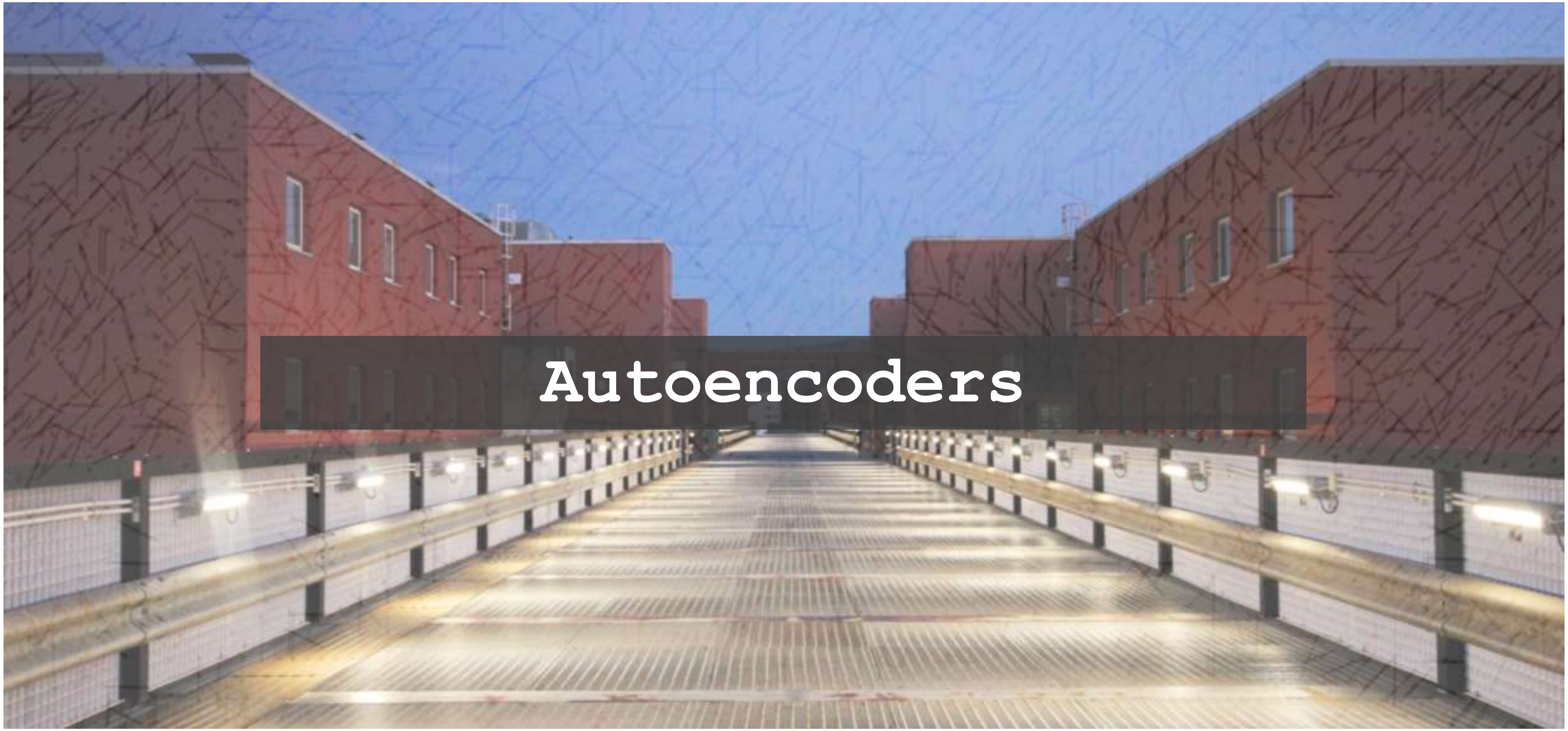
UNIVERSITÀ DELLA CALABRIA

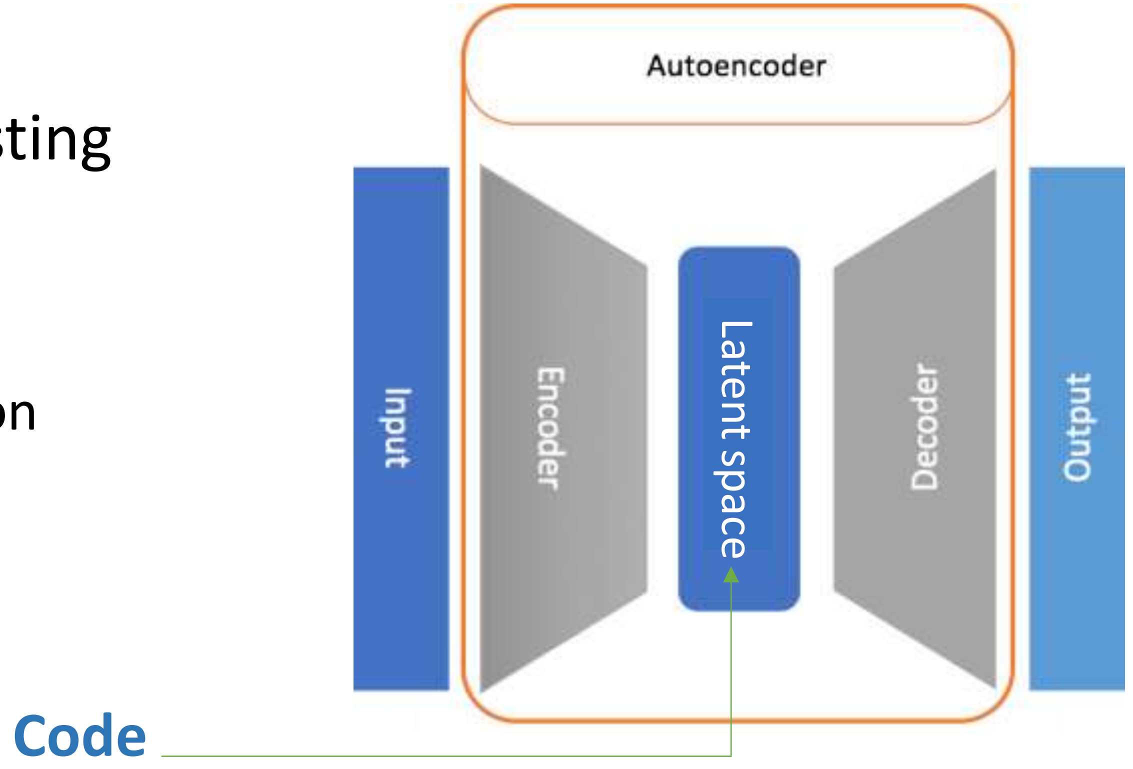


Autoencoders

Autoencoder

- An **autoencoder** is a neural network that is trained to produce as output (r) a **duplicate** of its input (x).

- The network may be viewed as consisting of two parts:
  - An **encoder** function $z = f(x)$
  - z is called **Code** (of the input)
  - A **decoder** that produces a reconstruction $r = g(z)$
  - The **objective** is $x \approx r$
  - The **loss function** is expressed as $L\left(x, g\left(f(x)\right)\right)$



Properties

- A trained autoencoder has **learnt and summarized** the main **characteristics** of the input data
- These characteristics are able to represent the original data in a **shorter data structure**
- **Statistical properties** of the original data are summarized too into a **latent space of network weights**

Applications

- Forcing $x = r$ (**strong risk of overfitting**)
  - Dimensionality reduction
  - Feature learning

- The real strength of an autoencoder is the capability of **abstract** the data instead of learning to perfectly copy them.
  - Usually they are restricted in finding approximations, producing an output that **likely can belong** to the **input data domain**
    - Data generation
    - Data completion
    - Data reconstruction
    - Anomaly detection

Issues

- The Code of an autoencoder can have useful **information about the input domain**
- An autoencoder, whose code size is lower than the input one, is called under-complete
  - The code is able to **compress and summarize the properties** of the input data
  - When the decoder is linear and L is the mean squared error, autoencoder = PCA.
- An autoencoder, whose code size is bigger than the input one, is called over-complete
  - The code is able to **map the input data in a higher dimensional domain** acting as **Kernel function** (do you remember SVMs?)

Regularized Autoencoders

- Autoencoder **issues**:
  - Size of the code
  - Excessive or reduced fitting capability of the encoder and the decoder

- **Regularized autoencoders** ideally **enables to choose** the **code size** and the **capacity** of the encoder and decoder according to the **complexity** of the input data distribution

- How to achieve this result?
  - **Change the loss function!**

Regularized Autoencoders

- The new loss function encourages the model to have other properties besides the ability to copy its input, e.g.:
  - sparsity of the representation
  - smallness of the derivative of the representation
  - robustness to noise or to missing inputs

- Short list of regularized autoencoders:
  - Sparse Autoencoders
  - Denoising Autoencoders
  - Penalizing Derivative Autoencoders

Sparse Autoencoders

- **Sparse Autoencoders** add a **sparsity penalty** on the code layer to the loss function:

$$L\left(x, g(f(x))\right) + \Omega(z)$$

- The component $\Omega(z)$ **penalizes the activations of too many nodes in the code layer**
  - This constraint is called the sparsity constraint. It is sparse because each unit only activates to a certain type of inputs, not all of them

- E.g.:

$$\Omega(z) = \lambda \sum_{i \in |h|} |z_i|$$

where λ is a constant

Denoising Autoencoders

- **Denoising Autoencoders** learn underlying patterns by changing the reconstruction error term of the cost function:

$$L\left(x, g\left(f\left(\tilde{x}\right)\right)\right)$$

where $\tilde{x}$ is **the original input affected by some noise distribution**

- Their main goal is to **deleted corruption** in a set of data

Penalizing Derivative Autoencoders

- Similarly to sparse autoencoders, we can define another penalty function

$$L\left(x, g\left(f(x)\right)\right) + \Omega(x, z)$$

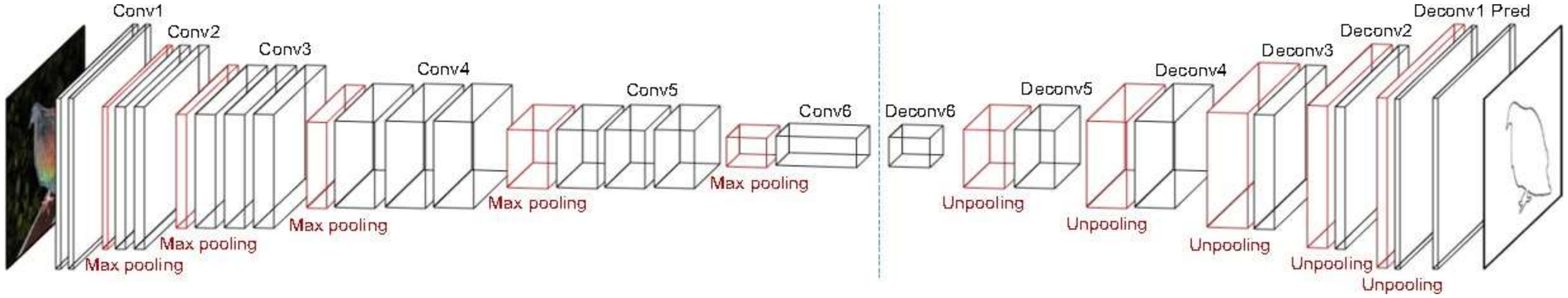
- where:

$$\Omega(x, z) = \lambda \sum_{i \in |h|} ||\nabla_x z_i||^2$$

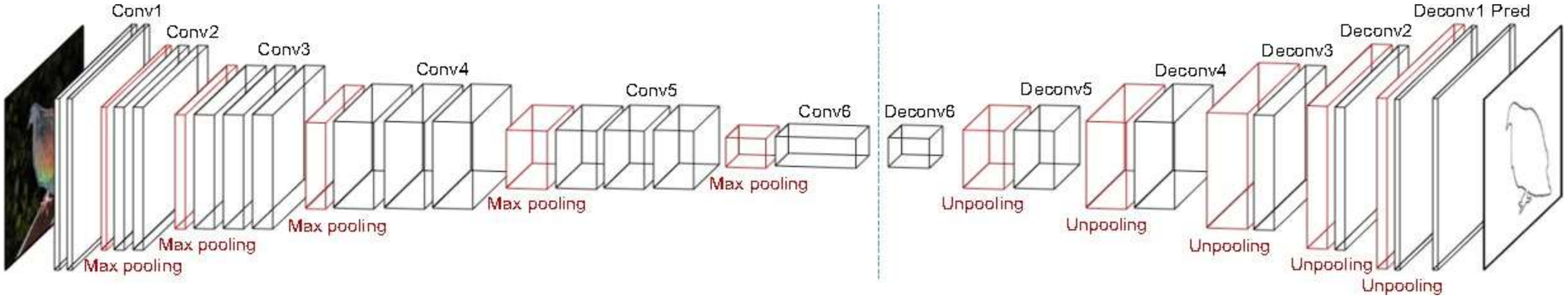
- with λ constant

- **The model is forced to learn a function that does not change much when x slightly changes**

Autoencoders



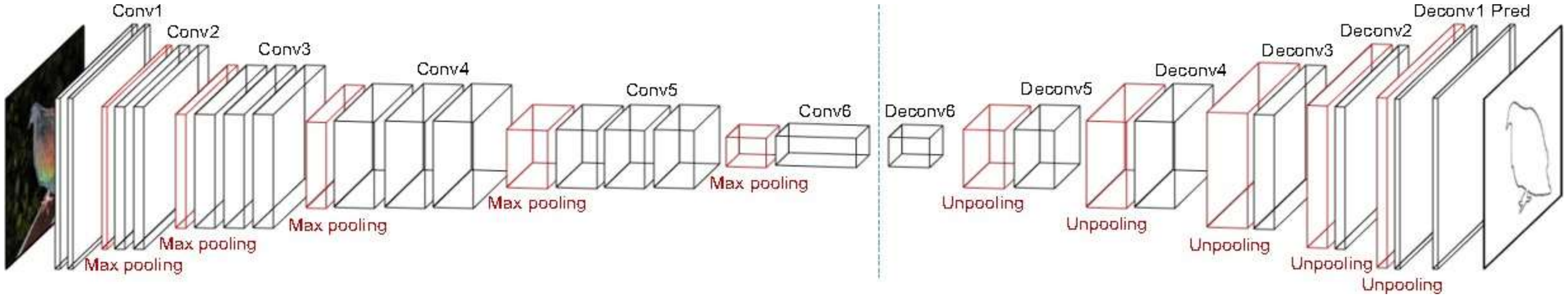
Autoencoders

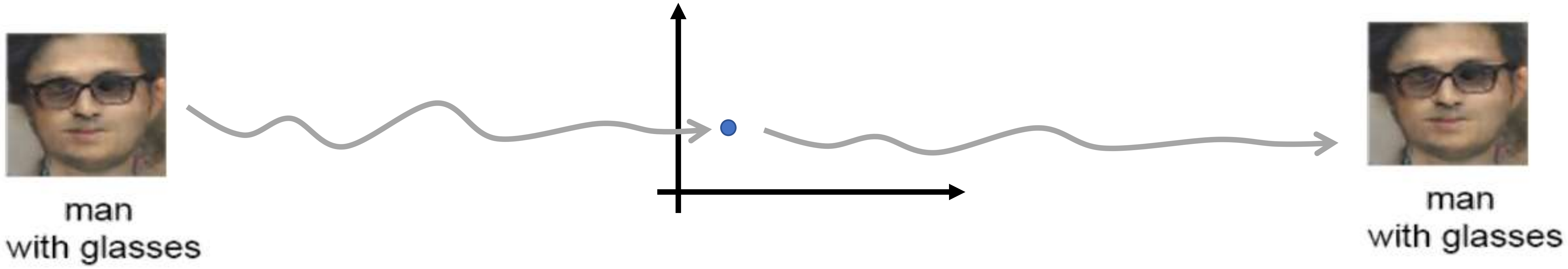


man
with glasses

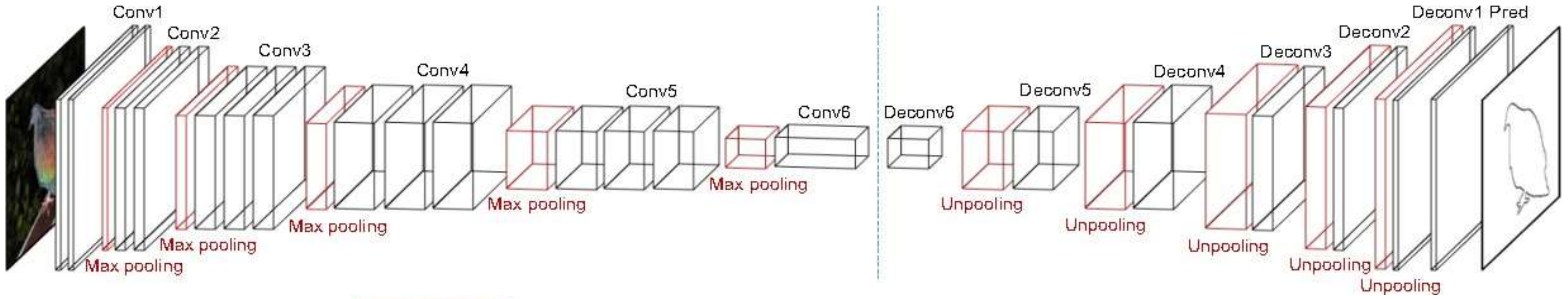
man
with glasses

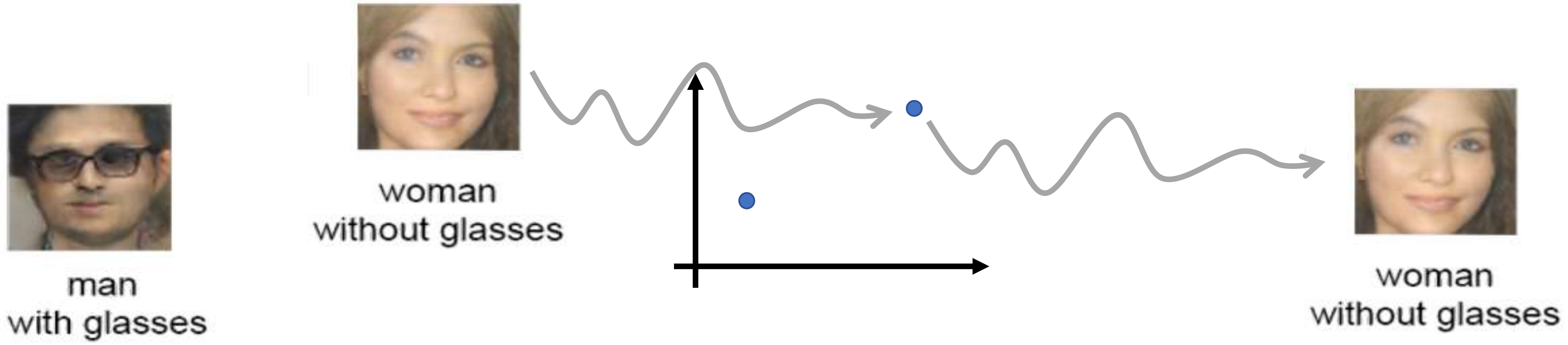
Autoencoders



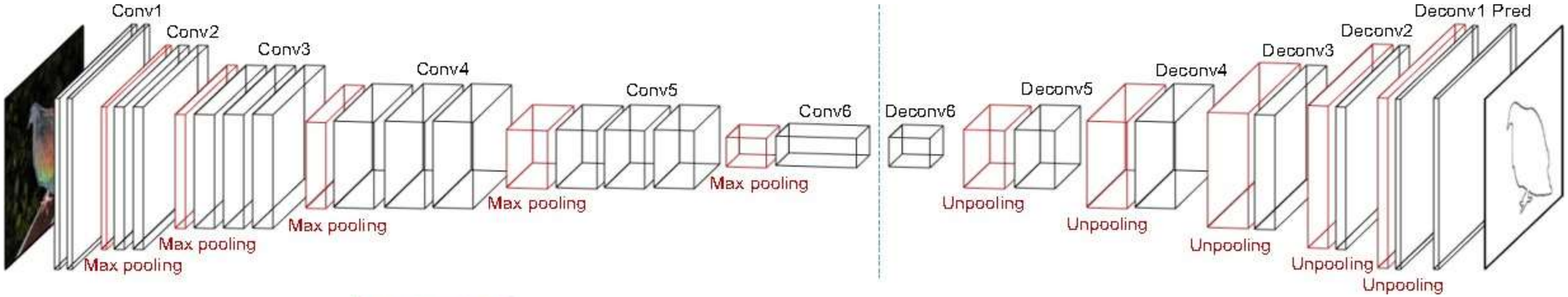


Autoencoders



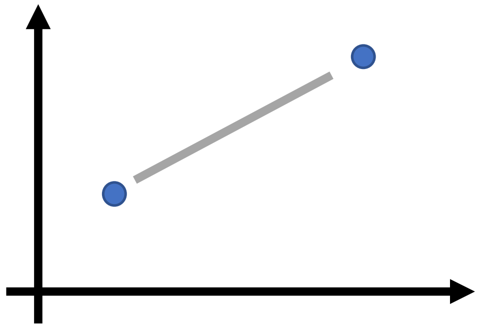


Autoencoders

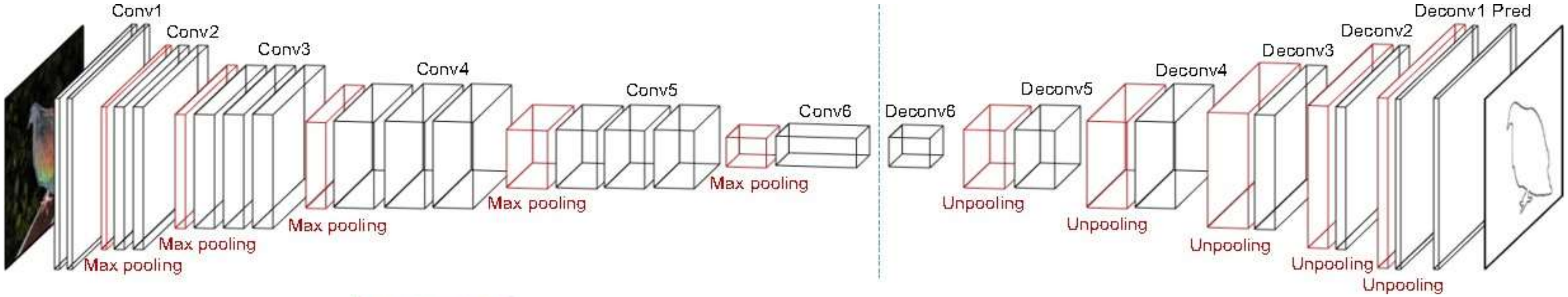


man
with glasses

woman
without glasses

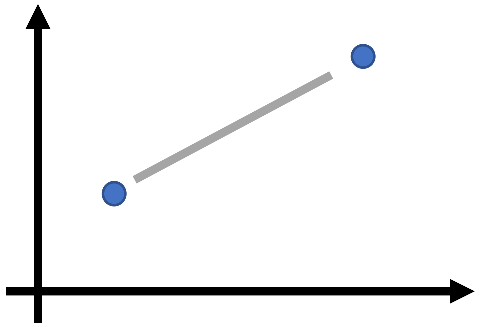


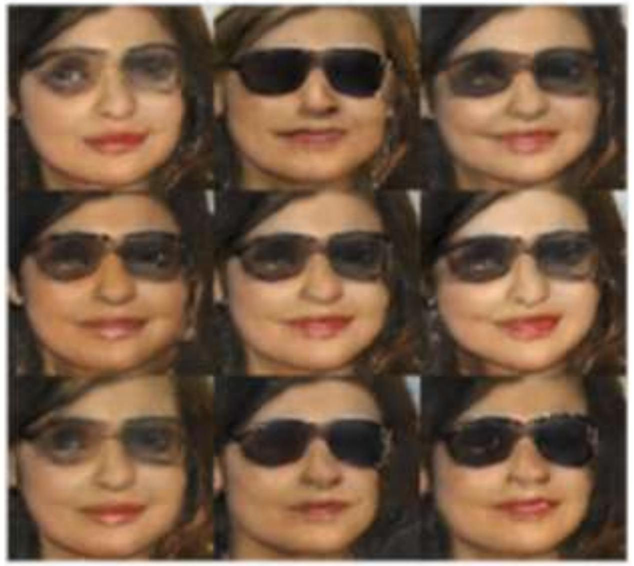
Autoencoders



man
with glasses

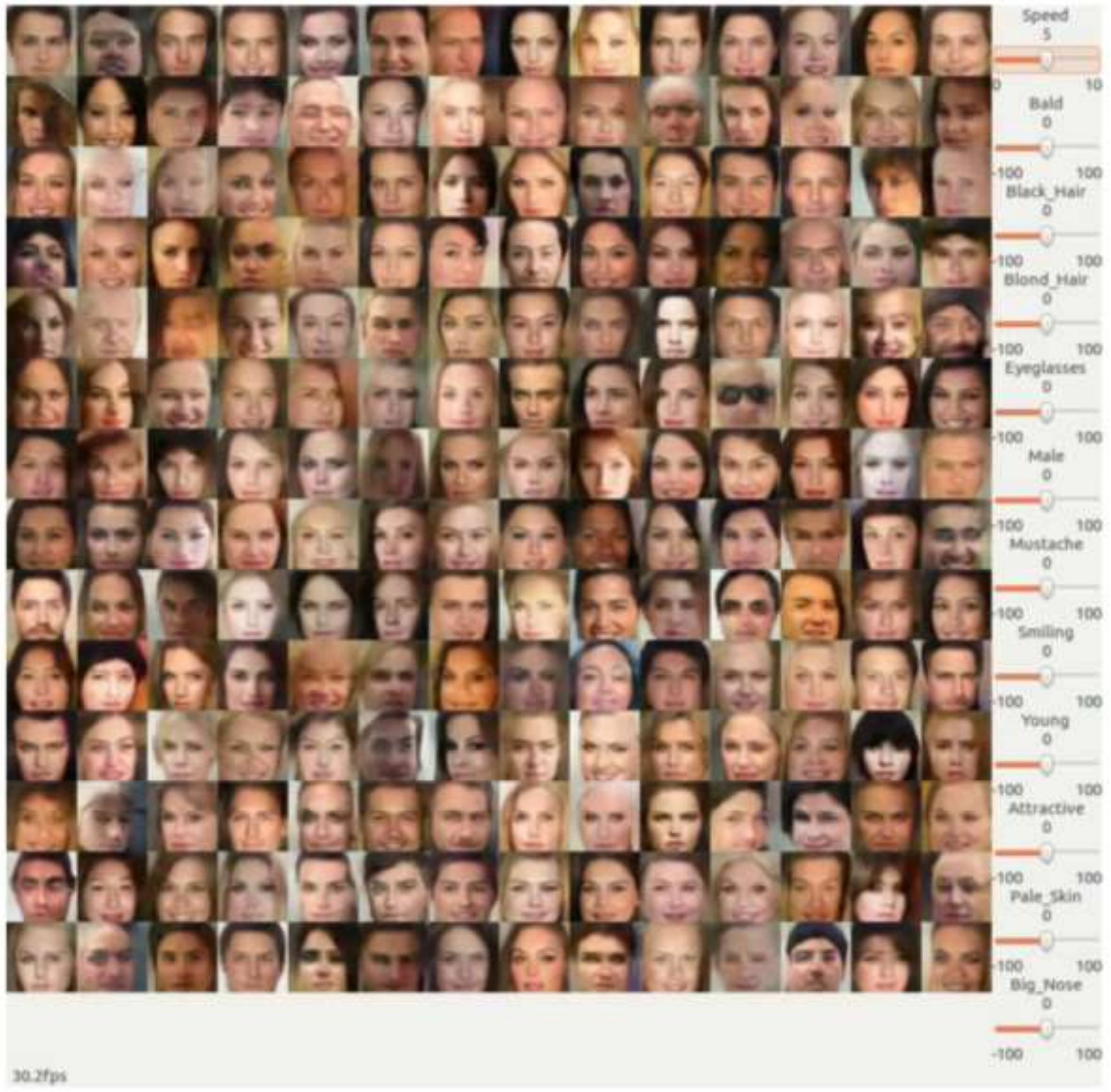
woman
without glasses





Autoencoders

- **DeepFakes!**
  - Immagini non reali, generate con tecniche di intelligenza artificiale
  - Altissima fedeltà, indistinguibili da reali fotografie

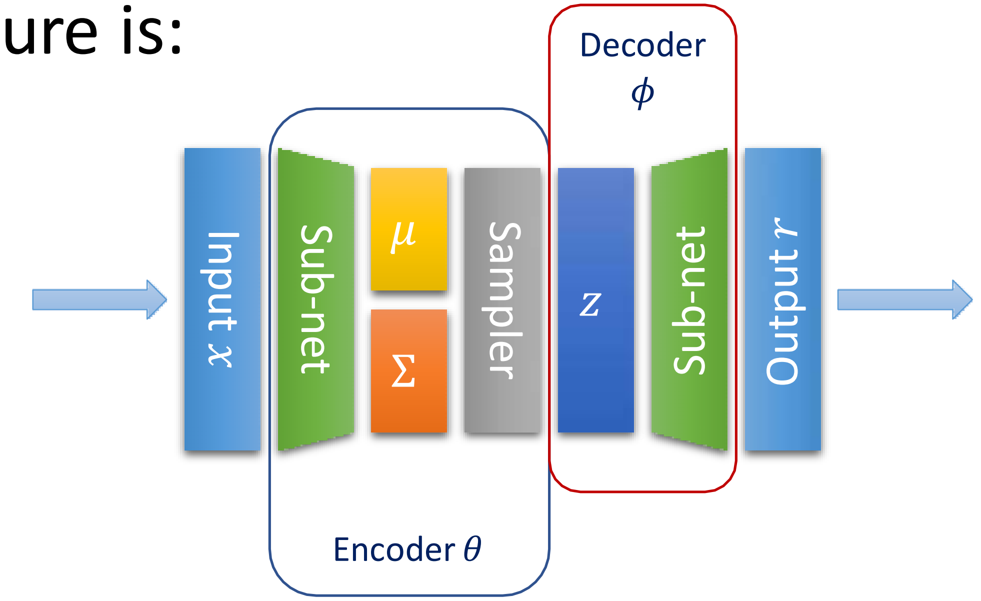


Speed 5
0 10
Bald 0
-100 100
Black_Hair 0
-100 100
Blond_Hair 0
-100 100
Eyeglasses 0
-100 100
Male 0
-100 100
Mustache 0
-100 100
Smiling 0
-100 100
Young 0
-100 100
Attractive 0
-100 100
Pale_Skin 0
-100 100
Big_Nose 0
-100 100
30.2fps

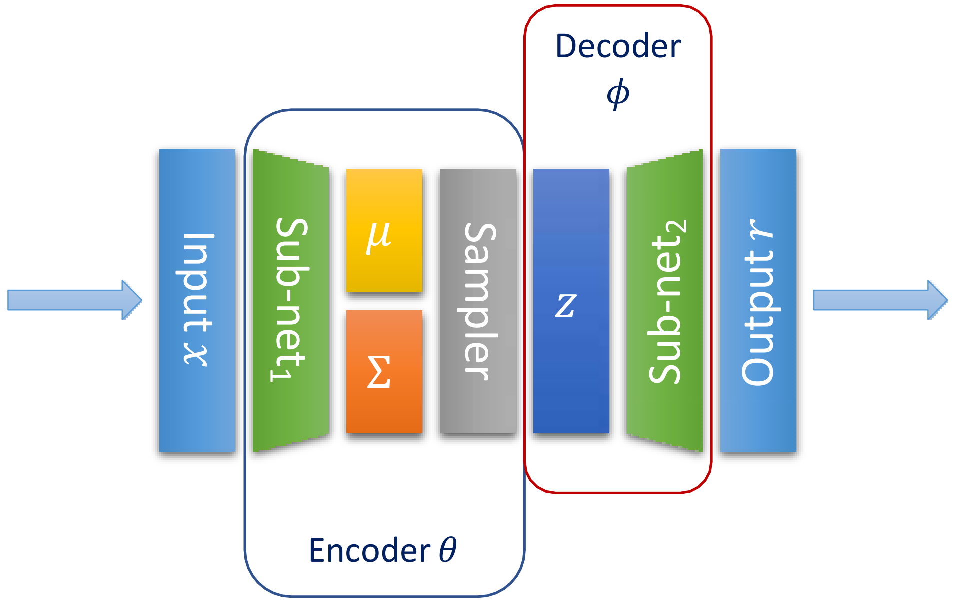
Variational Autoencoders

- To avoid overfitting and to increase generality we can add a random sampling

- The new architecture is:

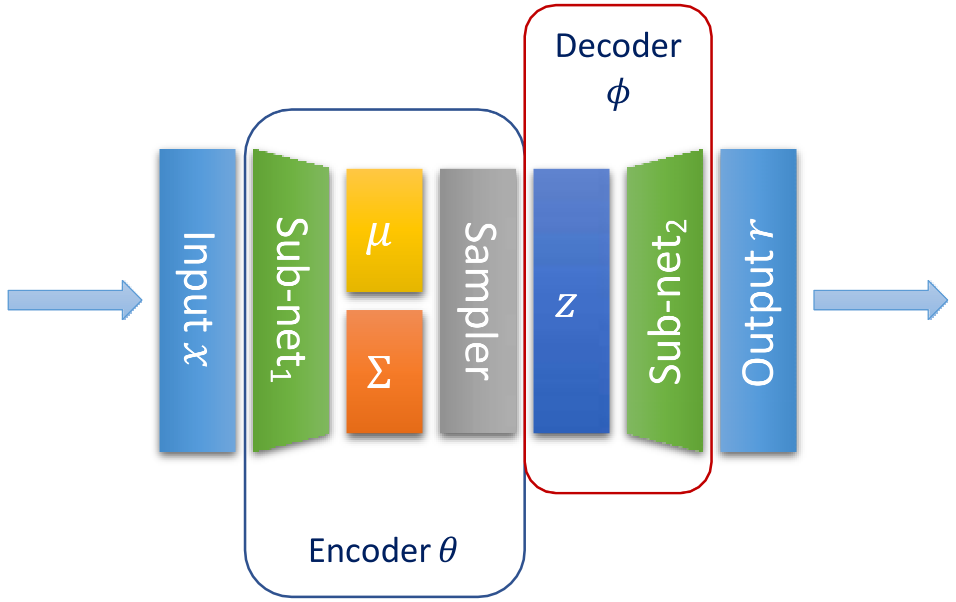


Variational Autoencoders



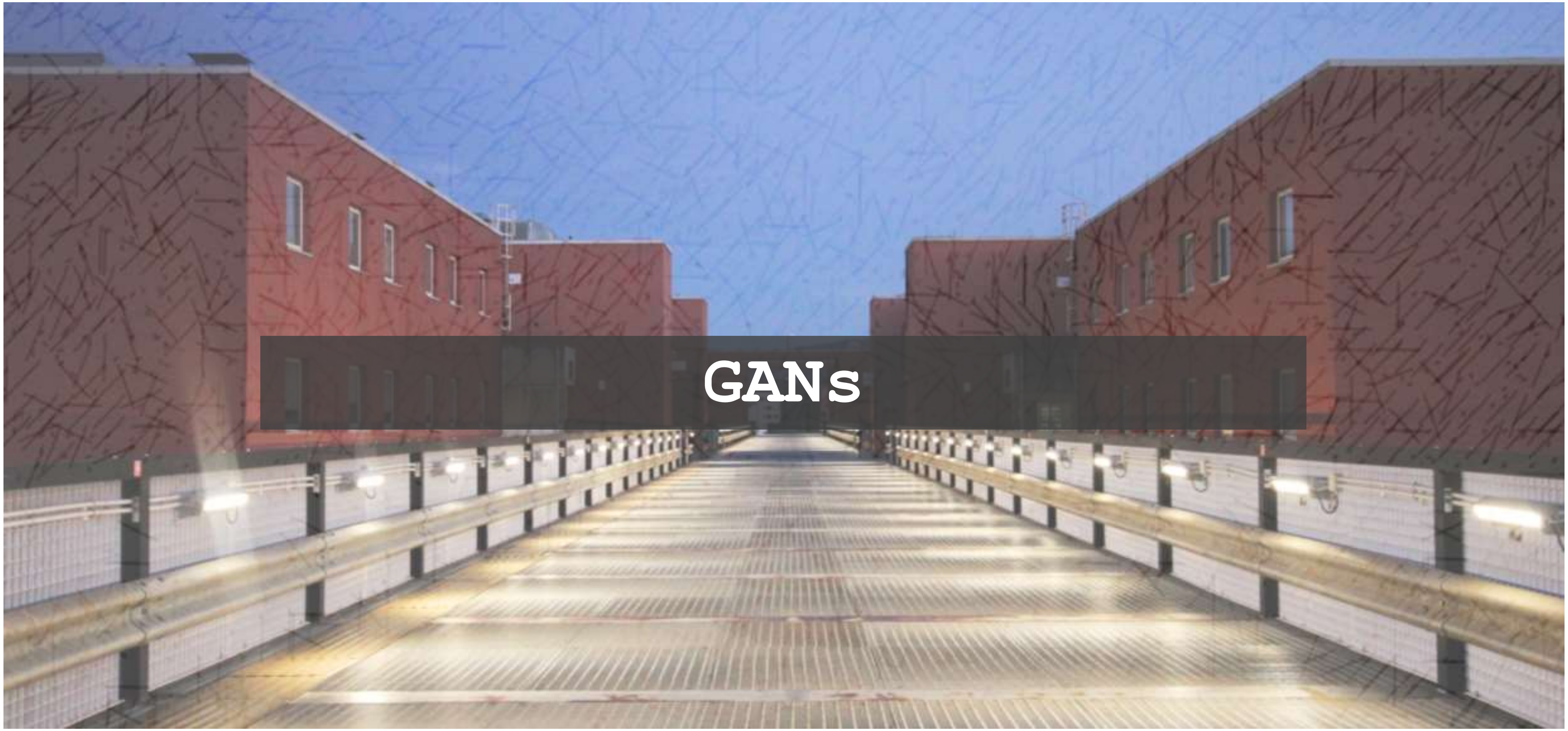
- The sub-net$_1$ computes two parameters of a Gaussian distribution
- The sampler exploits the parameters to normally sample the code
- The sub-net$_2$ generates two parameters of a Gaussian distribution

Variational Autoencoders



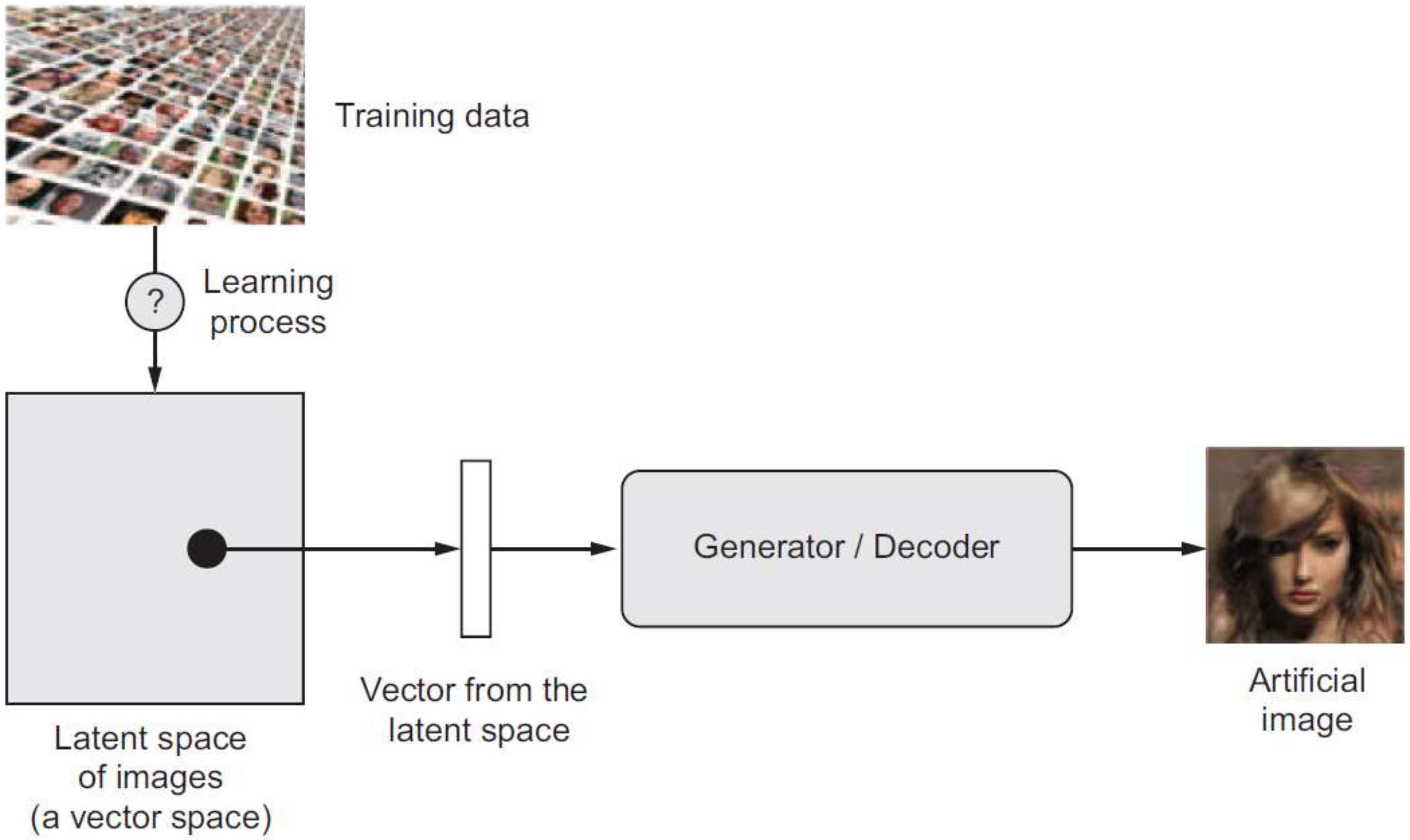
- The encoder, with weights and biases θ, samples $z \sim q_\theta(z|x)$
- The decoder, with weights and biases ϕ, generates $r \approx x$
    - It reconstructs $x \sim p_\phi(x|z)$

UNIVERSITÀ DELLA CALABRIA



GANs

Overview


Training data
?
Learning process
Latent space of images (a vector space)
Vector from the latent space
Generator / Decoder
Artificial image

Overview

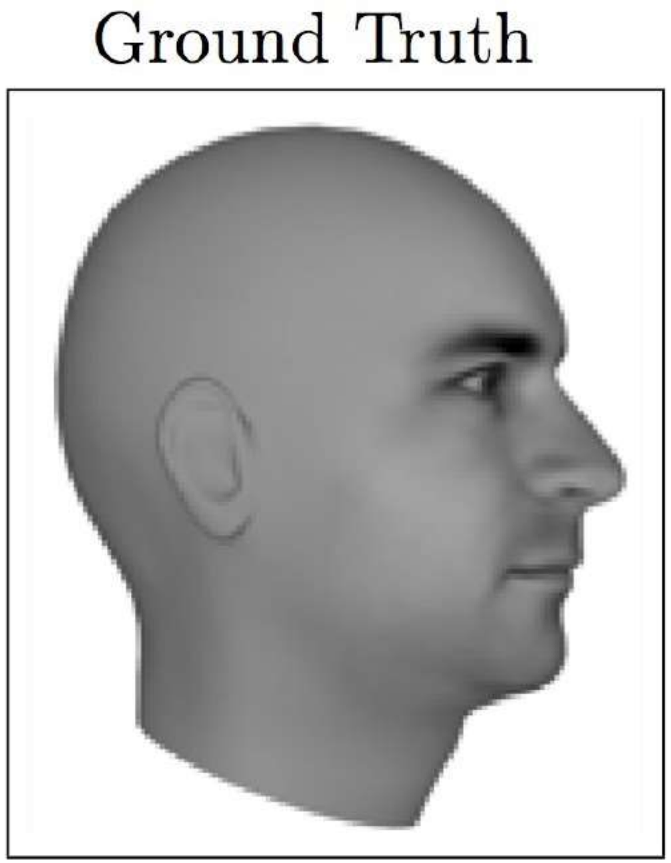
- In generative modeling, we'd like to train a network that models a distribution, such as a distribution over images.
- One way to judge the quality of the model is to sample from it. This field has seen rapid progress:

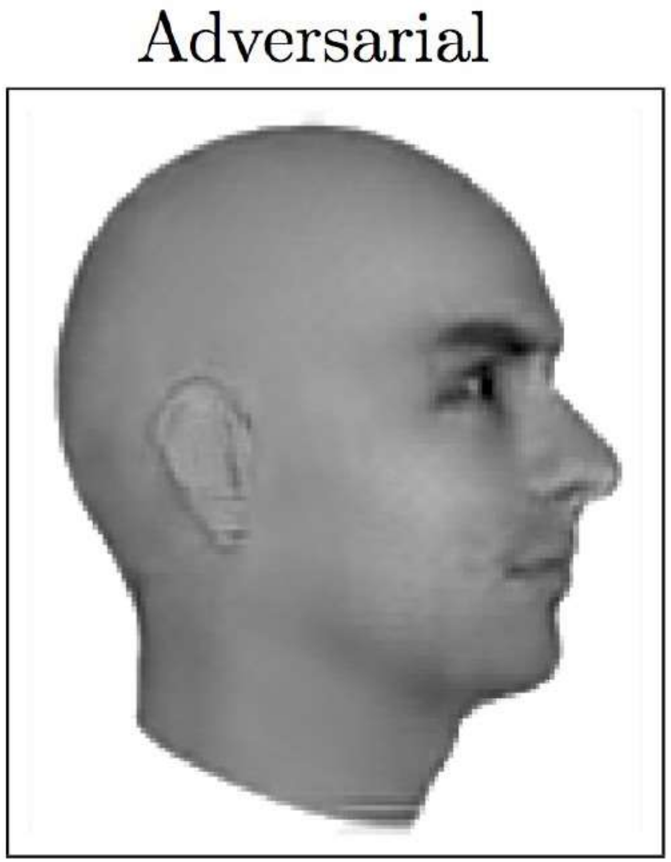
200

201

201

Example (1/3)

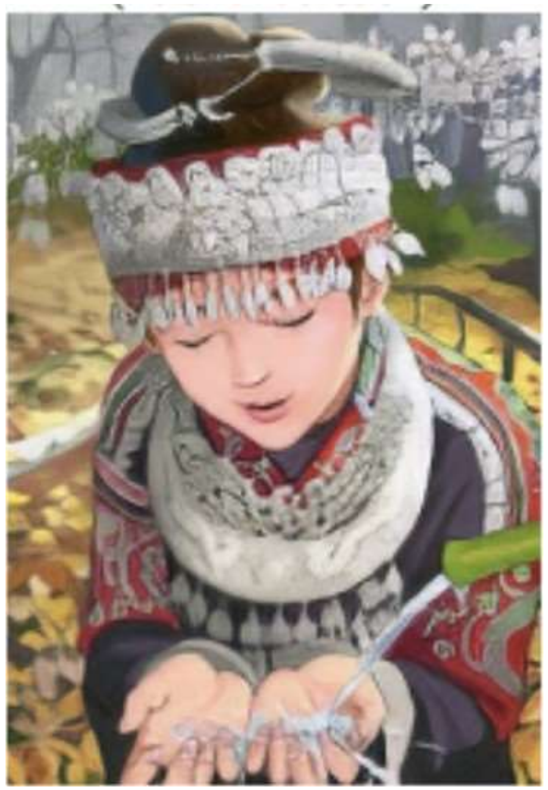


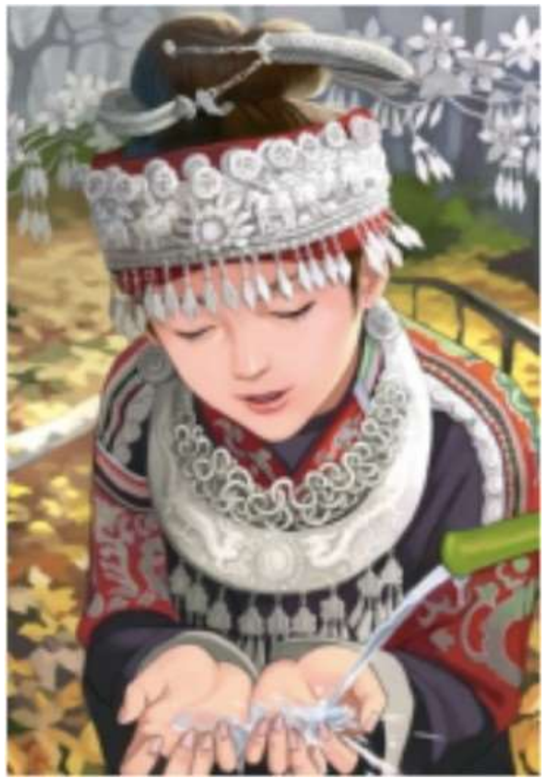


Lotter, William, Gabriel Kreiman, and David Cox. "Unsupervised learning of visual structure using predictive generative networks." *arXiv preprint arXiv:1511.06380* (2015).

Example (2/3)

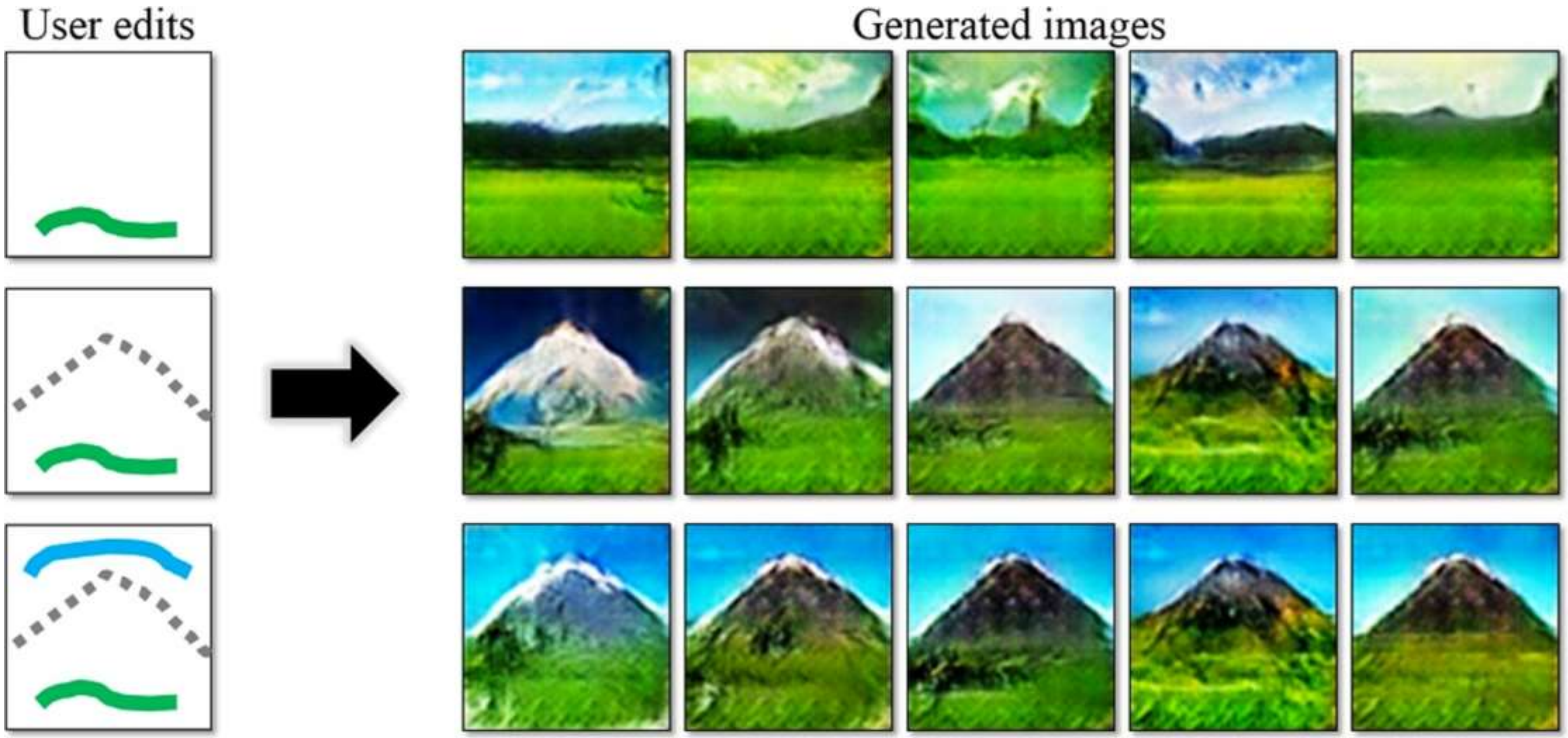
Which one is Computer generated?





Ledig, Christian, et al. "Photo-realistic single image super-resolution using a generative adversarial network." *arXiv preprint arXiv:1609.04802* (2016).

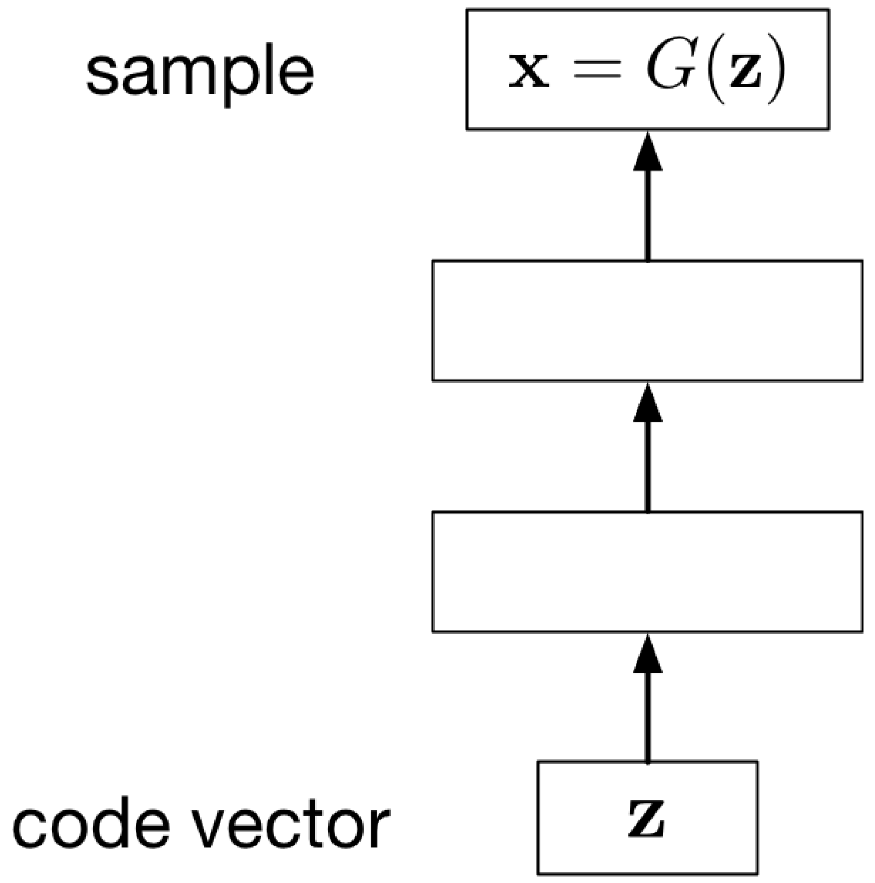
Example (3/3)



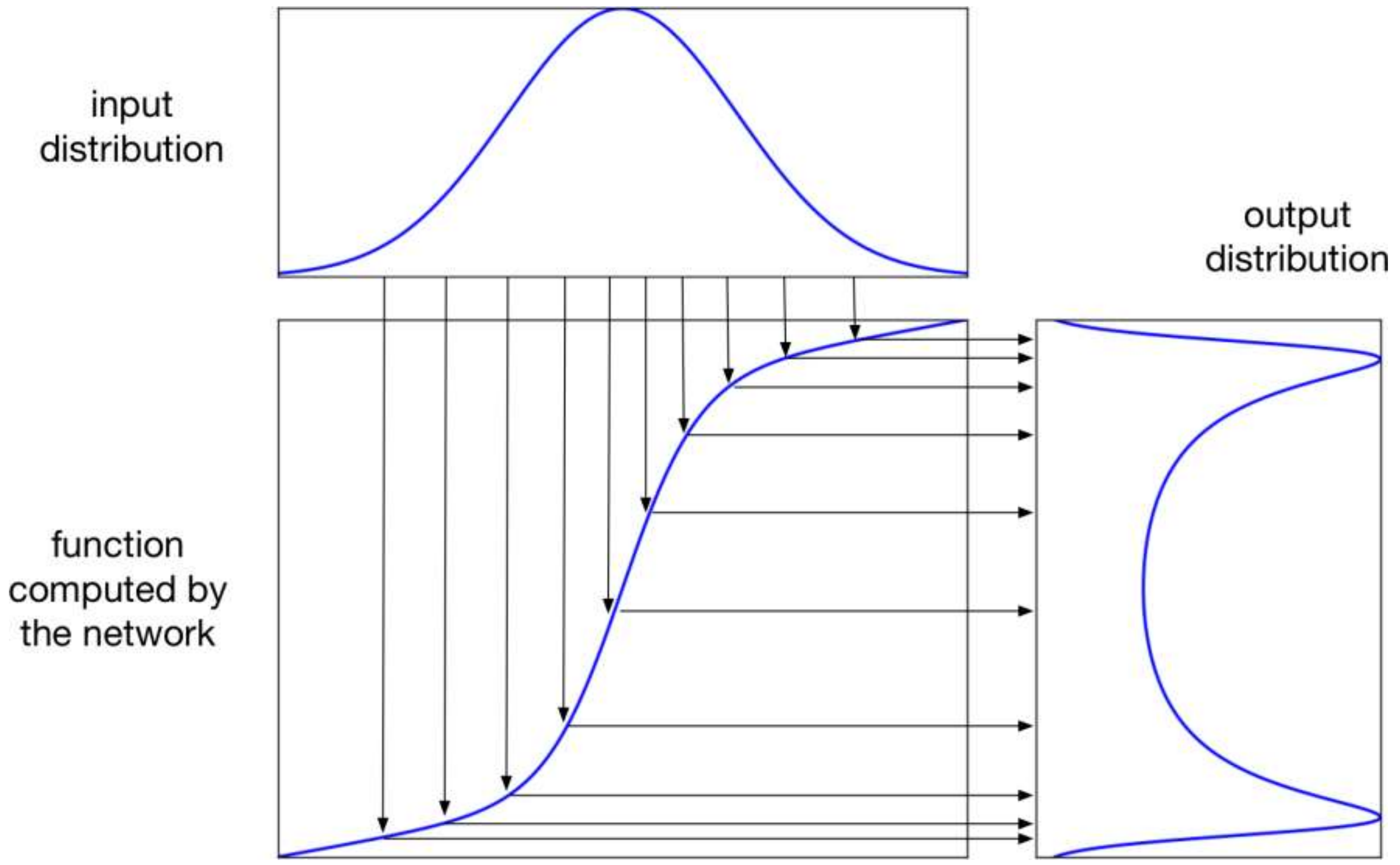
http://people.eecs.berkeley.edu/~junyanz/projects/gvm/

Implicit Generative Models

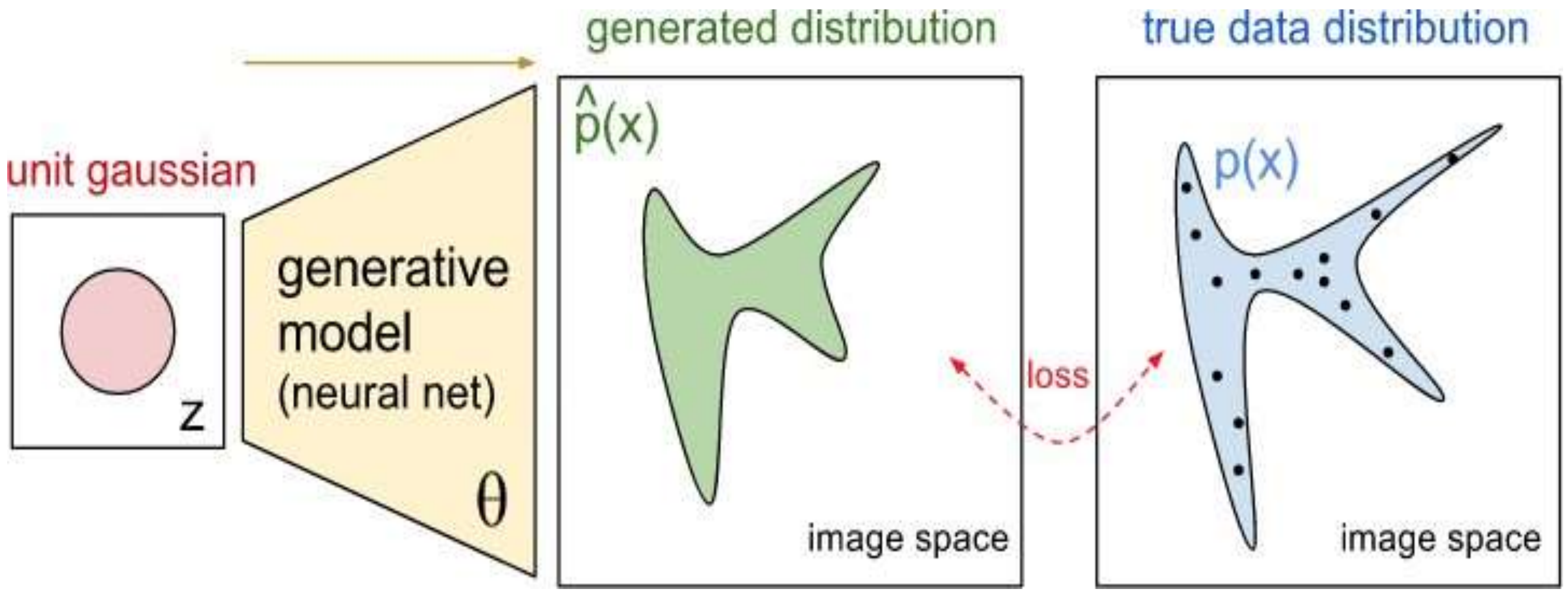
- Implicit generative models implicitly define a probability distribution
- Start by sampling the code vector **z** from a fixed, simple distribution
- The generator network computes a differentiable function *G* mapping **z** to an **x** in data space



1-Dimensional example

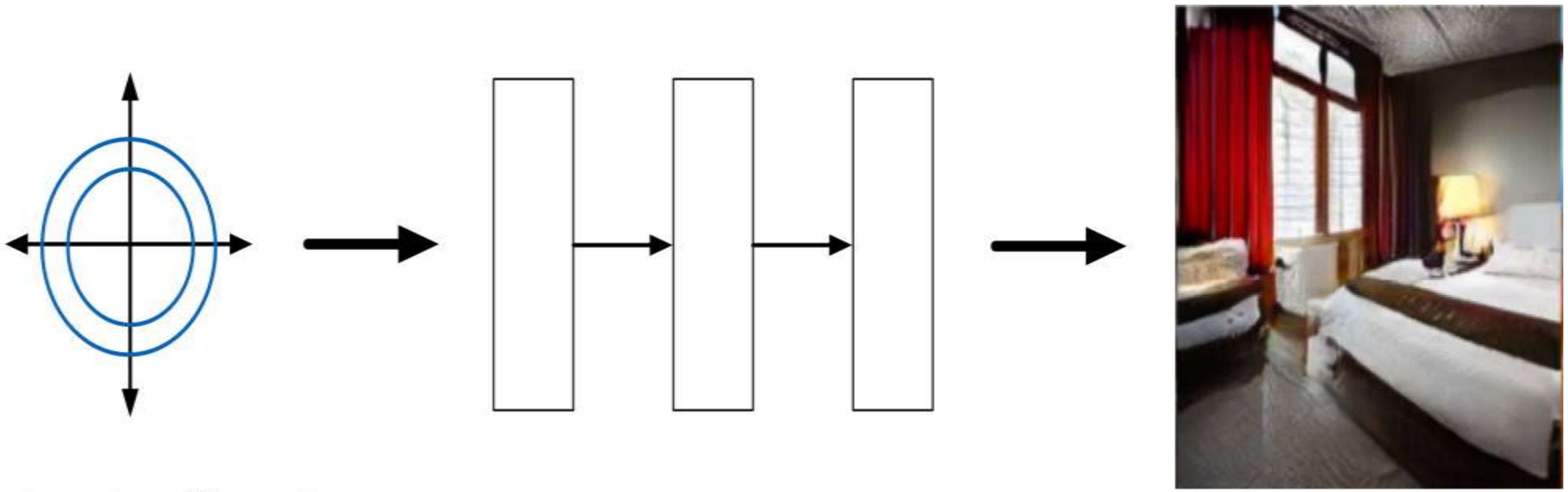


2-Dimensional example



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

More general approaches



Each dimension of the code vector is sampled independently from a simple distribution, e.g. Gaussian or uniform.

This is fed to a (deterministic) generator network.

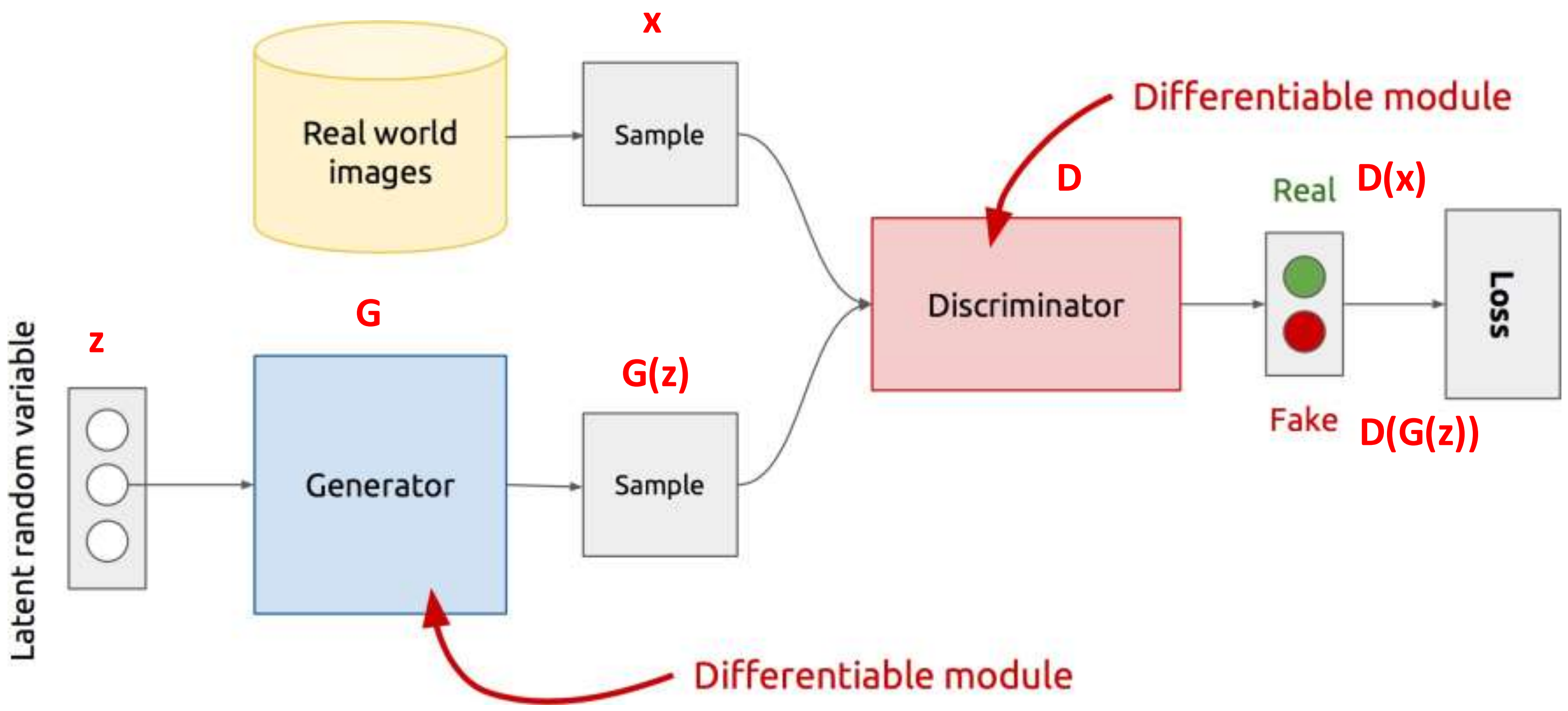
The network outputs an image.

GANs

- The advantage of implicit generative models:
  - if you have some criterion for evaluating the quality of samples, then you can compute its gradient with respect to the network parameters, and update the network's parameters to make the sample a little better

- The idea behind Generative Adversarial Networks (GANs): train two different networks
  - The generator network tries to produce realistic-looking samples
  - The discriminator network tries to figure out whether an image came from the training set or the generator network
  - The generator network tries to fool the discriminator network

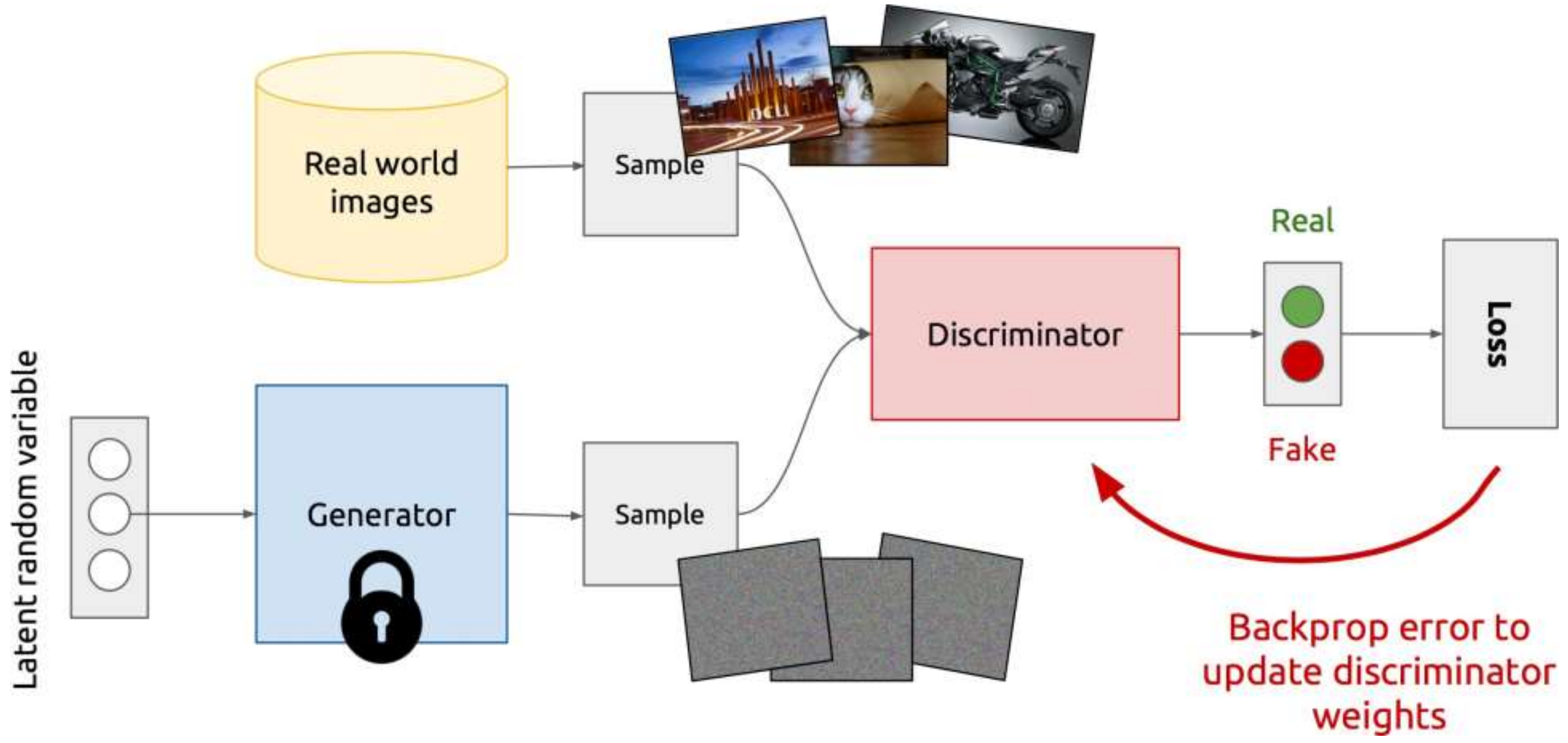
GAN's Architecture



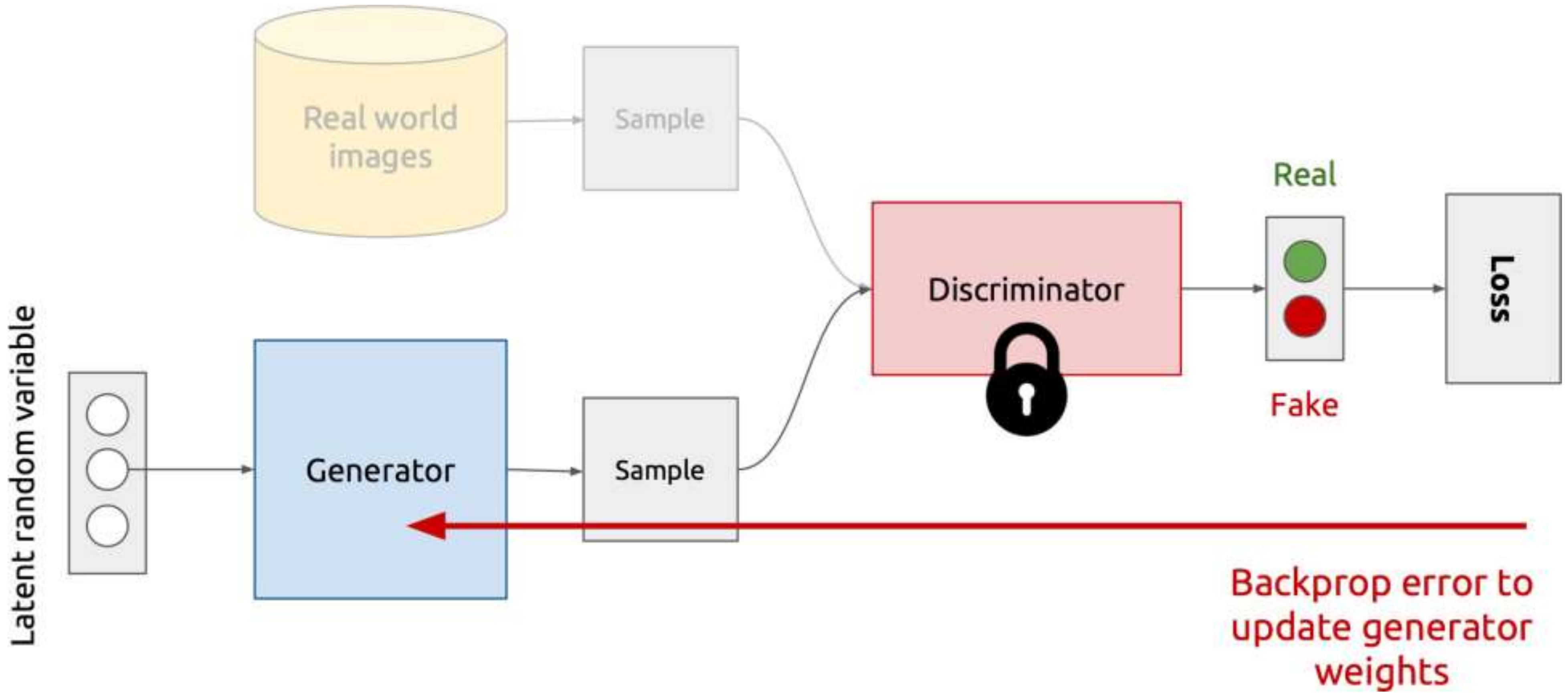
- **Z** is some random noise (Gaussian/Uniform).
- **Z** can be thought as the latent representation of the image.

https://www.slideshare.net/xavigiro/deep-learning-for-computer-vision-generative-models-and-adversarial-training-upc-2016

Training the Discriminator



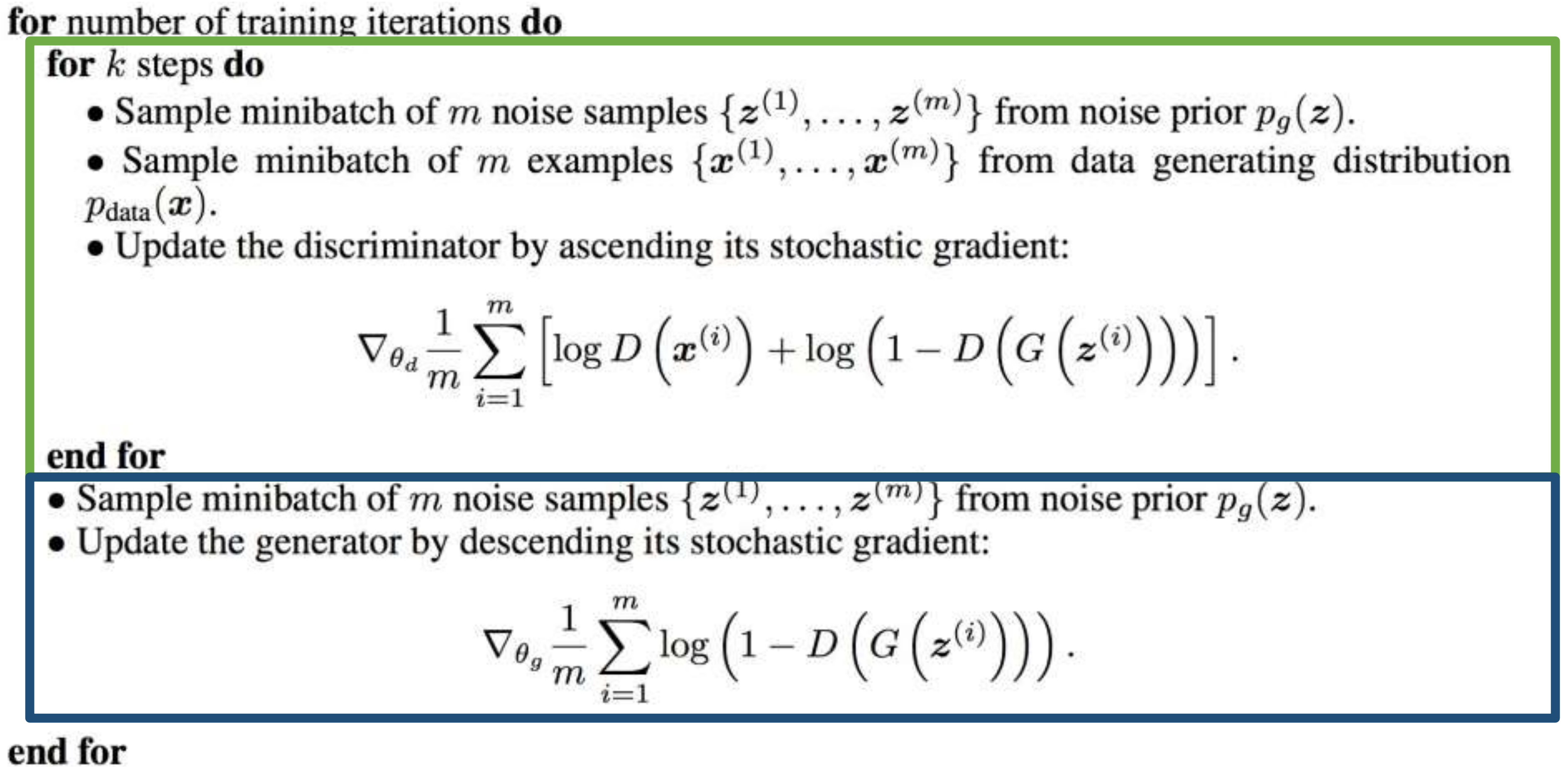
Training the Generator



Putting it all together

Discriminator updates

Generator updates



```
for number of training iterations do
    for $k$ steps do
        • Sample minibatch of $m$ noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
        • Sample minibatch of $m$ examples $\{\boldsymbol{x}^{(1)}, \dots, \boldsymbol{x}^{(m)}\}$ 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 $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ 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
```

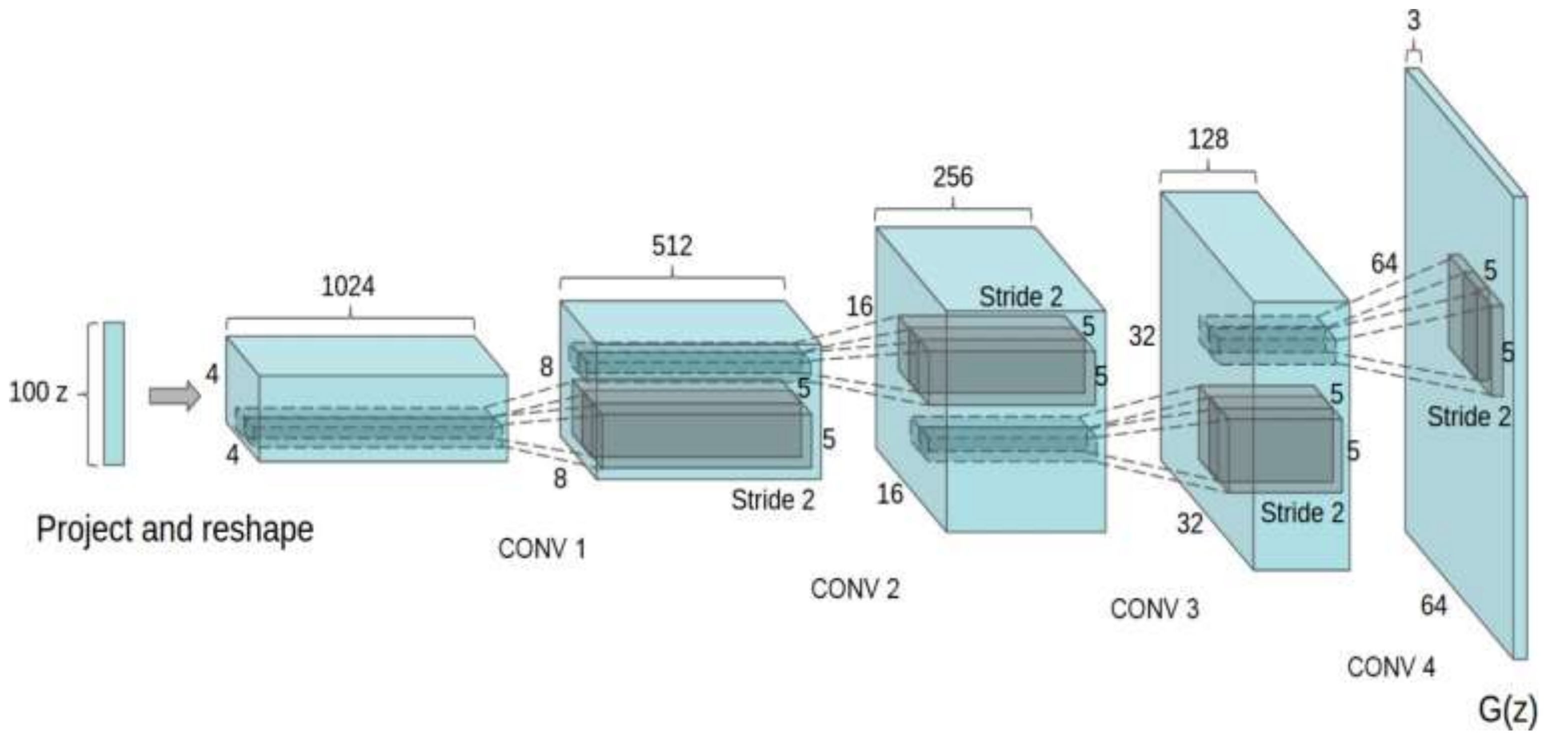
GAN Examples

- Celebrities and bedrooms

Karras et al., 2017. Progressive growing of GANs for improved quality, stability, and variation

Deep Convolutional GANs

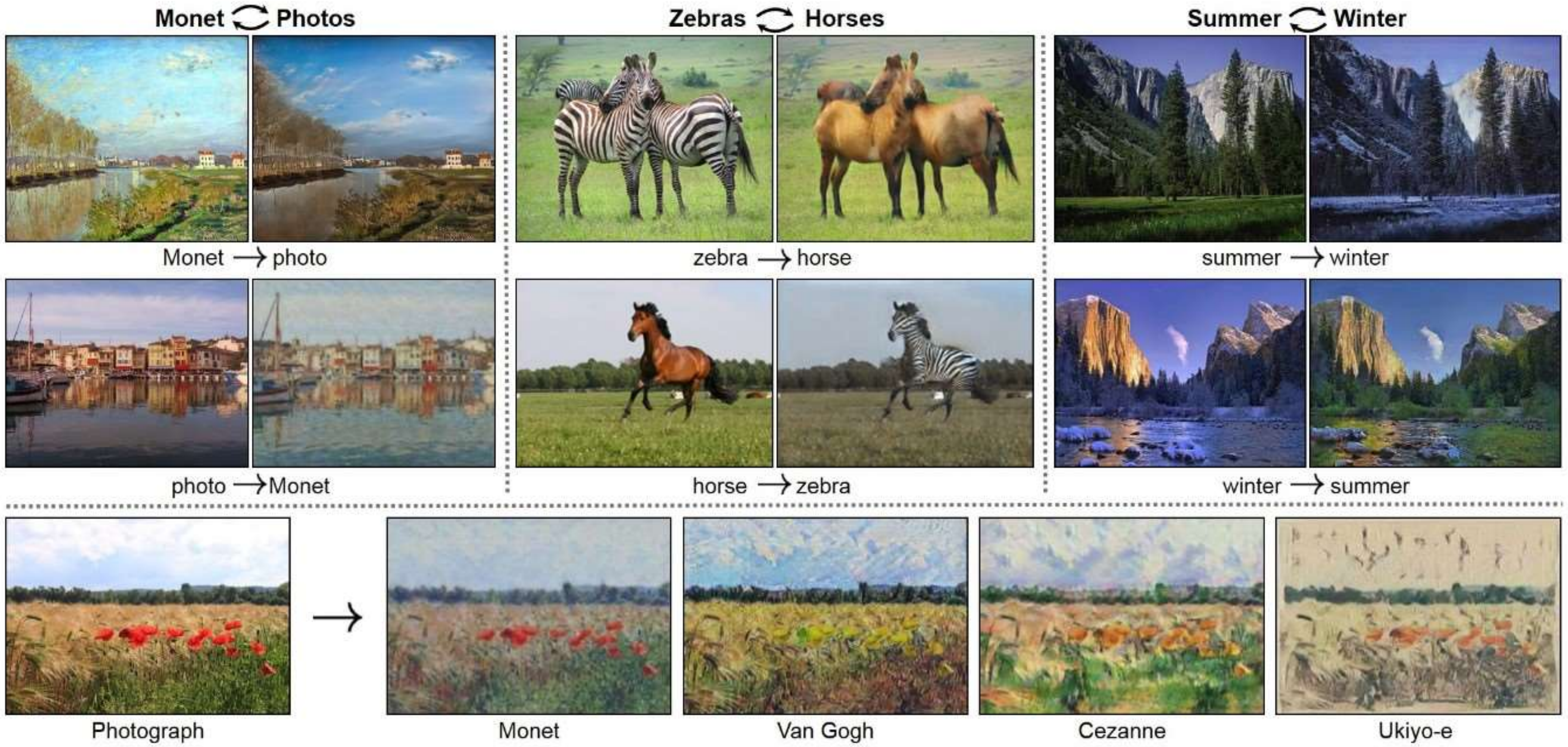
Generator Architecture



Key ideas:

- Replace FC hidden layers with Convolutions
  - **Generator:** Fractional-Strided convolutions
- Use Batch Normalization after each layer
- **Inside Generator**
  - Use ReLU for hidden layers
  - Use Tanh for the output layer

CycleGAN


Monet ⇄ Photos
Zebras ⇄ Horses
Summer ⇄ Winter
Monet → photo
zebra → horse
summer → winter
photo → Monet
horse → zebra
winter → summer
Photograph
→
Monet
Van Gogh
Cezanne
Ukiyo-e