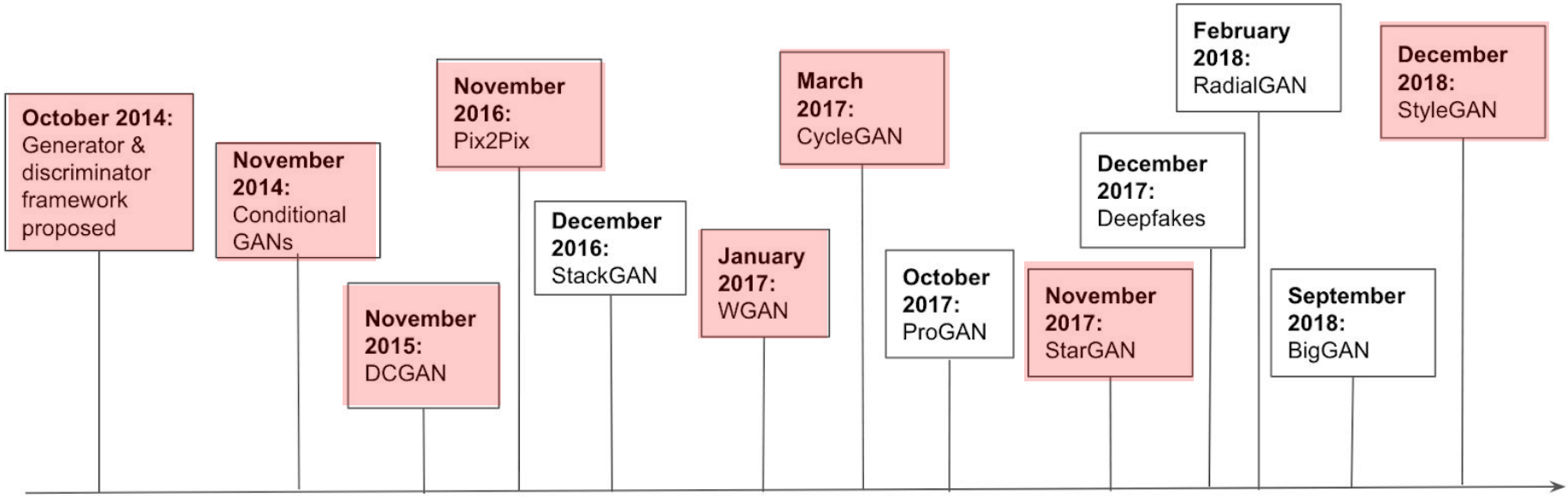
GAN

Generative Adversarial Network

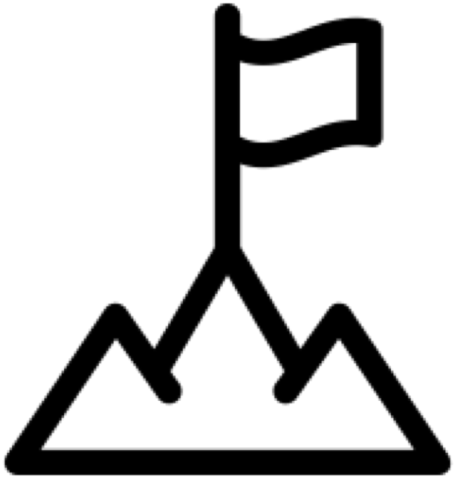
GAN의 발전

Timeline: key developments in GAN research

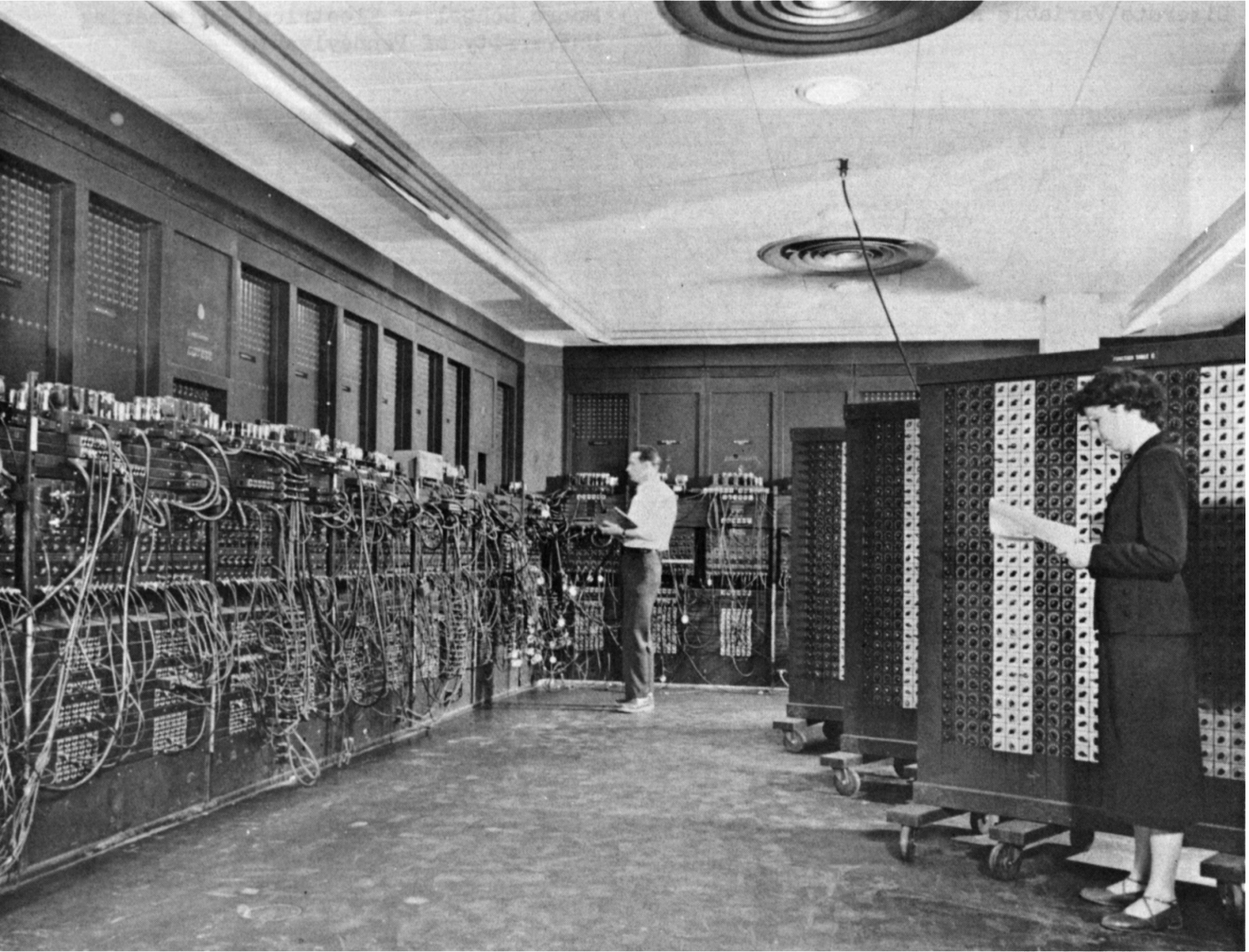


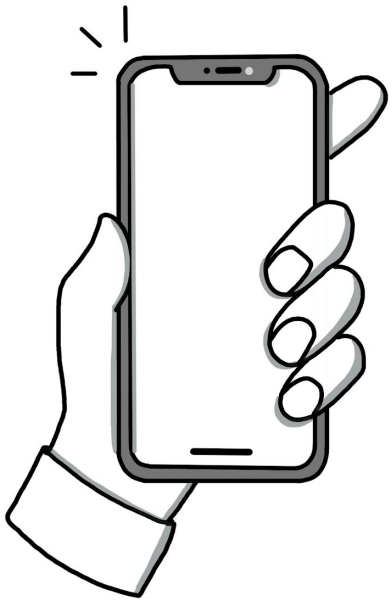
Generative Adversarial Nets (NIPS 2014)

https://arxiv.org/pdf/1406.2661.pdf



목표와 전략





오늘 우리는 다음과 같은 방법으로

머신러닝 코드를 배울 것입니다.

1. 간단한 코드를 구경하고
2. 코드가 동작하는 것을 경험하고
3. 해당 코드를 어떻게 이용하면 될지 추측합니다.

데이터 준비

```
import tensorflow as tf

(x_train, _), (x_test, _) = tf.keras.datasets.mnist.load_data()
x_train = (x_train.reshape(-1, 28, 28, 1) - 127.5) / 127.5
x_test = (x_test.reshape(-1, 28, 28, 1) - 127.5) / 127.5
print(x_train.shape, x_train[0].min(), x_train[0].max())
print(x_test.shape, x_test[0].min(), x_test[0].max())
```

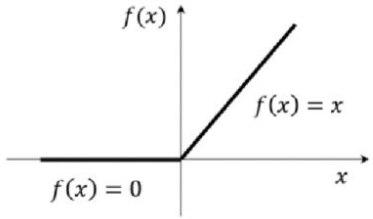
```
(60000, 28, 28, 1) -1.0 1.0
(10000, 28, 28, 1) -1.0 1.0
```

- min-max normalize: 0 ~ 255 범위의 각 픽셀값을 -1.0 ~ 1.0 사이값으로 정규화한다.

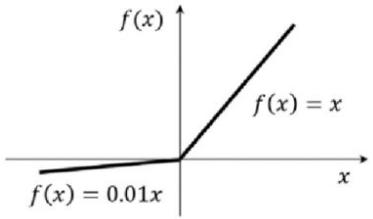
Vanilla GAN - Discriminator

```
# 판별기
def make_discriminator():
    dx = tf.keras.Input(shape=[28 * 28])
    dh = tf.keras.layers.Dense(128)(dx)
    dh = tf.keras.layers.LeakyReLU(alpha=0.2)(dh)
    dh = tf.keras.layers.Dense(128)(dh)
    dh = tf.keras.layers.LeakyReLU(alpha=0.2)(dh)
    dy = tf.keras.layers.Dense(1, activation='sigmoid')(dh)
    return tf.keras.Model(dx, dy, name='discriminator')
```

판별기의 activation 함수는 leakyReLU를 사용한다.



ReLU activation function



LeakyReLU activation function

Vanilla GAN - Generator

```
# 생성기
def make_generator():
    gx = tf.keras.Input(shape=[100])
    gh = tf.keras.layers.Dense(128)(gx)
    gh = tf.keras.layers.BatchNormalization()(gh)
    gh = tf.keras.layers.Activation('swish')(gh)
    gh = tf.keras.layers.Dense(128,)(gh)
    gh = tf.keras.layers.BatchNormalization()(gh)
    gh = tf.keras.layers.Activation('swish')(gh)
    gy = tf.keras.layers.Dense(28 * 28, activation='tanh')(gh)
    return tf.keras.Model(gx, gy, name='generator')
```

Vanilla GAN 학습

```
discriminator = make_discriminator()
generator = make_generator()
gan = VanillaGAN(generator, discriminator)
gan.fit(x_train.reshape(-1, 28 * 28), epochs=50, batch_size=128)
```

- Class Methods
  - `__init__(self, generator, discriminator)`
  - `discriminator_loss(self, y_real, y_fake)`
  - `generator_loss(self, y_fake)`
  - `train_step(self, real)`

Vanilla GAN Model - init

```
class VanillaGAN(tf.keras.Model):
    def __init__(self, generator, discriminator):
        super(VanillaGAN, self).__init__()

        self.generator = generator
        self.discriminator = discriminator

        self.d_optimizer = tf.keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.5)
        self.g_optimizer = tf.keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.5)

        self.d_loss_metric = tf.keras.metrics.Mean(name="d_loss")
        self.d_acc_metric = tf.keras.metrics.BinaryAccuracy(name="d_acc")
        self.g_loss_metric = tf.keras.metrics.Mean(name="g_loss")
        self.g_acc_metric = tf.keras.metrics.BinaryAccuracy(name="g_acc")

        self.compile()
```

Vanilla GAN Model

- train_step

```python
class VanillaGAN(tf.keras.Model):

    def train_step(self, real):
        noise = tf.random.normal([tf.shape(real)[0], 100])

        with tf.GradientTape() as g_tape, tf.GradientTape() as d_tape:
            fake = self.generator(noise)

            y_real = self.discriminator(real)
            y_fake = self.discriminator(fake)

            g_loss = self.generator_loss(y_fake)
            d_loss = self.discriminator_loss(y_real, y_fake)

            g_grads = g_tape.gradient(g_loss, self.generator.trainable_variables)
            d_grads = d_tape.gradient(d_loss, self.discriminator.trainable_variables)

        self.g_optimizer.apply_gradients(zip(g_grads, self.generator.trainable_variables))
        self.d_optimizer.apply_gradients(zip(d_grads, self.discriminator.trainable_variables))

        self.update_metrics(y_real, y_fake, g_loss, d_loss)
        return {
            "d_acc": self.d_acc_metric.result(),
            "g_acc": self.g_acc_metric.result(),
            "d_loss": self.d_loss_metric.result(),
            "g_loss": self.g_loss_metric.result(),
        }
```

Vanilla GAN Model - loss

```
class VanillaGAN(tf.keras.Model):

    def discriminator_loss(self, y_real, y_fake):
        real_loss = tf.keras.losses.binary_crossentropy(tf.ones_like(y_real), y_real)
        fake_loss = tf.keras.losses.binary_crossentropy(tf.zeros_like(y_fake), y_fake)
        d_loss = real_loss + fake_loss
        return d_loss

    def generator_loss(self, y_fake):
        g_loss = tf.keras.losses.binary_crossentropy(tf.ones_like(y_fake), y_fake)
        return g_loss

    def update_metrics(self, y_real, y_fake, g_loss, d_loss):
        self.g_loss_metric.update_state(g_loss)
        self.g_acc_metric.update_state(tf.ones_like(y_fake), y_fake)
        self.d_loss_metric.update_state(d_loss)
        self.d_acc_metric.update_state(tf.ones_like(y_real), y_real)
        self.d_acc_metric.update_state(tf.zeros_like(y_fake), y_fake)
```

Why?

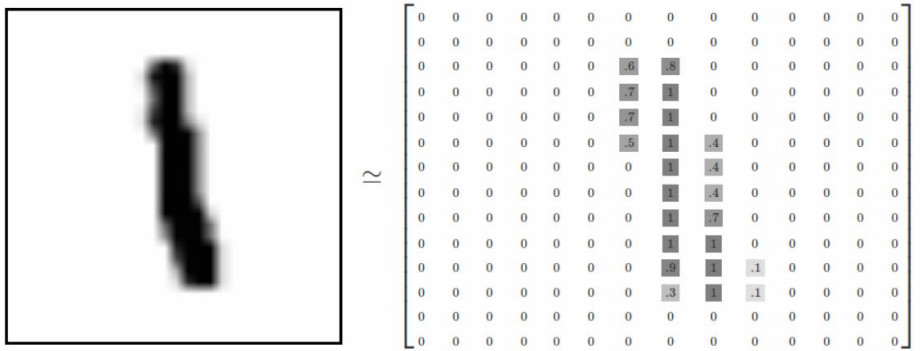
GAN은 왜 필요하지?

그럴듯한 걸 만드는 생성기를 만들고 싶어.

MNIST 이미지 생성 함수?

MNIST 데이터

(28, 28) 로 배열되어있는
784개의 숫자들



Each image is 28x28 array that can interpret as a big array of numbers. Font: MNIST For ML Beginners

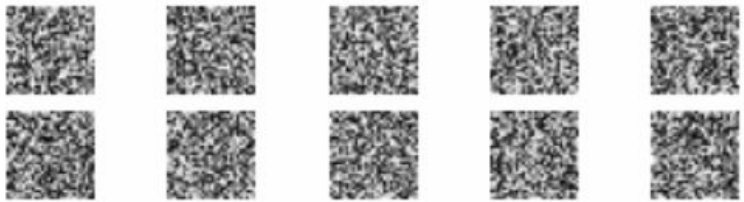
적절한 이미지를 만들어 내는
방법은 없을까?

MNIST 이미지 생성 함수?

```
[17] def generator(number):
         return np.random.rand(number, 28, 28)

     samples = generator(10)
```

적절한 이미지를 만들어 내는
generator 함수를 만드는 것.

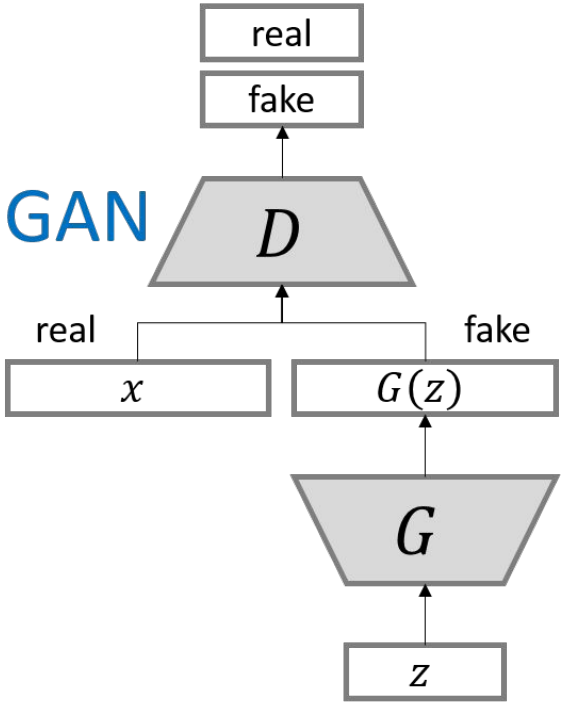
```
[18] for i in range(10):
         plt.subplot(5, 5, 1 + i)
         plt.imshow(samples[i], cmap='gray')
         plt.axis('off')

     plt.show()
```



Generative Adversarial Nets (NIPS 2014)

적대적으로 동작하는 G(생성)모델과 D(판별)모델을 동시에 학습시키는 새로운 framework를 제안.

- Generator
  - 실제 이미지 distribution을 학습하여 그럴듯한 이미지를 생성
  - 목적: D가 최대한 실수하게 만드는 것
- Discriminator
  - 진짜 이미지인지 G가 생성한 이미지인지 판별
  - 목적: 최대한 정확하게 진짜/가짜를 판별하는 것이다.

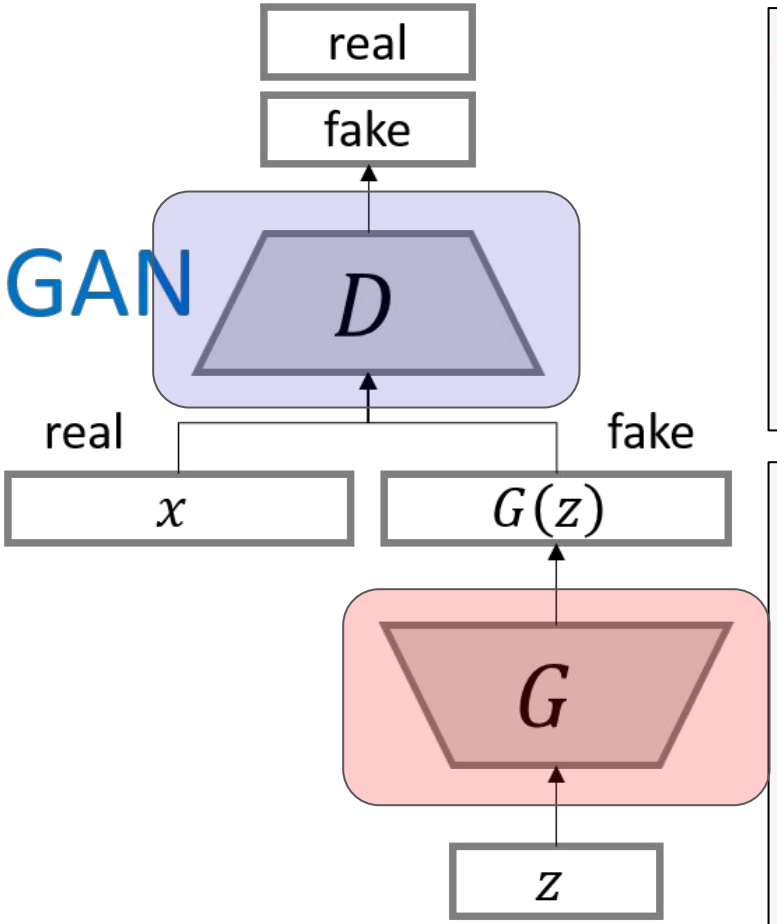


Generator & Discriminator

- Generator: 모작 화가
- Discriminator: 진품 감별사

1. 모작 화가가 모작을 만든다.
2. 진품 감별사가 모작과 진품으로 학습하여 감별을 한다.
3. 모작 화가는 감별사의 능력을 무력화하는 정밀한 모작을 만든다.
4. 감별사는 정밀한 모작을 보고 정밀한 감별 능력을 학습한다.

서로 경쟁하면서 협업이 된다. Adversarial!!




```python
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    dh = tf.keras.layers.LeakyReLU(alpha=0.2)(dh)
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```

```python
# 생성기
def make_generator():
    gx = tf.keras.Input(shape=[100])
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    return tf.keras.Model(gx, gy, name='generator')
```
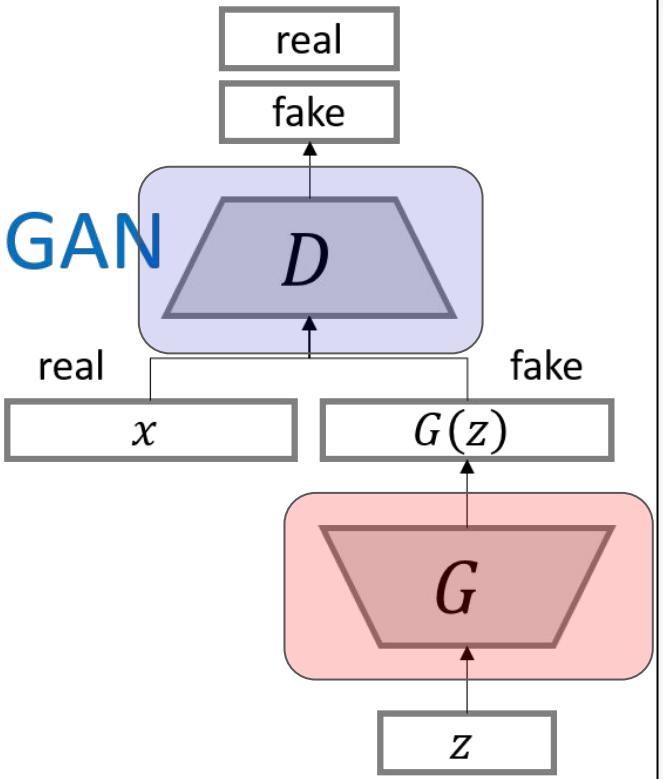

실제 이미지 판별 결과

생성 이미지 판별 결과

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




```python
class VanillaGAN(tf.keras.Model):

    def train_step(self, real):
        noise = tf.random.normal([tf.shape(real)[0], 100])

        with tf.GradientTape() as g_tape, tf.GradientTape() as d_tape:
            fake = self.generator(noise)

            y_real = self.discriminator(real)
            y_fake = self.discriminator(fake)

            g_loss = self.generator_loss(y_fake)
            d_loss = self.discriminator_loss(y_real, y_fake)

            g_grads = g_tape.gradient(g_loss, self.generator.trainable_variables)
            d_grads = d_tape.gradient(d_loss, self.discriminator.trainable_variables)

        self.g_optimizer.apply_gradients(zip(g_grads, self.generator.trainable_variables))
        self.d_optimizer.apply_gradients(zip(d_grads, self.discriminator.trainable_variables))

        self.update_metrics(y_real, y_fake, g_loss, d_loss)
        return {
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            "d_loss": self.d_loss_metric.result(),
            "g_loss": self.g_loss_metric.result(),
        }
```
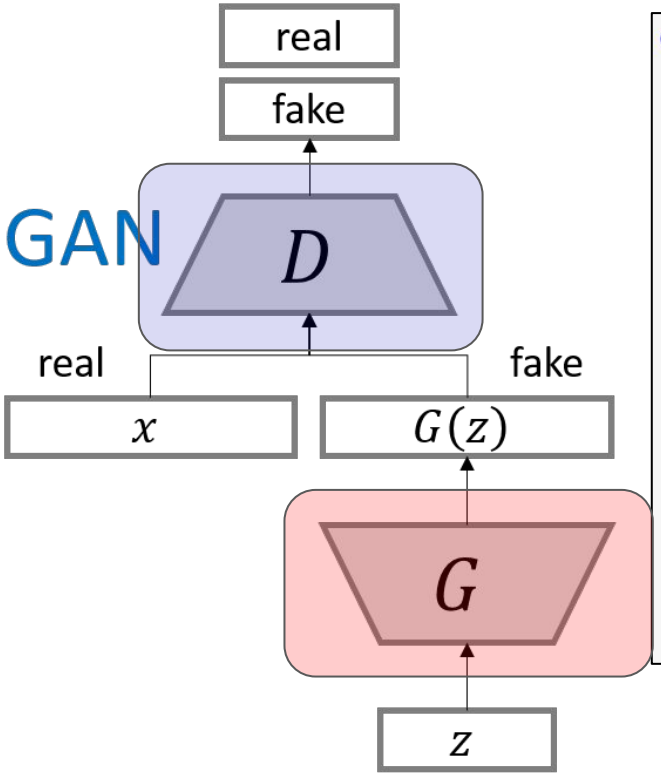

실제 이미지 판별 결과

생성 이미지 판별 결과

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




```python
class VanillaGAN(tf.keras.Model):

    def discriminator_loss(self, y_real, y_fake):
        real_loss = tf.keras.losses.binary_crossentropy(tf.ones_like(y_real), y_real)
        fake_loss = tf.keras.losses.binary_crossentropy(tf.zeros_like(y_fake), y_fake)
        d_loss = real_loss + fake_loss
        return d_loss

    def generator_loss(self, y_fake):
        g_loss = tf.keras.losses.binary_crossentropy(tf.ones_like(y_fake), y_fake)
        return g_loss

    def update_metrics(self, y_real, y_fake, g_loss, d_loss):
        self.g_loss_metric.update_state(g_loss)
        self.g_acc_metric.update_state(tf.ones_like(y_fake), y_fake)
        self.d_loss_metric.update_state(d_loss)
        self.d_acc_metric.update_state(tf.ones_like(y_real), y_real)
        self.d_acc_metric.update_state(tf.zeros_like(y_fake), y_fake)
```

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**

가짜 샘플 준비 • Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.

진짜 샘플 준비 • 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:

판별기 학습

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right].$$

  end for

가짜 샘플 준비 • 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:

생성기 학습

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

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

학습 및 모니터링

```
import matplotlib.pyplot as plt

class Monitor(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        x_rnd = np.random.randn(5 * 100).reshape(5, 100)
        generated = self.model.generator(x_rnd)
        for i in range(5):
            plt.subplot(1, 5, 1 + i)
            plt.axis('off')
            plt.imshow(generated[i].numpy().reshape(28, 28), cmap='gray_r')
        plt.show()
```

```
discriminator = make_discriminator()
generator = make_generator()
gan = VanillaGAN(generator, discriminator)
gan.fit(x_train.reshape(-1, 28 * 28), epochs=50, batch_size=128, callbacks=[Monitor()])
```

callback을 이용하여 epoch마다 generator로 생성하는 이미지를 출력해준다.

실습. 데이터는 MNIST

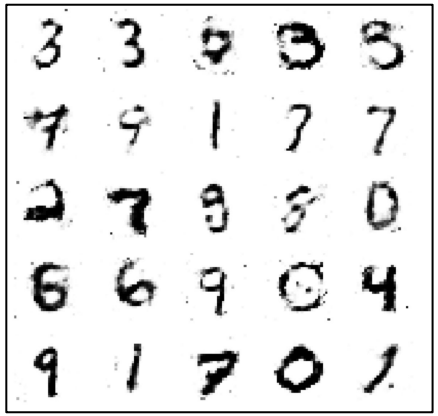
만들어보자. VanillaGAN

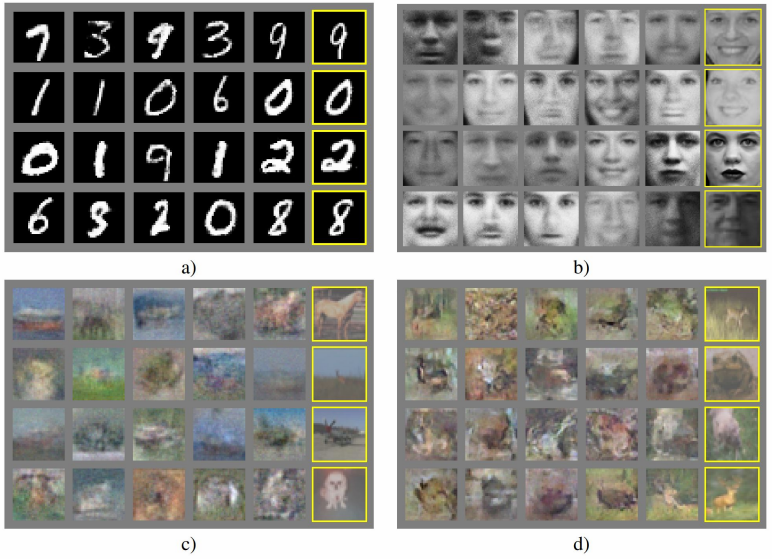
복사해서 붙여넣기는 금지.

처음부터 끝까지 눈으로 따라가면서 직접 작성해봅시다.

vanillaGAN 결과 확인

```
import matplotlib.pyplot as plt
import numpy as np

x_test = np.random.normal(size=2500).reshape(25, 100)
images = generator.predict(x_test)

for i in range(25):
    plt.subplot(5, 5, 1 + i)
    plt.axis('off')
    plt.imshow(images[i].reshape(28, 28), cmap='gray_r')
```

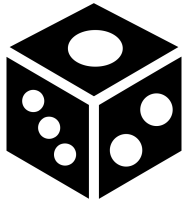




What?

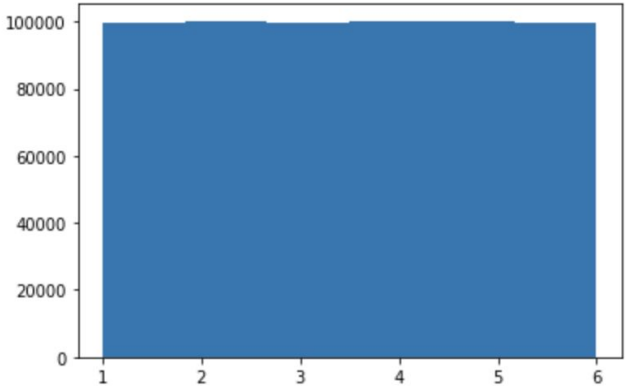
Distribution(분포)을 학습한다는 것은 무슨 뜻이야?
아니, 그 전에 Distribution이란 대체 뭘까?

"실제 이미지 distribution을 학습하여 그럴듯한 이미지를 생성"



Dice

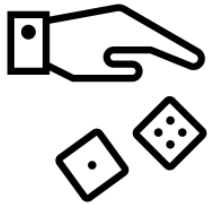
확률변수: 주사위 눈

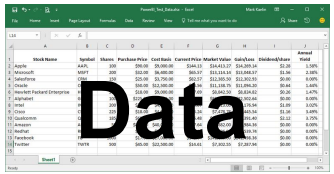



```python
import random

def dice():
    return random.randint(1, 6)

number = 600000
result = [dice() for i in range(number)]
```

```python
import matplotlib.pyplot as plt
plt.hist(result, bins=6)
plt.show()
```

통계

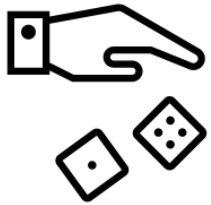


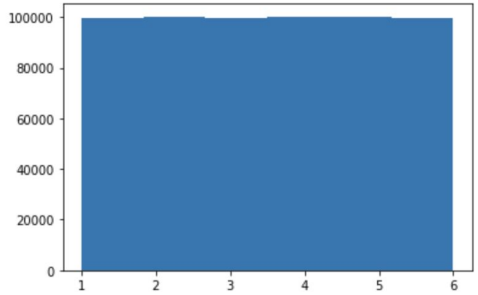


Model

확률

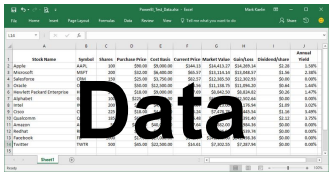
통계





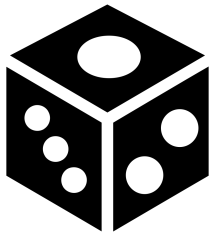
(1 + 2 + 3 + 4 + 5 + 6) / 6

평균: 3.5



Data

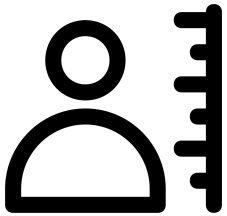
Model



1 * ⅙ + 2 * ⅙ + 3 * ⅙ + 4 * ⅙ + 5 * ⅙ + 6 * ⅙

기댓값: 3.5

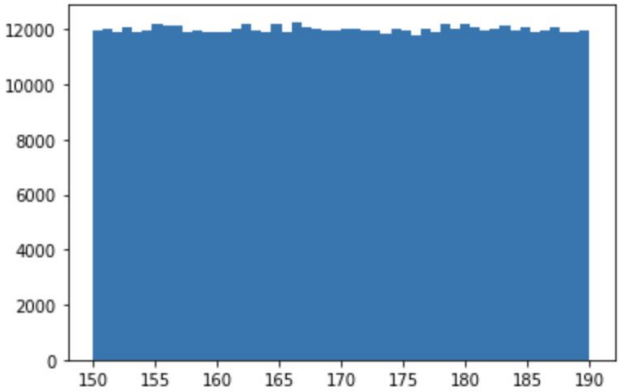
확률



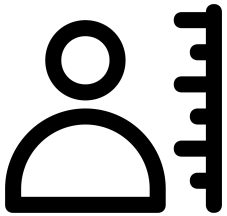
사람
확률변수: 키

```python
import random

def height(min, max):
    return min + (max - min) * random.random()

number = 600000
result = [height(150, 190) for i in range(number)]
```

```python
import matplotlib.pyplot as plt
plt.hist(result, bins=50)
plt.show()
```



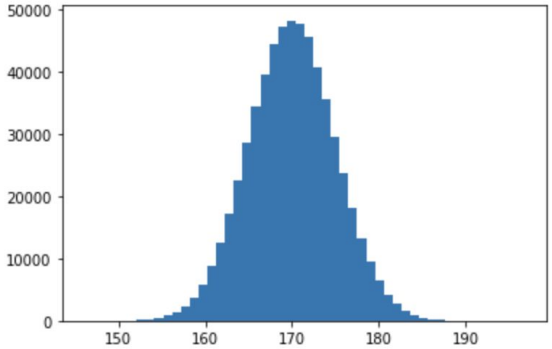
질문 1) 현재의 height() 함수는 키를 생성하기에 괜찮은 함수인가?



사람
확률변수: 키

```python
import numpy as np

def height(mean, std):
    return mean + std * np.random.randn()

number = 600000
result = [height(170, 5) for i in range(number)]
```

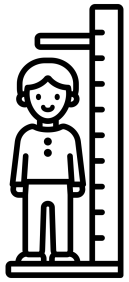
```python
import matplotlib.pyplot as plt
plt.hist(result, bins=50)
plt.show()
```

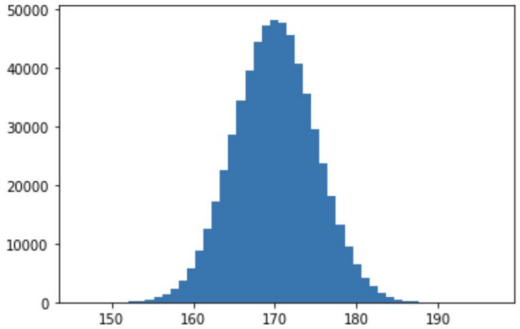


random한 무언가는 정규분포를 이용하면 꽤 그럴듯한 함수가 된다.

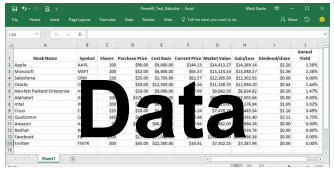
질문 2) 그 이유를 설명할 수 있는가?

통계





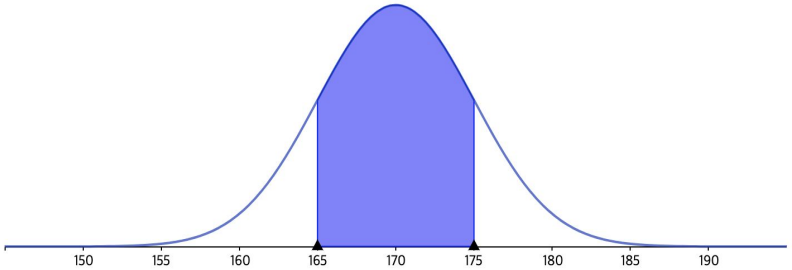
World



Data

Model

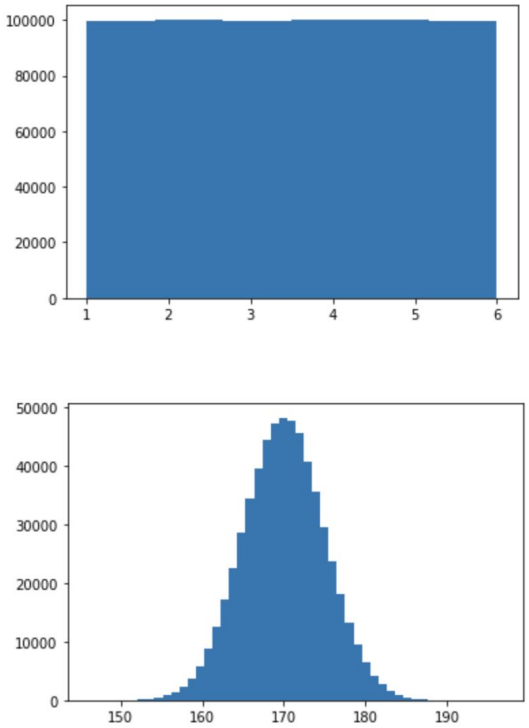
μ = 170 σ = 5



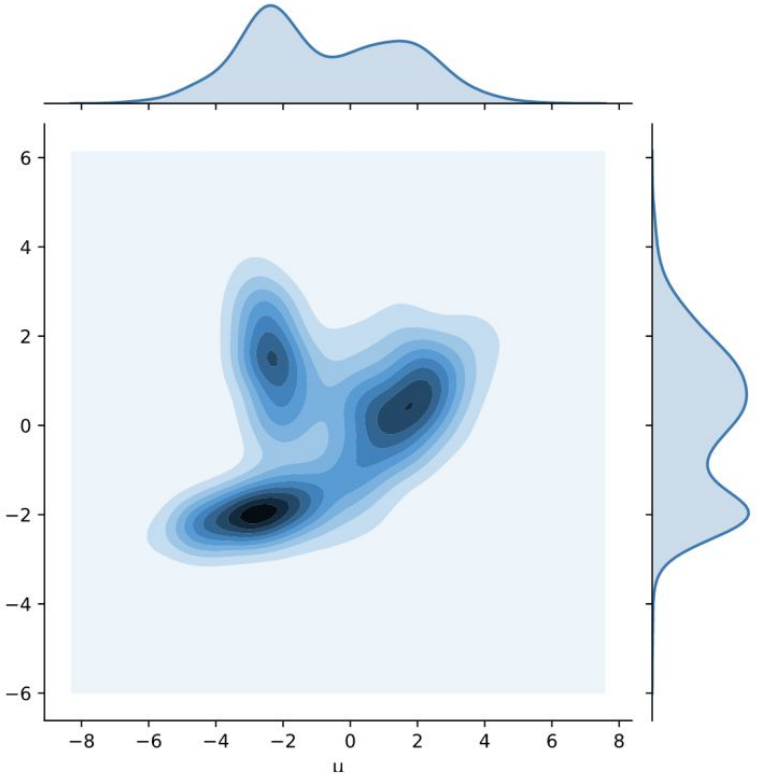
$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

확률

확률분포라는 것은 무엇인가?

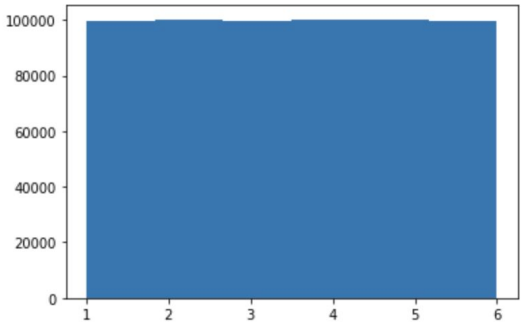


변수가 한 개 – 분포

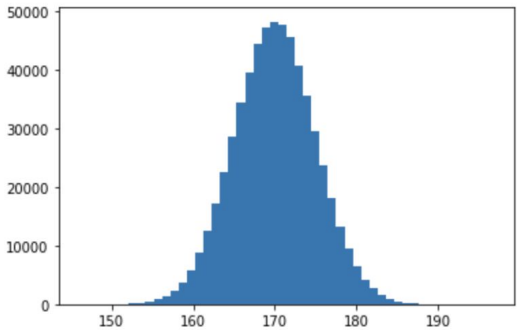


변수가 두 개 – 분포

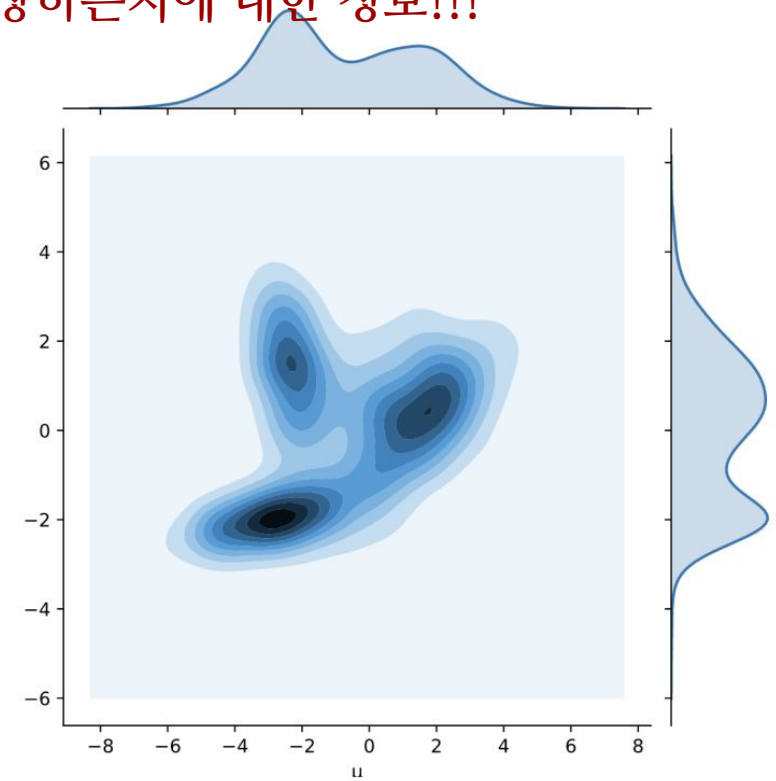
확률분포 => 데이터 포인트가 어디서 등장하는지에 대한 정보!!!



데이터포인트가 균등하게 찍혀있음.



데이터포인트가 170 가까이에
집중되어 찍혀있음.

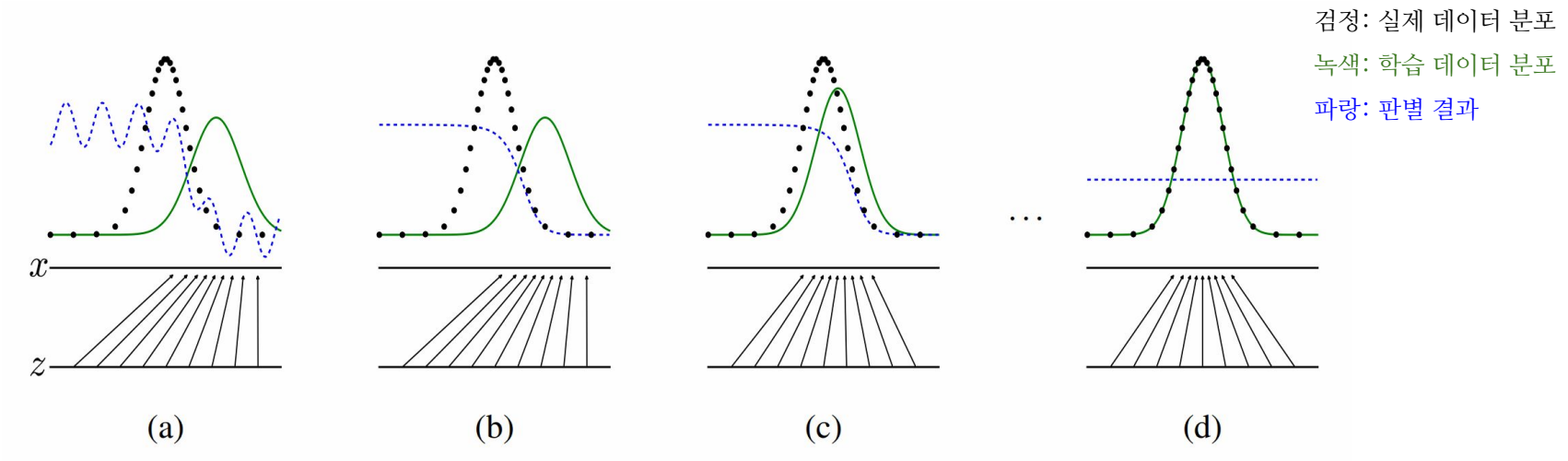


진하게 표시된 곳에 데이터포인트가
집중되어 찍혀있음.

정리 – 확률변수, 확률분포

- 확률 변수
  - 확률적으로 값이 결정되는 변수 (예: 주사위의 눈, 사람의 키)
- **확률 분포**
  - 확률변수가 특정한 값을 가질 확률을 알려주는 함수
  - 데이터포인트가 어디에 주로 찍히는지에 대한 정보

GAN의 동작 원리



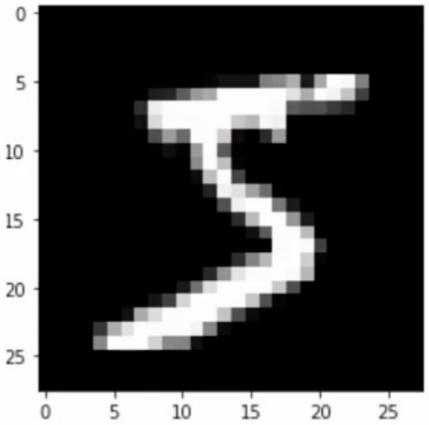
A. 처음에는 생성 분포도 실제 분포와 다르고, 판별기도 엉망이다.

B. 판별기가 학습하면서 실제 분포의 데이터와 생성 분포를 구분한다.

C. 생성 분포가 실제 분포와 비슷한 형태로 구성되기 시작한다.

D. 생성 분포가 실제 분포와 비슷한 형태를 갖게 되면 판별기는 구분을 못하므로 ½ 확률로 찍기를 한다.

MNIST 한 장은 784차원 공간의 한 점



개별 Mnist - (28, 28)

Mnist 셋: (60000, 28, 28)

28

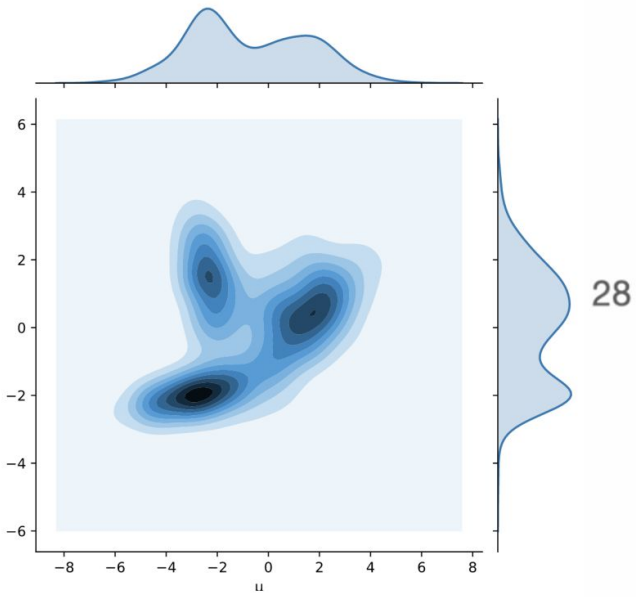
28

2차원 형태

784차원 공간의 한 점

784개의 숫자 (= 28 * 28)

MNIST 이미지는 확률변수가 784개

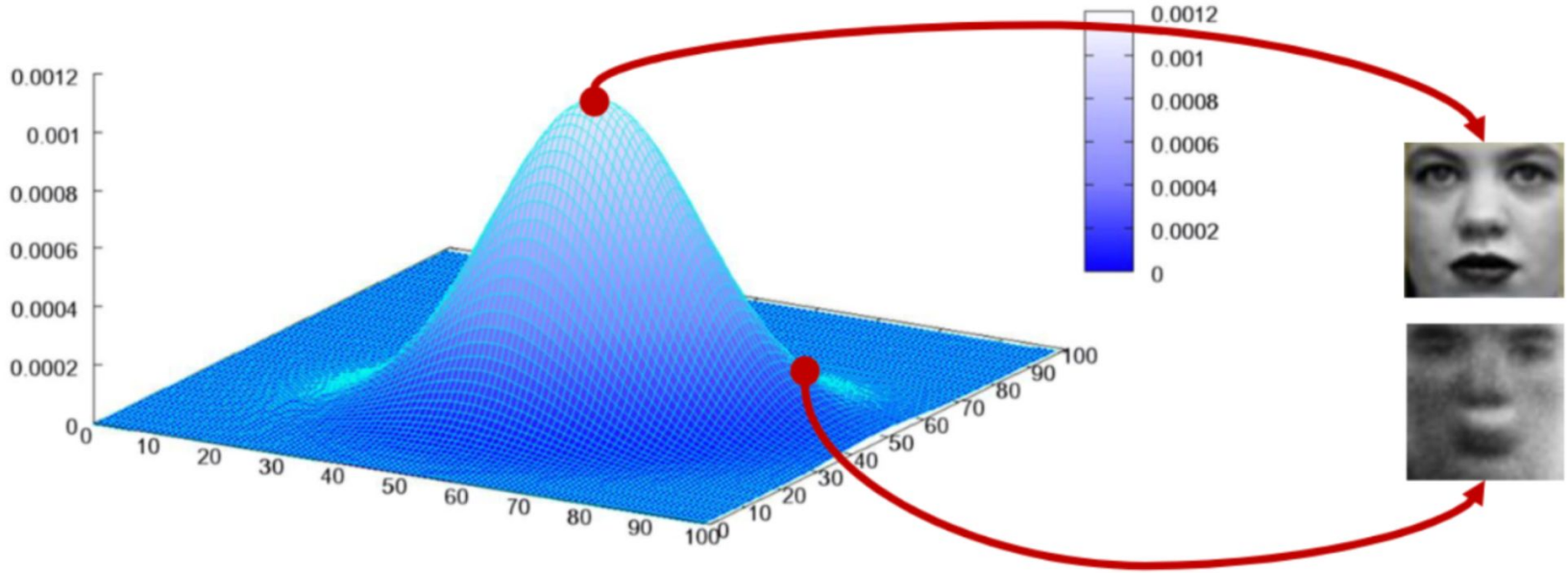


확률변수 2개

확률변수 784개

이미지의 분포 함수를 알고 있다면,

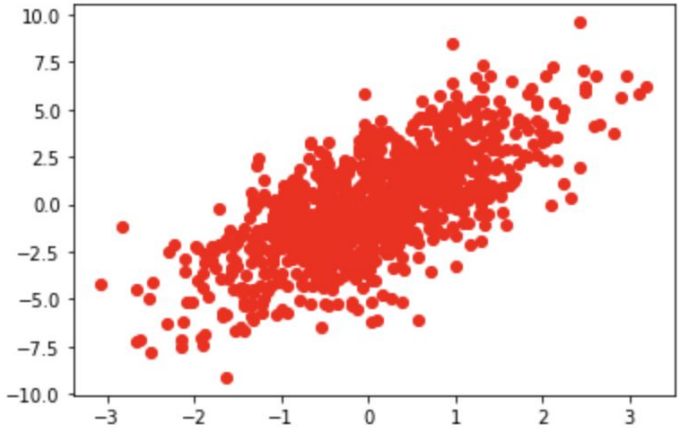
그 함수를 통해 뽑은 데이터는 그럴듯한 이미지가 되겠구나!



작은 차원의 분포 함수를 학습해보자.

```
# 데이터 준비
x_train = np.random.randn(120000).reshape(60000, 2)
print(x_train.shape)

# 분포 변형
x_train[:, 1] = 2 * x_train[:, 0] + 2 * x_train[:, 1]

plt.scatter(x_train[:1000, 0], x_train[:1000, 1], color='red')
plt.show()
```

```
(60000, 2)
```

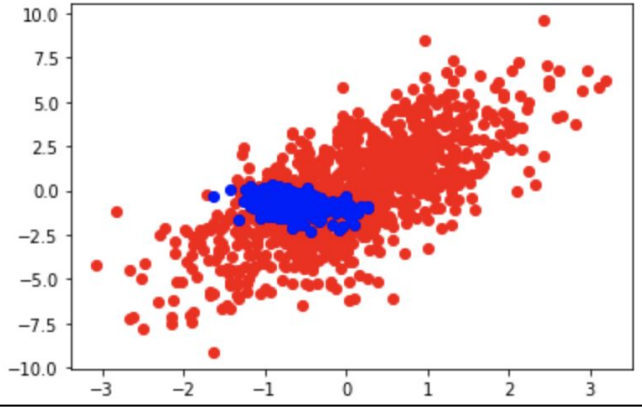


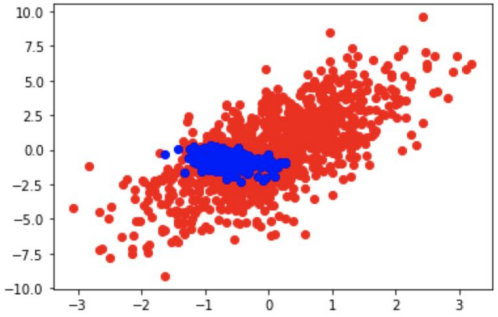
작은 차원의 분포 함수를 학습해보자.

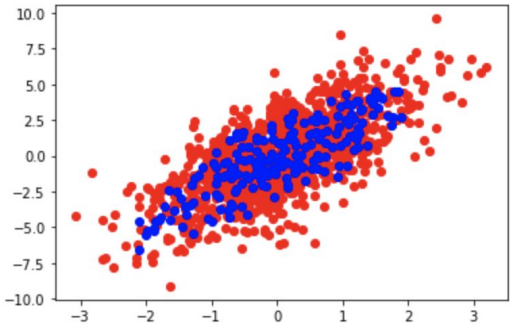
```
class Monitor(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        plt.scatter(x_train[:1000, 0], x_train[:1000, 1], color='red')
        x_gen = generator.predict(np.random.rand(1000).reshape(200, 5))
        plt.scatter(x_gen[:, 0], x_gen[:, 1], color='blue')
        plt.show()
```

```
# 학습
gan.fit(x_train, epochs=20, batch_size=100, callbacks=[Monitor()])
```

```
Epoch 1/20
600/600 [==============================] - ETA: 0s - d_acc: 0.8088 - g_acc:
```







실습. VanillaGAN

작은 차원의 데이터 분포

복사해서 붙여넣기는 금지.

처음부터 끝까지 눈으로 따라가면서 직접 작성해봅시다.

How?

어떻게 학습되는 걸까?

수식의 의미도 살짝 음미해 봅시다.

Loss Function

- MSE (Mean Square Error)

$$loss_i = (y_i - \hat{y}_i)^2$$

- Cross Entropy

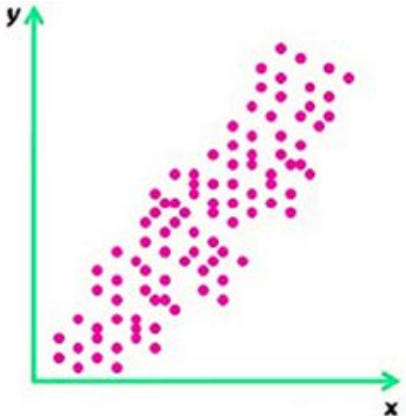
$$error = -\sum_i^n y_i \log \hat{y}_i \qquad loss_i = -(\, y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i))$$

- activation function – softmax

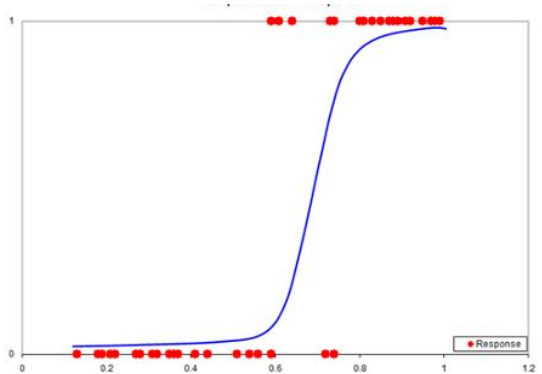
$$softmax(x_i) = \frac{e^{x_i}}{e^{x_1} + e^{x_2} + ... + e^{x_n}} = \frac{e^{x_i}}{\sum_c^n e^{x_c}}$$

선형회귀와 로지스틱회귀

- 최적의 그래프를 어떻게 찾을까?
  a. 그래프와 각 데이터의 오차를 구한다.
  b. 오차를 모두 더한다.
  c. 오차의 합이 최소가 되게 한다.

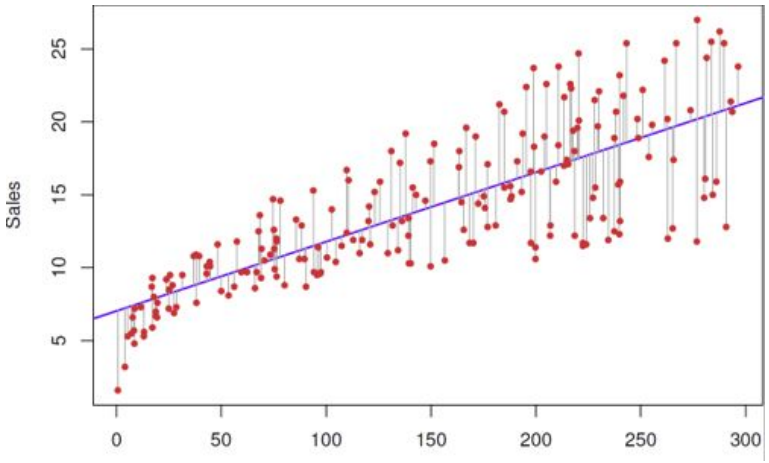


$$y = w_1 x_1 + w_0$$



$$y = class(w_1 x_1 + w_0)$$

선형회귀와 최소제곱추정



$$\hat{y} = f_w(x_i)$$

$$loss_i = (y_i - \hat{y}_i)^2$$

$$sum\ of\ loss = \sum_i^n (y_i - \hat{y}_i)^2$$

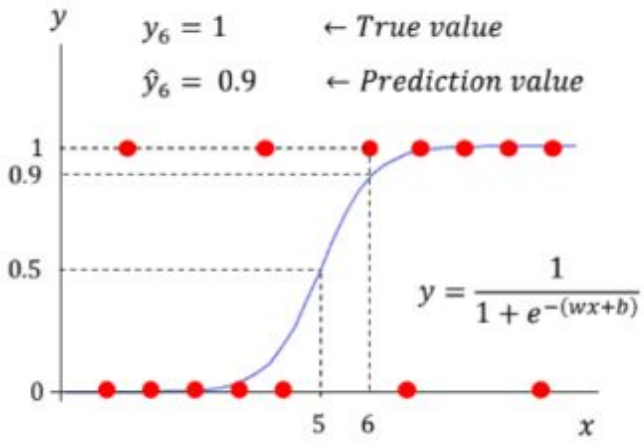
$$\underset{w}{\operatorname{argmin}} \sum_i^n (y_i - f_w(x_i))^2$$

분산의 수식과 비교해보자.

$$s^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1}$$

```python
# 모델 생성 or 선택
model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Input(shape=(2, )))
model.add(tf.keras.layers.Dense(1))
model.compile(
    optimizer='adam',
    loss='mse'
)
```

로지스틱회귀와 크로스 엔트로피



$$\hat{y} = f_w(x_i)$$

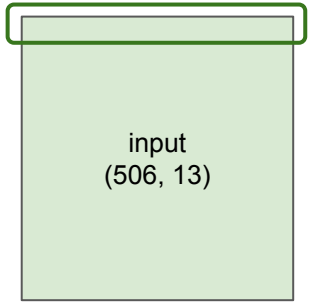
$$loss_i = -(y_i log(\hat{y}_i) + (1-y_i) log(1-\hat{y}_i))$$

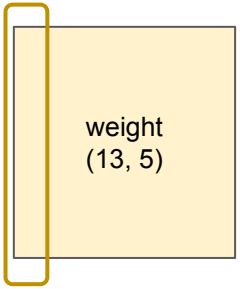
$$\underset{w}{\operatorname{argmin}} \sum_{i}^{n} loss_i$$

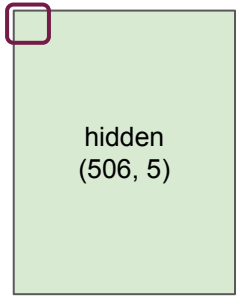
$$E(S) = \sum_{i=1}^{c} - p_i \log_2 p_i$$

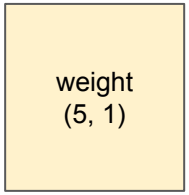
$$\text{Loss} = -\sum y_i \cdot \log \hat{y}_i$$

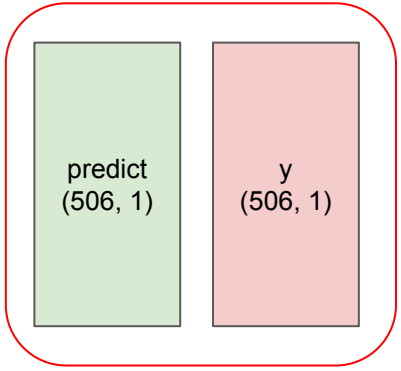
```python
# 모델 생성 or 선택
model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Input(shape=(2, )))
model.add(tf.keras.layers.Dense(1))
model.add(tf.keras.layers.Activation("sigmoid"))
model.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    metrics=["accuracy"]
)
```

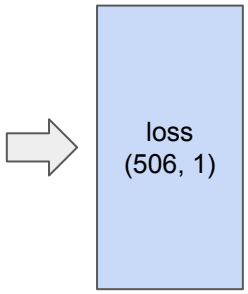






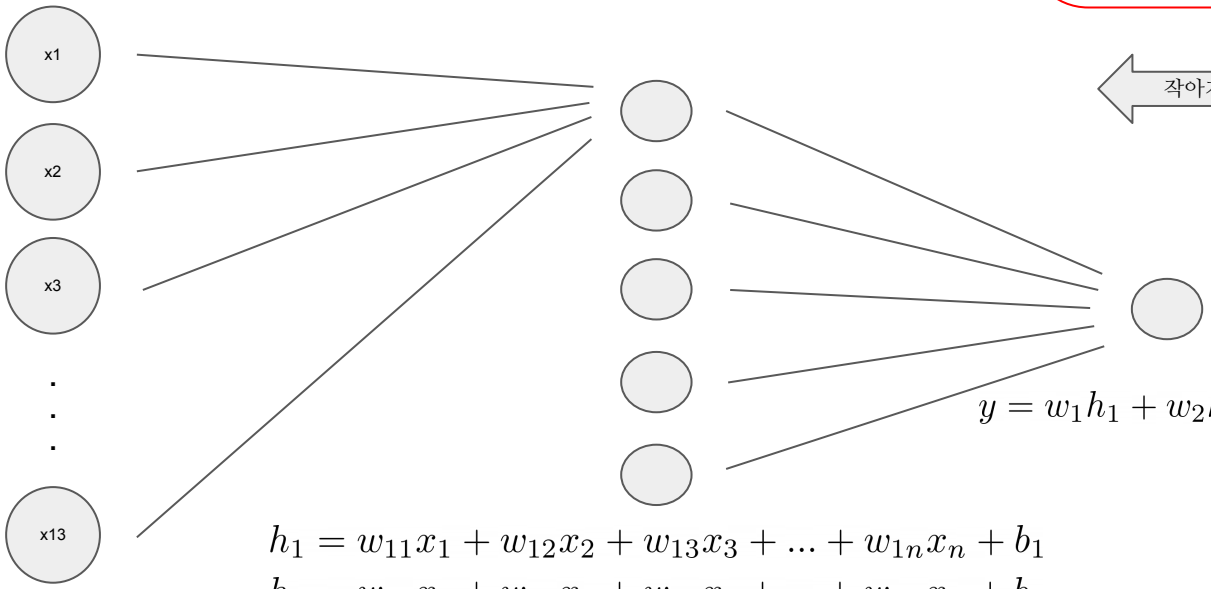






$\sum$

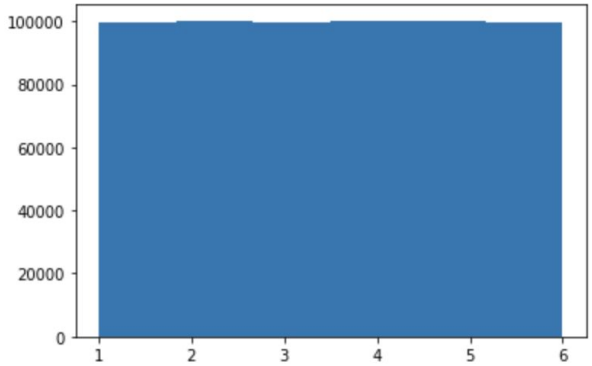
작아지는 방향으로 weight 조정



$$y = w_1h_1 + w_2h_2 + w_3h_3 + w_4h_3 + w_5h_5 + b$$

$$h_1 = w_{11}x_1 + w_{12}x_2 + w_{13}x_3 + ... + w_{1n}x_n + b_1$$
$$h_2 = w_{21}x_1 + w_{22}x_2 + w_{23}x_3 + ... + w_{2n}x_n + b_2$$

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



1 ~ 3 기대값 = (1 * 100 + 2 * 100 + 3 * 100) / 300

= 2

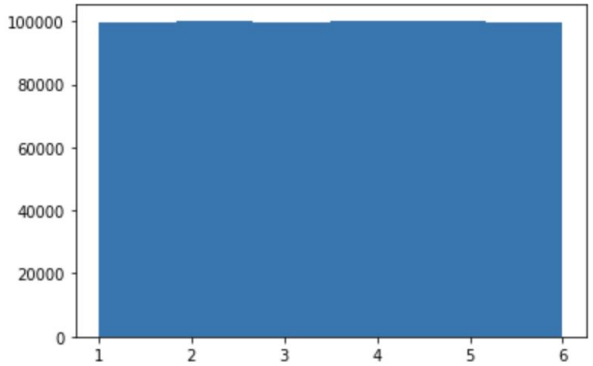
5 ~ 6 기대값 = (5 * 100 + 6 * 100) / 200

= 5.5

확률변수 X가 연속형 확률변수일때

$$\mathbf{E[X]} = \int_{-\infty}^{\infty} xf(x)dx$$

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



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확률변수 X가 연속형 확률변수일때

$$\mathbf{E[X]} = \int_{-\infty}^{\infty} \boldsymbol{x f(x) dx}$$

$$V(G,D) = \int_{\boldsymbol{x}} p_{\text{data}}(\boldsymbol{x}) \log(D(\boldsymbol{x}))dx + \int_z p_{\boldsymbol{z}}(\boldsymbol{z}) \log(1 - D(g(\boldsymbol{z})))dz$$

$$= \int_{\boldsymbol{x}} p_{\text{data}}(\boldsymbol{x}) \log(D(\boldsymbol{x})) + p_g(\boldsymbol{x}) \log(1 - D(\boldsymbol{x}))dx$$

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

$$V(G,D) = \int_{\boldsymbol{x}} p_{\text{data}}(\boldsymbol{x}) \log(D(\boldsymbol{x}))dx + \int_z p_{\boldsymbol{z}}(\boldsymbol{z}) \log(1 - D(g(\boldsymbol{z})))dz$$

$$= \int_{\boldsymbol{x}} p_{\text{data}}(\boldsymbol{x}) \log(D(\boldsymbol{x})) + p_g(\boldsymbol{x}) \log(1 - D(\boldsymbol{x}))dx$$

- $y = a \log y + b \log(1 - y)$ 형태
- $a, b \in R^2$ 와 $y \in [0,1]$ 에 대해 최댓값은 $\frac{a}{a+b}$

$$D^*_G(\boldsymbol{x}) = \frac{p_{data}(\boldsymbol{x})}{p_{data}(\boldsymbol{x}) + p_g(\boldsymbol{x})}$$

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

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

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

$$C(G) = \max_D V(G, D)$$

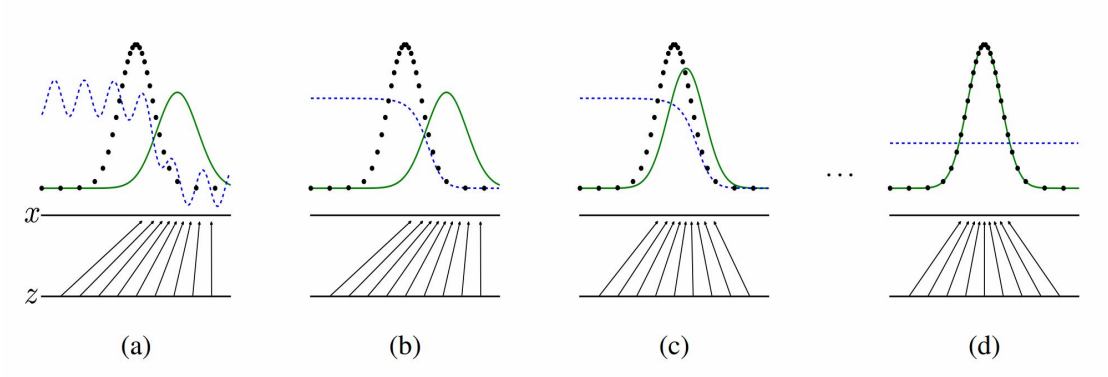
$$= \mathbb{E}_{\boldsymbol{x} \sim p_{\text{data}}} \left[\log \frac{p_{\text{data}}(\boldsymbol{x})}{P_{\text{data}}(\boldsymbol{x}) + p_g(\boldsymbol{x})} \right] + \mathbb{E}_{\boldsymbol{x} \sim p_g} \left[\log \frac{p_g(\boldsymbol{x})}{p_{\text{data}}(\boldsymbol{x}) + p_g(\boldsymbol{x})} \right]$$

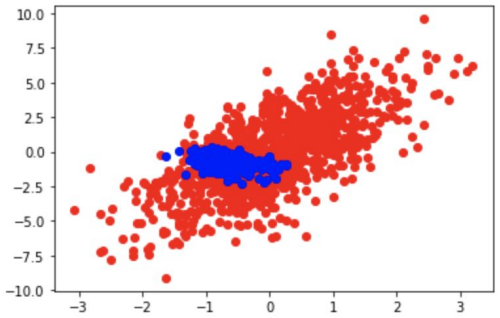
$$= -\log(4) + KL\left(p_{\text{data}} \middle\| \frac{p_{\text{data}} + p_g}{2} \right) + KL\left(p_g \middle\| \frac{p_{\text{data}} + p_g}{2} \right)$$

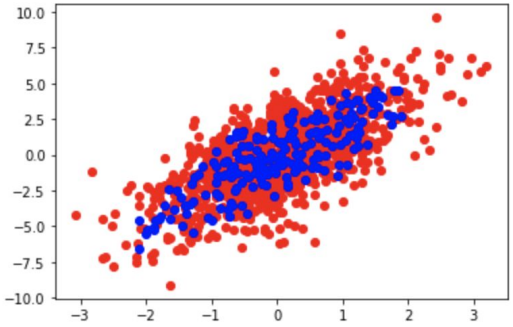
$$= -\log(4) + 2 \cdot JSD\left(p_{\text{data}} \| p_g \right)$$

C(G)를 최대화 하는 것 = JSD를 최대화 하는 것

분포의 차이(거리)가 중요했다.







분포의 차이를 재는 주요한 도구

- KL Divergence
- JS Divergence

분포의 차이를 재는 주요한 도구

- Kullback-Liebler Divergence
  - 상대적인 엔트로피 차이
  - 비대칭적
  - 분포가 같을 때, 0

$$D_{KL} = E[-\log q(x)] - E[-\log p(x)]$$

$$D_{KL}(p\|q) = \int_x p(x) \log \frac{p(x)}{q(x)}\, dx$$

- Jenson-Shannon Divergence
  - [0, 1] 사이의 거리로 한정됨
  - 대칭적 (거리 개념)

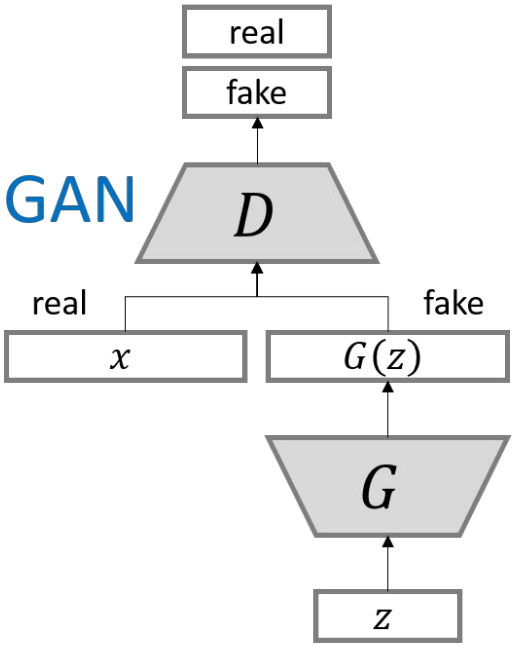
$$D_{JS}(p\|q) = \frac{1}{2} D_{KL}(p\| \frac{p+q}{2}) + \frac{1}{2} D_{KL}(q\| \frac{p+q}{2})$$

쉬어갑시다.

Vanilla GAN 의미와 한계

- 의미
  - 마르코프 체인이 전혀 필요 없이 backprop만으로 학습이 된다.
  - 특별히 어떤 추론(inference)도 필요 없다.
  - 다양한 함수들이 모델에 접목될 수 있다.
  - 마르코프 체인을 썼을 때에 비해 훨씬 선명한(sharp) 이미지를 결과로 얻을 수 있다.
- 한계
  - 학습이 불안정하고, 고해상도 이미지는 생성하지 못하는 한계
    - imbalance: D, G의 학습이 균형적으로 이루어져야 한다.
    - Mode Collapsing: G가 특정 개체만 생성해 버리는 상태에 돌입할 수 있다.
    - Oscillation: D, G의 학습이 진동하는 경우가 생긴다.

GAN의 세계 입성 완료




```python
class VanillaGAN(tf.keras.Model):

    def train_step(self, real):
        noise = tf.random.normal([tf.shape(real)[0], 100])

        with tf.GradientTape() as g_tape, tf.GradientTape() as d_tape:
            fake = self.generator(noise)

            y_real = self.discriminator(real)
            y_fake = self.discriminator(fake)

            g_loss = self.generator_loss(y_fake)
            d_loss = self.discriminator_loss(y_real, y_fake)

            g_grads = g_tape.gradient(g_loss, self.generator.trainable_variables)
            d_grads = d_tape.gradient(d_loss, self.discriminator.trainable_variables)

        self.g_optimizer.apply_gradients(zip(g_grads, self.generator.trainable_variables))
        self.d_optimizer.apply_gradients(zip(d_grads, self.discriminator.trainable_variables))

        self.update_metrics(y_real, y_fake, g_loss, d_loss)
        return {
            "d_acc": self.d_acc_metric.result(),
            "g_acc": self.g_acc_metric.result(),
            "d_loss": self.d_loss_metric.result(),
            "g_loss": self.g_loss_metric.result(),
        }
```

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

실습. 다음 데이터셋으로 Vanilla GAN을 구성해보자.

Fashion Mnist / Cifar10

복사해서 붙여넣기는 금지.

처음부터 끝까지 눈으로 따라가면서 직접 작성해봅시다.

Deep Convolutional GAN (ICLR 2016)

https://arxiv.org/pdf/1511.06434.pdf

DCGAN - Discriminator

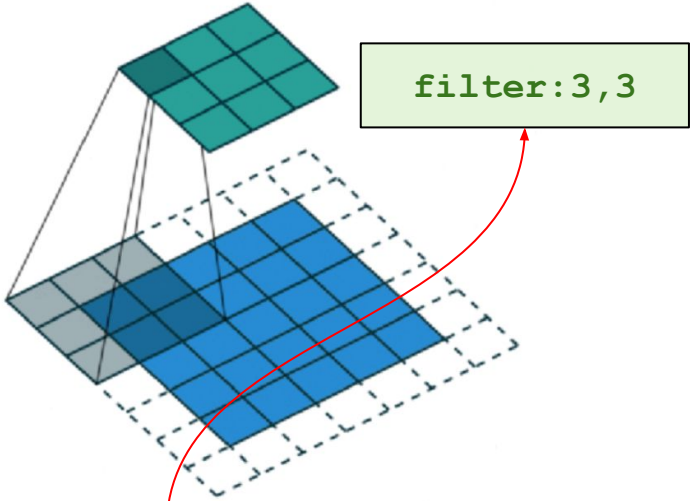
```
# 판별기
def make_discriminator():
    dx = tf.keras.Input([28, 28, 1])
    dh = tf.keras.layers.Conv2D(64, 5, 2, padding='same')(dx)
    dh = tf.keras.layers.LeakyReLU(alpha=0.2)(dh)
    dh = tf.keras.layers.Conv2D(128, 5, 2, padding='same')(dh)
    dh = tf.keras.layers.LeakyReLU(alpha=0.2)(dh)
    dh = tf.keras.layers.Flatten()(dh)
    dy = tf.keras.layers.Dense(1, activation='sigmoid')(dh)
    return tf.keras.Model(dx, dy, name='discriminator')
```

DCGAN - Generator

```
# 생성기
def make_generator():
    gx = tf.keras.Input([100])
    gh = tf.keras.layers.Dense(7 * 7 * 128)(gx)
    gh = tf.keras.layers.Reshape([7, 7, 128])(gh)
    gh = tf.keras.layers.Conv2DTranspose(128, 5, 2, padding='same')(gh)
    gh = tf.keras.layers.BatchNormalization()(gh)
    gh = tf.keras.layers.Activation('swish')(gh)
    gh = tf.keras.layers.Conv2DTranspose(64, 5, 2, padding='same')(gh)
    gh = tf.keras.layers.BatchNormalization()(gh)
    gh = tf.keras.layers.Activation('swish')(gh)
    gy = tf.keras.layers.Conv2D(1, 7, activation='tanh', padding='same')(gh)
    return tf.keras.Model(gx, gy, name='generator')
```

Conv2D vs Conv2DTranspose

판별자(Discriminator)

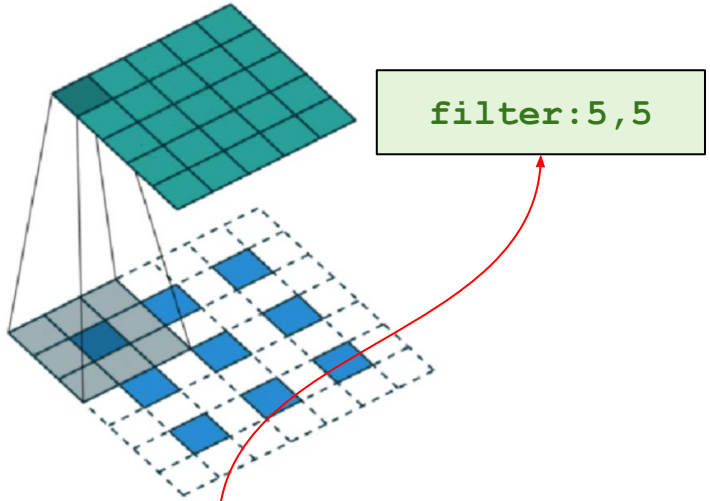



```
Conv2D(64, 3, 2, padding='same')
```

출력 특징맵 사이즈가 절반으로 줄어든다.

stride=2

생성자(Generator)




```
Conv2DTranspose(64, 5, 2, padding='same')
```

출력 특징맵 사이즈가 두 배로 커진다.

stride=2

DCGAN 학습 및 모니터링

```
class Monitor(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        x_rnd = np.random.randn(5 * 100).reshape(5, 100)
        generated = self.model.generator(x_rnd)
        for i in range(5):
            plt.subplot(1, 5, 1 + i)
            plt.axis('off')
            plt.imshow(generated[i].numpy().reshape(28, 28), cmap='gray_r')
        plt.show()
```

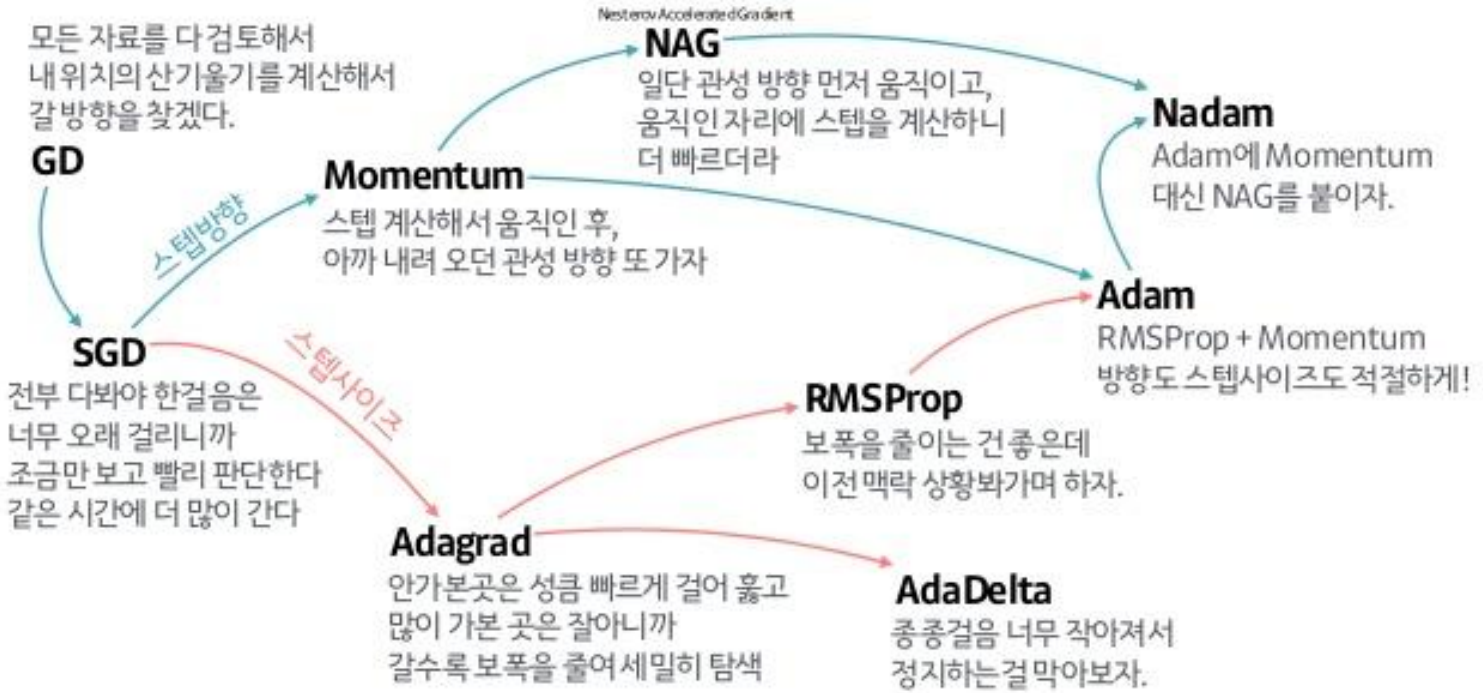
```
tf.keras.backend.clear_session()

discriminator = make_discriminator()
generator = make_generator()
gan = DCGAN(generator, discriminator)
gan.fit(x_train, epochs=50, batch_size=128, callbacks=[Monitor()])
```

callback을 이용하여 epoch마다 generator로 생성하는 이미지를 출력해준다.

DCGAN Model - init

```
class DCGAN(tf.keras.Model):
    def __init__(self, generator, discriminator):
        super(DCGAN, self).__init__()

        self.generator = generator
        self.discriminator = discriminator

        self.d_optimizer = tf.keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.5)
        self.g_optimizer = tf.keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.5)

        self.d_loss_metric = tf.keras.metrics.Mean(name="d_loss")
        self.d_acc_metric = tf.keras.metrics.BinaryAccuracy(name="d_acc")
        self.g_loss_metric = tf.keras.metrics.Mean(name="g_loss")
        self.g_acc_metric = tf.keras.metrics.BinaryAccuracy(name="g_acc")

        self.compile()
```

산 내려오는 작은 오솔길 잘찾기(Optimizer)의 발달 계보



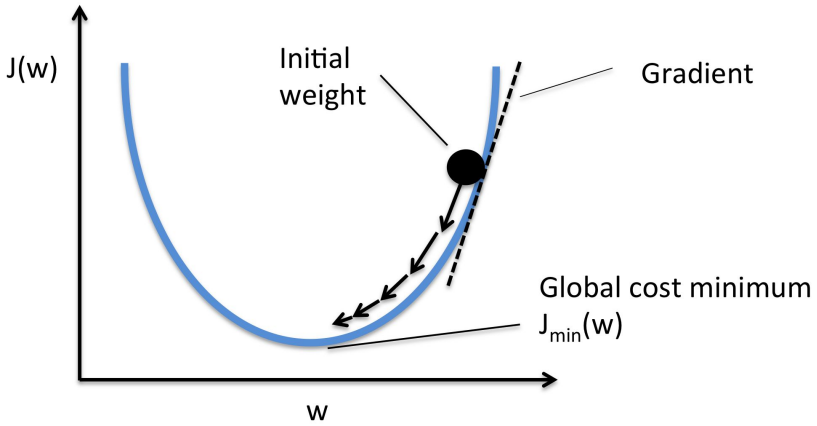
하용호, 자습해도 모르겠던 딥러닝, 머리속에 인스톨 시켜드립니다

Gradient Descent (경사하강법)

함수의 기울기(경사)를 구하여 함수의 극값에 이를 때까지 기울기가 낮은 쪽으로 반복하여 이동하는 방법.

- 이걸 배치 단위로 하면
  => Stochastic GD (SGD)

$$W(t+1) = W(t) - \alpha \frac{\partial}{\partial w} Cost(w)$$



(수식의 해석)

다음 가중치 =

현재 가중치에서

가중치에 따라 Cost(Loss)가 변화되는 양에

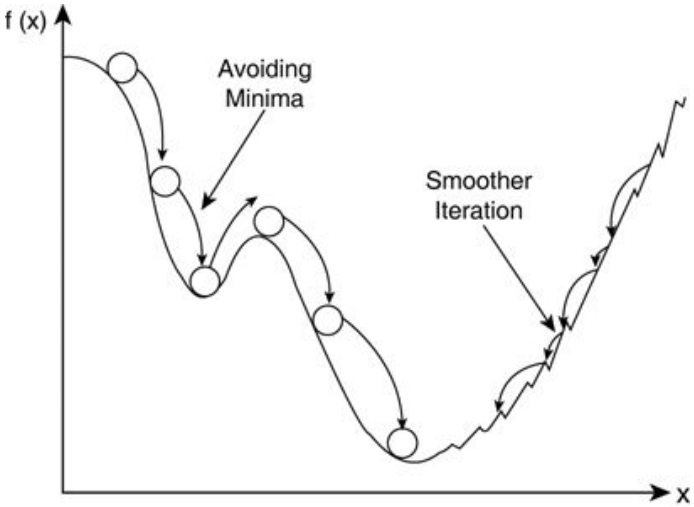
학습 비율을 곱한 만큼 뺀 값

Momentum (관성)

이전에 이동했던 방향을 기억해서 다음 이동의 방향에 반영.

$$V(t) = m * V(t-1) - \alpha \frac{\partial}{\partial w} Cost(w)$$

$$W(t+1) = W(t) + V(t)$$



(수식의 해석)

다음 가중치 = 현재 가중치랑 **이번 변경값**을 합한다.

단, **이번 변경값**은 **GD의 미분 계산량**에서 **지난번 변경값**을 추가로 반영하면 돼

Adagrad (Adaptive Gradient)

많이 이동한 변수(w)는 최적값에 근접했을 것이라는 가정하에, 많이 이동한 변수(w)를 기억해서 다음 이동의 거리를 줄인다.

$$G(t) = G(t-1) + \left(\frac{\partial}{\partial w(t)} Cost(w(t))\right)^2$$

$$= \sum_{i=0}^{t} \left(\frac{\partial}{\partial w(i)} Cost(w(i))\right)^2$$

$$W(t+1) = W(t) - \alpha * \frac{1}{\sqrt{G(t) + \epsilon}} * \frac{\partial}{\partial w(i)} Cost(w(i))$$

- RMSprop – 한동안 이동하지 않았으면 다시 많이 이동하자.

(수식의 해석)

다음 가중치 = 현재 가중치에서 GD의 미분 계산량을 뺄 때, 현재까지 해당 가중치를 변경한 양의 합(제곱합의 제곱근)으로 나눈 값을 쓰자.

Adam (RMSprop + Momentum)

$$M(t) = \beta_1 M(t-1) + (1-\beta_1)\frac{\partial}{\partial w(t)} Cost(w(t))$$

$$V(t) = \beta_2 V(t-1) + (1-\beta_2)\left(\frac{\partial}{\partial w(i)} Cost(w(i))\right)^2$$

$$\hat{M}(t) = \frac{M(t)}{1-\beta_1^{\,t}} \qquad \hat{V}(t) = \frac{V(t)}{1-\beta_2^{\,t}}$$

$$W(t+1) = W(t) - \alpha * \frac{\hat{M}(t)}{\sqrt{\hat{V}(t)+\epsilon}}$$

(수식의 해석)

다음 가중치 =

Momentum과 Adagrad을 **모두 반영**하여 현재의 가중치에서 뺀다.

- beta_1 – Momentum 적용 비율, 0이면 Momentum 사용하지 않음.
- beta_2 – Adagrad 적용 비율, 0이면 Adagrad 사용하지 않음.

DCGAN Model - train_step

```
class DCGAN(tf.keras.Model):
    ...
    def train_step(self, real):
        noise = tf.random.normal([tf.shape(real)[0], 100])

        with tf.GradientTape() as g_tape, tf.GradientTape() as d_tape:
            fake = self.generator(noise, training=True)

            y_real = self.discriminator(real, training=True)
            y_fake = self.discriminator(fake, training=True)

            g_loss = self.generator_loss(y_fake)
            d_loss = self.discriminator_loss(y_real, y_fake)

            g_grads = g_tape.gradient(g_loss, self.generator.trainable_variables)
            d_grads = d_tape.gradient(d_loss, self.discriminator.trainable_variables)

        self.g_optimizer.apply_gradients(zip(g_grads, self.generator.trainable_variables))
        self.d_optimizer.apply_gradients(zip(d_grads, self.discriminator.trainable_variables))

        self.update_metrics(y_real, y_fake, g_loss, d_loss)
        return {
            "d_acc": self.d_acc_metric.result(),
            "g_acc": self.g_acc_metric.result(),
            "d_loss": self.d_loss_metric.result(),
            "g_loss": self.g_loss_metric.result(),
        }
```

DCGAN Model - loss

```
class DCGAN(tf.keras.Model):
    ...
    def discriminator_loss(self, y_real, y_fake):
        real_loss = tf.keras.losses.binary_crossentropy(tf.ones_like(y_real), y_real)
        fake_loss = tf.keras.losses.binary_crossentropy(tf.zeros_like(y_fake), y_fake)
        d_loss = real_loss + fake_loss
        return d_loss

    def generator_loss(self, y_fake):
        g_loss = tf.keras.losses.binary_crossentropy(tf.ones_like(y_fake), y_fake)
        return g_loss

    def update_metrics(self, y_real, y_fake, g_loss, d_loss):
        self.g_loss_metric.update_state(g_loss)
        self.g_acc_metric.update_state(tf.ones_like(y_fake), y_fake)
        self.d_loss_metric.update_state(d_loss)
        self.d_acc_metric.update_state(tf.ones_like(y_real), y_real)
        self.d_acc_metric.update_state(tf.zeros_like(y_fake), y_fake)
```

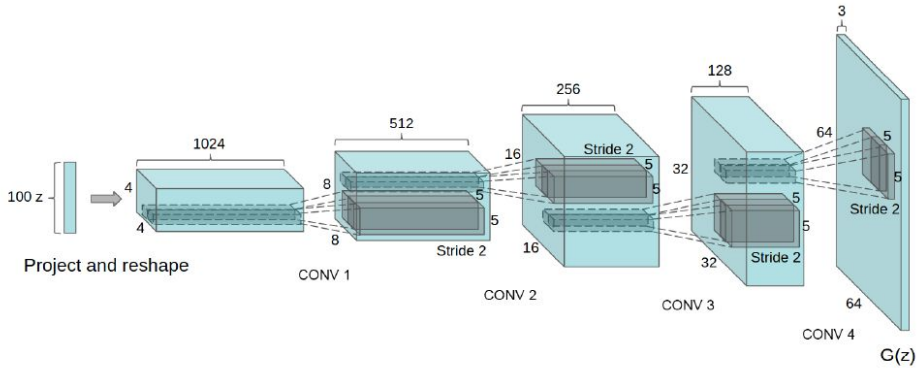
학습 및 모니터링

```
import matplotlib.pyplot as plt

class Monitor(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        x_rnd = np.random.randn(5 * 100).reshape(5, 100)
        generated = self.model.generator(x_rnd)
        for i in range(5):
            plt.subplot(1, 5, 1 + i)
            plt.axis('off')
            plt.imshow(generated[i].numpy().reshape(28, 28), cmap='gray_r')
        plt.show()
```

```
tf.keras.backend.clear_session()

discriminator = make_discriminator()
generator = make_generator()
gan = DCGAN(generator, discriminator)
gan.fit(x_train, epochs=50, batch_size=128, callbacks=[Monitor()])
```

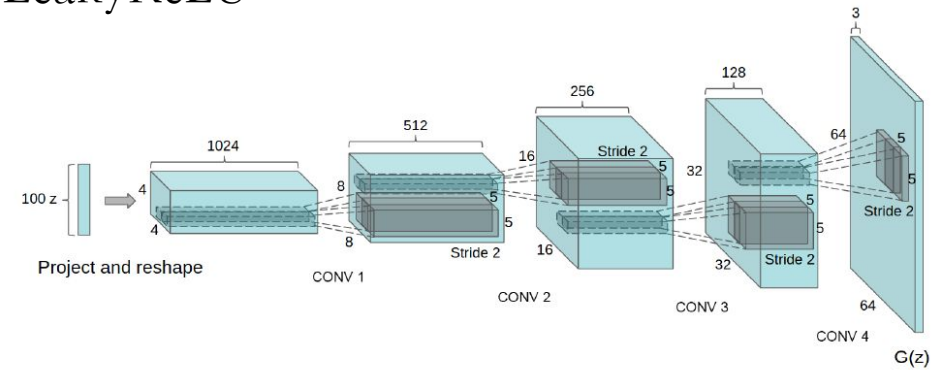
DCGAN (ICLR 2016)

- convolutional GAN 구조로 보다 안정적인 학습이 가능함.
- 필터 시각화를 통해 이미지의 특징을 잘 잡는 필터가 학습됨을 설명함.
- generator의 입력에 사용하는는 노이즈 벡터가
  이미지의 semantic한 특징에 대해 산술 속성을 보임.



Architecture guidelines

- pooling layer를 사용하지 않음. Convolution stride를 이용하여 대체
- generator/discriminator에 Batch Normalization 사용
- Fully-Connected layer 사용 안함.
- generator 은닉층 활성화 함수 - ReLU
- discriminator 은닉층 활성화 함수 - LeakyReLU



Generator Architecture

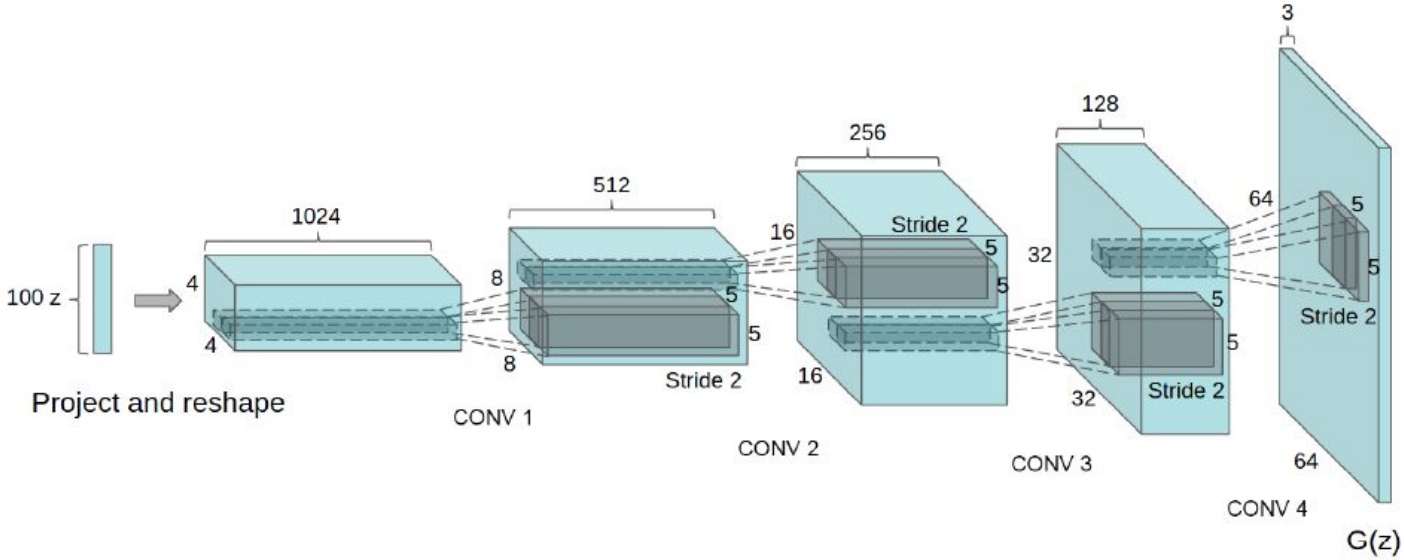
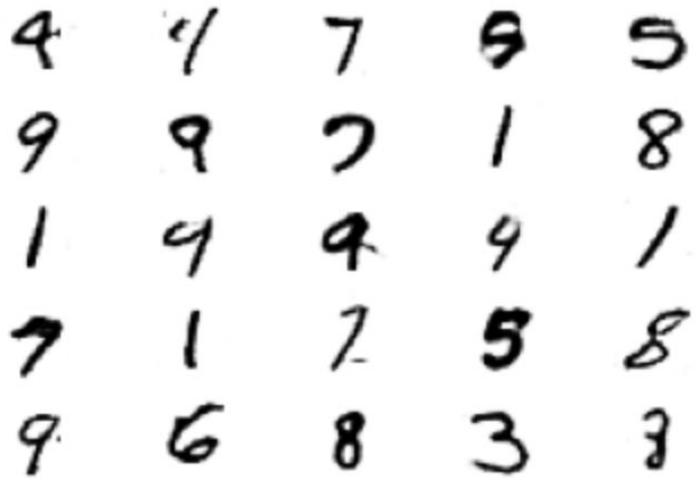


Figure 1: DCGAN generator used for LSUN scene modeling. A 100 dimensional uniform distribution Z is projected to a small spatial extent convolutional representation with many feature maps. A series of four fractionally-strided convolutions (in some recent papers, these are wrongly called deconvolutions) then convert this high level representation into a 64×64 pixel image. Notably, no fully connected or pooling layers are used.

결과 확인

vanilla GAN과 비교하여 훨씬 결과가 좋은 것을 확인 수 있다.

```
import matplotlib.pyplot as plt
import numpy as np

x_test = np.random.normal(size=2500).reshape(25, 100)
images = gan.generator.predict(x_test)
for i in range(25):
    plt.subplot(5, 5, 1 + i)
    plt.axis('off')
    plt.imshow(images[i].reshape(28, 28), cmap='gray_r')
```



walking in the latent space

학습한 manifold 위를 이동하며 생성되는 이미지 사이에 서서히 창문이 생기고, 가구의 방향/형태가 바뀌는 등의 현상을 관찰할 수 있다. 이는 모델이 흥미로운 representation을 학습한 것을 의미한다.

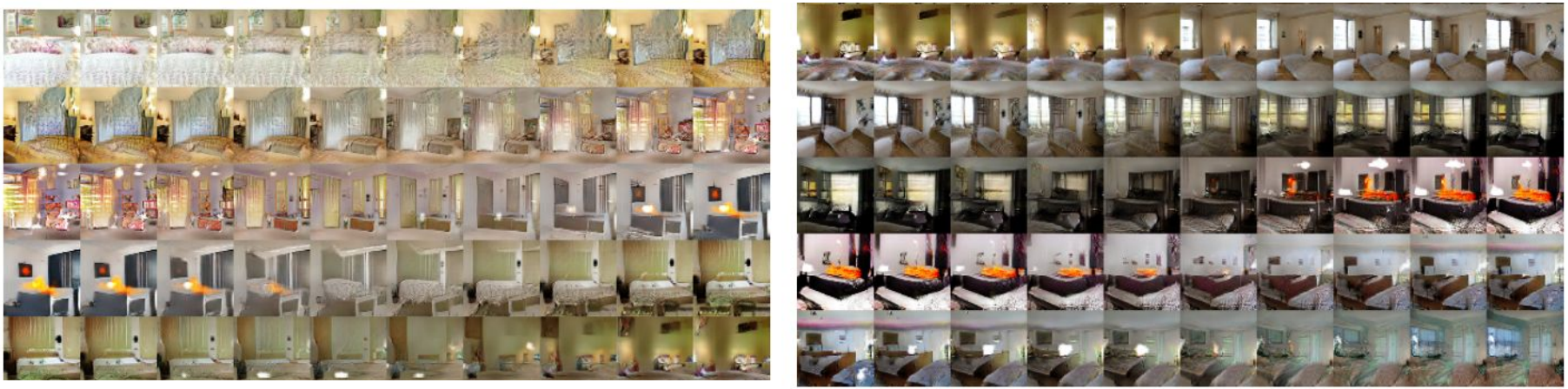
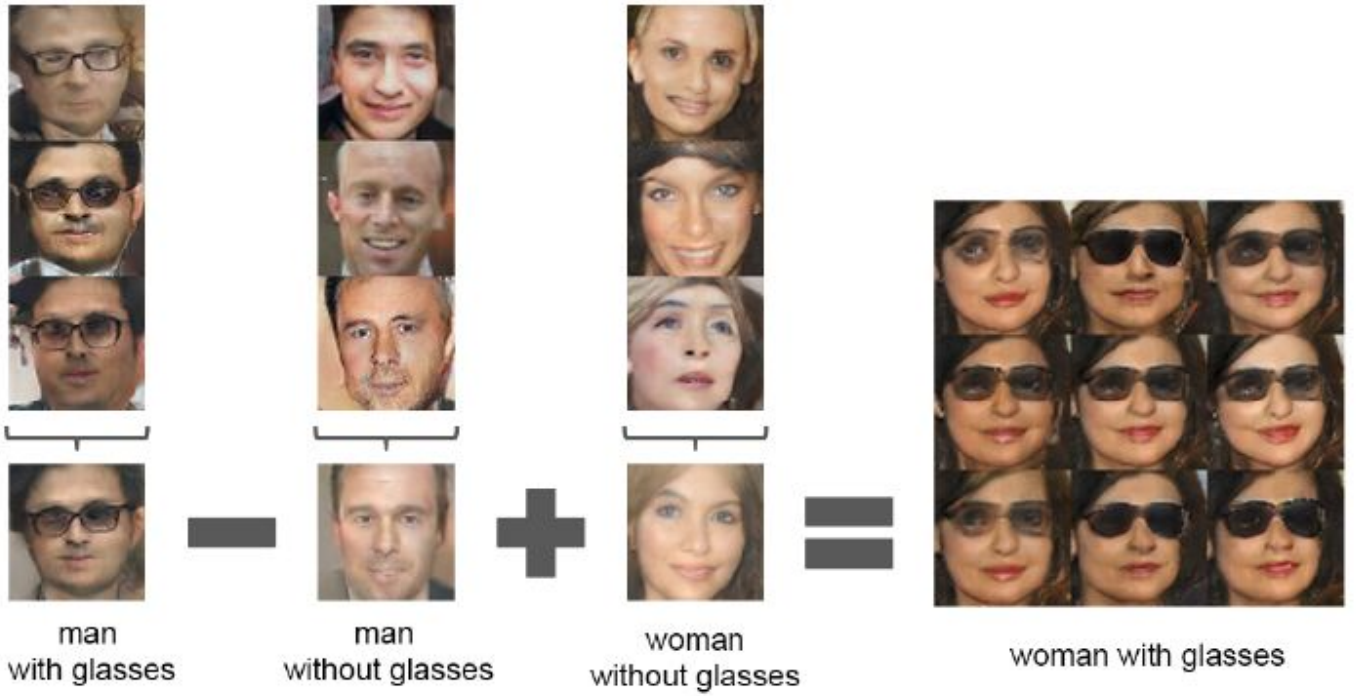


Figure 4: Top rows: Interpolation between a series of 9 random points in Z show that the space learned has smooth transitions, with every image in the space plausibly looking like a bedroom. In the 6th row, you see a room without a window slowly transforming into a room with a giant window. In the 10th row, you see what appears to be a TV slowly being transformed into a window.

벡터 연산이 가능함을 보여줌



What?

벡터 연산이 가능하다는 것은
무슨 의미가 있지?

Manifold를 학습했다고 할 수 있다.

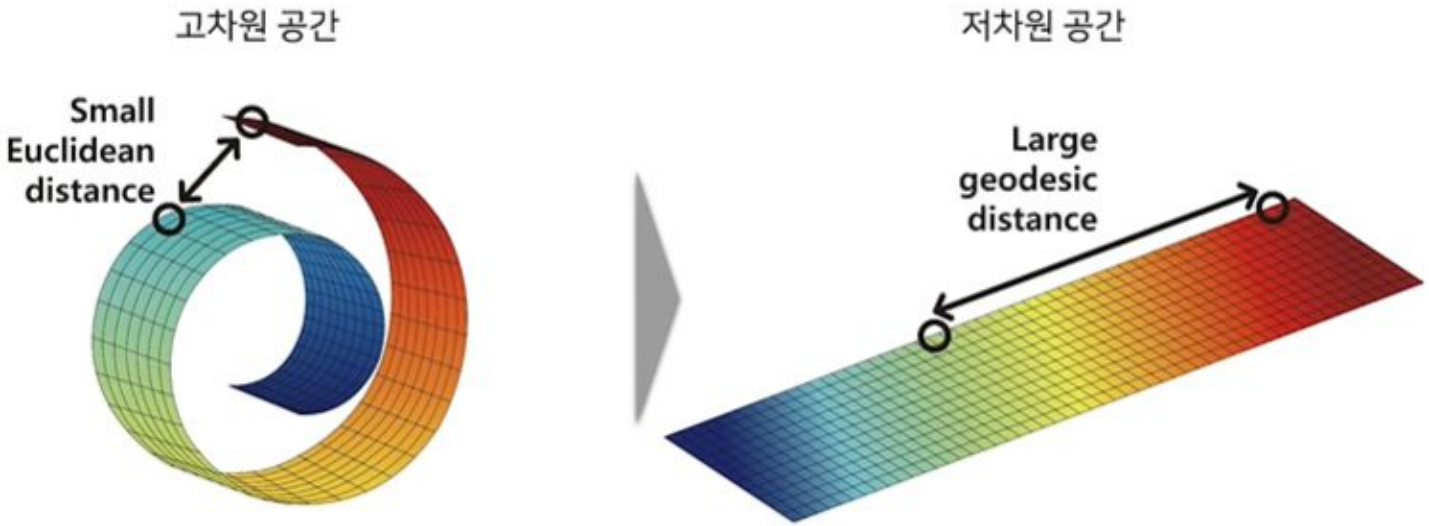
의미를 보존하는 공간, Manifold

일반적으로 두 이미지를 선형 보간하는 경우의 중간 이미지

잠재 공간(latent space)의 두 벡터를 선형 보간하면 상대적으로 자연스러운 중간 이미지를 보여준다.

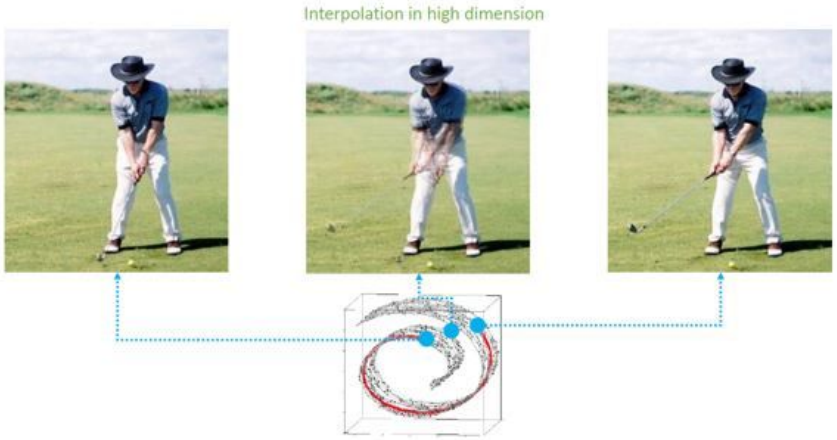
의미를 보존하는 공간, **Manifold**

고차원 데이터라 할지라도, 의미를 가지는 피쳐를 모아둔 **조밀한 저차원 공간**이 존재하며 이를 Manifold라고 한다. sparse 한 고차원 데이터를 간추려서 저차원 공간으로 나타낼수 있다는 뜻.

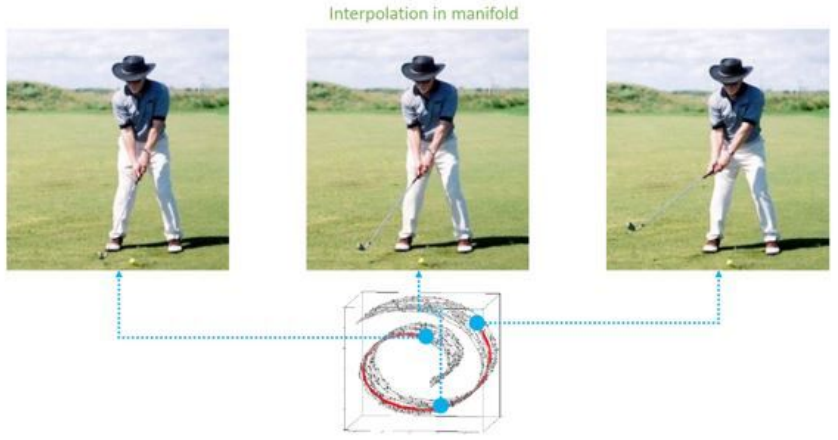


의미를 보존하는 공간, **Manifold**

- 고차원 공간에서 중간값 – 팔이 2개 골프채가 2개로 좌우 이미지의 중간 위치
- manifold 공간에서 중간값 – 공을 치는 중간과정 모습



Distance in high dimension



Distance in manifold

Manifold 상에서 중간 이미지 확인

```
import matplotlib.pyplot as plt
import numpy as np

vectors = []
for j in range(len(x_test) - 1):
    for i in range(11):
        vectors.append((1 - 0.1 * i) * x_test[j] +
                       (0.1 * i) * x_test[j + 1])

images = gan.generator.predict(np.array(vectors))
for j in range(len(x_test) - 1):
    for i in range(11):
        plt.subplot(1, 11, 1 + i)
        plt.axis('off')
        plt.imshow(images[10 * j + i].reshape(28, 28), cmap='gray_r')
    plt.show()
```

DCGAN 의미와 한계

- 의미
  - GAN 훈련을 위한 안정적인 구조를 제시
  - 적대적 네트워크를 통해 이미지의 좋은 representation을 학습할 수 있음을 입증.
  - 흥미로운 latent space 학습
- 한계
  - 모델의 불안정성 문제는 여전함
  - 학습을 오래할수록 Mode Collapsing 등의 이상현상 발생가능성 증가함

실습. 다음 데이터셋으로 DCGAN을 구성해보자.

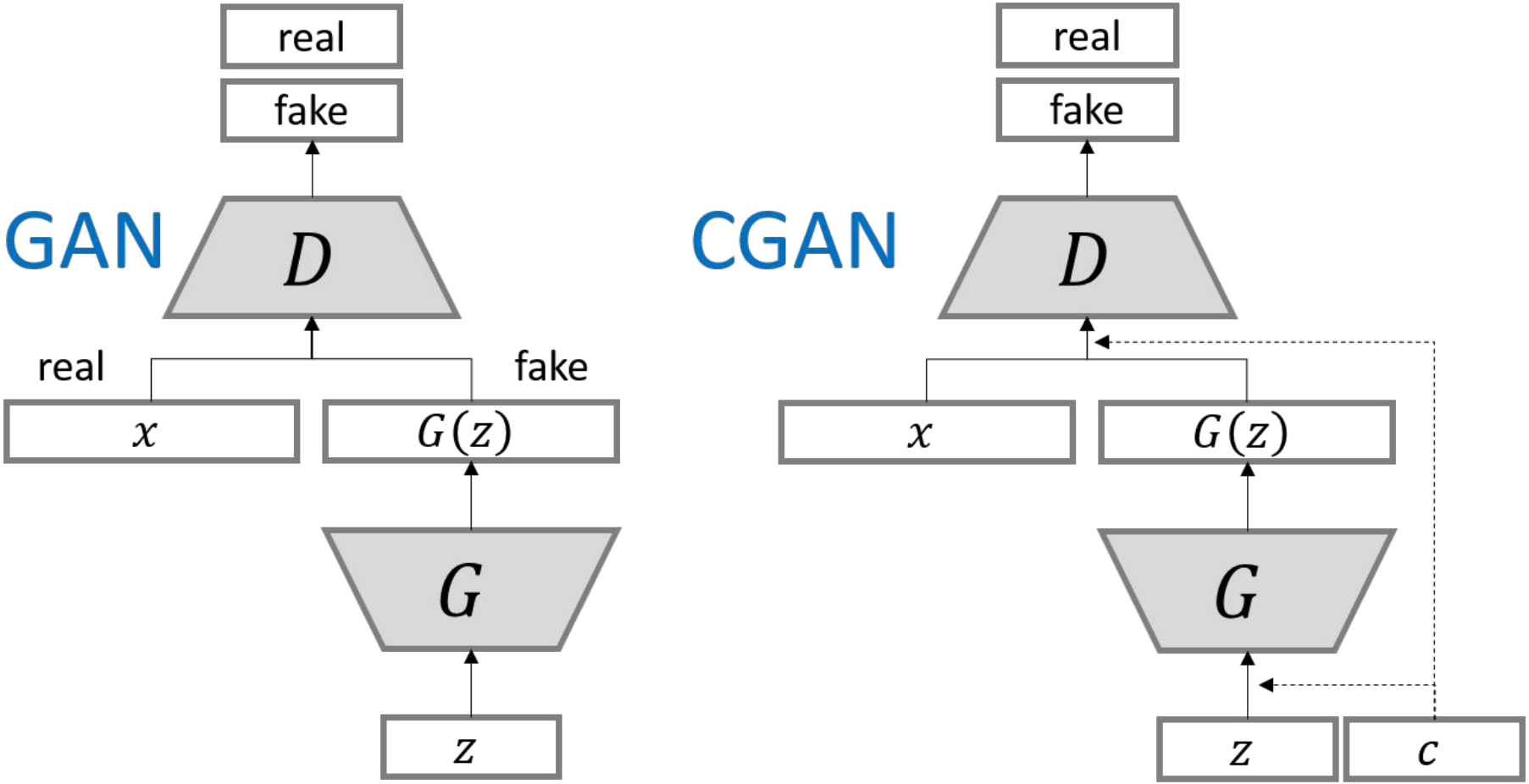
Fashion Mnist / Cifar10

복사해서 붙여넣기는 금지.

처음부터 끝까지 눈으로 따라가면서 직접 작성해봅시다.

Conditional GAN (2014)

https://arxiv.org/pdf/1411.1784.pdf


GAN
real
fake
D
real
fake
x
G(z)
G
z
CGAN
real
fake
D
x
G(z)
G
z
c

CGAN - Discriminator

```
def make_discriminator():
    dx1 = tf.keras.Input(shape=[28, 28, 1])
    dh1 = tf.keras.layers.Flatten()(dx1)

    dx2 = tf.keras.Input(shape=[1])
    dh2 = tf.keras.layers.Embedding(10, 28 * 28)(dx2)
    dh2 = tf.keras.layers.Flatten()(dh2)

    dh = tf.keras.layers.add([dh1, dh2])
    dh = tf.keras.layers.Reshape([28, 28, 1])(dh)
    dh = tf.keras.layers.Conv2D(64, 5, 2, padding='same')(dh)
    dh = tf.keras.layers.LeakyReLU(alpha=0.2)(dh)
    dh = tf.keras.layers.Conv2D(128, 5, 2, padding='same')(dh)
    dh = tf.keras.layers.LeakyReLU(alpha=0.2)(dh)
    dh = tf.keras.layers.Flatten()(dh)
    dy = tf.keras.layers.Dense(1, activation='sigmoid')(dh)
    return tf.keras.Model([dx1, dx2], dy, name='discriminator')
```

CGAN - Generator

```
def make_generator():
    gx1 = tf.keras.Input(shape=[100])

    gx2 = tf.keras.Input(shape=[1])
    gh2 = tf.keras.layers.Embedding(10, 100)(gx2)
    gh2 = tf.keras.layers.Flatten()(gh2)

    gh = tf.keras.layers.add([gx1, gh2])
    gh = tf.keras.layers.Dense(7 * 7 * 128)(gh)
    gh = tf.keras.layers.Reshape([7, 7, 128])(gh)
    gh = tf.keras.layers.Conv2DTranspose(128, 5, 2, padding='same')(gh)
    gh = tf.keras.layers.BatchNormalization()(gh)
    gh = tf.keras.layers.Activation('swish')(gh)
    gh = tf.keras.layers.Conv2DTranspose(64, 5, 2, padding='same')(gh)
    gh = tf.keras.layers.BatchNormalization()(gh)
    gh = tf.keras.layers.Activation('swish')(gh)
    gy = tf.keras.layers.Conv2D(1, 7, activation='tanh', padding='same')(gh)
    return tf.keras.Model([gx1, gx2], gy, name='generator')
```

CGAN 학습 및 모니터링

```
class Monitor(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        x_rnd = np.random.randn(5 * 100).reshape(5, 100)
        generated = self.model.generator(x_rnd)
        for i in range(5):
            plt.subplot(1, 5, 1 + i)
            plt.axis('off')
            plt.imshow(generated[i].numpy().reshape(28, 28), cmap='gray_r')
        plt.show()
```

```
tf.keras.backend.clear_session()

discriminator = make_discriminator()
generator = make_generator()
gan = CGAN(generator, discriminator)
gan.fit([x_train, y_train.reshape([-1, 1])],
        epochs=50, batch_size=128, callbacks=[Monitor()])
```

CGAN Model - init

```
class CGAN(tf.keras.Model):
    def __init__(self, generator, discriminator):
        super(CGAN, self).__init__()
        self.compile()

        self.generator = generator
        self.discriminator = discriminator

        self.d_optimizer = tf.keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.5)
        self.g_optimizer = tf.keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.5)

        self.d_loss_metric = tf.keras.metrics.Mean(name="d_loss")
        self.d_acc_metric = tf.keras.metrics.BinaryAccuracy(name="d_acc")
        self.g_loss_metric = tf.keras.metrics.Mean(name="g_loss")
        self.g_acc_metric = tf.keras.metrics.BinaryAccuracy(name="g_acc")
```

CGAN Model - train_step

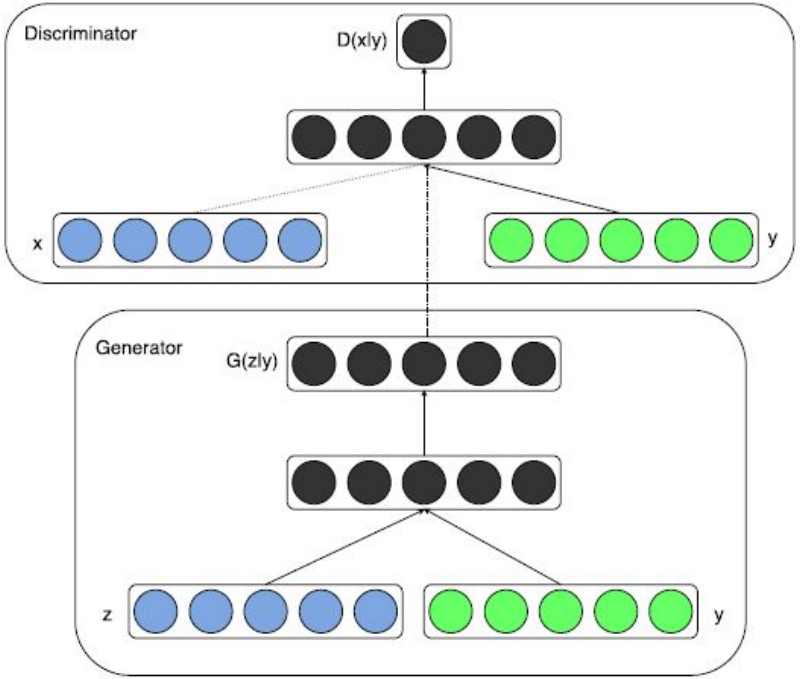
```
class CGAN(tf.keras.Model):
    ...
    def train_step(self, inputs):
        real, label = inputs[0]
        noise = tf.random.normal([tf.shape(real)[0], 100])

        with tf.GradientTape() as g_tape, tf.GradientTape() as d_tape:
            fake = self.generator([noise, label], training=True)

            y_real = self.discriminator([real, label], training=True)
            y_fake = self.discriminator([fake, label], training=True)

            g_loss = self.generator_loss(y_fake)
            d_loss = self.discriminator_loss(y_real, y_fake)

            g_grads = g_tape.gradient(g_loss, self.generator.trainable_variables)
            d_grads = d_tape.gradient(d_loss, self.discriminator.trainable_variables)

        self.g_optimizer.apply_gradients(zip(g_grads, self.generator.trainable_variables))
        self.d_optimizer.apply_gradients(zip(d_grads, self.discriminator.trainable_variables))

        self.update_metrics(y_real, y_fake, g_loss, d_loss)
        return {
            "d_acc": self.d_acc_metric.result(),
            "g_acc": self.g_acc_metric.result(),
            "d_loss": self.d_loss_metric.result(),
            "g_loss": self.g_loss_metric.result(),
        }
```

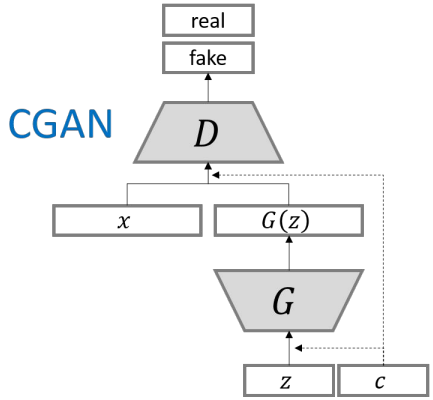
CGAN Model - loss

```
class CGAN(tf.keras.Model):
    ...
    def discriminator_loss(self, y_real, y_fake):
        real_loss = tf.keras.losses.binary_crossentropy(tf.ones_like(y_real), y_real)
        fake_loss = tf.keras.losses.binary_crossentropy(tf.zeros_like(y_fake), y_fake)
        d_loss = real_loss + fake_loss
        return d_loss

    def generator_loss(self, y_fake):
        g_loss = tf.keras.losses.binary_crossentropy(tf.ones_like(y_fake), y_fake)
        return g_loss

    def update_metrics(self, y_real, y_fake, g_loss, d_loss):
        self.g_loss_metric.update_state(g_loss)
        self.g_acc_metric.update_state(tf.ones_like(y_fake), y_fake)
        self.d_loss_metric.update_state(d_loss)
        self.d_acc_metric.update_state(tf.ones_like(y_real), y_real)
        self.d_acc_metric.update_state(tf.zeros_like(y_fake), y_fake)
```

Conditional GAN (2014)

- 입력 조건에 맞는 이미지를 생성하는 GAN
- discriminator와 generator에 이미지와 보조변수 Y를 함께 입력으로 사용함
- 조건부 이미지 생성은 물론 이미지태깅, multi-modal model의 학습에 이용 가능





CGAN Loss

GAN의 목적함수

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

CGAN의 목적함수

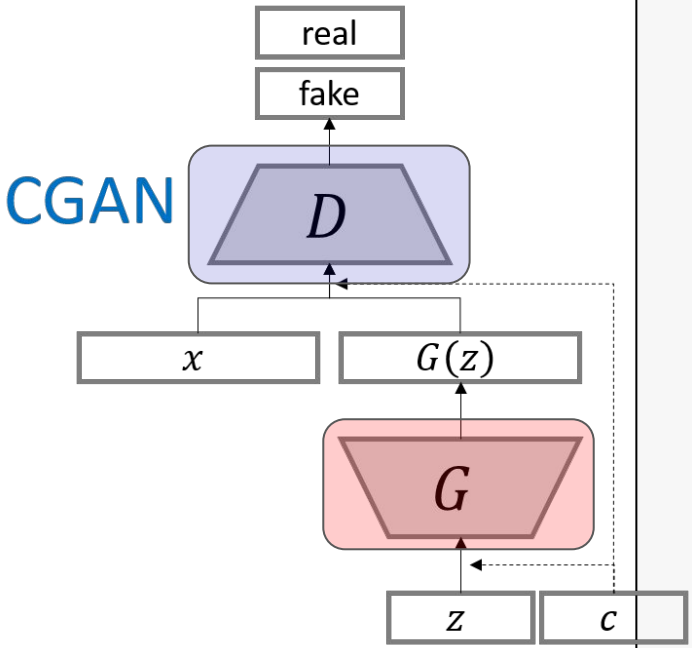
$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x}|\boldsymbol{y})] + \mathbb{E}_{\boldsymbol{z}\sim p_z(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z}|\boldsymbol{y})))]$$

일반 GAN의 목적함수에 input 변수 x, z만 조건부 변수 x|y, z|y로 바뀐 모습이다.

실제 이미지 판별 결과

생성 이미지 판별 결과

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[logD(x|y)] + E_{z\sim p_z(z)}\left[\log\left(1 - D\left(G(z|y)\right)\right)\right]$$




```python
class CGAN(tf.keras.Model):
    ...
    def train_step(self, inputs):
        real, label = inputs[0]
        noise = tf.random.normal([tf.shape(real)[0], 100])

        with tf.GradientTape() as g_tape, tf.GradientTape() as d_tape:
            fake = self.generator([noise, label], training=True)

            y_real = self.discriminator([real, label], training=True)
            y_fake = self.discriminator([fake, label], training=True)

            g_loss = self.generator_loss(y_fake)
            d_loss = self.discriminator_loss(y_real, y_fake)

            g_grads = g_tape.gradient(g_loss, self.generator.trainable_variables)
            d_grads = d_tape.gradient(d_loss, self.discriminator.trainable_variables)

        self.g_optimizer.apply_gradients(zip(g_grads, self.generator.trainable_variables))
        self.d_optimizer.apply_gradients(zip(d_grads, self.discriminator.trainable_variables))

        self.update_metrics(y_real, y_fake, g_loss, d_loss)
        return {
            "d_acc": self.d_acc_metric.result(),
            "g_acc": self.g_acc_metric.result(),
            "d_loss": self.d_loss_metric.result(),
            "g_loss": self.g_loss_metric.result(),
        }
```

결과확인

```
import numpy as np

x_test = np.random.normal(size=[10, 100])

for j in range(10):
    images = gan.generator.predict([x_test, np.full(10, j)])
    plt.figure(figsize=(15, 15))
    for i in range(10):
        plt.subplot(1, 10, 1 + i)
        plt.axis('off')
        plt.imshow(images[i, :, :, 0], cmap='gray_r')
    plt.show()
```

결과확인


G(z, label: 0)
G(z, label: 1)
G(z, label: 2)
G(z, label: 3)
G(z, label: 4)
G(z, label: 5)
G(z, label: 6)
G(z, label: 7)
G(z, label: 8)
G(z, label: 9)

장단점

- 장점
  - 구현이 매우 간단함.
  - 생성되는 데이터를 원하는 대로 통제할 수 있다는 부분에서 의미있는 연구.
  - 다양한 application으로의 확장가능성으로 Conditional GAN의 잠재력을 보임.
- 단점
  - 의미있는 수준의 성능을 보이지는 못함.
  - GAN의 여러 단점을 그대로 가지고 있음.
  - 논문의 결과는 매우 preliminary한 것이라 저자들도 인정하고있음.

실습. 다음 데이터셋으로 CGAN을 구성해보자.

Fashion Mnist / Cifar10

복사해서 붙여넣기는 금지.

처음부터 끝까지 눈으로 따라가면서 직접 작성해봅시다.

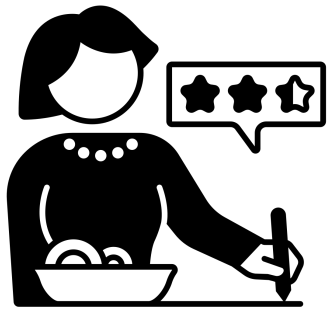
Wasserstein GAN (NIPS 2017)

https://arxiv.org/pdf/1701.07875.pdf

WGAN - Critic

```
# 판별기
def make_critic():
    dx = tf.keras.Input([28, 28, 1])
    dh = tf.keras.layers.Conv2D(64, 5, 2, padding='same')(dx)
    dh = tf.keras.layers.LeakyReLU(alpha=0.2)(dh)
    dh = tf.keras.layers.Conv2D(128, 5, 2, padding='same')(dh)
    dh = tf.keras.layers.LeakyReLU(alpha=0.2)(dh)
    dh = tf.keras.layers.Flatten()(dh)
    dy = tf.keras.layers.Dense(1)(dh)
    return tf.keras.Model(dx, dy, name='critic')
```

- 판별기의 이름이 Critic(비평가)로 달라졌다.
  - 그냥 판별이 아니라 수준에 따라 별점을 주겠다는 의미
- 판별기의 최종 dense layer에 sigmoid 함수를 사용하지 않는다.



WGAN - Generator

```
# 생성기
def make_generator():
    gx = tf.keras.Input([100])
    gh = tf.keras.layers.Dense(7 * 7 * 128)(gx)
    gh = tf.keras.layers.Reshape([7, 7, 128])(gh)
    gh = tf.keras.layers.Conv2DTranspose(128, 5, 2, padding='same')(gh)
    gh = tf.keras.layers.BatchNormalization()(gh)
    gh = tf.keras.layers.Activation('swish')(gh)
    gh = tf.keras.layers.Conv2DTranspose(64, 5, 2, padding='same')(gh)
    gh = tf.keras.layers.BatchNormalization()(gh)
    gh = tf.keras.layers.Activation('swish')(gh)
    gy = tf.keras.layers.Conv2D(1, 7, activation='tanh', padding='same')(gh)
    return tf.keras.Model(gx, gy, name='generator')
```

WGAN Model - init

```
class WGAN(tf.keras.Model):
    def __init__(self, generator, critic):
        super(WGAN, self).__init__()
        self.compile()

        self.generator = generator
        self.critic = critic

        self.c_optimizer = tf.keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.5)
        self.g_optimizer = tf.keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.5)

        self.c_loss_metric = tf.keras.metrics.Mean(name="c_loss")
        self.g_loss_metric = tf.keras.metrics.Mean(name="g_loss")

        self.compile()
```

- 더이상 정확도는 계산하지 않는다.

WGAN Model - train_step

```
class WGAN(tf.keras.Model):
    ...
    def train_step(self, real):
        noise = tf.random.normal([tf.shape(real)[0], 100])

        with tf.GradientTape() as g_tape, tf.GradientTape() as c_tape:
            fake = self.generator(noise, training=True)

            y_real = self.critic(real, training=True)
            y_fake = self.critic(fake, training=True)

            g_loss = self.generator_loss(y_fake)
            c_loss = self.critic_loss(y_real, y_fake)

            g_grads = g_tape.gradient(g_loss, self.generator.trainable_variables)
            c_grads = c_tape.gradient(c_loss, self.critic.trainable_variables)

        self.g_optimizer.apply_gradients(zip(g_grads, self.generator.trainable_variables))
        self.c_optimizer.apply_gradients(zip(c_grads, self.critic.trainable_variables))

        self.update_metrics(g_loss, c_loss)
        return {
            "c_loss": self.c_loss_metric.result(),
            "g_loss": self.g_loss_metric.result(),
        }
```

- 더이상 정확도는 계산하지 않는다.

WGAN Model - loss

```
class WGAN(tf.keras.Model):
    ...
    def critic_loss(self, y_real, y_fake):
        y_true = tf.concat([-tf.ones_like(y_real), tf.ones_like(y_fake)], axis=0)
        y_pred = tf.concat([y_real, y_fake], axis=0)
        c_loss = -tf.reduce_mean(y_true * y_pred)
        return c_loss

    def generator_loss(self, y_fake):
        g_loss = -tf.reduce_mean(-tf.ones_like(y_fake) * y_fake)
        return g_loss

    def update_metrics(self, g_loss, c_loss):
        self.g_loss_metric.update_state(g_loss)
        self.c_loss_metric.update_state(c_loss)
```

- 더이상 정확도는 계산하지 않는다.
- loss로 Wasserstein Distance를 사용.

경고. 코드의 변화가 간단해 보여서 만만하게 생각하면 안됨. 데미지를 크게 입을 수 있음.

학습 및 모니터링

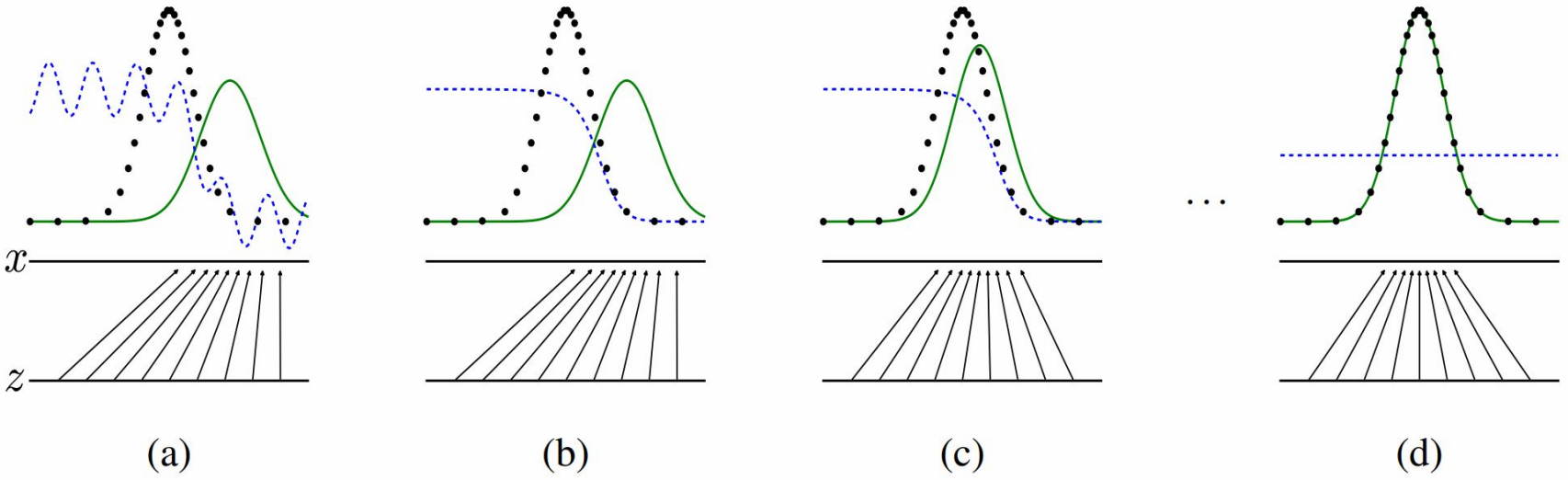
```
import matplotlib.pyplot as plt

class Monitor(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        x_rnd = np.random.randn(5 * 100).reshape(5, 100)
        generated = self.model.generator(x_rnd)
        for i in range(5):
            plt.subplot(1, 5, 1 + i)
            plt.axis('off')
            plt.imshow(generated[i].numpy().reshape(28, 28), cmap='gray_r')
        plt.show()
```

```
tf.keras.backend.clear_session()

critic = make_critic()
generator = make_generator()
gan = WGAN(generator, critic)
gan.fit(x_train, epochs=20, batch_size=128, callbacks=[Monitor()])
```

Why?

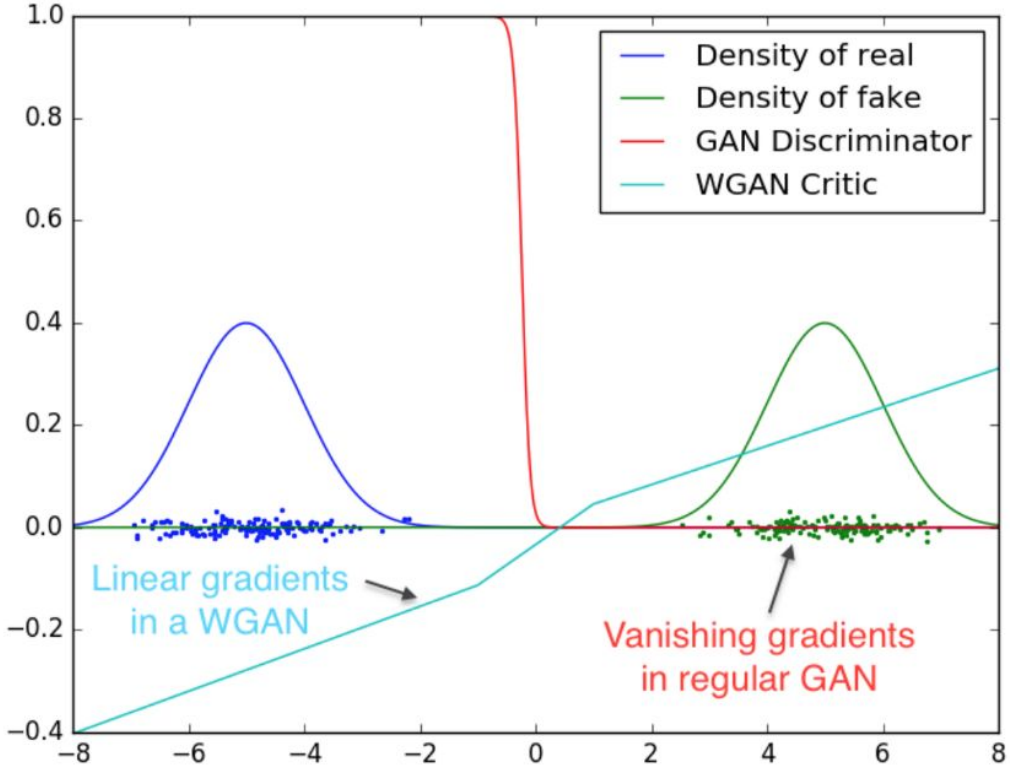
이름도 어려운 Wasserstein을 배워야 하는 건 왜 때문일까?

GAN의 분포 학습은 이제 시작
분포를 학습한다는 의미를 조금 깊게 생각해보자

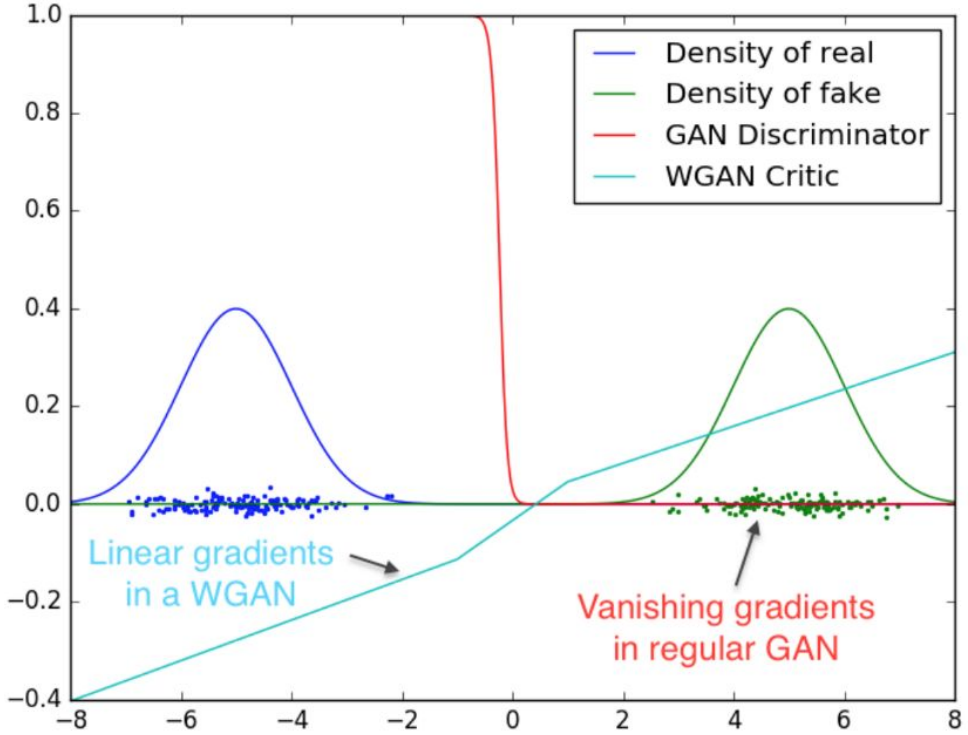


- G 함수(분포)가 업데이트 되면서 **실제 분포**를 흉내낸다.
- G 함수의 weights를 조금씩 업데이트 해가는 것.
- 판별기가 G 함수가 생성한 데이터를 1이라고 할 확률이 올라가는 방향으로 업데이트
- 분포의 겹치는 면적이 늘어나면 1이라고 할 확률이 올라간다.

분포가 완전히 분리되면 학습은 어떻게 될까?



분포의 거리(차이)를 계산하는 방법이 없을까?



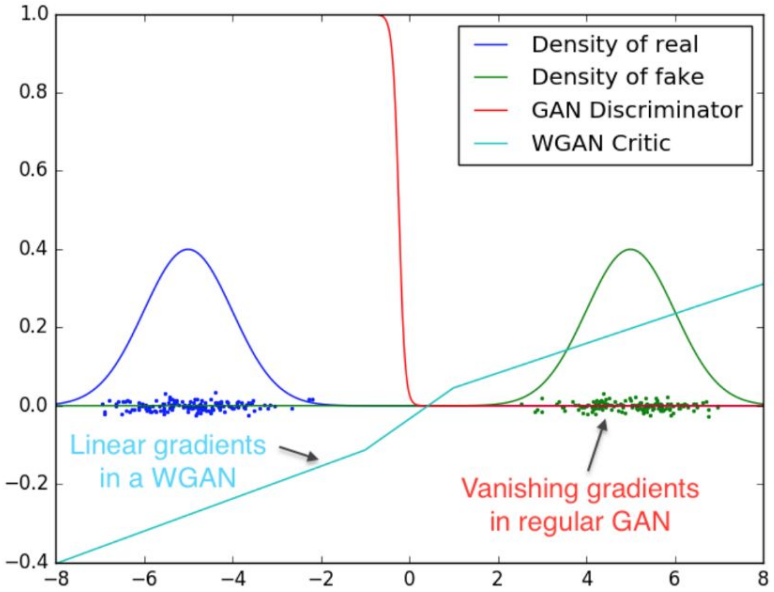
Wasserstein Distance

삽질의 양으로 거리를 측정해보자.

분포의 거리(차이)를 계산하는 방법이 없을까?

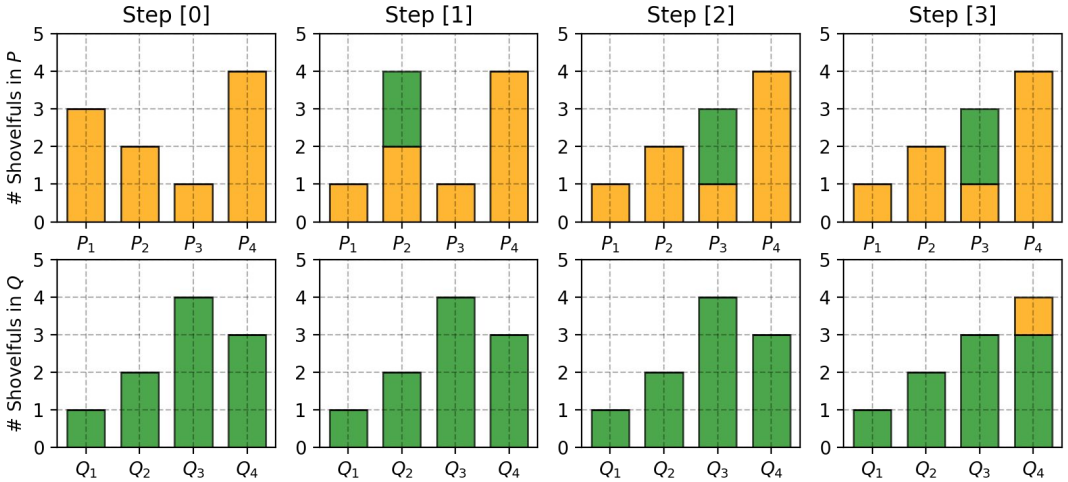
Wasserstein GAN

- Wasserstein 거리 도입. EM(Earth-Mover) Distance 라고도 불림
- 실제 분포에 가까워지는 걸 표현하는 수식
- 겹치는 분포가 아니어도
  가까워지는 만큼 값이 작아진다.
- JS Divergence는 분포가 분리되는 경우
  loss의 변화가 없어. 학습이 불가하네!



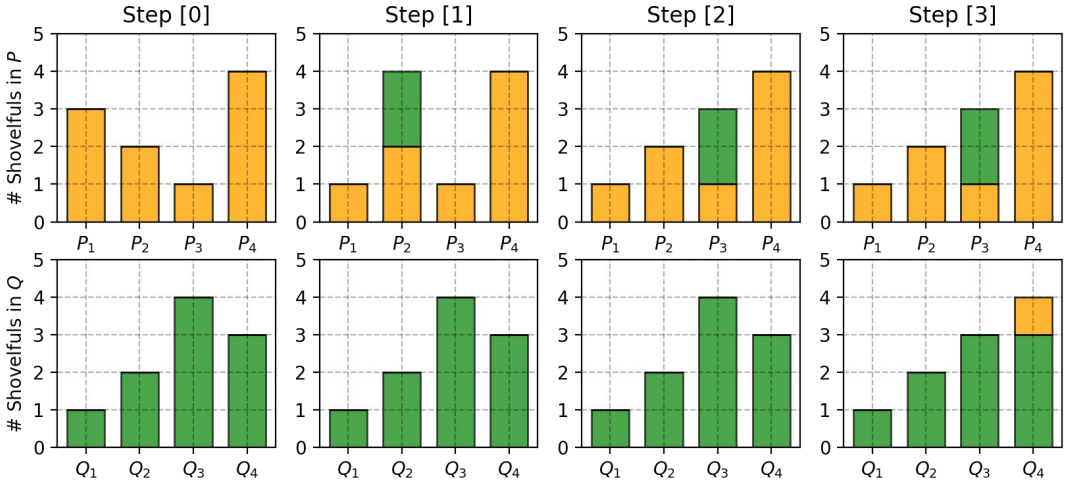
Wasserstein Distance - EM(Earth-Mover) Distance

- 두 확률분포간의 거리를 측정하는 지표
- Earth Mover's distance (EM distance) 라는 다른 이름이 있음.
- 확률 분포의 차이 = 최소한의 흙더미를 옮기는 비용
- 비용은 옮겨진 흙의 양과 이동한 거리를 곱하여 정량화합니다.



P를 Q처럼 바꾸기 위해서는

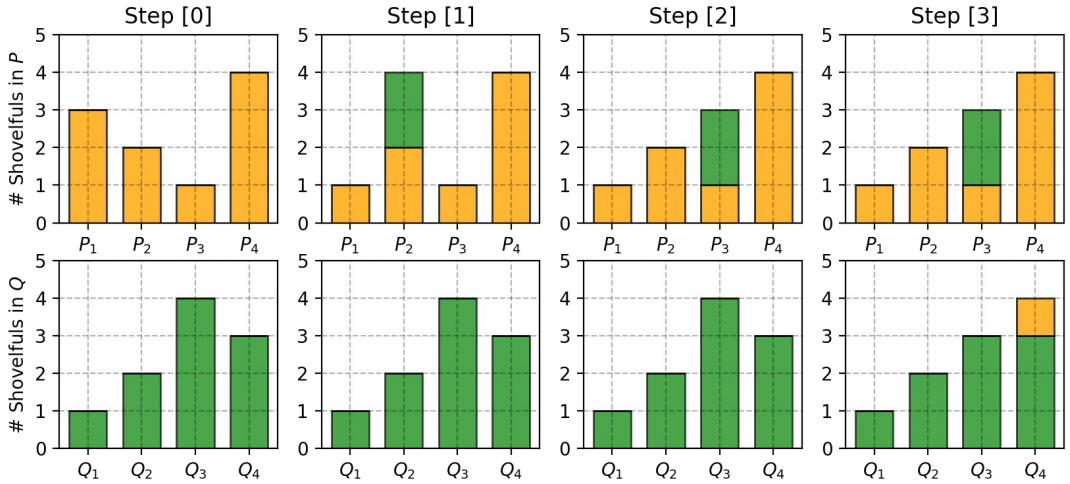
1. P1에서 2만큼을 P2로 이동시킵니다. => (P1, Q1)이 같아집니다.
2. P2에서 2만큼을 P3로 이동시킵니다. => (P2, Q2)가 같아집니다.
3. Q3에서 1만큼을 Q4로 이동시킵니다. => (P3, Q3)과 (P4, Q4)가 같아집니다.



P를 Q처럼 바꾸기 위해서는

Pi와 Qi가 같아지게 하는데 드는 비용을 δi라고 표시하면, δi+1 = δi + Pi − Qi로 나타낼수 있습니다. 따라서 위의 과정을 수식으로 표현하면 아래와 같습니다.

$$\delta_0 = 0$$
$$\delta_1 = 0 + 3 - 1 = 2$$
$$\delta_2 = 2 + 2 - 2 = 2$$
$$\delta_3 = 2 + 1 - 4 = -1$$
$$\delta_4 = -1 + 4 - 3 = 0$$



최종적으로 Earth Mover's distance W = Σ| δi| = 5 가 됩니다.

방금 우리가 한 걸 수식으로 표현한 것!

- Wasserstein Distance
- EM(Earth-Mover) Distance

$$W(p_r, p_g) = \inf_{\gamma \sim \Pi(p_r, p_g)} \mathbb{E}_{(x,y)\sim\gamma} [\|x - y\|]$$

EM 이동 계획들 중 최소값을 찾으라는 의미

그러나!

이 수식을 그대로 이용하기는 어려워서 변환이 필요함.

그리고, 그 유도 과정은 이해가 어려움.

일단 중간과정 스킵하고 결론부터 보자.

$$L(p_r, p_g) = W(p_r, p_g) = \max_{w \in W} \mathbb{E}_{x \sim p_r}[f_w(x)] - \mathbb{E}_{z \sim p_r(z)}[f_w(g_\theta(z))]$$

유도된 수식

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

GAN Loss

- 기존의 loss와 비슷한 패턴이 보인다.
- D(x) 함수를 학습하는 대신 fw(x) 함수를 학습하면 되는 것으로 보임.
- Kantorovich-Rubinstein duality를 이용한 수식 유도.

다음의 내용으로 정리할 수 있다.

$$L(p_r, p_g) = W(p_r, p_g) = \max_{w \in W} \mathbb{E}_{x \sim p_r}[f_w(x)] - \mathbb{E}_{z \sim p_r(z)}[f_w(g_\theta(z))]$$

유도된 수식

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

GAN Loss

- 분포의 거리를 측정하는 Wasserstein Distance 거리를 Loss 함수로 사용해보자.
- 거리를 재려면 상상속의 fw함수가 필요하다.
- 사용하려는 loss가 이전의 Gan loss 함수와 모양이 비슷.
- Gan에서 D함수를 학습했듯 상상속의 fw함수도 딥러닝이 학습하면 되겠네?
- 상상속의 f함수가 Critic 함수임.

어려운 수식 유도과정, 조금만 알아보자.

$$W(p_r, p_g) = \inf_{\gamma \sim \Pi(p_r, p_g)} \mathbb{E}_{(x,y)\sim\gamma} [\|x - y\|]$$

아까 봤던 애. 얘는 못씀. 미분 안되서 안됨.

$$W(p_r, p_g) = \frac{1}{K} \sup_{\|f\|_L \leq K} \mathbb{E}_{x\sim p_r}[f(x)] - \mathbb{E}_{x\sim p_g}[f(x)]$$

미분 가능한 연속함수로 대체하려고 등장한 수식

새로운 수식은 까다로움. 사용을 위해 다음의 조건을 만족해야 함.

1. 유도된 W 함수 ≦ 기존 W 함수
2. 특정 조건을 만족하는 우리에게 필요한 **상상속의 f 함수** 특징
   a. 특정 조건(K-lipschitz 연속)을 만족해야만 수식이 성립
   b. K=1: f 함수는 어떤 지점에서도 **기울기**가 1을 넘지 않음을 의미

상상속의 f함수를 딥러닝이 찾게 하자.

$$W(p_r, p_g) = \frac{1}{K} \sup_{\|f\|_L \leq K} \mathbb{E}_{x \sim p_r}[f(x)] - \mathbb{E}_{x \sim p_g}[f(x)]$$

미분 가능한 연속함수로 대체하려고 등장한 수식

$$W(p_r, p_g) = \max_{w \in W} \mathbb{E}_{x \sim p_r}[f_w(x)] - \mathbb{E}_{z \sim p_r(z)}[f_w(g_\theta(z))]$$

딥러닝이 수식을 최대로 만드는 f를 찾으면 된다

f(x) 직접 계산해내는 건 불가능하니,

딥러닝을 통해 fw(x)를 찾아보자.

새로운 수식은 까다로움. 사용을 위해 다음의 조건을 만족해야 함.

1. 유도된 W 함수 ≦ 기존 W 함수
2. 특정 조건을 만족하는 우리에게 필요한 **상상속의 f 함수** 특징
   a. 특정 조건(K-lipschitz 연속)을 만족해야만 수식이 성립
   b. K=1: f 함수는 어떤 지점에서도 **기울기**가 1을 넘지 않음을 의미

WGAN Loss Function

$$W(p_r, p_g) = \max_{w \in W} \mathbb{E}_{x \sim p_r}[f_w(x)] - \mathbb{E}_{z \sim p_r(z)}[f_w(g_\theta(z))]$$

- Critic 손실 함수
  - W를 최대화 => -W를 최소화

$$L^{(D)} = -\mathbb{E}_{x \sim p_{data}} D_w(x) + \mathbb{E}_z D_w(G(z))$$

log가 없음.

최종 sigmoid activation을 사용하지 않음.

- Generator 손실 함수
  - W를 최소화

$$L^{(G)} = -\mathbb{E}_z D_w(G(z))$$

수식을 간결히 하기 위해 사용하는

판별함수의 정답

- real: 1.0
- fake: -1.0

WGAN Model - loss

```
class WGAN(tf.keras.Model):
    ...
    def critic_loss(self, y_real, y_fake):
        y_true = tf.concat([-tf.ones_like(y_real), tf.ones_like(y_fake)], axis=0)
        y_pred = tf.concat([y_real, y_fake], axis=0)
        c_loss = -tf.reduce_mean(y_true * y_pred)
        return c_loss

    def generator_loss(self, y_fake):
        g_loss = -tf.reduce_mean(-tf.ones_like(y_fake) * y_fake)
        return g_loss

    def update_metrics(self, g_loss, c_loss):
        self.g_loss_metric.update_state(g_loss)
        self.c_loss_metric.update_state(c_loss)
```

수식을 간결히 하기 위해 사용하는 판별함수의 정답

- real: −1.0
- fake: 1.0

$$L^{(D)} = -\mathbb{E}_{x\sim p_{data}} D_w(x) + \mathbb{E}_z D_w(G(z))$$

$$L^{(G)} = -\mathbb{E}_z D_w(G(z))$$

코드의 의미. D(x) =〉

- 정답을 맞추면 1 (1, 1) or (−1, −1)
- 정답을 틀리면 −1 (1, −1) or (−1, 1)

고생했어요.

쉬어갑시다.

WGAN 의미와 한계

- 의미
  - GAN 분야에서 학습이 잘 안되던 문제를 해결한 핵심 논문
  - 판별기가 먼저 학습이 끝나도 generator가 안정적으로 학습할 수 있게 되었다.
    - 실제 구현도 판별기 5회 학습과 생성기 1회 학습의 페어로 제안,
- 한계
  - 1-lipschitz 조건을 만족시키기 위한 방법이 weight clipping이라는 비효율적인 방법.
    - 휴리스틱한 방법의 제안. 학습된 weight가 clipping 포인트에 몰린다.
  - Momentum-based Optimizer로는 학습이 잘 안됨.