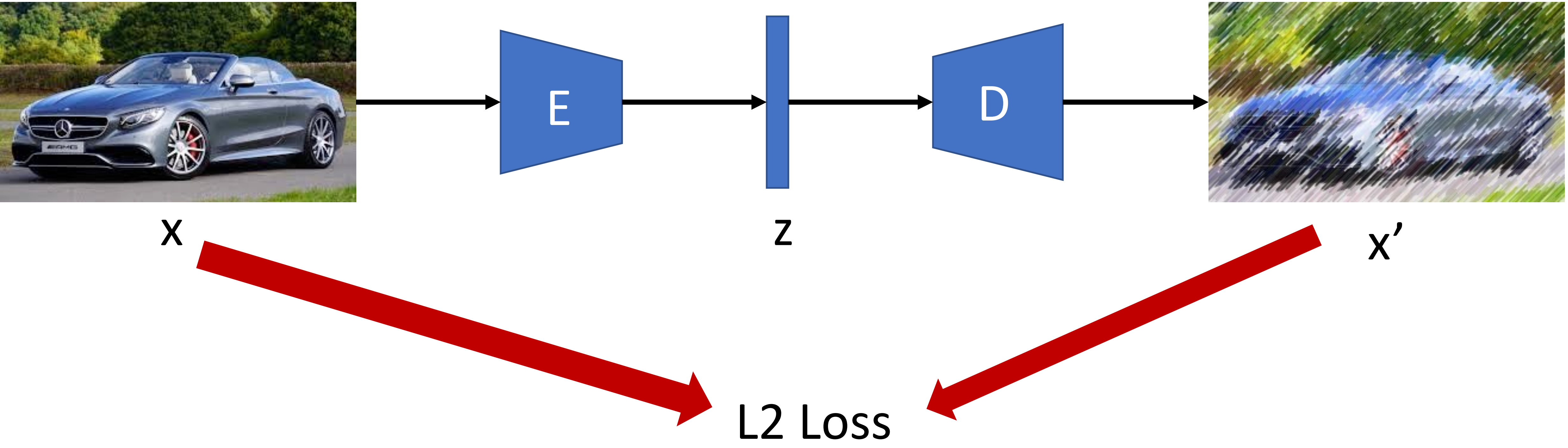
Back to generative models

- Need a probabilistic model we can sample from
- Write probabilistic model so that training images are highly likely
  - Probabilistic model maps noise from standard Gaussian to image
  - But which noise generates which training image?

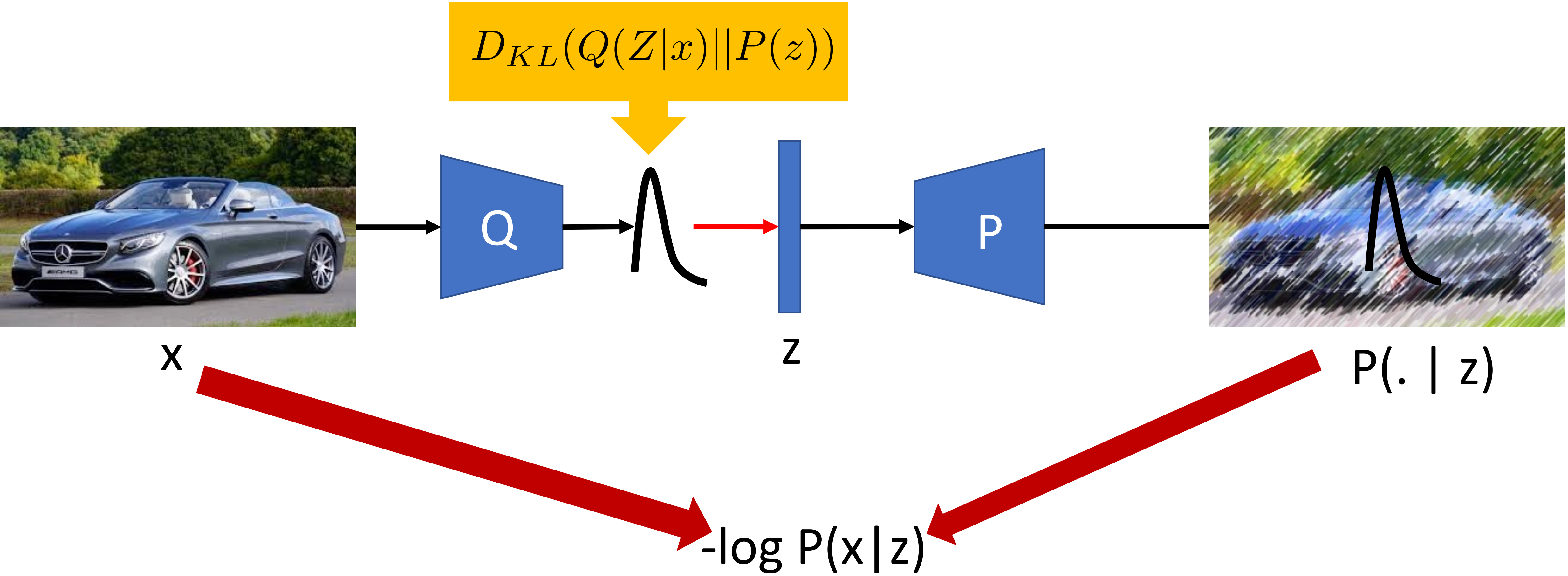


Autoencoders

- Maps each image to a particular latent code
- But not a probabilistic model!



Variational autoencoders



Tutorial on Variational Autoencoders. Carl Doersch. https://arxiv.org/pdf/1606.05908.pdf