aCubeIT

Generative Adversarial Networks

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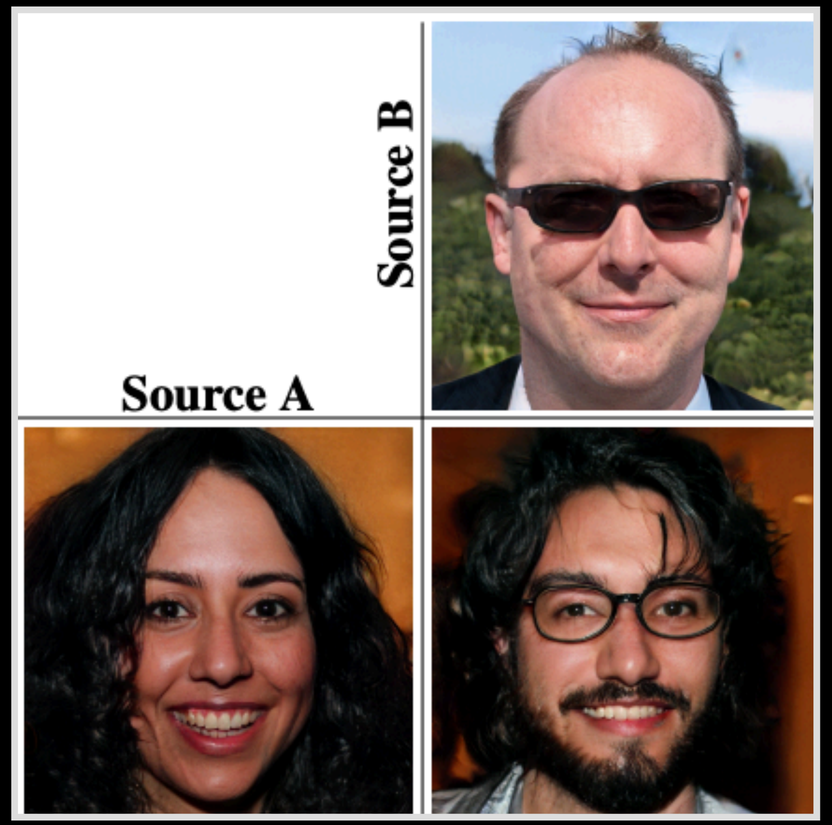
L03 - Deep Learning for Life Sciences Course

Generative Adversarial Networks (GANs)

Creating content



Which face is fake ?

Karras et al., 2019. *Analyzing and improving the image quality of stylegan.*

Generative Adversarial Networks (GANs)

2014

2015

2016

2017

2018

2019

Generative Adversarial Networks (GANs)


2014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2016


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2018


2019

- Generative modelling → progress in facial image generation

Generative Adversarial Networks (GANs)


2014


2015


2016


2017


2018


2019

- Generative modelling → progress in facial image generation
- Newer and more sophisticated methods every year

Supervised Learning

Supervised Learning

1	...	...
2	...	...
3	...	...

Training Data

Supervised Learning

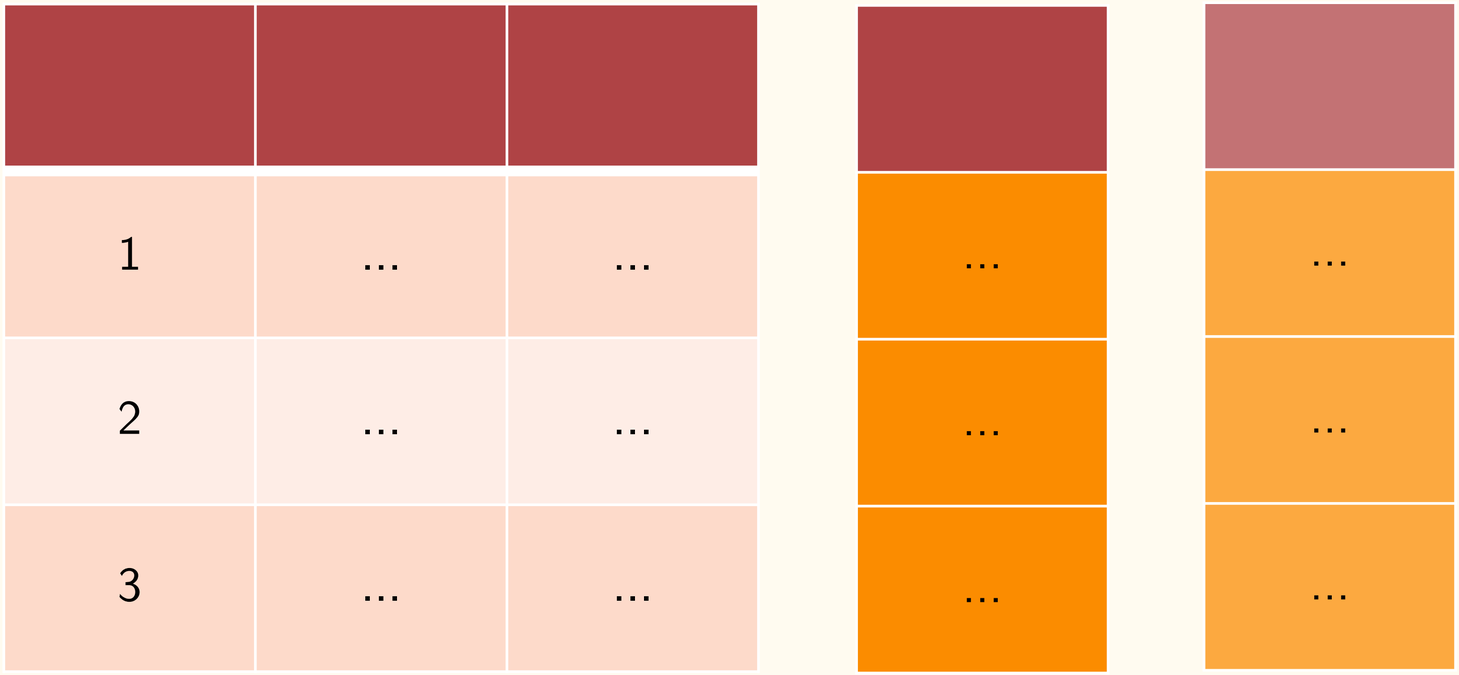
1	...	...
2	...	...
3	...	...

Training Data

...
...
...

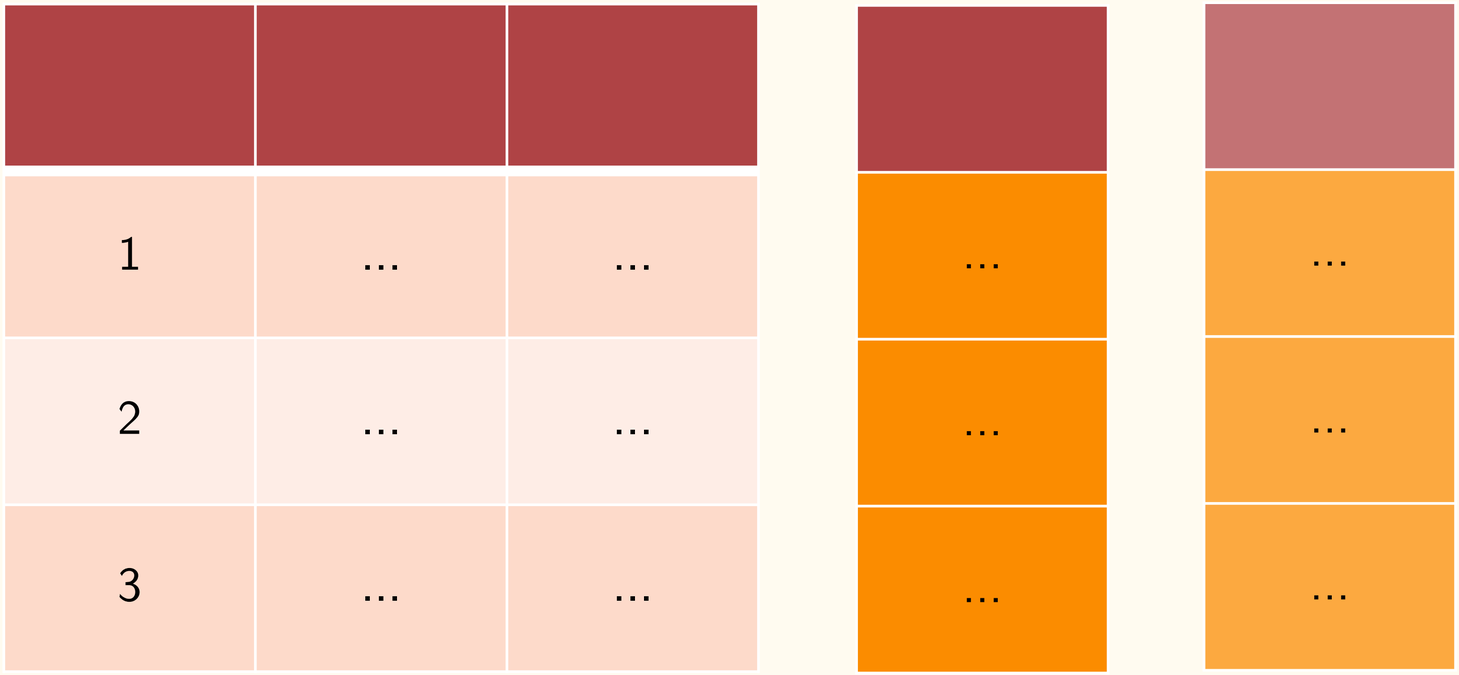
Labels

Supervised Learning



Training Data Labels Predictions

Supervised Learning



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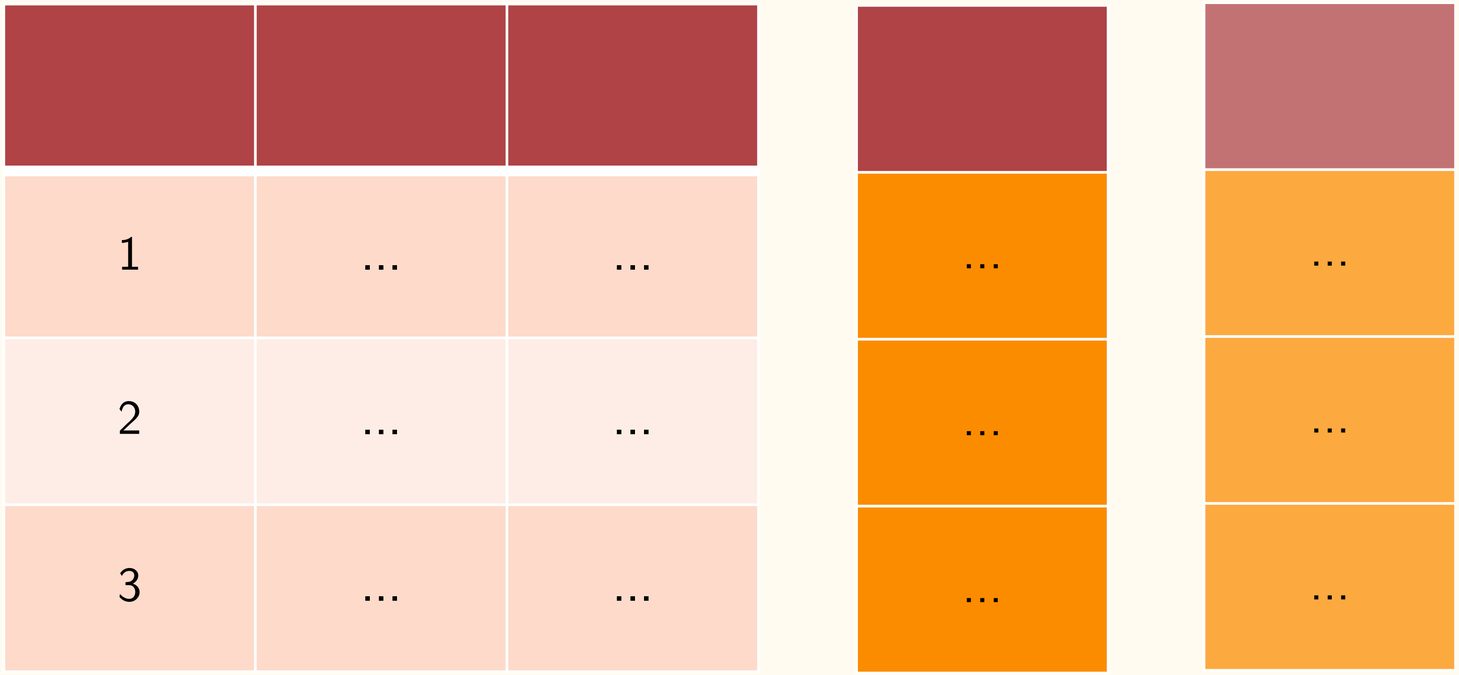
So far we've seen models which:

Supervised Learning



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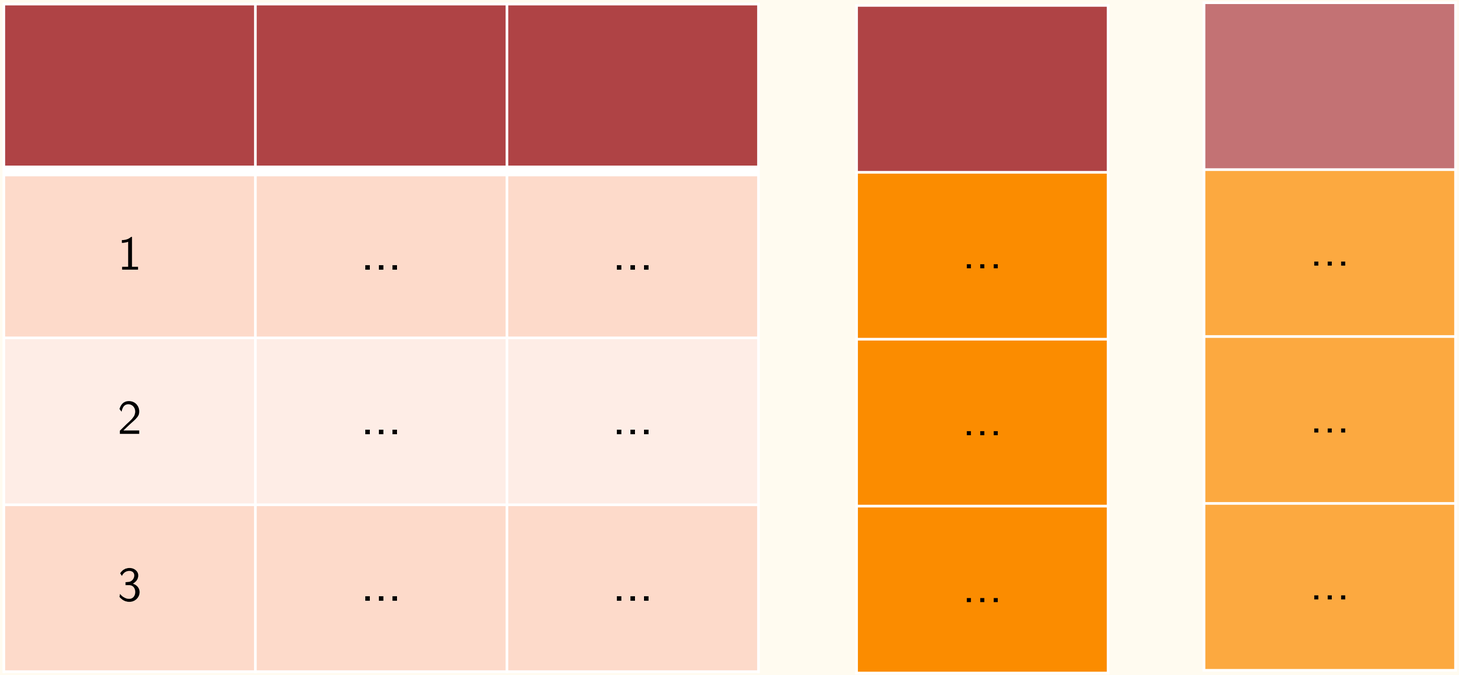

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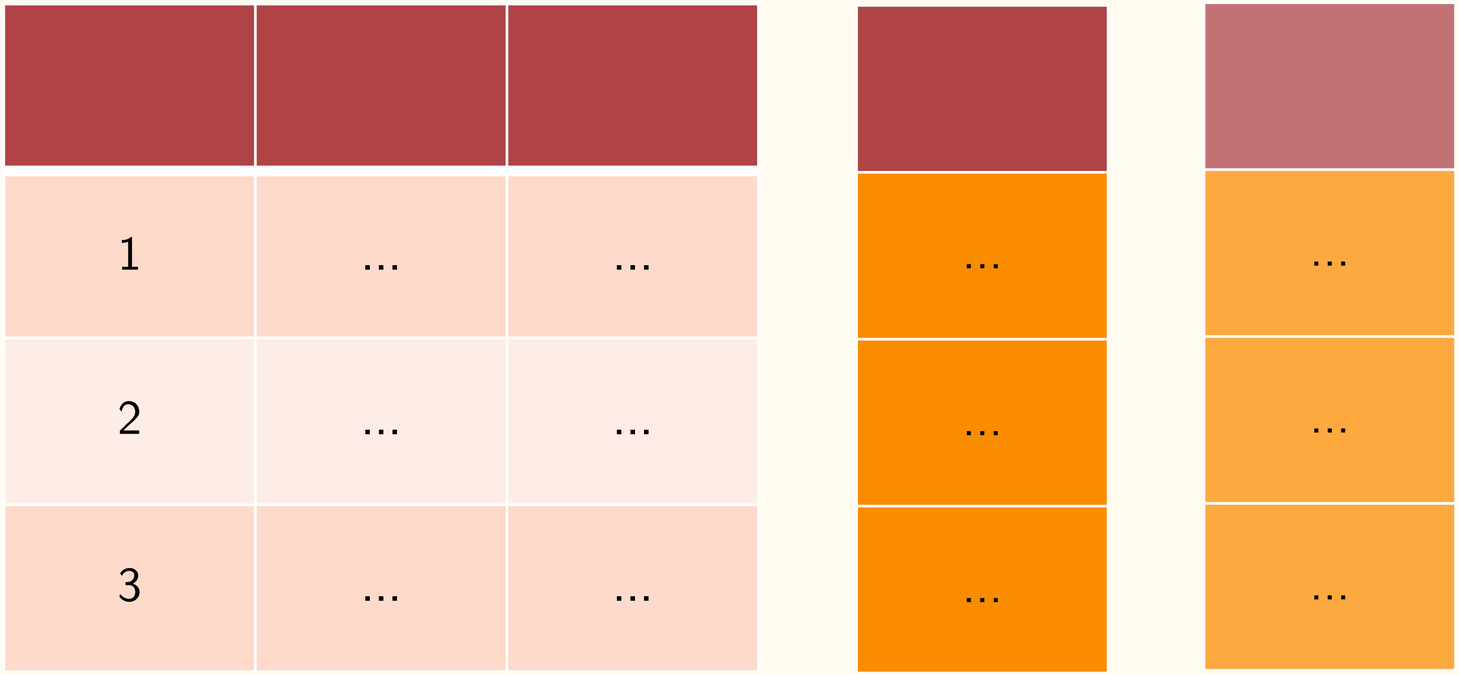

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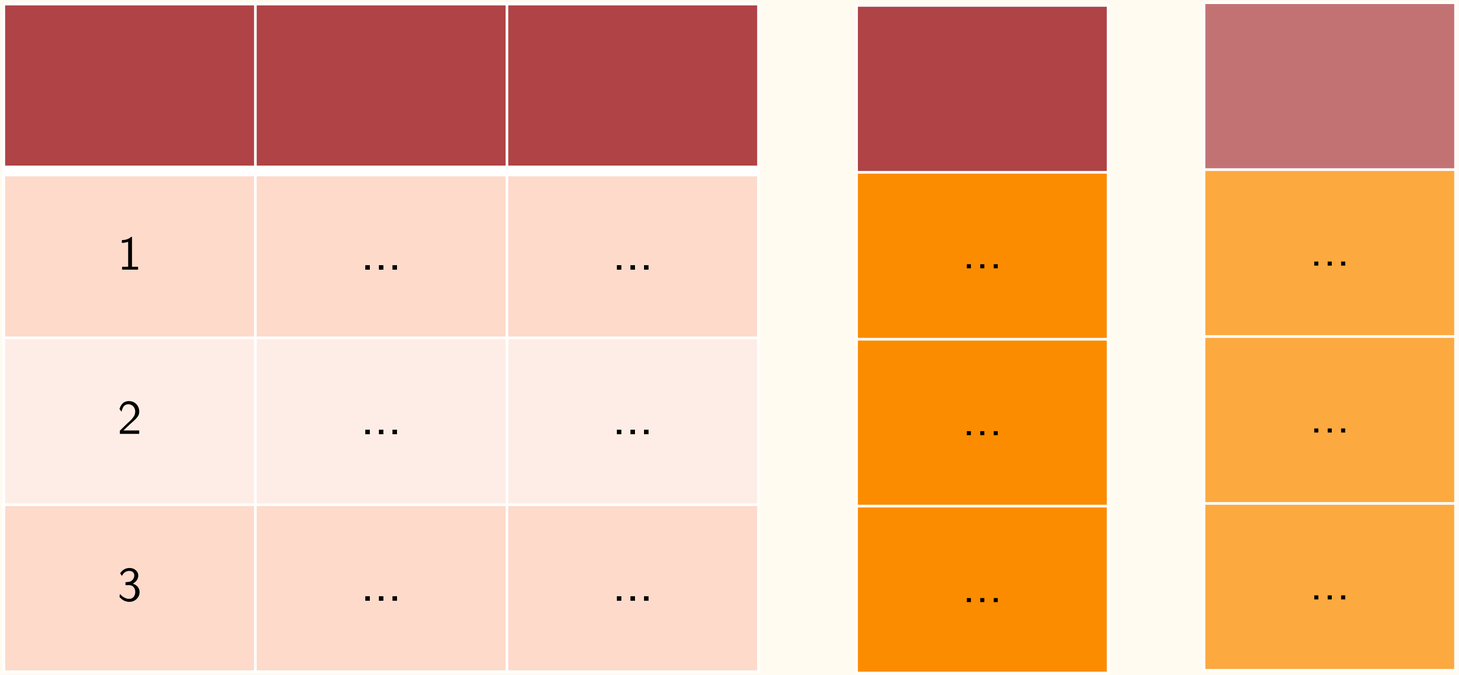

Training Data Labels Predictions

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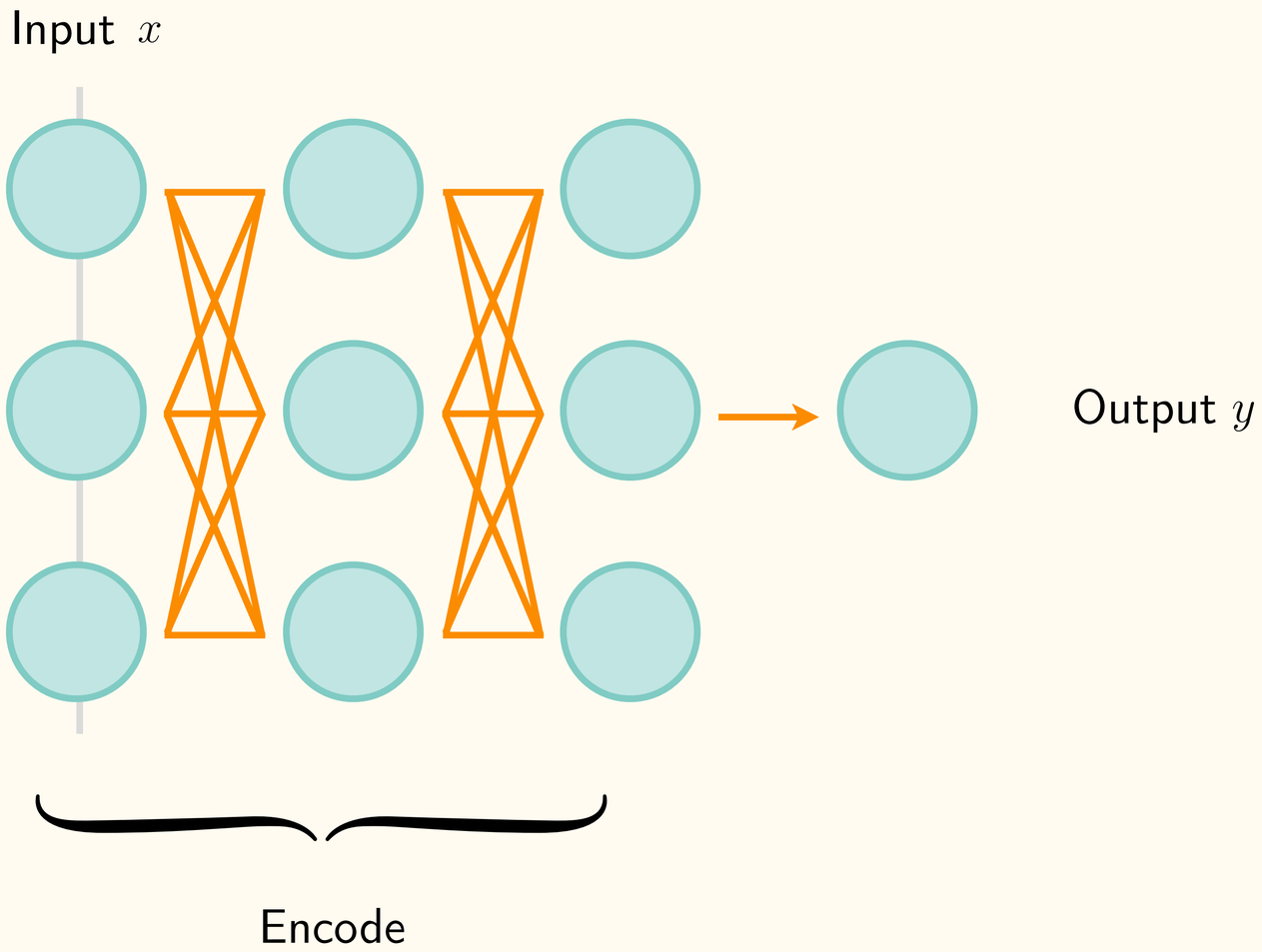

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Unsupervised Learning

Unsupervised Learning

- Generative models are different.

Unsupervised Learning

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Unsupervised Learning

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- Instead of taking a sample as *input*, they produce a sample as *output*.

Unsupervised Learning

Unsupervised Learning

- Train model on photographs of cats

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  - Learn to produce new cat-like images

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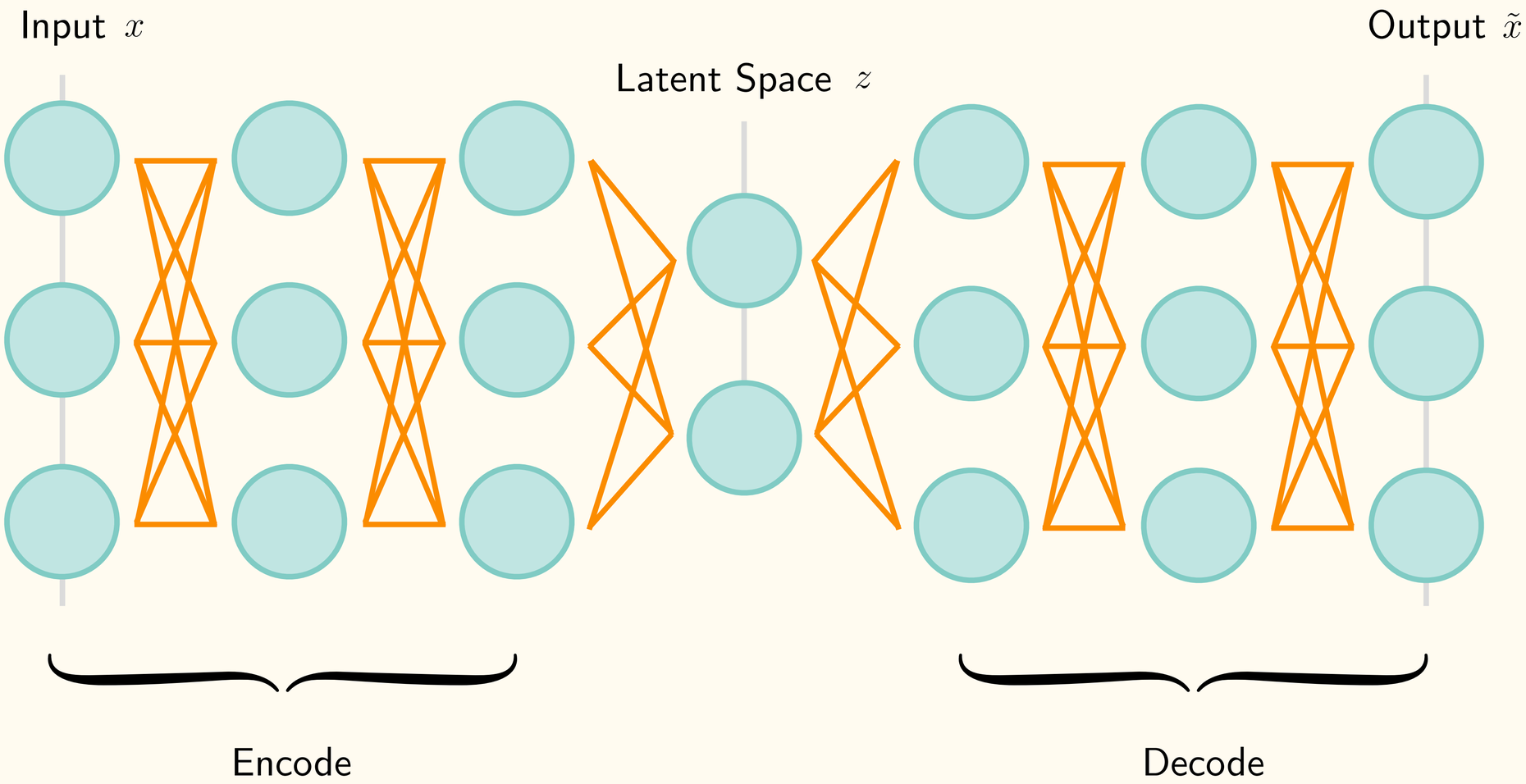
- A generative model is trained on samples which are drawn from a:

probability distribution

- Its job is to produce new samples from that same probability distribution.

Auto-Encoder



Auto-Encoder

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- **Encoder**: samples → compressed representations

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- What if we take *random vectors* in the latent space (picking a random value for each component of the vector) and pass them through the decoder ?

- If everything goes well, the decoder should produce a completely *new sample* that *resembles* the ones it was trained on.

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  - Doesn't work very well.

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- But if we pick a vector from *outside* that region ?
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- Decoder has only learned to work for the *particular* latent vectors from encoder
  - Not for *arbitrary* ones.

Variational Auto-Encoder (VAE)

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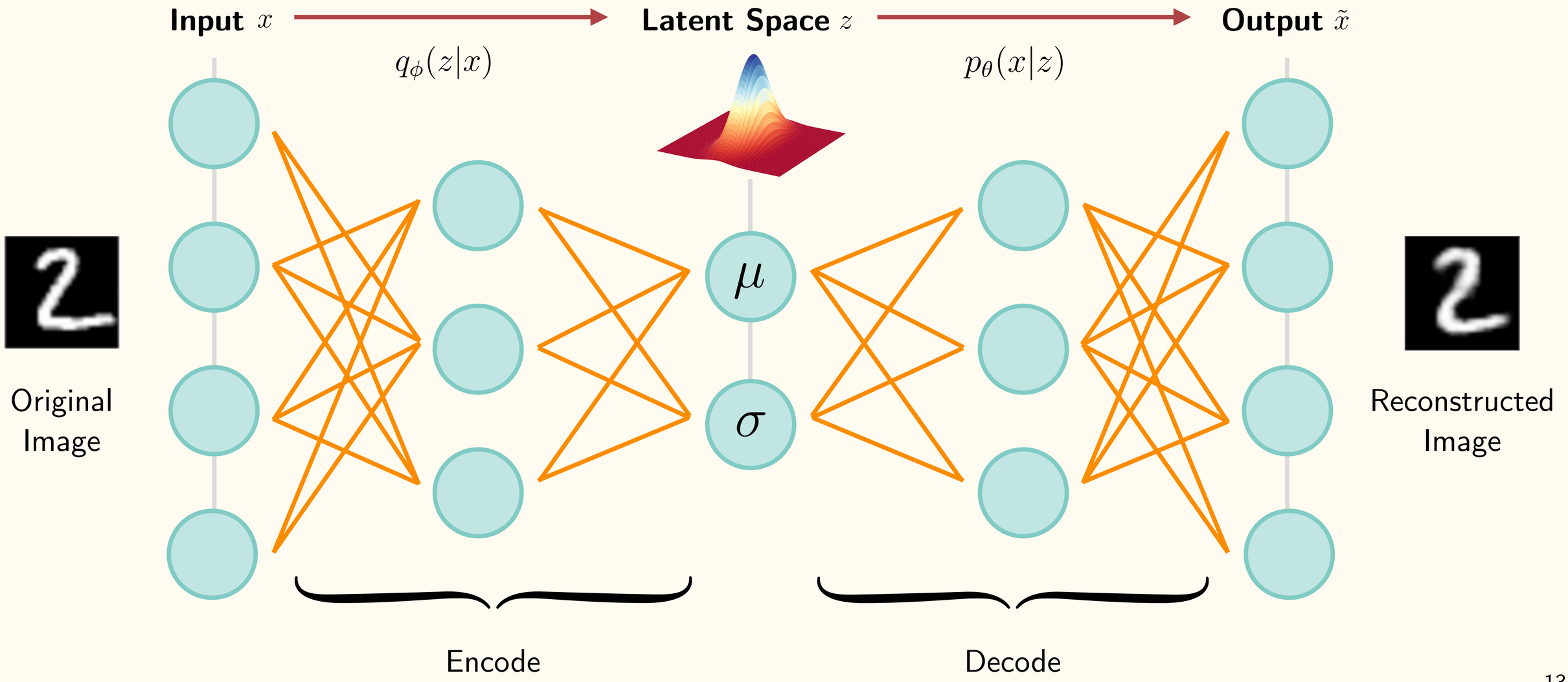
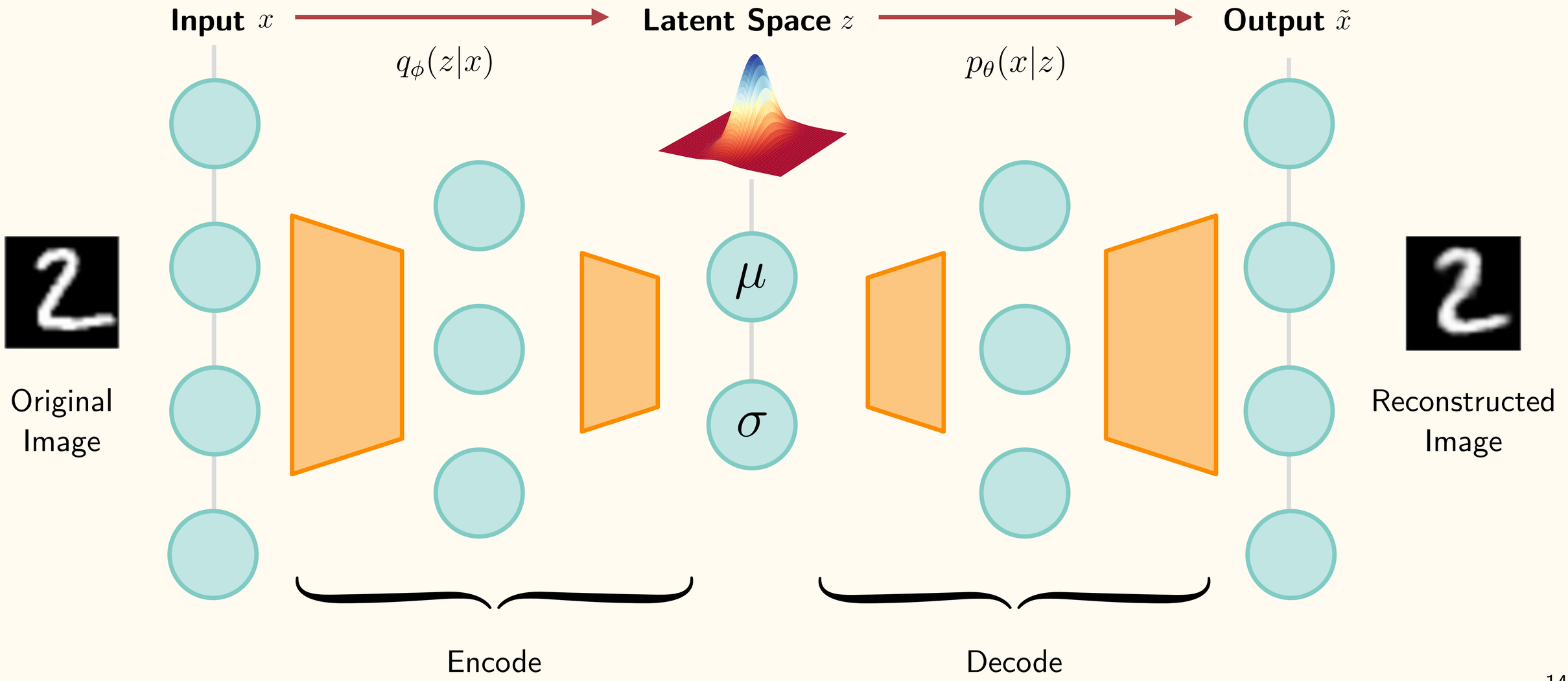
  - We can *expect* the decoder to work well on them

- We add random noise to the latent vector
  - Prevents decoder from being too sensitive to details

Variational Auto-Encoder (VAE)

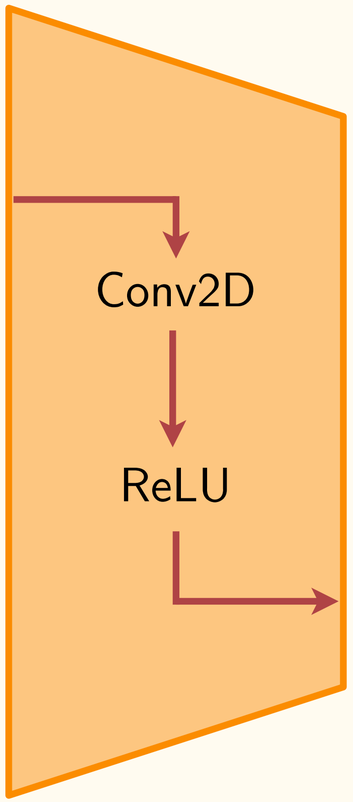


Simplified VAE Representation



Encoder-Decoder

Encode



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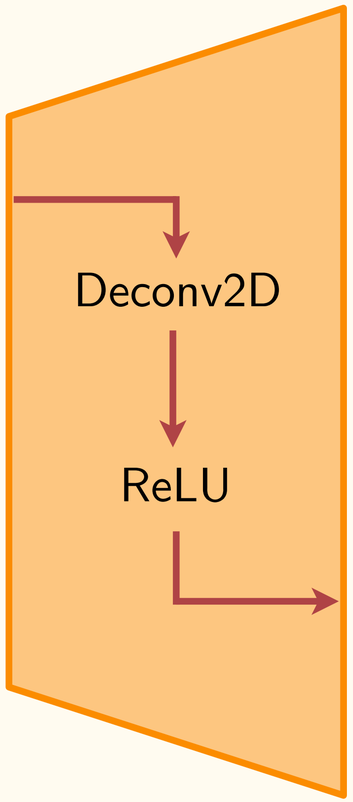

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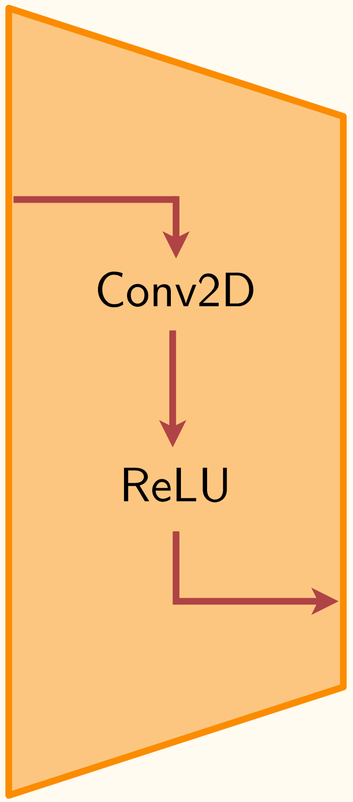

- An **encoder** is just a convolutional operation coupled with an activation function

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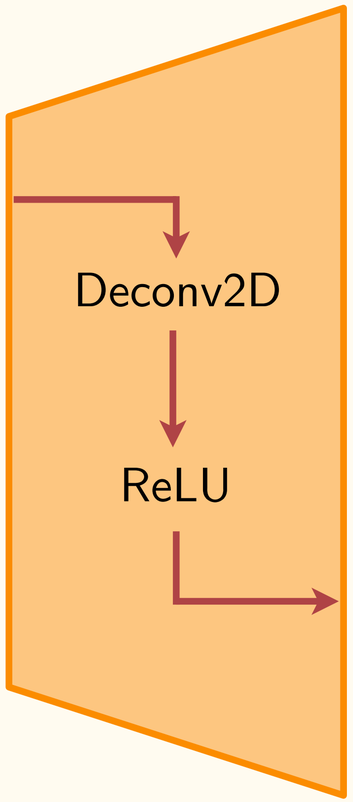

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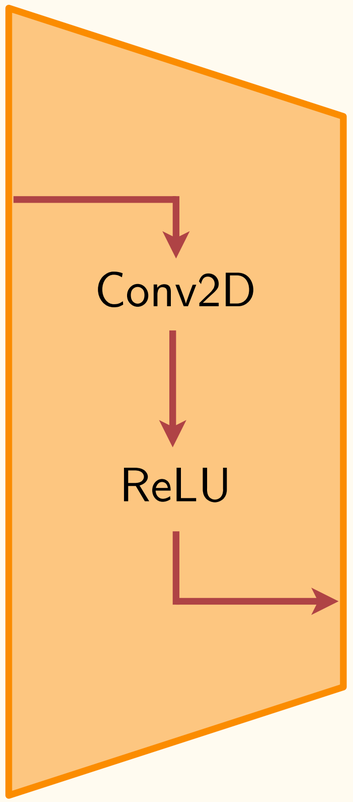

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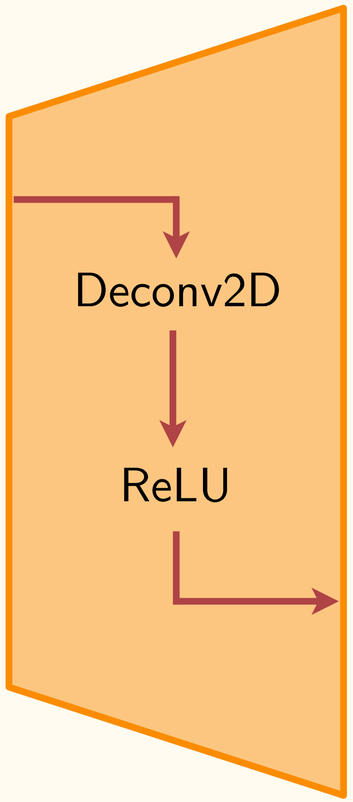

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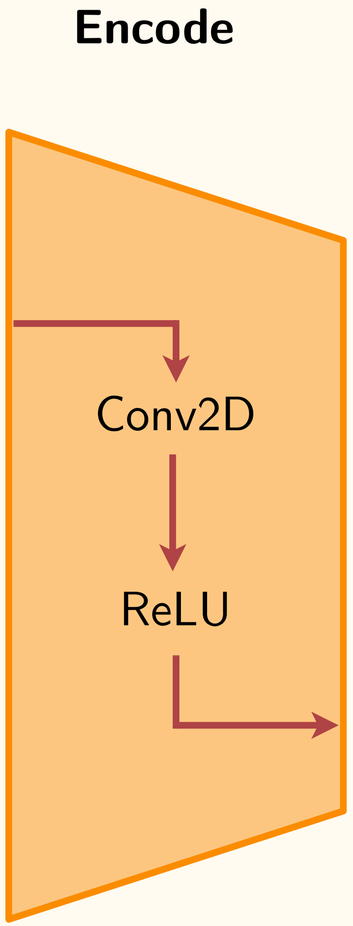
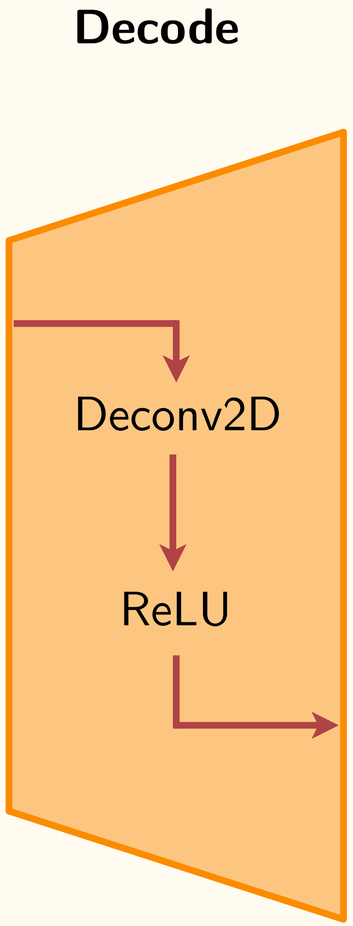


- An **encoder** is just a convolutional operation coupled with an activation function
- A **decoder** is de-convolutional operation and activation function



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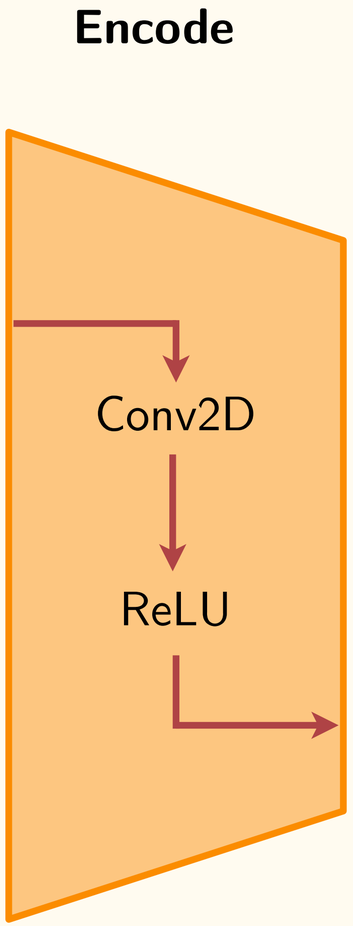

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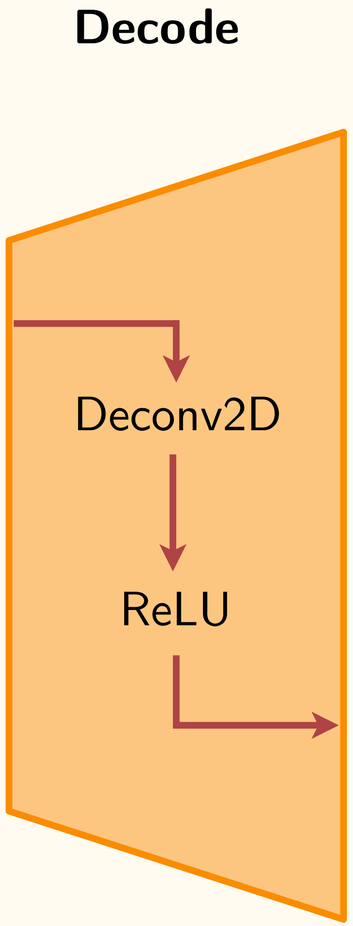

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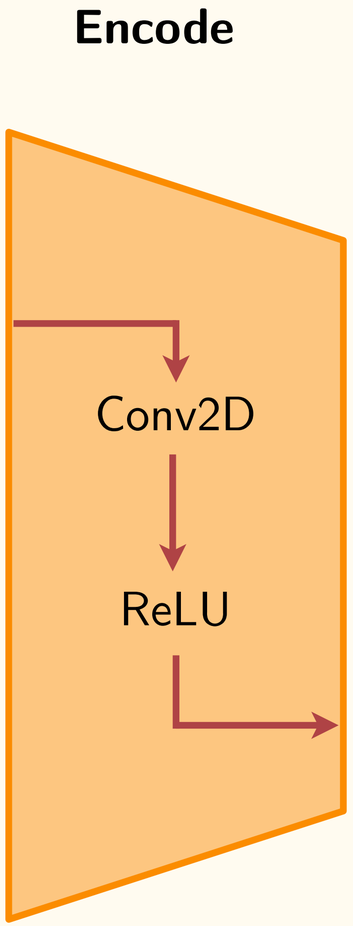

- An **encoder** is just a convolutional operation coupled with an activation function
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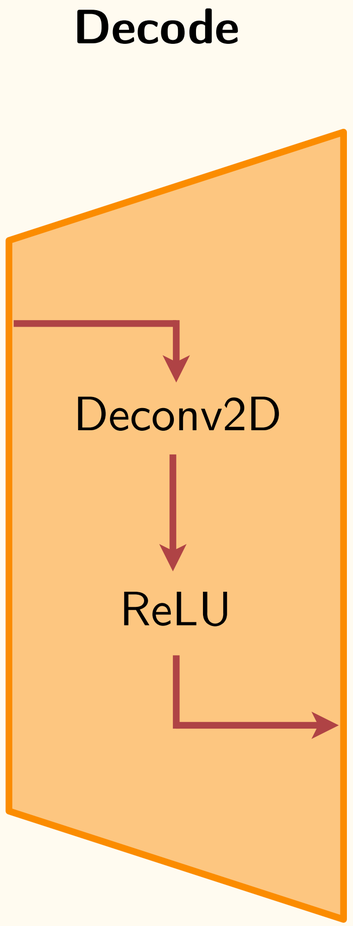
- De-conv2D is just a **transposed** Conv2D



Encoder-Decoder

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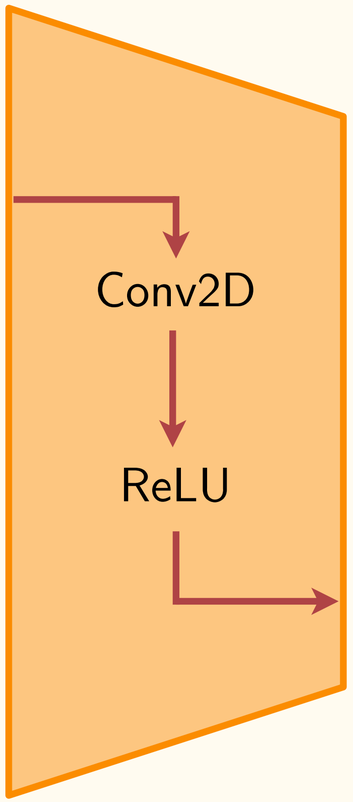
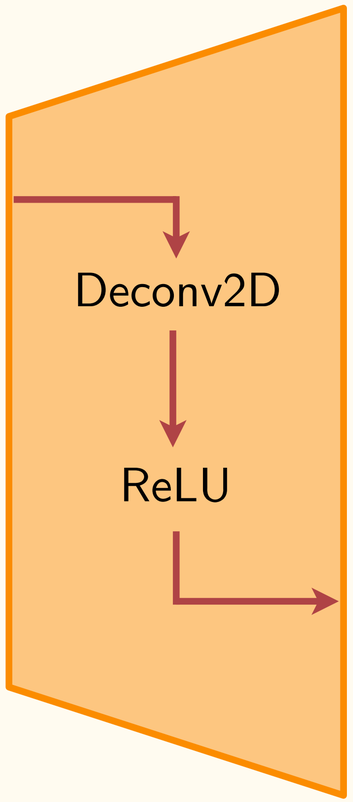


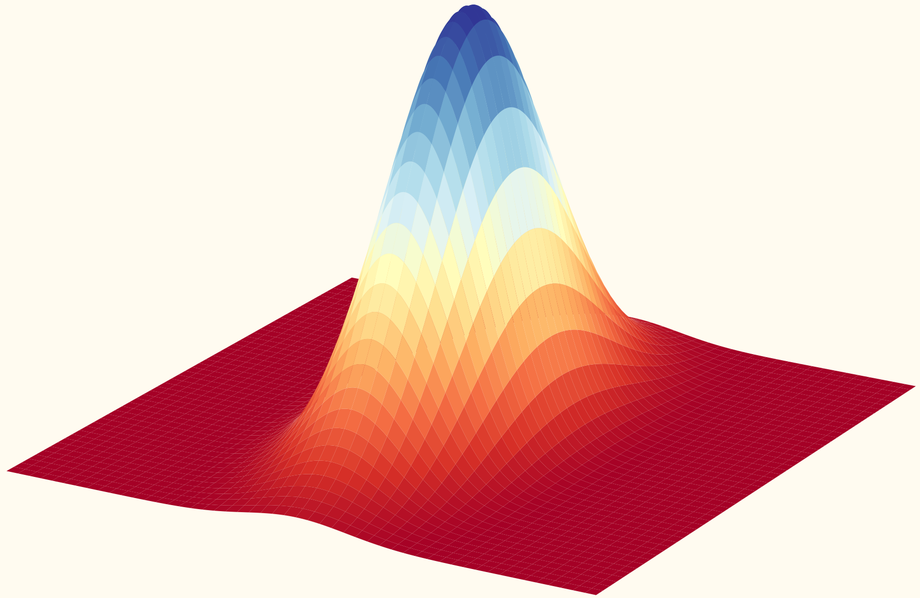

```
# Encoder
tf.nn.conv2d()
tf.nn.relu()

# Decoder
tf.nn.conv2d_transpose()
tf.nn.relu()
```

Decode



Latent Distribution



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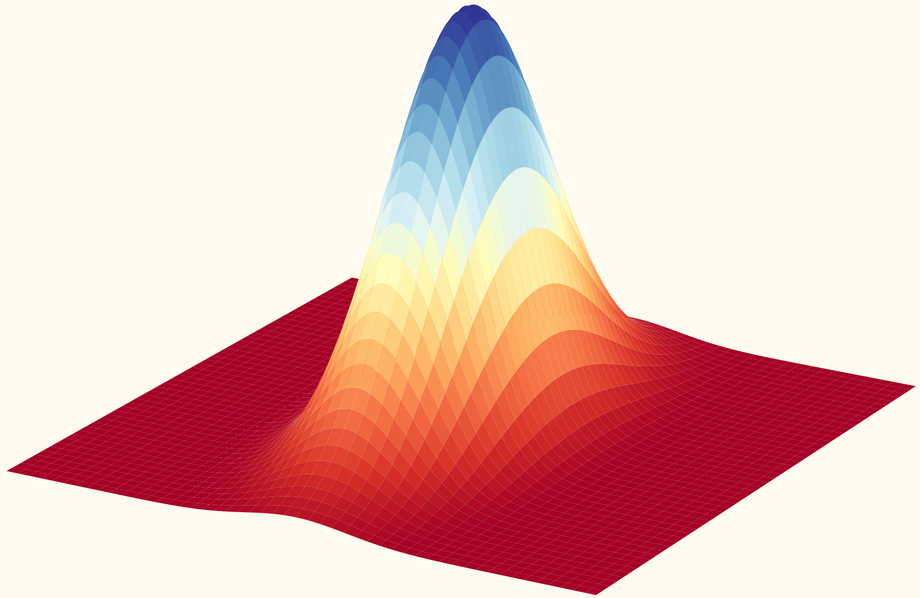

- The latent vector $z \sim (\mu, \sigma)$

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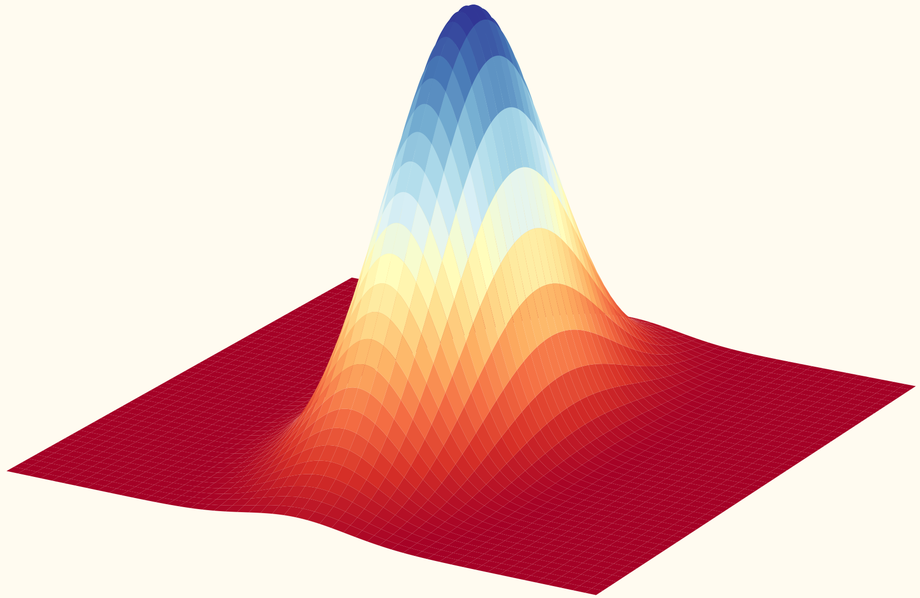

- The latent vector $z \sim (\mu, \sigma)$
- Compressed representation of input x

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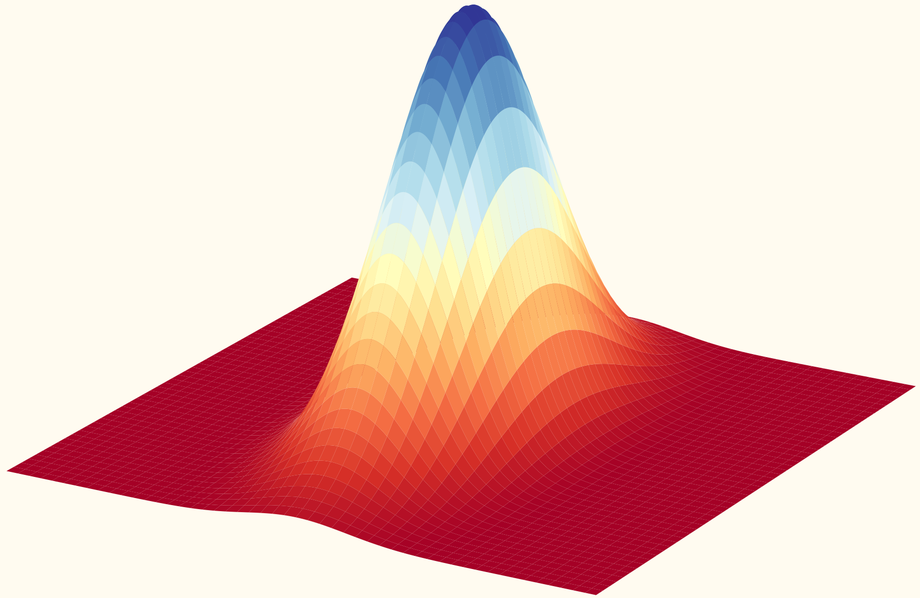

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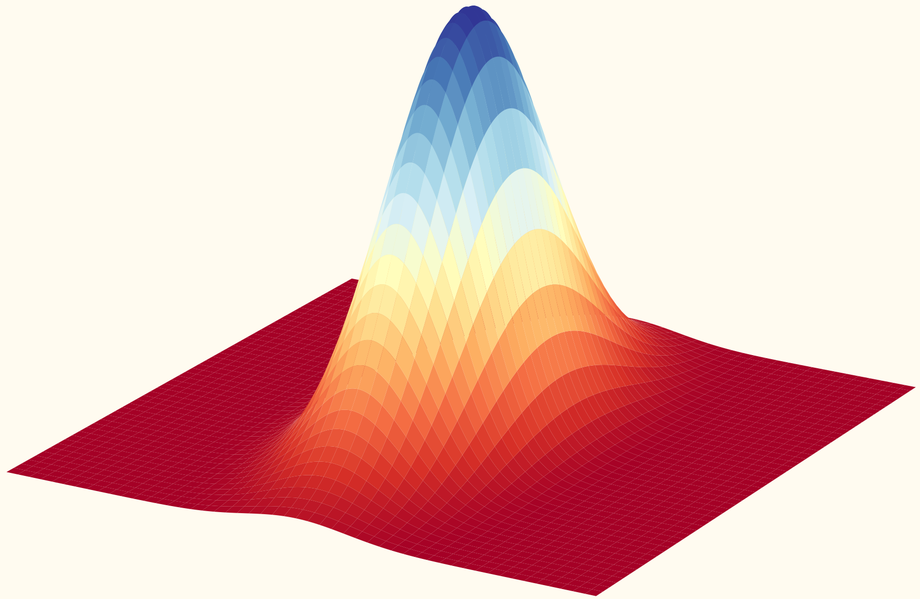

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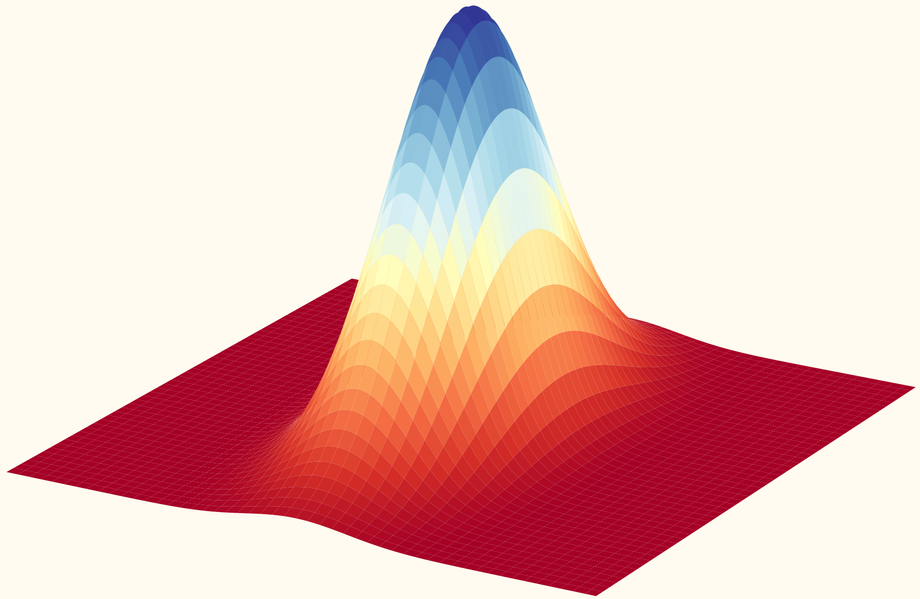
- Compressed representation of input x

- q_Φ(z|x) encodes x to z

Latent Distribution



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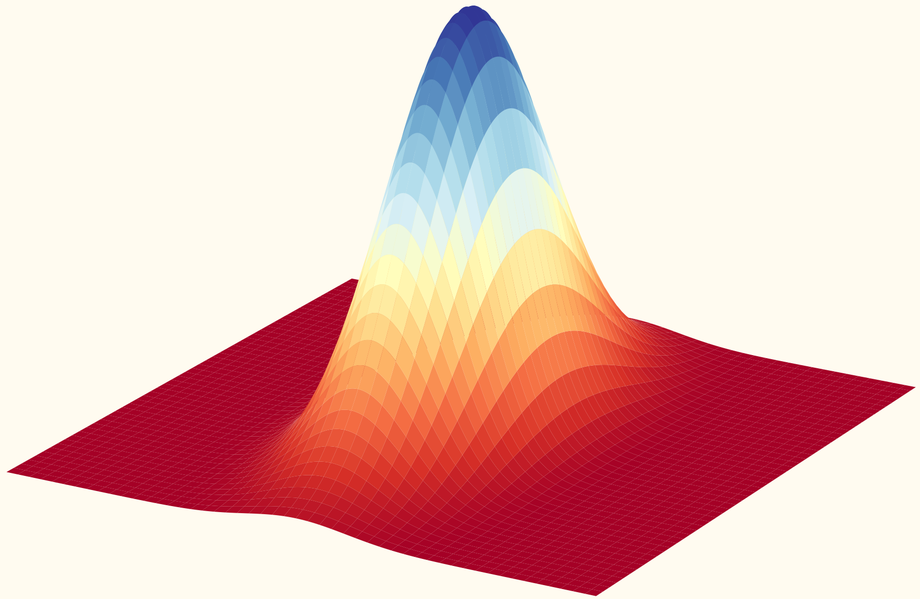
- q_Φ(z|x) encodes x to z
- p_θ(x|z) decodes z to x

Latent Distribution



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- q_Φ(z|x) encodes x to z
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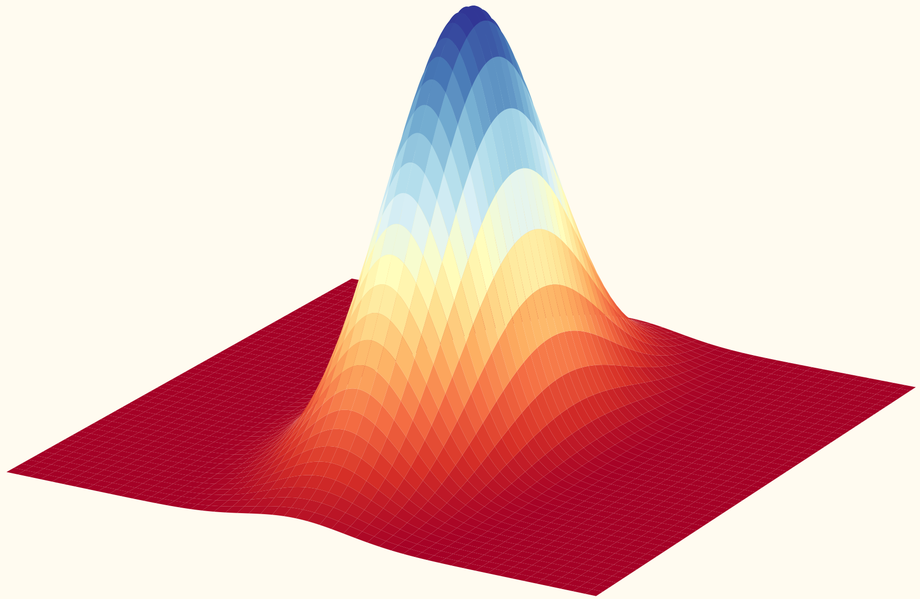
- θ and Φ represent weights and biases

Latent Distribution



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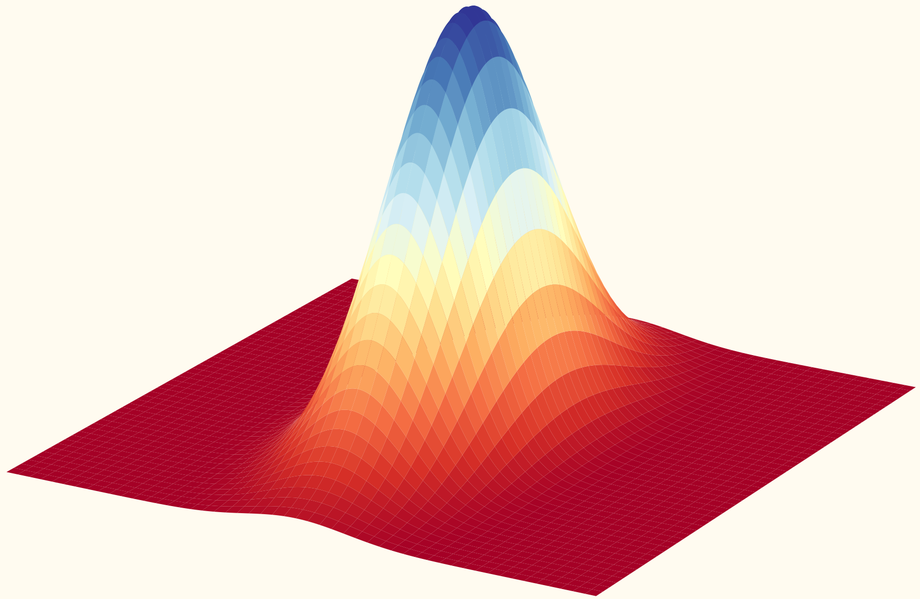

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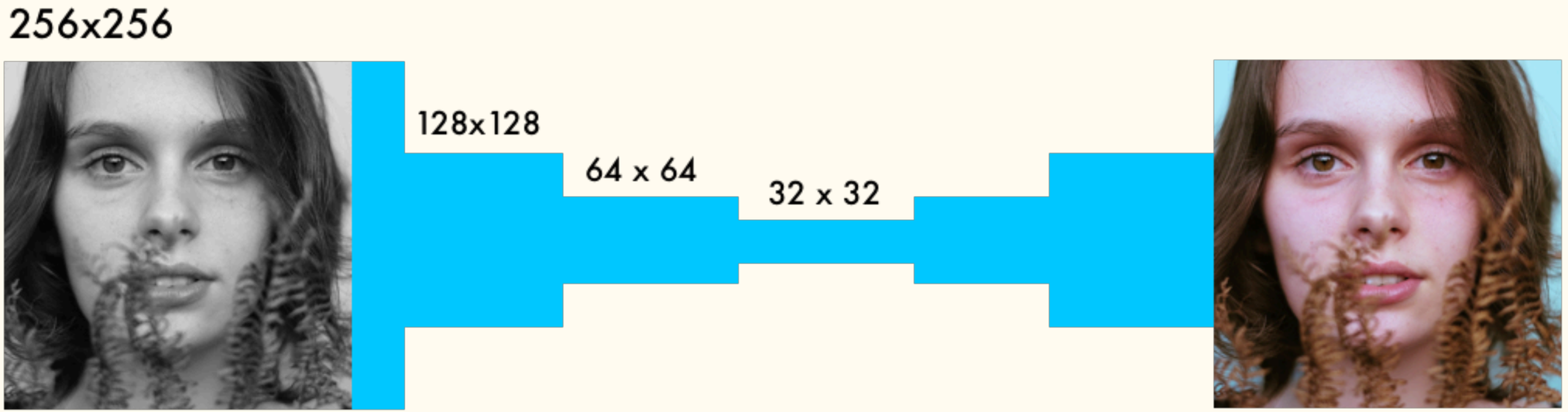
- θ and Φ represent weights and biases

- Remember: we **sample** from the distribution z → lossy reconstruction

VAE Applications

Colorize B&W images

- Encoder-Decoder architecture
- Inception ResNet V2 Classifier



Emil Wallner, 2017. *Colorizing B&W Photos with Neural Networks.* FloydHub.

Generative Adversarial Network

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- Works similarly to VAEs
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- But trains in a different way:
  - Passes random vectors into the generator
  - Directly evaluates the outputs on how well they follow the expected distribution

Generative Adversarial Network

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- Essentially create a loss function to measure:

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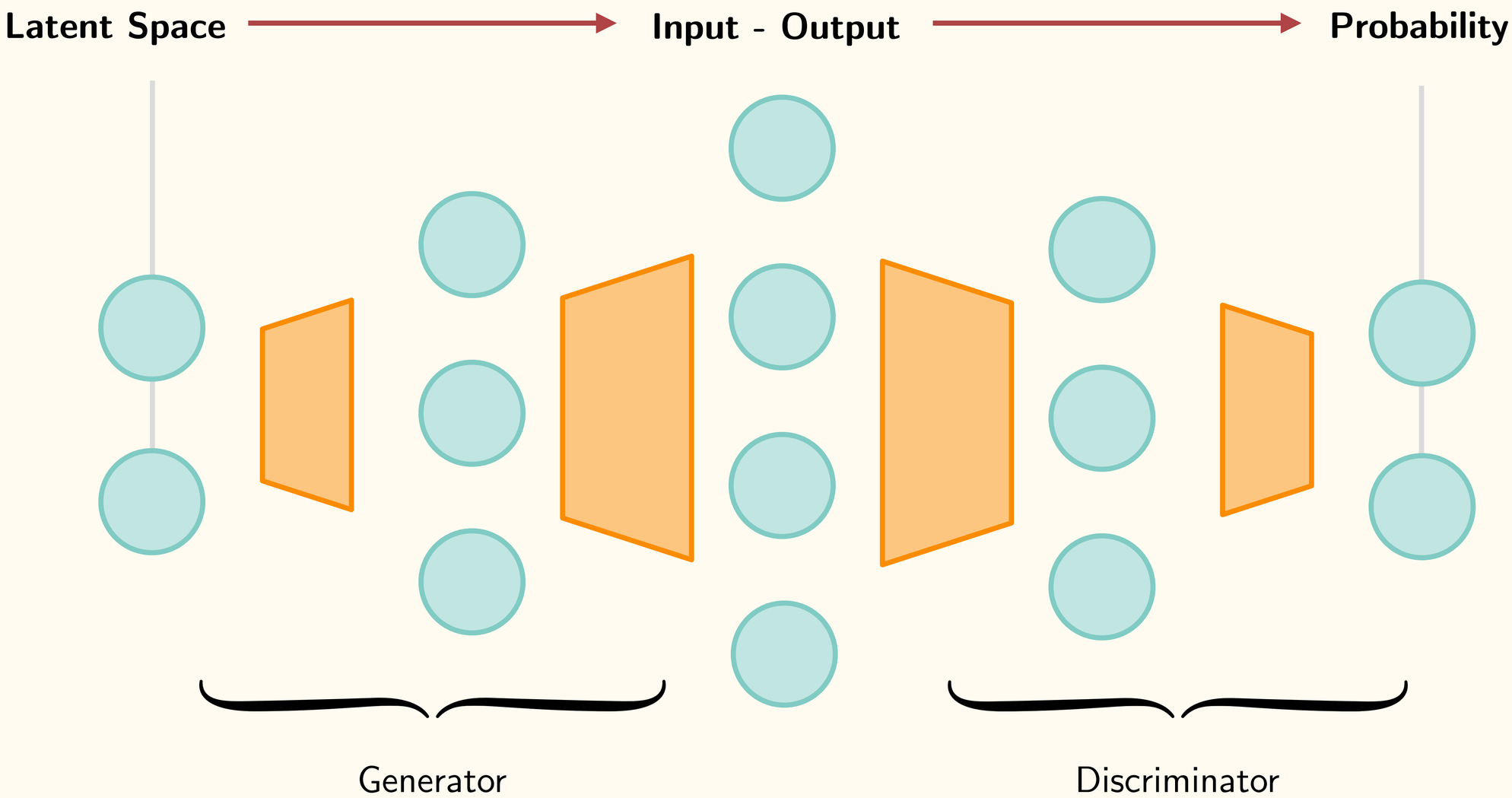
  - GAN learns the loss function from the data.

Generative Adversarial Network



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- **Generator**: takes random vectors → generates synthetic samples

- **Discriminator**: tries to *distinguish* between 
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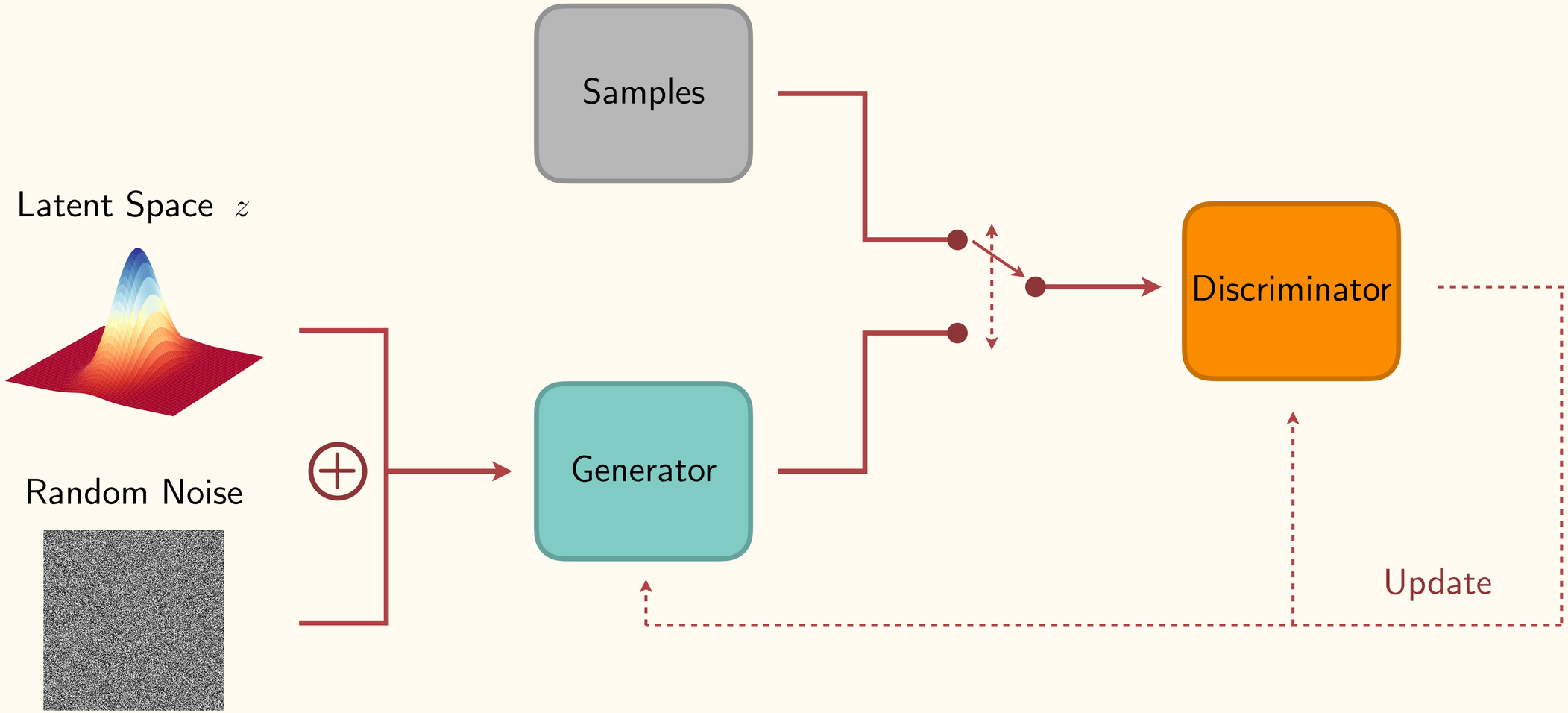
  - It takes a sample as input and outputs a **probability** of being a real sample
    - This acts as a loss function for the generator.

Generative Adversarial Network



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- **Generator** and **discriminator** are run *simultaneously*.

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Generative *Adversarial* Network**s**

GAN Applications

Colorize B&W images

- Even more advanced and realistic
- GAN based architecture

Jason Antic, 2018. *DeOldify: Colorizing and Restoring Old Images and Videos with Deep Learning*. FloydHub.

VAE vs GANs

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Roughly:

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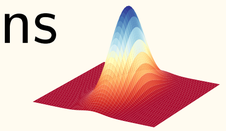
- VAEs tend to produce higher-quality distributions 

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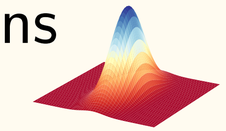
- VAEs tend to produce higher-quality distributions 

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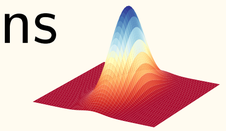
- VAEs tend to produce higher-quality distributions 

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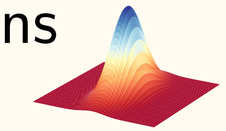
- VAEs tend to produce higher-quality distributions 

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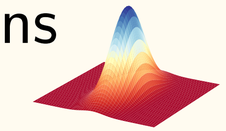
- VAEs tend to produce higher-quality distributions 

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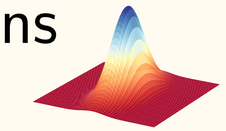
- VAEs tend to produce higher-quality distributions 

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Very active field of research → Things changing constantly !

Application: Predicting Drug-Target Binding Affinity

[1] Zhao Lingling et al., 2020. *GANsDTA: Predicting Drug-Target Binding Affinity Using GANs*. Frontiers in Genetics, Volume 10.

Application: Predicting Drug-Target Binding Affinity

- Challenging in Drug Discovery

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- Semi-supervised GAN based methods can help [1]

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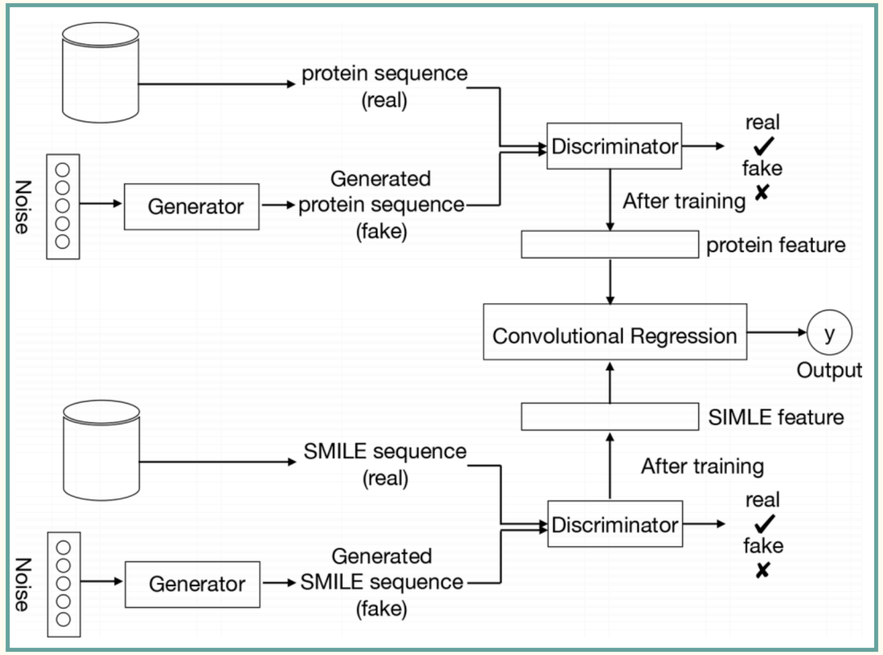

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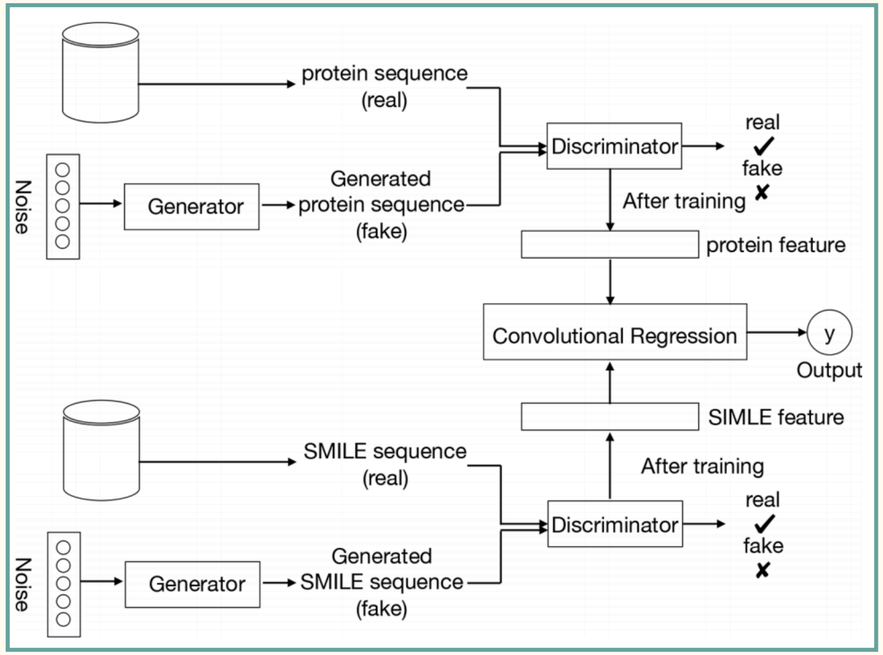

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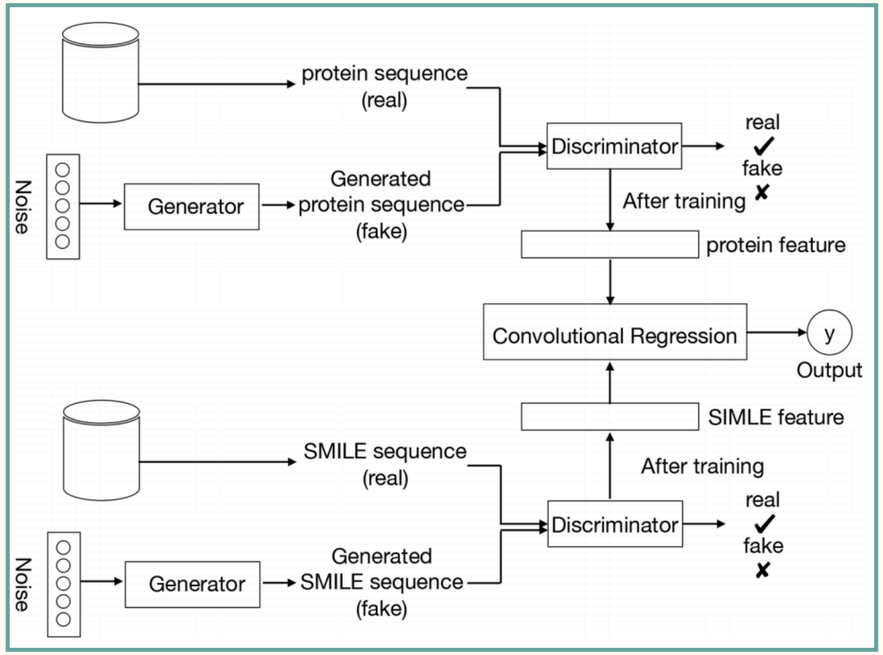

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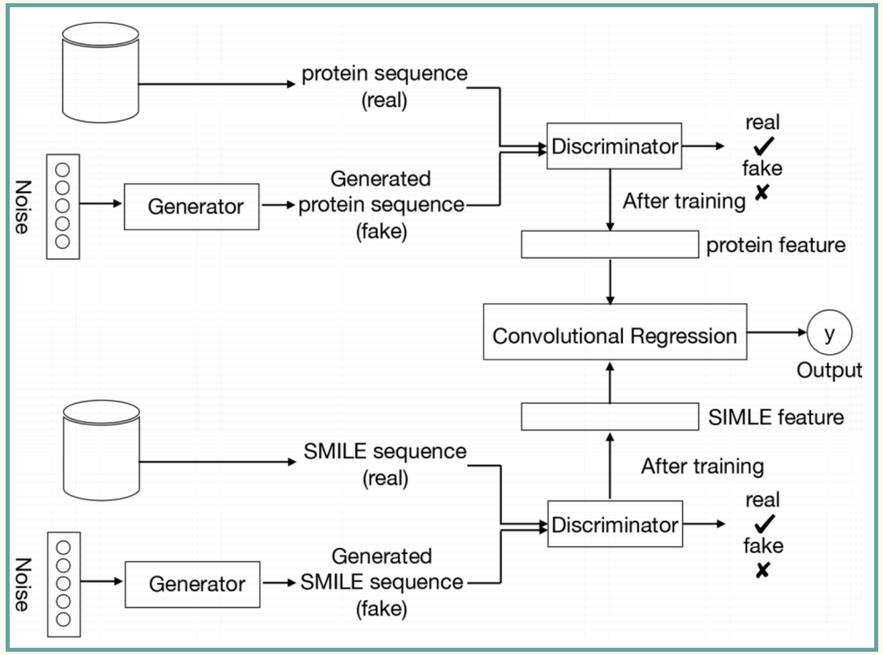

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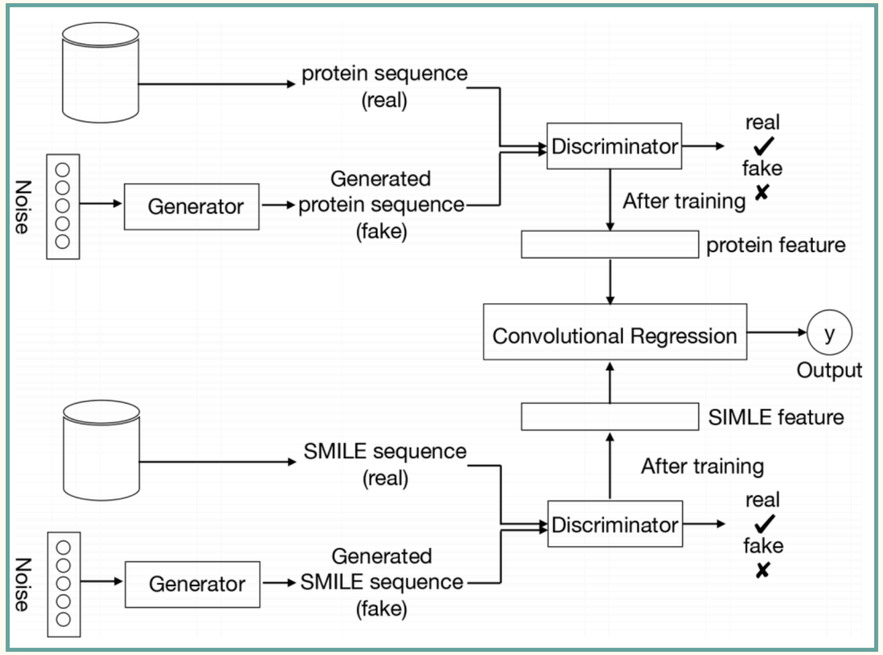

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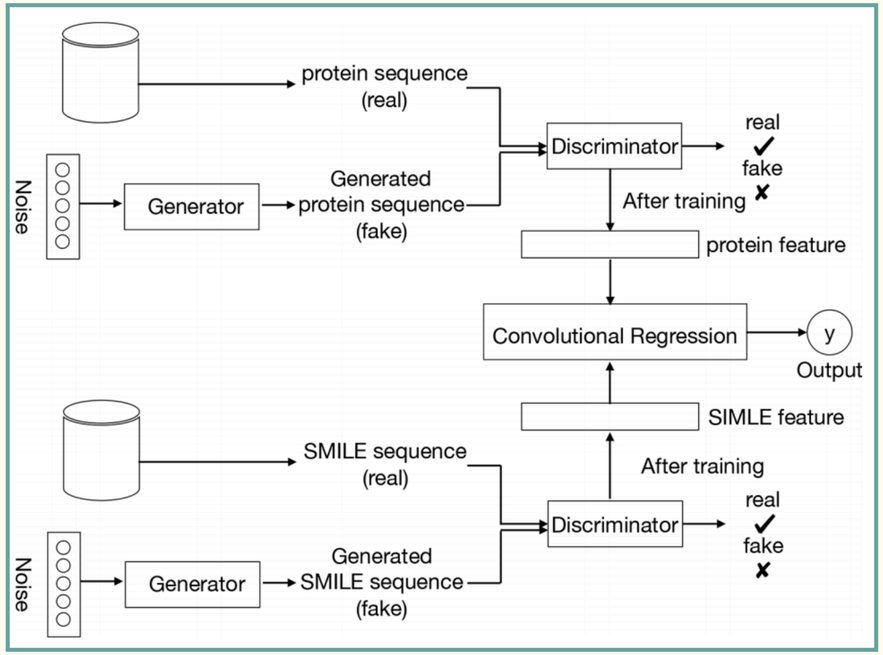

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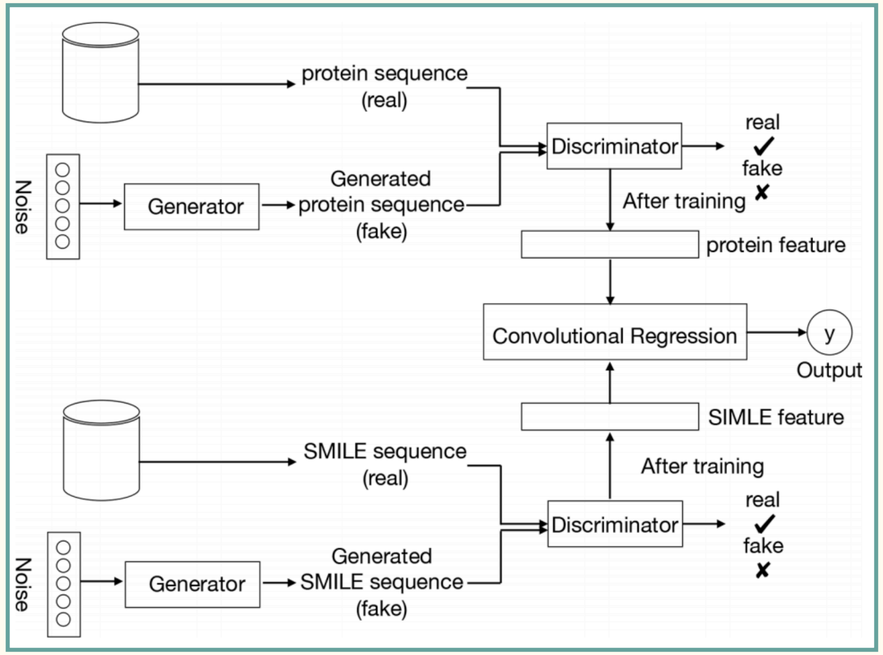

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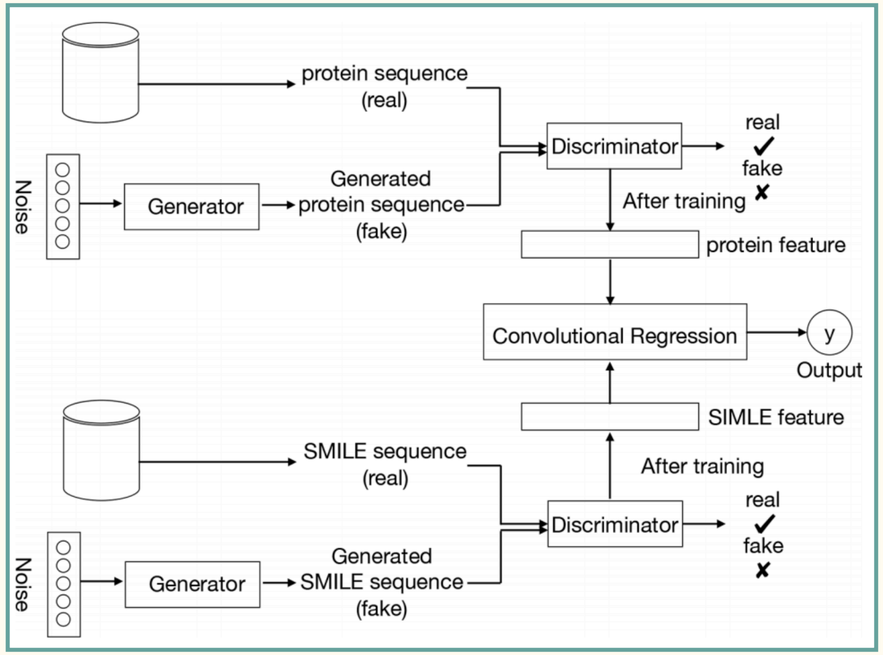

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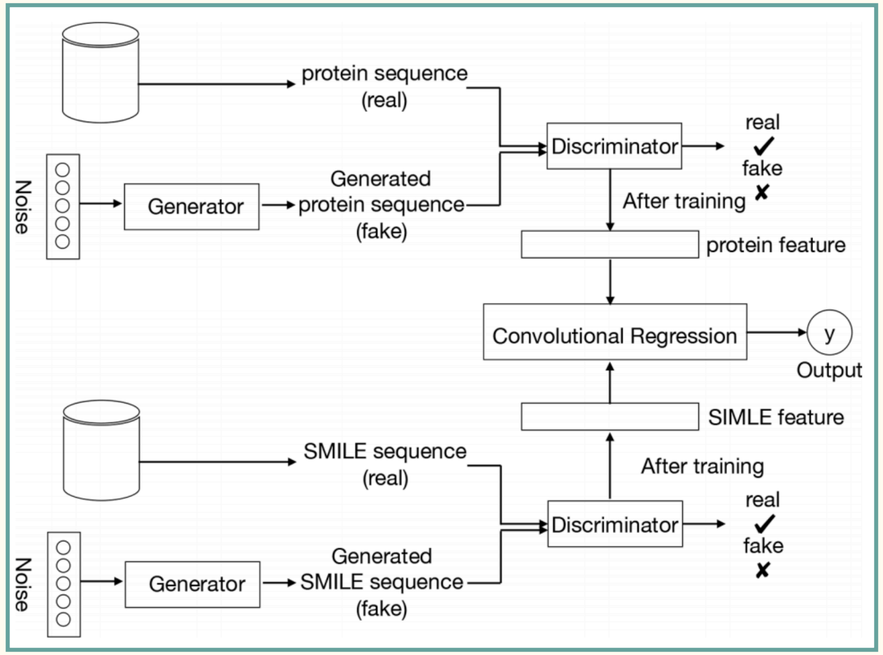

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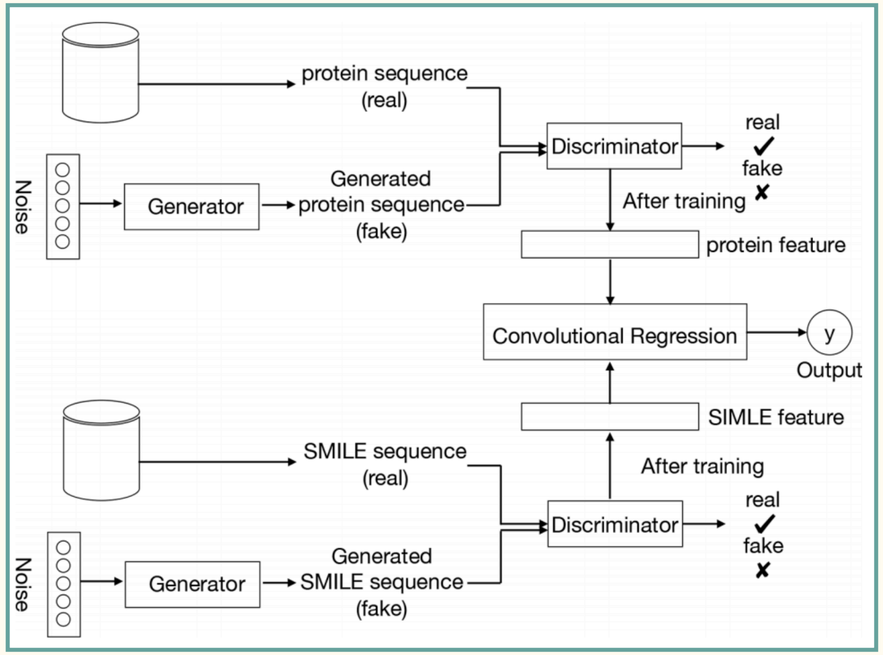

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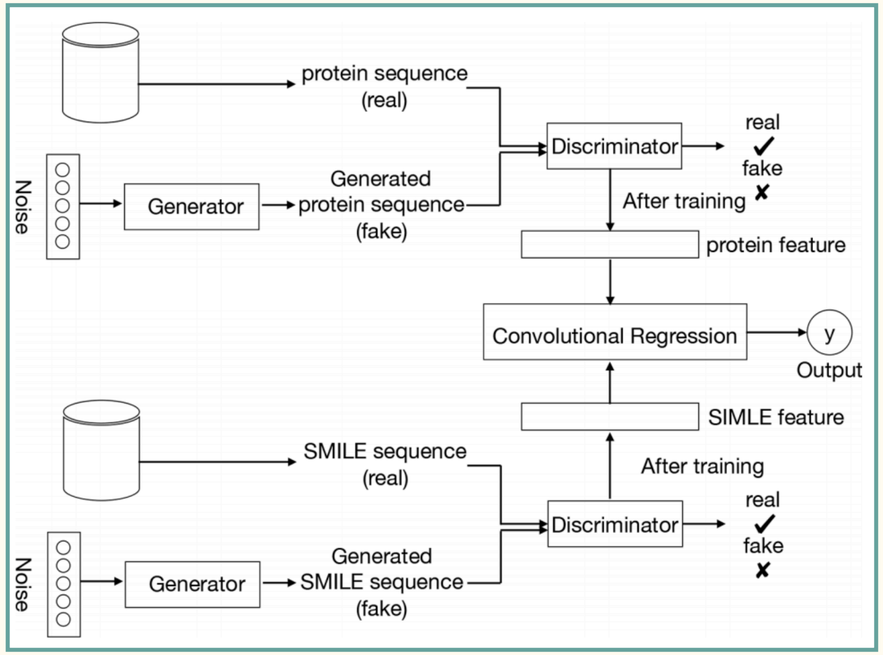

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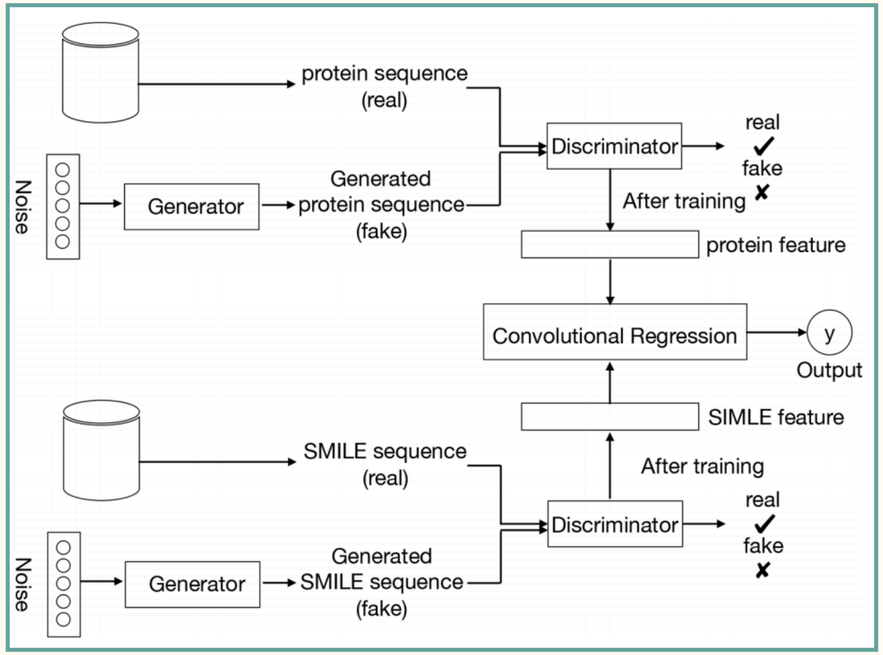

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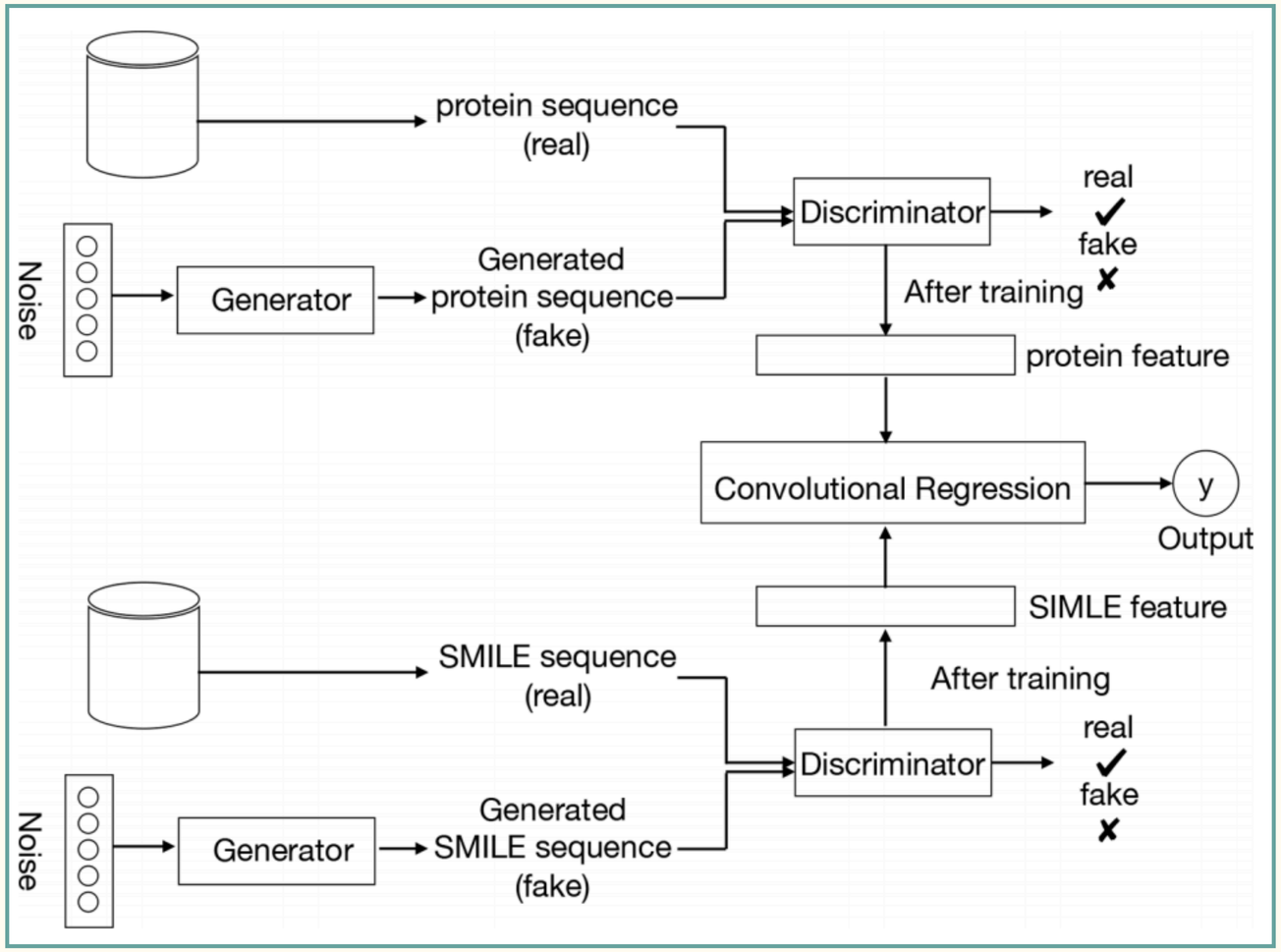

Future Work

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Thank you !

aCubeIT

Ackruti Trade Center, MIDC, Mumbai, IND

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+91 9892512129

prakash@acubeit.com