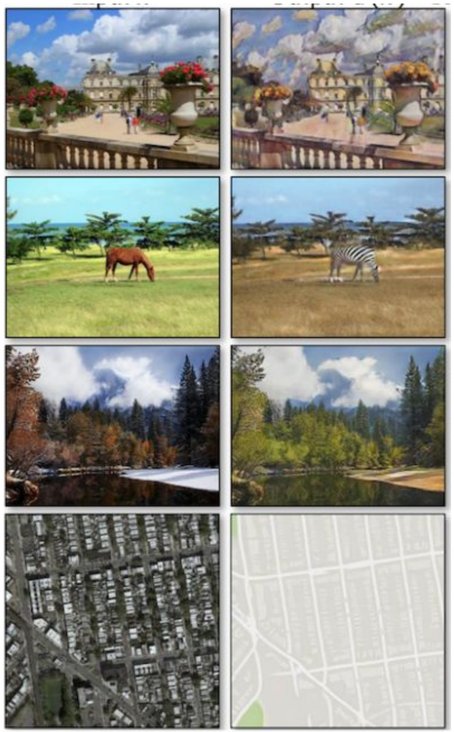
Some GAN Applications

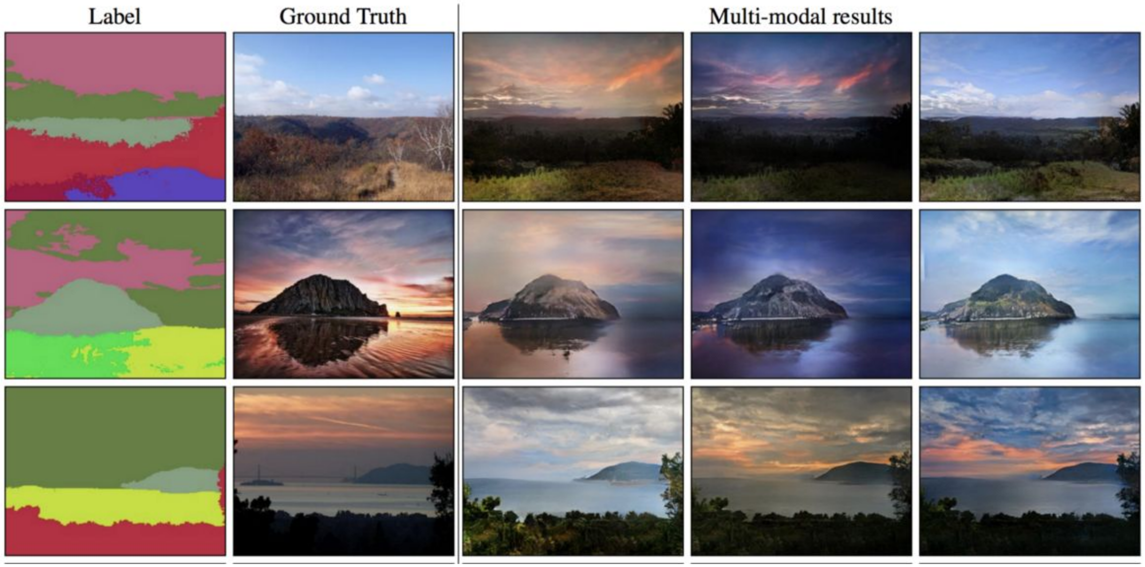
Generate New Samples of Image Datasets

Image-to-Image Translation



Text-to-Image Translation

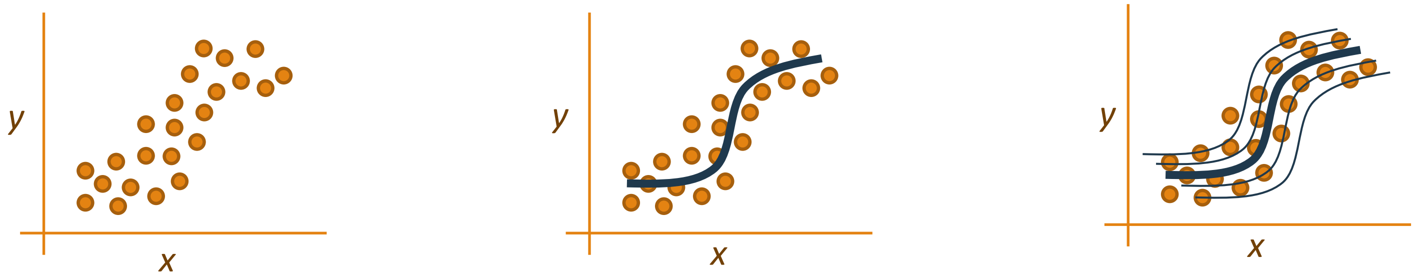
Semantic-Image-to-Photo Translation



http://nvidia-research-mingyuliu.com/gaugan

Generative Adversarial Networks

Generating synthetic samples



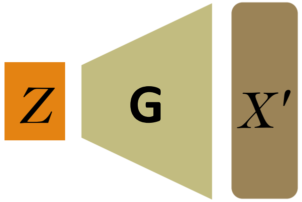
Generating synthetic samples

Global idea: Generating new synthetic samples without modeling the density estimation (for "complex" distributions)

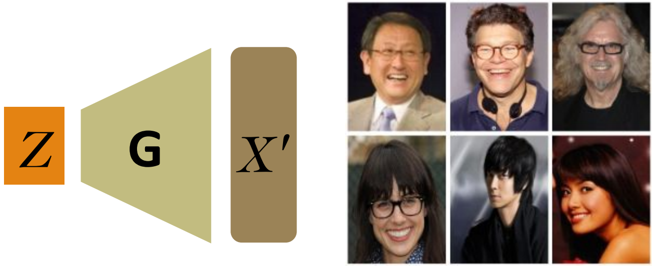
Solution: Sampling from something simple (noise) and learning a transformation to the real (training) distribution

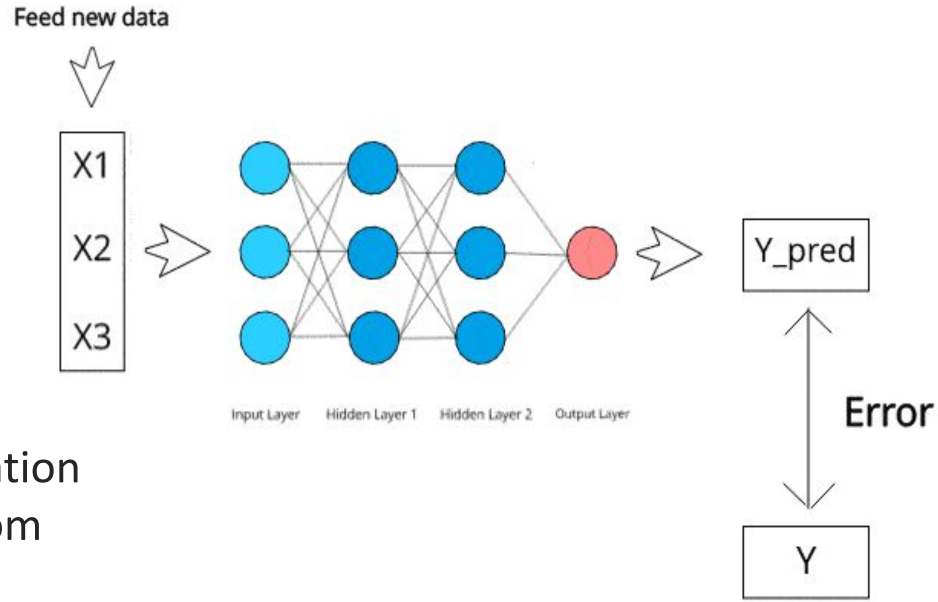
Main components of the **Generative Model:**

- **Generator** Neural Network **G**
- **Noise** (latent space) Z
- **Fake sample** from the training distribution X'



How Generator Learn?





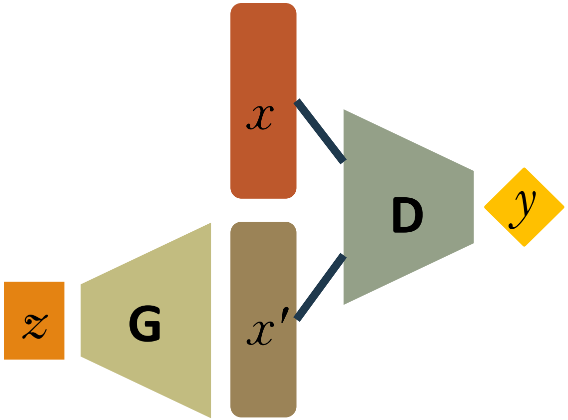
Using **another model** that gives information about how close/far are the samples from real data **Discriminator**

Generative Adversarial Networks

Generative Adversarial Networks: Construct a generative model by raising an arms race between two neural networks, a **generator** and a **discriminator**

- Discriminator (**D**) tries to distinguish between real data (X) from the real data distribution and fake data (X') from the generator (**G**)

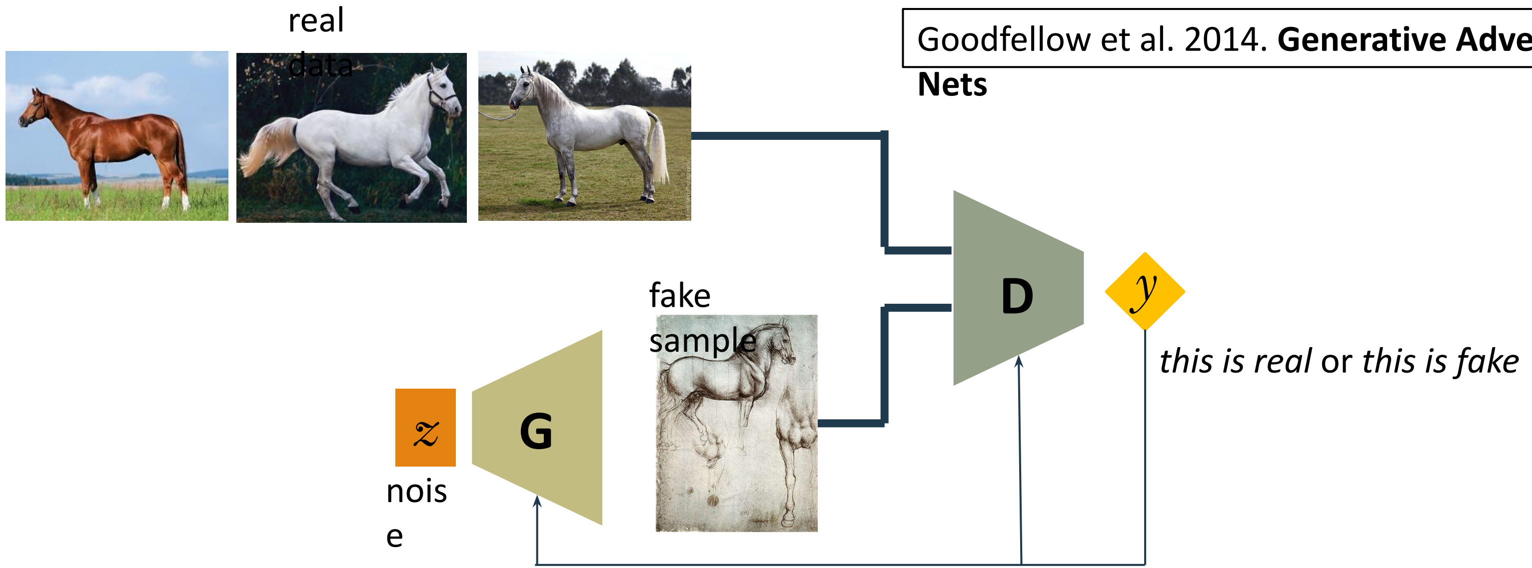
- Generator (**G**) learns how to create synthetic/fake data samples (X') by sampling random noise (Z) to fool the discriminator (**D**)



Generative Adversarial Networks

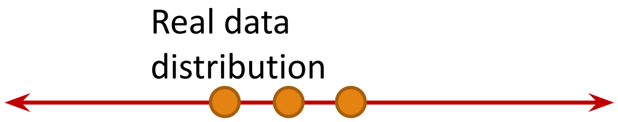
Generative Adversarial Networks: Build a generative model by raising an arms race between two neural networks, a **generator** and a **discriminator**

Goodfellow et al. 2014. **Generative Adversarial Nets**



GAN Training

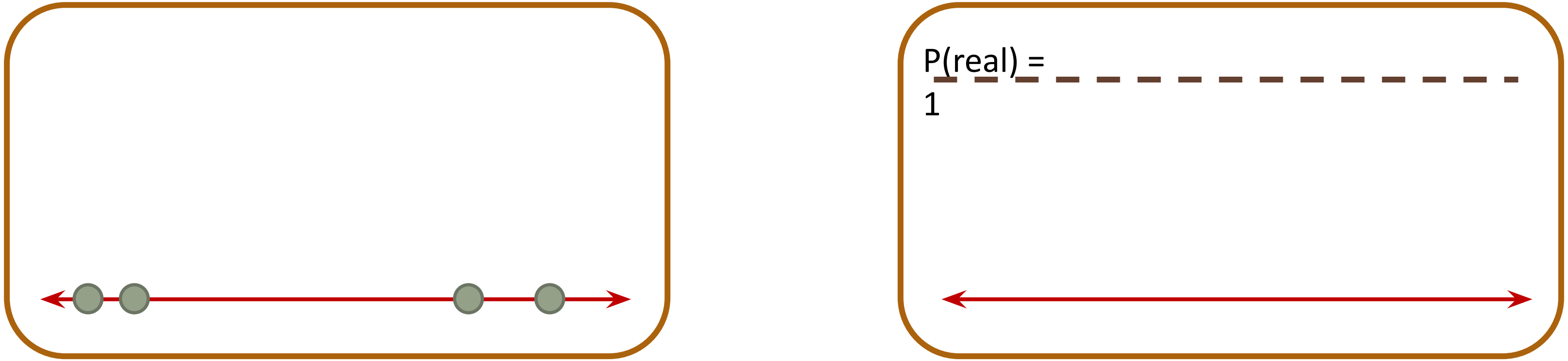
GAN training intuition



GAN Training

Step 1:

Generator samples from the noise to create data samples to imitate real data



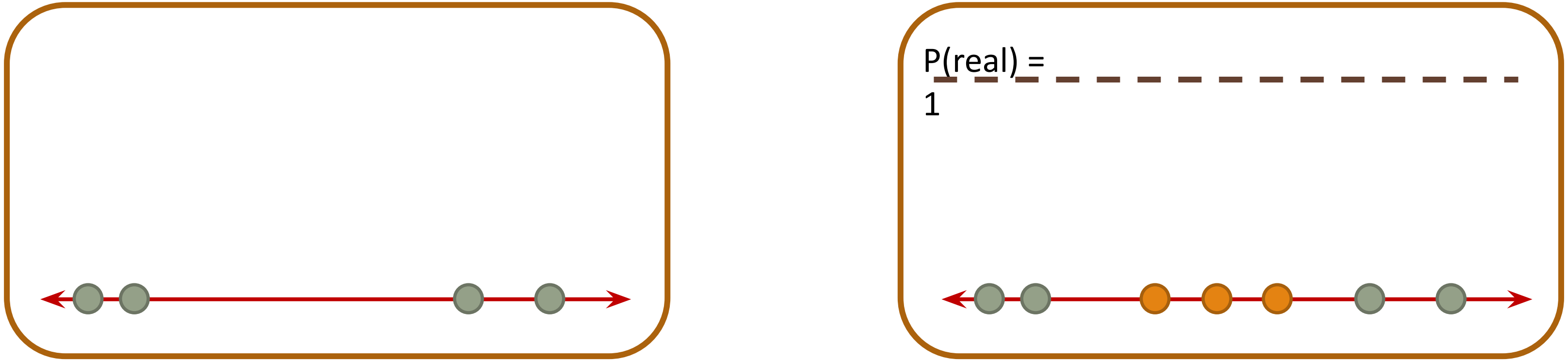
Generator

Discriminator

GAN Training

Step 2:

Discriminator gets fake samples from the generator and real samples from the real data distribution



Generator

Discriminator

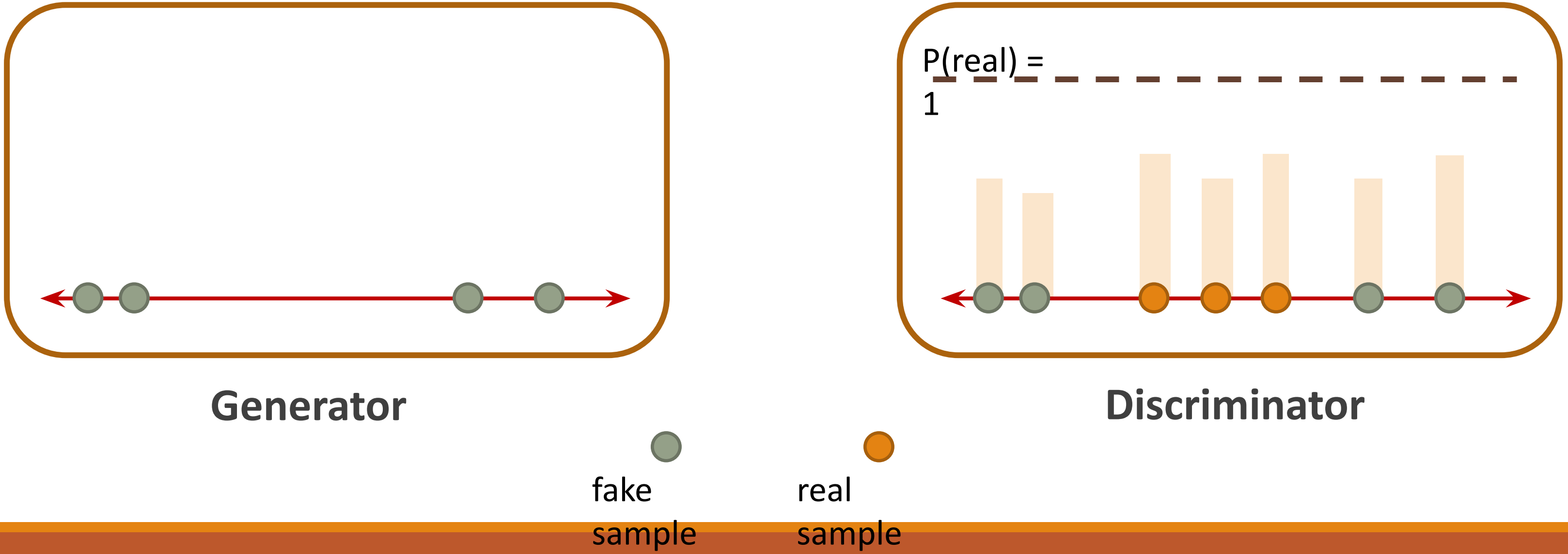
fake sample

real sample

GAN Training

Step 3:

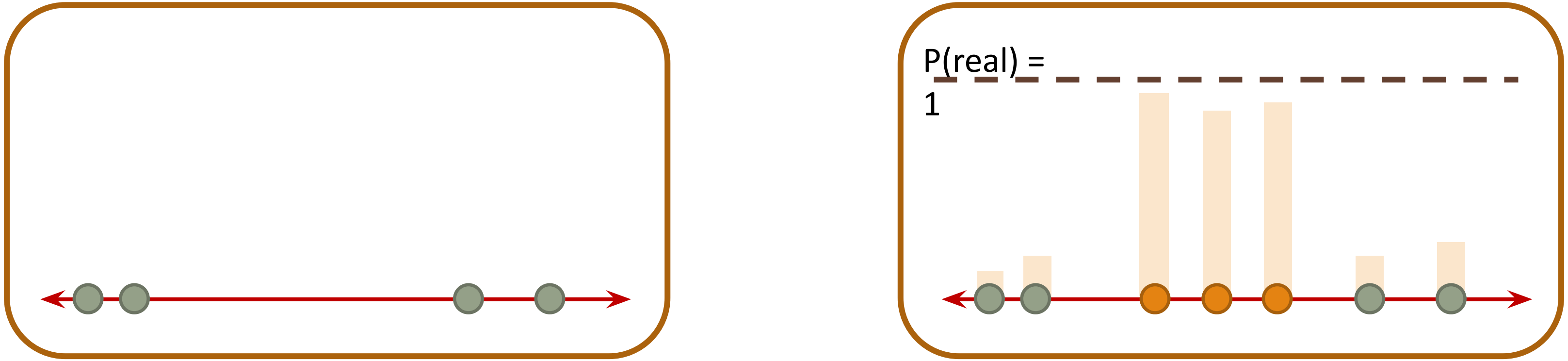
Discriminator learn how to distinguish between real and fake data (*supervised learning*)



GAN Training

Step 3:

Discriminator learn how to distinguish between real and fake data (*supervised learning*)



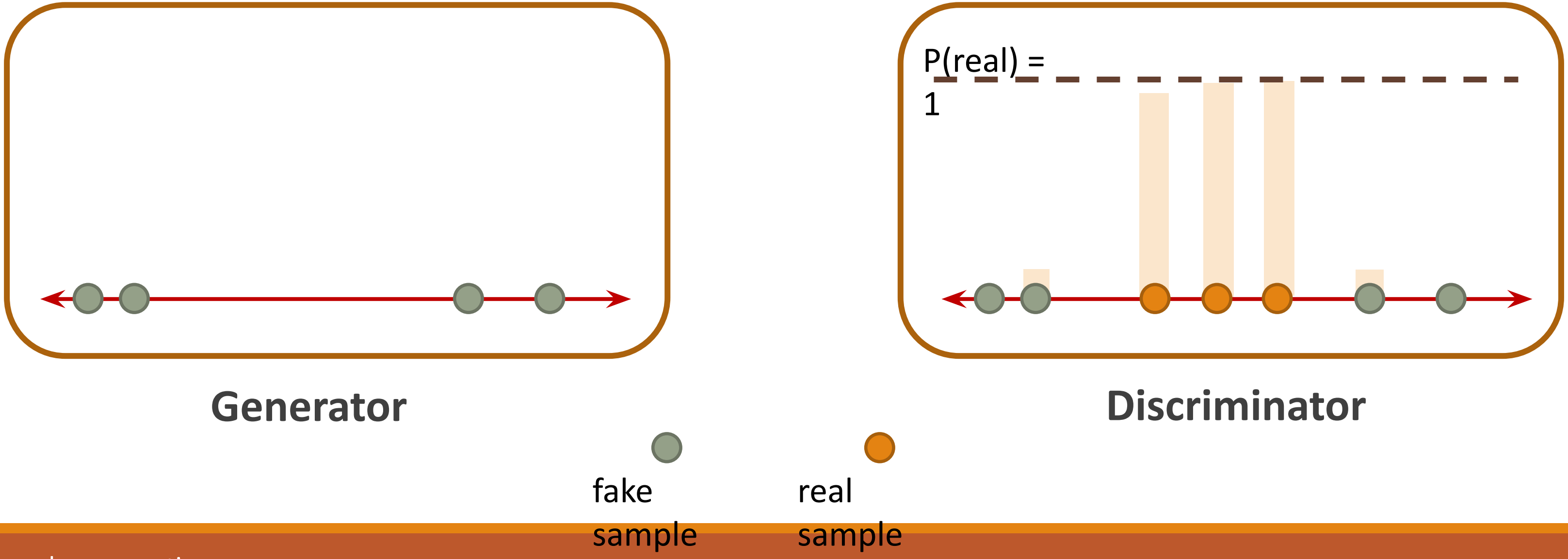
Generator

Discriminator

GAN Training

Step 3:

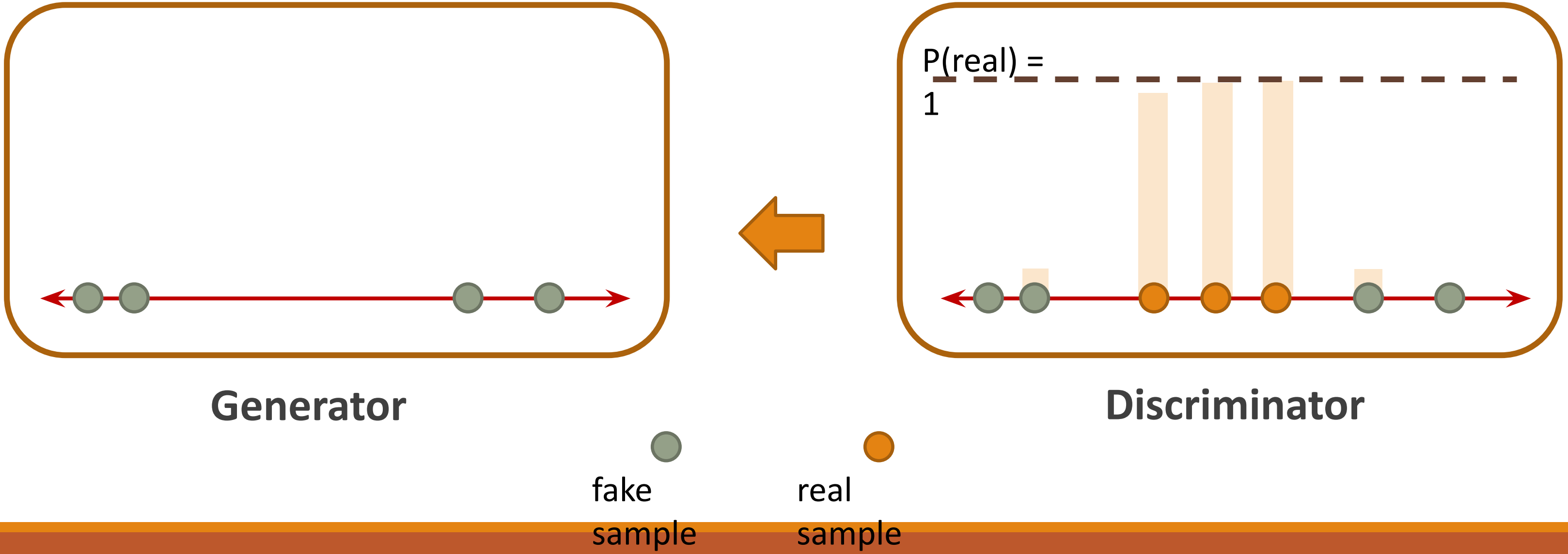
Discriminator learn how to distinguish between real and fake data (*supervised learning*)



GAN Training

Step 4:

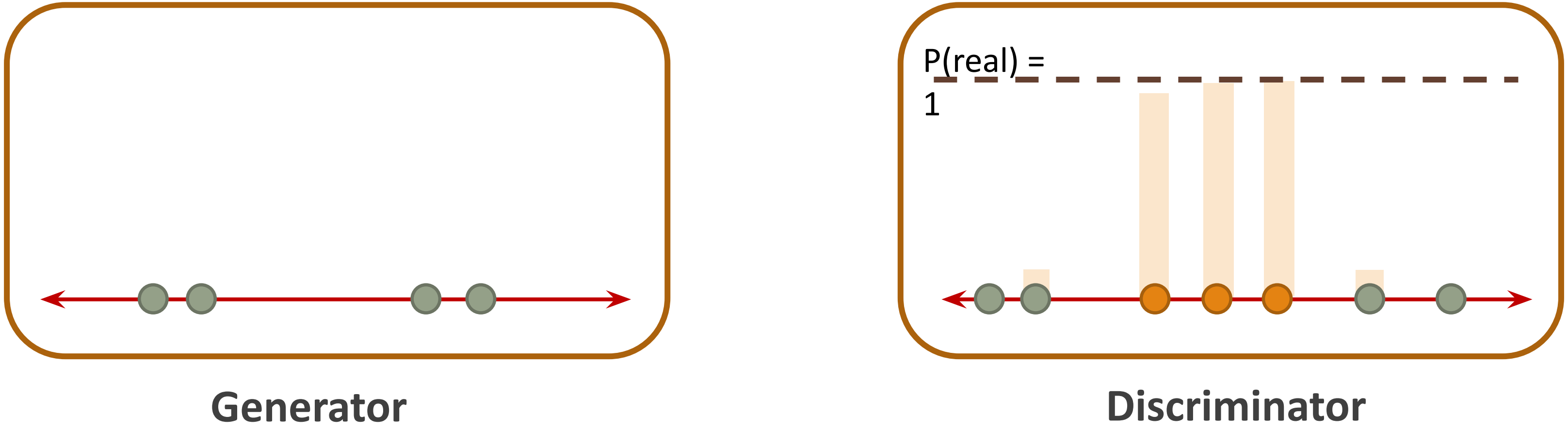
Generator get discriminator feedback and updates its parameters (weights) to improve the synthetic data



GAN Training

Step 4:

Generator get discriminator feedback and updates its parameters (weights) to improve the synthetic data



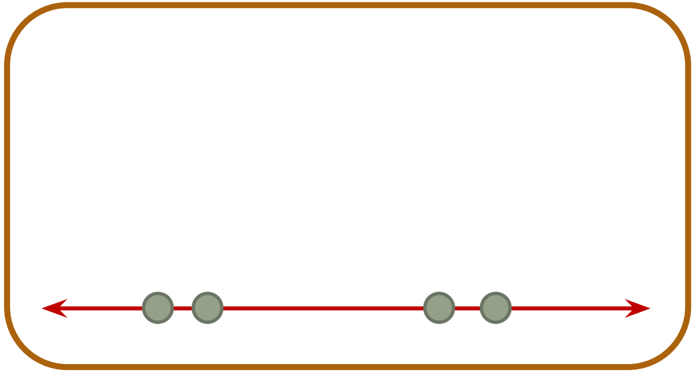
fake sample

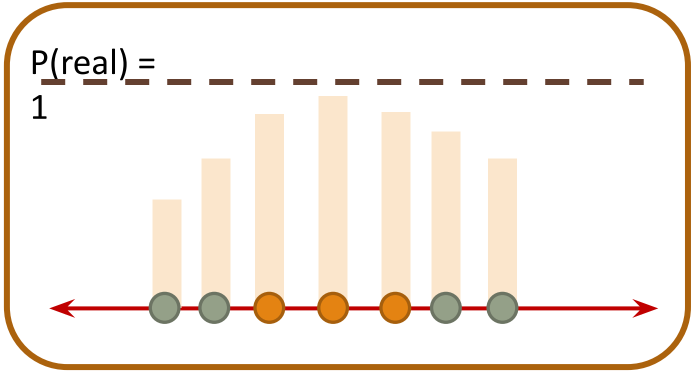
real sample

GAN Training

Step 5:

Discriminator gets samples (real and fake) and learns how to distinguish between real and fake data (*supervised learning*)





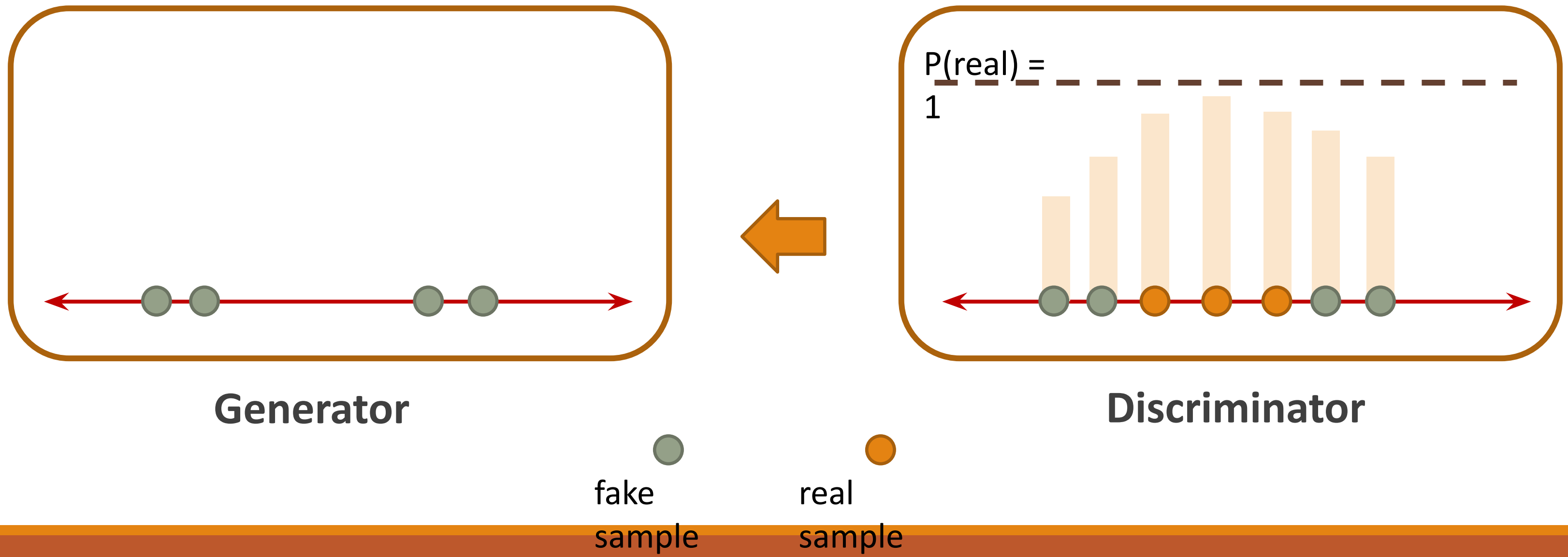
Generator

Discriminator

GAN Training

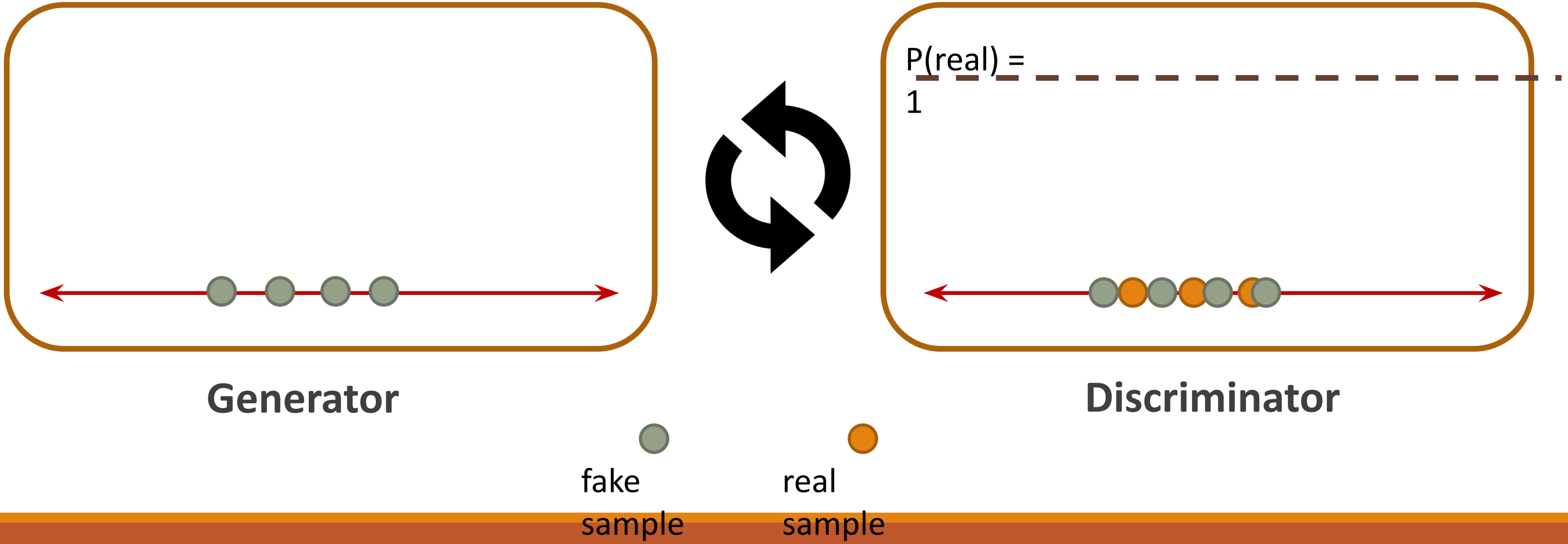
Step 5:

Generator get discriminator feedback and updates its parameters (weights) to improve the synthetic data



GAN Training

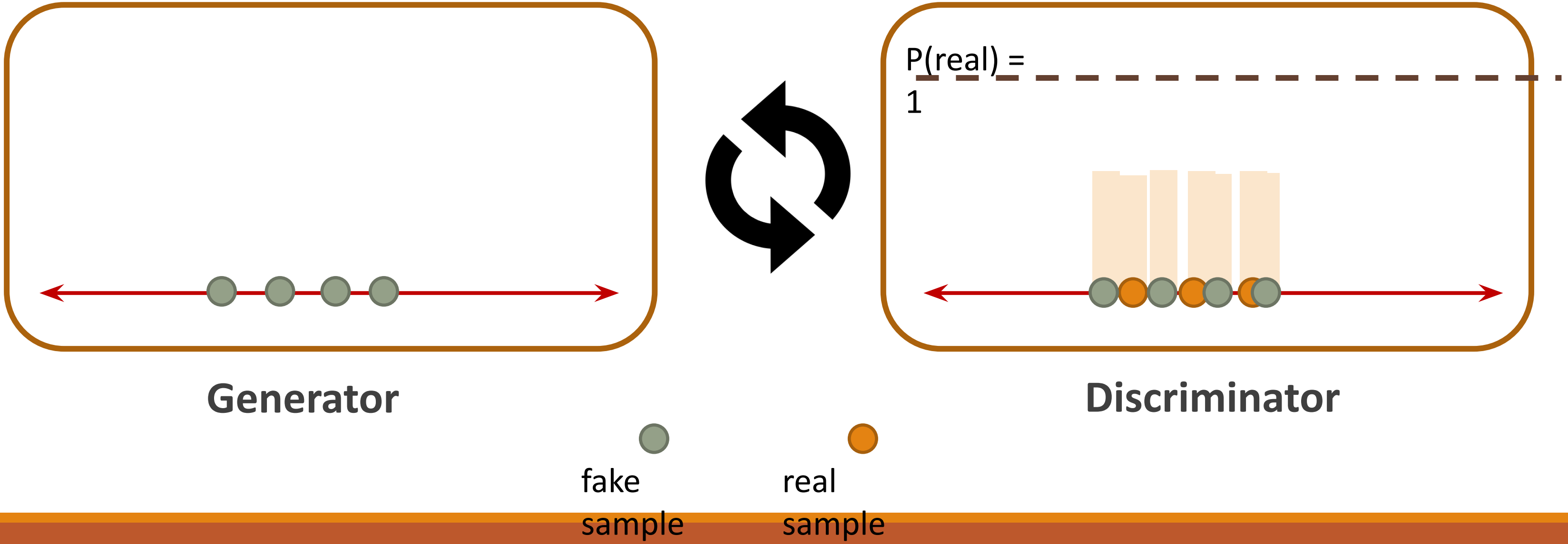
This steps are repeated until the generator is able to fool the discriminator by generating fake data samples that are indistinguishable from the real ones



GAN Training

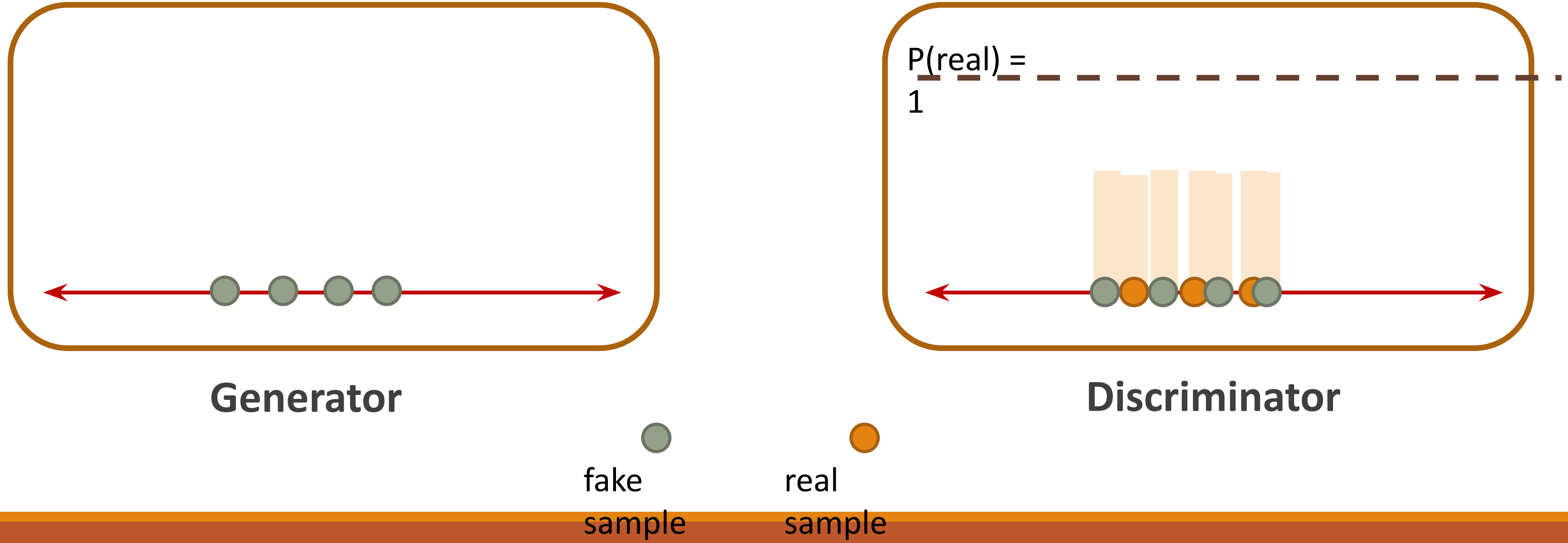
This steps are repeated until the generator is able to fool the discriminator by generating fake data samples that are indistinguishable from the real ones

- Discriminator is not able to distinguish between real and fake (random output)



GAN Training

After finishing the training process, the generator network can be used to create samples



GAN Training. Mathematical Model

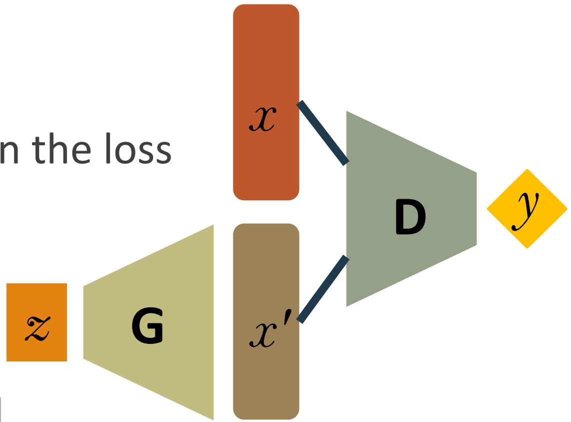
Discriminator is trained to correctly classify the input data as either real or fake

- **maximize** the probability that any real data input x is classified as real □ **maximize D(x)**
- **minimize** the probability that any fake sample x' is classified as real □ **minimize D(G(z))**

Generator is trained to fool the Discriminator by generating realistic data

- **maximize** the probability that any fake sample is classified as real
  □ **maximize D(G(z))**

In practice, the logarithm of the probability (e.g. log D(…)) is used in the loss functions



GAN training as a minmax optimization problem

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

GAN Training. General Algorithm

Steps of the main training loop:

1. Train discriminator

1.1. Train discriminator on real data

1.1.1 Sample a batch of data from real dataset (x)

1.1.2 Get loss from the discriminator output with input x

1.2 Train the discriminator on data produced by the generator

1.2.1 Sample a batch of data from random latent space (z)

1.2.2 Get samples (x') from the generator with input z

1.2.3 Get loss from the discriminator output with input x'

1.3 Update discriminator weights according to the losses

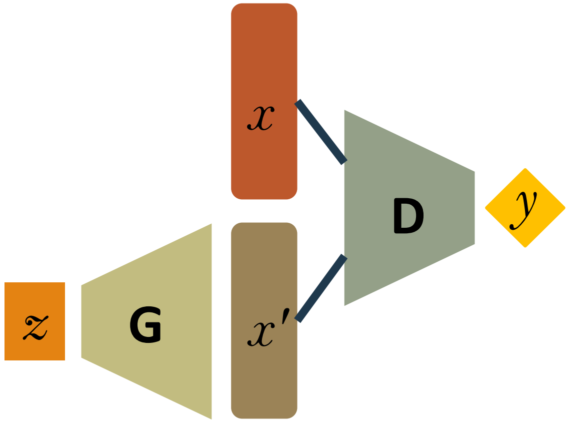
2. Train the generator

2.1 Sample a batch of data from random latent space (z)

2.2 Get samples (x') from the generator with input z

2.3 Get loss from the discriminator output with input x'

2.4 Update generator weights according to the losses



GAN Training. General Algorithm

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

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

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

GAN Training. General Code

0. Create ANNs

```python
class Generator(nn.Module):
    """
    Class that defines the the Generator Neural Network
    """
    def __init__(self, input_size, hidden_size, output_size):
        super(Generator, self).__init__()

        self.net = nn.Sequential(
            nn.Linear(input_size, hidden_size),
            nn.SELU(),
            nn.Linear(hidden_size, hidden_size),
            nn.SELU(),
            nn.Linear(hidden_size, output_size),
            nn.SELU(),
        )

    def forward(self, x):
        x = self.net(x)
        return x
```

```python
class Discriminator(nn.Module):
    """
    Class that defines the the Discriminator Neural Network
    """
    def __init__(self, input_size, hidden_size, output_size):
        super(Discriminator, self).__init__()

        self.net = nn.Sequential(
            nn.Linear(input_size, hidden_size),
            nn.ELU(),
            nn.Linear(hidden_size, hidden_size),
            nn.ELU(),
            nn.Linear(hidden_size, output_size),
            nn.Sigmoid()
        )

    def forward(self, x):
        x = self.net(x)
        return x
```

GAN Training. General Code

1. Train discriminator

```
# 1. Train the discriminator
discriminator.zero_grad()
# 1.1 Train discriminator on real data
input_real = get_data_samples(batch_size)
discriminator_real_out = discriminator(input_real.reshape(batch_size, 2))
discriminator_real_loss = discriminator_loss(discriminator_real_out, real_data_target(batch_size))
discriminator_real_loss.backward()
# 1.2 Train the discriminator on data produced by the generator
input_fake = read_latent_space(batch_size)
generator_fake_out = generator(input_fake).detach()
discriminator_fake_out = discriminator(generator_fake_out)
discriminator_fake_loss = discriminator_loss(discriminator_fake_out, fake_data_target(batch_size))
discriminator_fake_loss.backward()
# 1.3 Optimizing the discriminator weights
discriminator_optimizer.step()
```

GAN Training. General Code

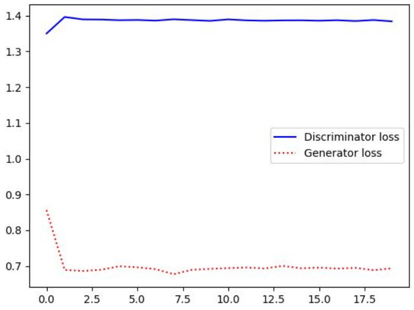
2. Train discriminator

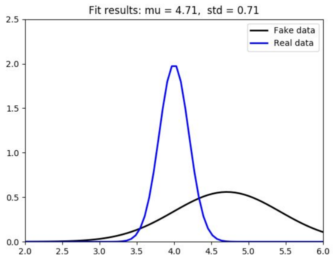
```
# 2. Train the generator
if batch_number % freeze_generator_steps == 0:
  generator.zero_grad()
  # 2.1 Create fake data
  input_fake = read_latent_space(batch_size)
  generator_fake_out = generator(input_fake)
  # 2.2 Try to fool the discriminator with fake data
  discriminator_out_to_train_generator = discriminator(generator_fake_out)
  discriminator_loss_to_train_generator = generator_loss(discriminator_out_to_train_generator,
                                                          real_data_target(batch_size))
  discriminator_loss_to_train_generator.backward()
  # 2.3 Optimizing the generator weights
  generator_optimizer.step()
```

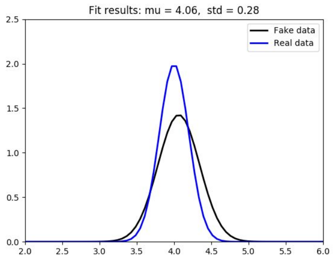
GAN Training. Source Code Example 1

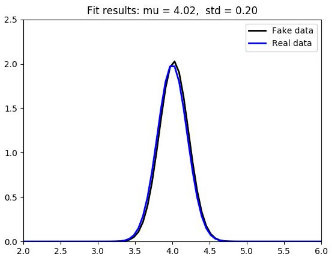
Example: Train a generator to create vectors of a given size that contains float numbers that follow a normal distribution given the mean and the standard deviation

- Real dataset samples: Vectors of real numbers that follow a normal distribution
- Source code: https://colab.research.google.com/drive/1gbTlefMoY6eQDlZXpCU9PVINo55Yb3ly





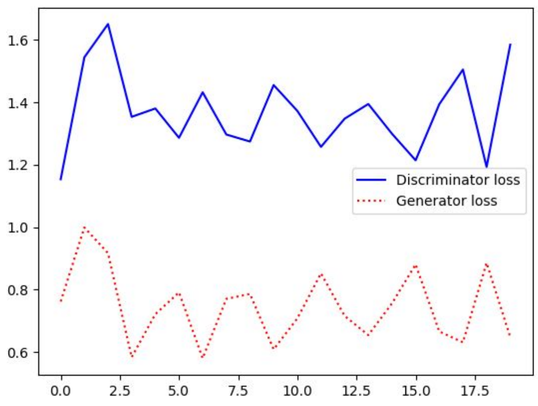


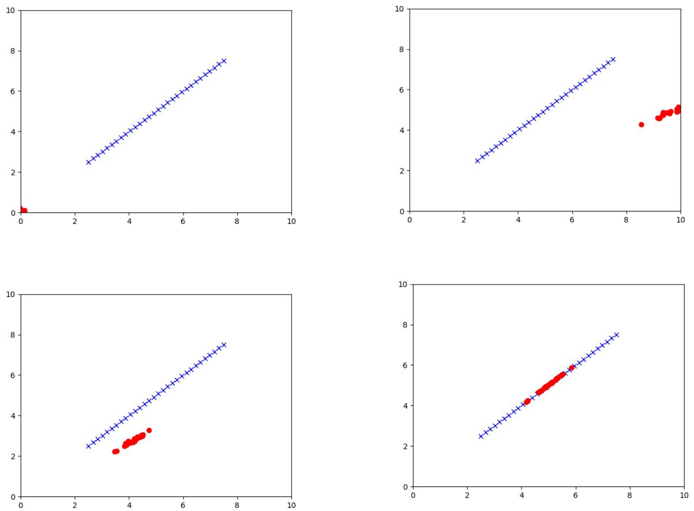


GAN Training. Source Code Example 2

Example: Train a generator to create 2D points (x, y) that belong to a line in the 2D space

- Real dataset samples: Points (x, y) that belong to the line
- Source code: https://colab.research.google.com/drive/1kV4RQ9M2yrIohjvnfmqtFh_vgY4L-k4s





- Test *freezing* the generator and increasing the number of epochs

GAN Training. Source Code Example 3

Example: Train a generator to create samples of handwritten digits of MNIST dataset.

The MNIST dataset is one of the most common datasets used for image classification and generation. It contains 60,000 training images and 10,000 testing images of handwritten digits (from 0 to 9)

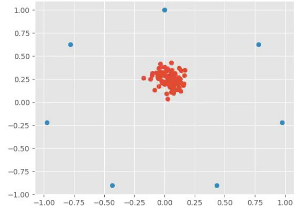
- Real dataset samples: Digits from MNIST dataset
- Source code: https://colab.research.google.com/drive/1FVdtHJK3vertqUVIMl

Real data

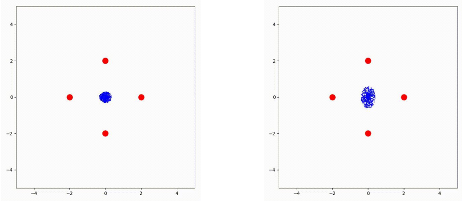
Generated data during training

Not all is good news

- **Non-convergence:** the model parameters oscillate, destabilize and never converge



- **Mode collapse:** the generator collapses which produces limited varieties of samples



- **Diminished gradient:** the discriminator gets too successful that the generator gradient vanishes and learns nothing