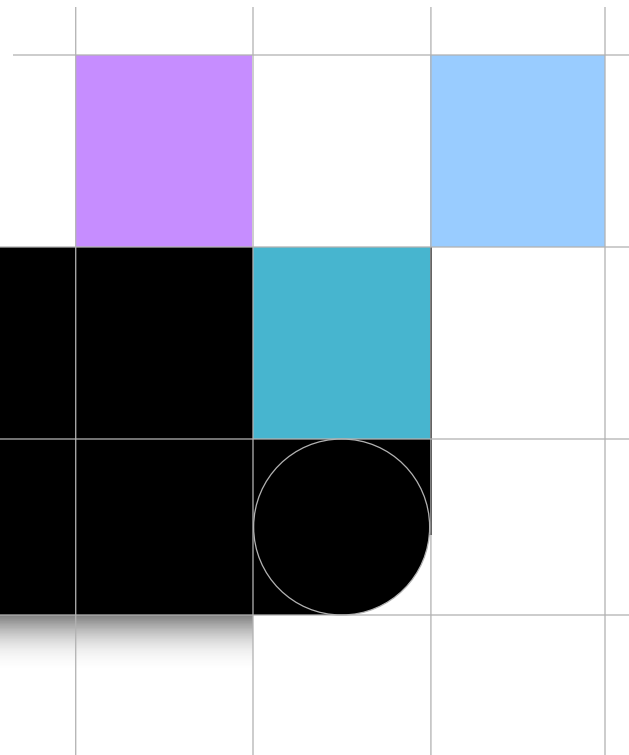


## Chapter 15

# Object Detection, GAN

오 세 종

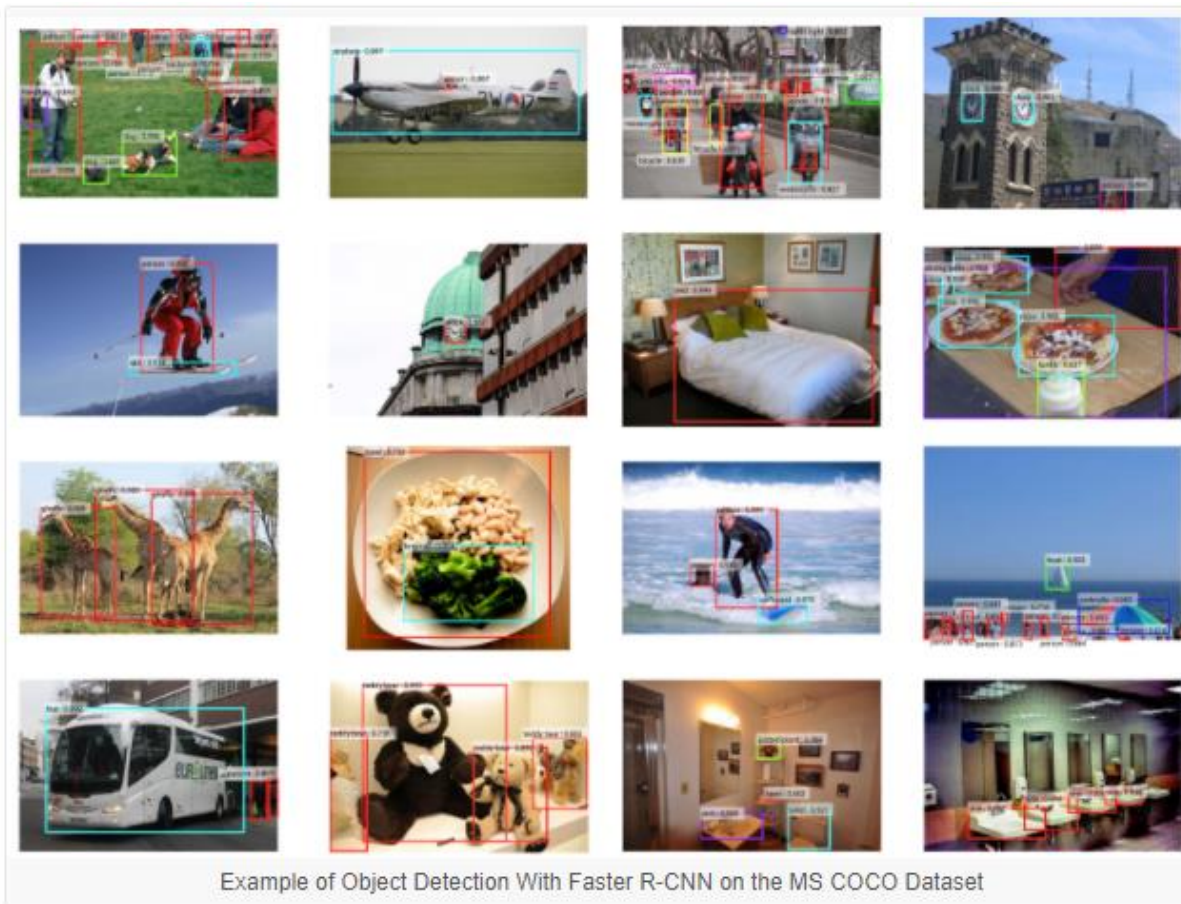


# Contents



1. Object Detection
2. GAN
3. Applications of GAN

# 1. Object Detection

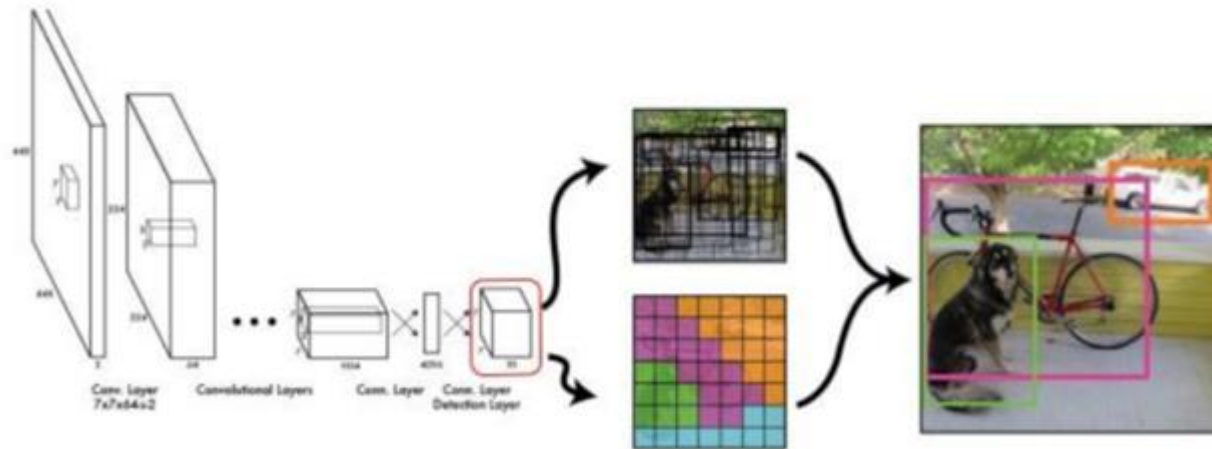


- 학습시 이미지데이터 + object 좌표(xywh) with 레이블 필요
- <https://blog.roboflow.com/how-to-train-yolov8-on-a-custom-dataset/>
- 예측결과: object 좌표(xywh) with 레이블

# 1. Object Detection

- YOLO model
  - 조셉 레드몬에 의해 2015년 소개
  - real time object detection 추구
  - 9000 개 이상의 object 탐지

YOLO: You Only Look Once



<https://www.datascienceprophet.com/object-detection-with-yolo-exploring-the-latest-deep-learning-techniques/>

# 1. Object Detection

- Example: Keras-cv + YOLO model
  - requirement

```
pip install keras-cv  
pip install opencv-python
```

# 1. Object Detection

15\_Object detection example.py

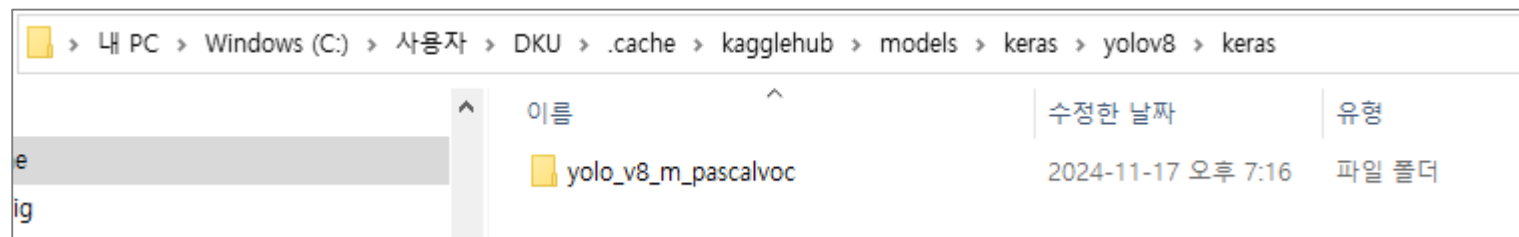
```
import os

os.environ["KERAS_BACKEND"] = "tensorflow"

import keras
import keras_cv
import numpy as np

from keras_cv import visualization
import matplotlib.pyplot as plt

# Load a pretrained model
pretrained_model = keras_cv.models.YOLOV8Detector.from_preset(
    "yolo_v8_m_pascalvoc", bounding_box_format="xywh"
)
```



# 1. Object Detection

```
# Load an image from a URL or local path
filepath = "C:/Users/DKU/Downloads/gCNcJJI.jpeg"
image = keras.utils.load_img(filepath)
image = np.array(image)

visualization.plot_image_gallery(
    np.array([image]),
    value_range=(0, 255),
    rows=1,
    cols=1,
    scale=5,
)
plt.show()
```



# 1. Object Detection

```
# resize image
inference_resizing = keras_cv.layers.Resizing(
    640, 640, pad_to_aspect_ratio=True,
    bounding_box_format="xywh"
)

image_batch = inference_resizing([image])

class_ids = [
    "Aeroplane", "Bicycle", "Bird", "Boat", "Bottle",
    "Bus", "Car", "Cat", "Chair", "Cow", "Dining Table",
    "Dog", "Horse", "Motorbike", "Person", "Potted Plant",
    "Sheep", "Sofa", "Train", "Tvmonitor", "Total", ]

class_mapping = dict(zip(range(len(class_ids)), class_ids))
```

```
>>> class_mapping
{0: 'Aeroplane', 1: 'Bicycle', 2: 'Bird', 3: 'Boat', 4: 'Bottle', 5: 'Bus', 6: 'Car', 7: 'Cat', 8: 'Chair', 9: 'Cow',
 10: 'Dining Table', 11: 'Dog', 12: 'Horse', 13: 'Motorbike', 14: 'Person', 15: 'Potted Plant', 16: 'Sheep', 17: 'Sof
a', 18: 'Train', 19: 'Tvmonitor', 20: 'Total'}
```





# 1. Object Detection

```
visualization.plot_bounding_box_gallery(  
    image_batch,  
    value_range=(0, 255),  
    rows=1,  
    cols=1,  
    y_pred=y_pred,  
    scale=5,  
    font_scale=0.7,  
    bounding_box_format="xywh",  
    class_mapping=class_mapping,  
)  
plt.show()
```

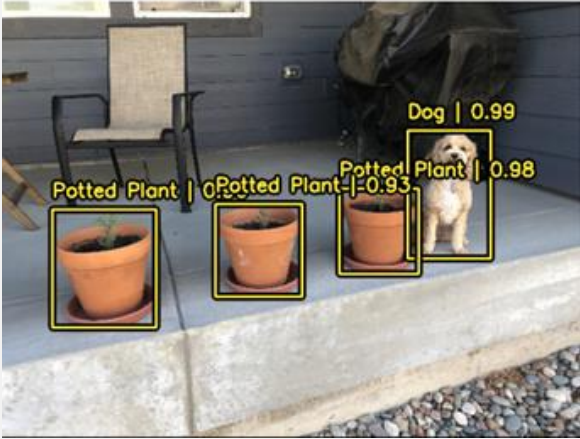


## [Exercise]

- 이미지를 load하면 object detection 결과를 보여주는 앱을 개발한다

Object Detection Test

Load image

The image shows a small dog sitting on a concrete ledge next to three potted plants. Yellow bounding boxes are drawn around each of the three potted plants and the dog. Labels with confidence scores are placed above each box: 'Potted Plant | 0.96' for the first plant, 'Potted Plant | 0.95' for the second, 'Potted Plant | 0.93' for the third, and 'Dog | 0.99' for the dog.

Object list

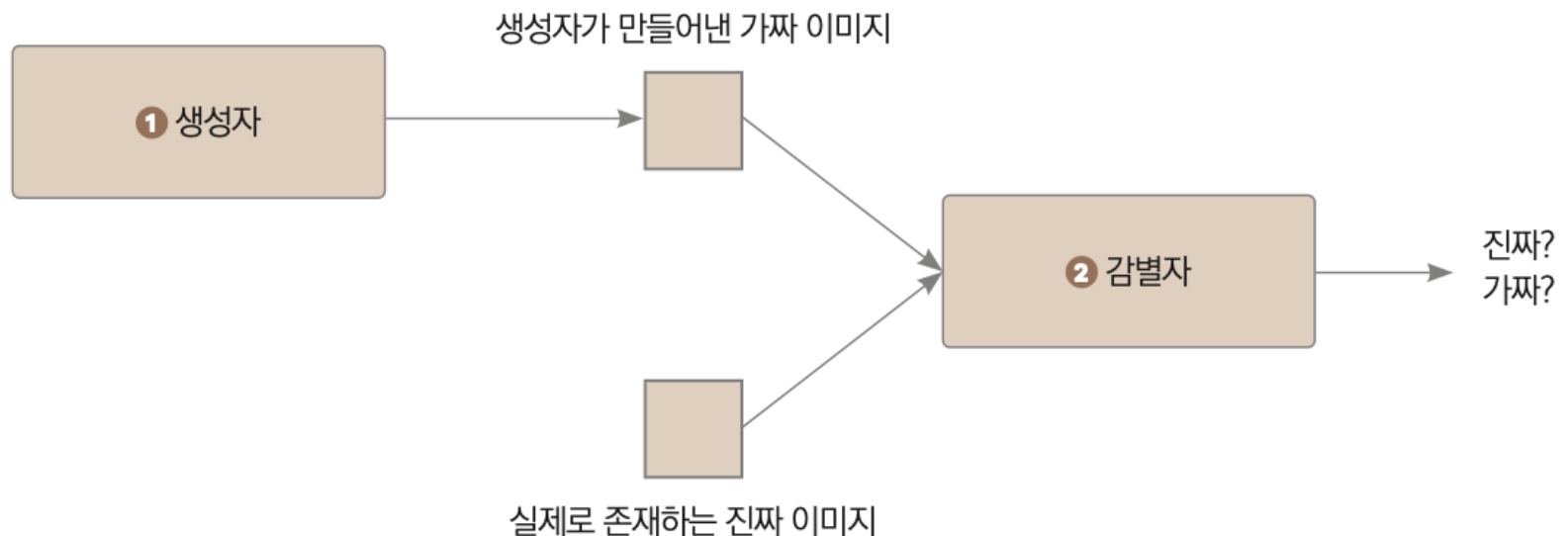
---

1. Dog (0.99)
2. Potted Plant (0.96)
3. Potted Plant (0.95)
4. Potted Plant (0.93)

## 2. GAN

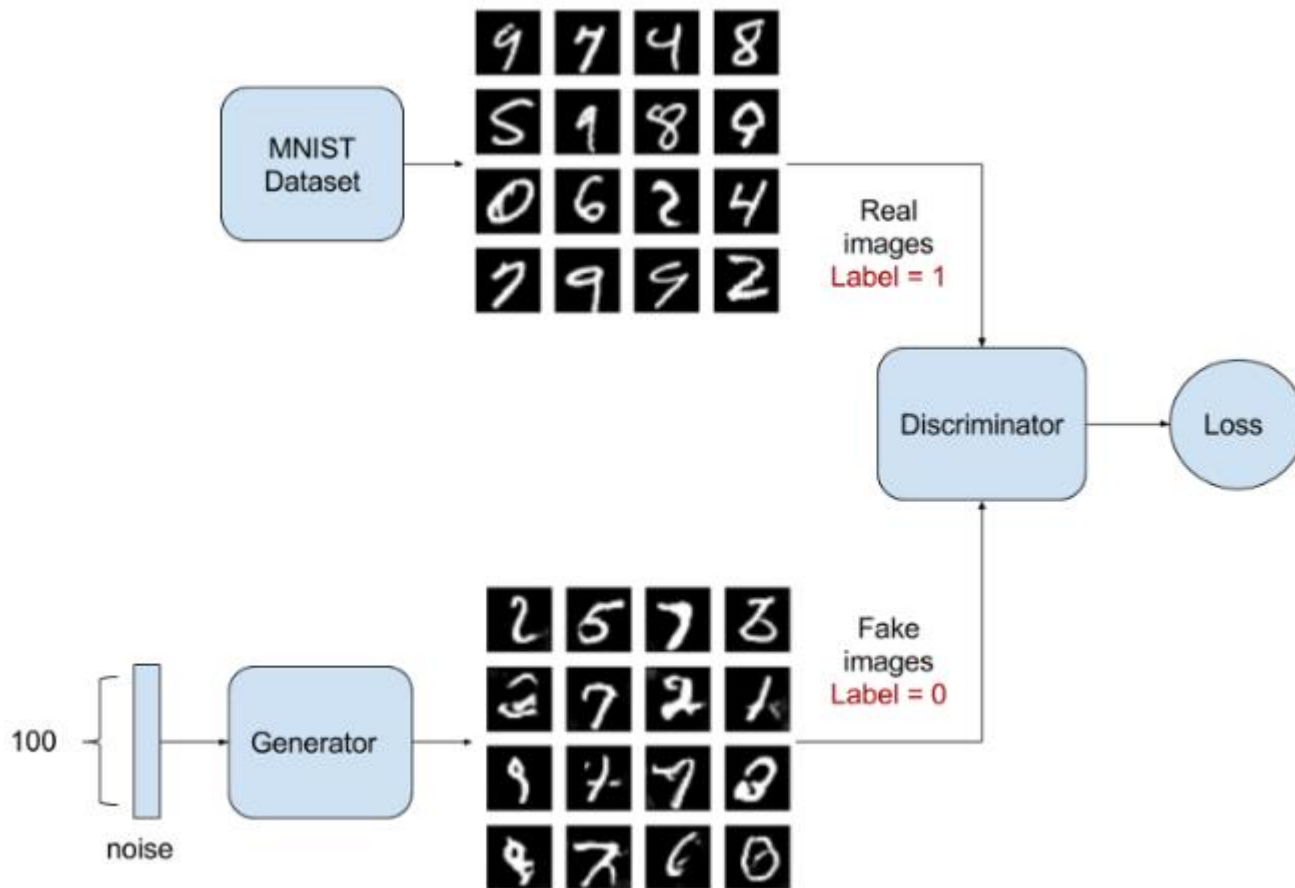
- GAN (Generative Adversarial Networks)

- 진짜와 너무나도 똑같아서 구별이 가지 않는 가짜 그림이 있다고 하면, 그 그림은 진짜일까, 가짜일까
- GAN은 이런 생각에서 출발한 모델
- ❶ 가짜 이미지를 만들어내도록 학습되는 생성자와 ❷ 가짜와 진짜 이미지를 구별하는 감별자를 경쟁시켜 학습하면, 생성자가 점점 진짜와 같은 이미지를 만들게 되는 원리



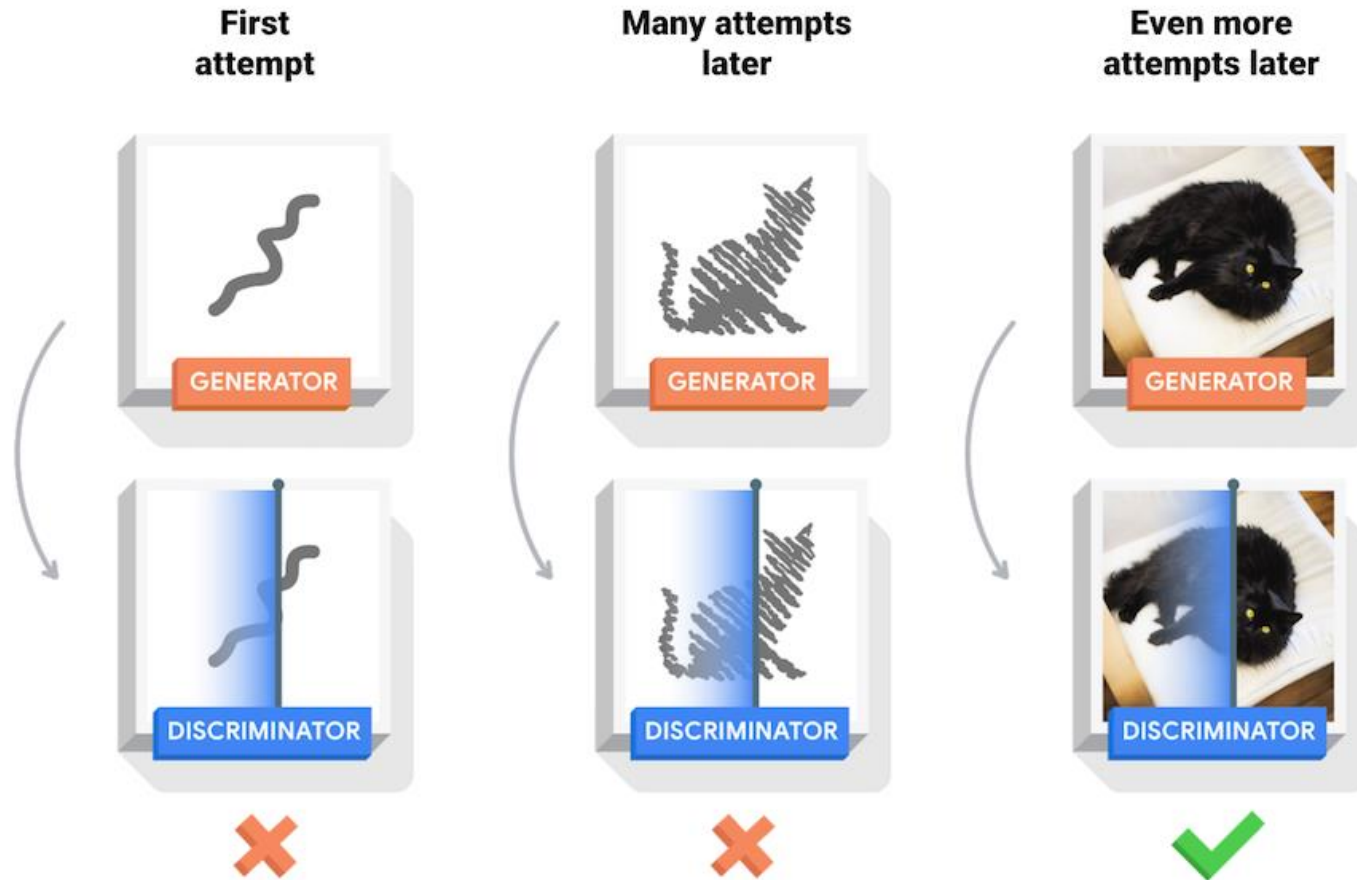
## 2. GAN

- Gan concept



<https://towardsdatascience.com/gan-by-example-using-keras-on-tensorflow-backend-1a6d515a60d0>

## 2. GAN



<https://www.tensorflow.org/tutorials/generative/dcgan?hl=ko>

## 2. GAN

### ● GAN의 장단점

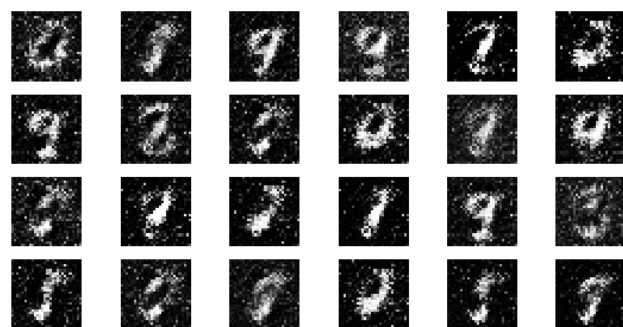
#### ▼ GAN 장단점

장점	단점
<ul style="list-style-type: none"><li>일반적인 학습 방법에 비해 자연스러운 이미지를 생성할 수 있습니다.</li><li>정답과 단순히 비교하는 것이 아니라, 감별자를 이용해 학습하므로 좋은 성능을 낼 수 있습니다.</li></ul>	<ul style="list-style-type: none"><li>학습이 올바르게 이루어지기 어렵고 필요한 데이터 수가 많아야 합니다.</li><li>사용하는 특징의 개수에 매우 민감하기 때문에 좋은 성능을 내는 특징의 개수를 정하기 어렵습니다.</li></ul>

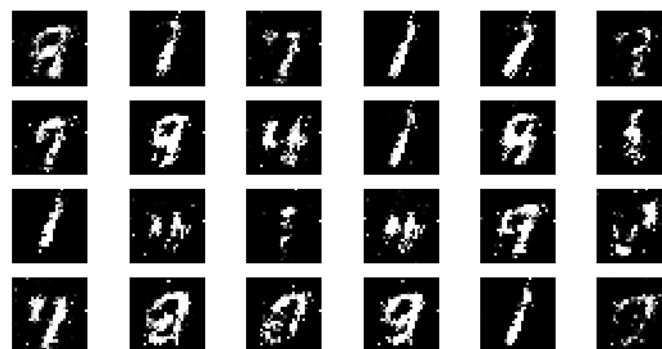
#### ▼ GAN 장단점

<ul style="list-style-type: none"><li>이미지 생성, 화질 올리기 등</li><li>인코더 디코더에서 디코더를 학습할 때 사용하기 좋습니다.</li></ul>
--

## Real images

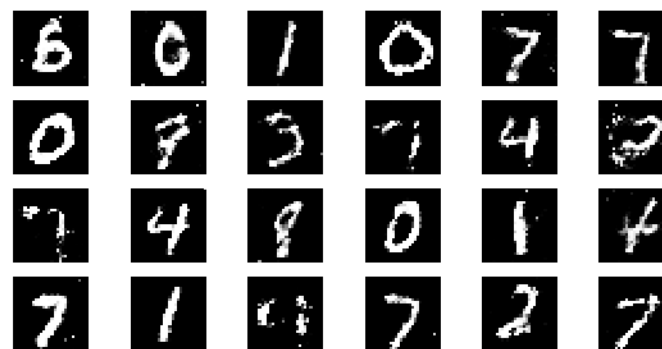


epoch 1



epoch 50

## Fake images

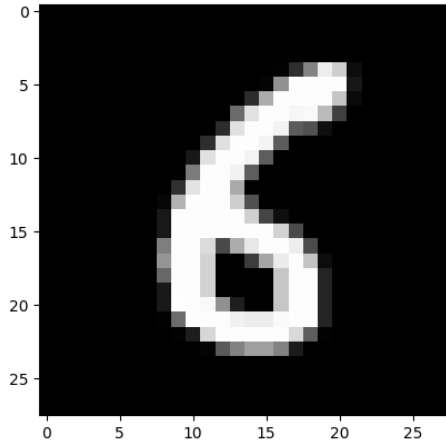


epoch 50

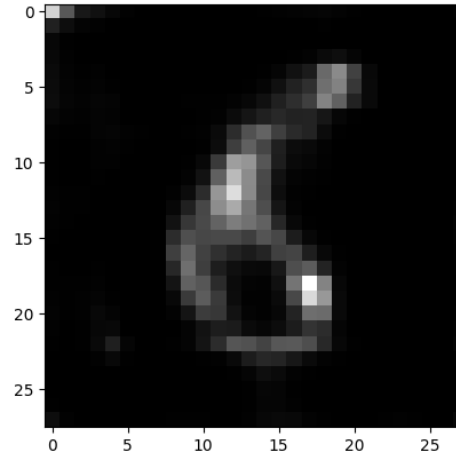


## 2. GAN

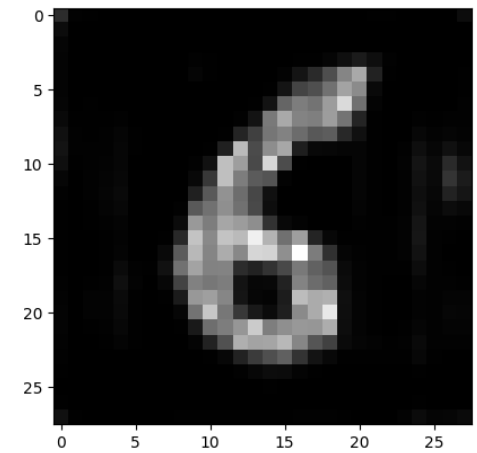
- 존재하지 않는 숫자의 이미지를 생성해 보자



실제 이미지



GAN으로 생성한  
가짜 이미지  
(epoch=300)



GAN으로 생성한  
가짜 이미지  
(epoch=500)

## 2. GAN

- Note

- Keras 3.6 버전에서는 GAN code 실행이 안되니 3.4.1 버전으로 downgrade 할 것

```
pip install keras==3.4.1  
pip install tensorflow==2.16.2
```

## 2. GAN

- Import modules

15\_keras\_GAN\_example.py

```
import numpy as np
import keras.backend as K
from keras.models import Sequential
from keras.layers import Conv2D, Activation, Dropout, Flatten,
    Dense, BatchNormalization, Reshape, UpSampling2D, LeakyReLU
from keras.optimizers import RMSprop
from keras.preprocessing import image
from keras.preprocessing.image import array_to_img
from skimage import color

import warnings ; warnings.filterwarnings('ignore')

import matplotlib.pyplot as plt
from tqdm import tqdm                                # progress bar
```

## 2. GAN

- Prepare data

```
K.clear_session()

# load data
img = image.load_img('d:/data/6_img.png', target_size=(28,28))
img = color.rgb2gray(img)
img_array_train = image.img_to_array(img)
img_array_train = np.expand_dims(img_array_train, axis=0)

Xtrain = img_array_train
Xtrain = Xtrain / 255

img_shape = (img_array_train.shape[1], img_array_train.shape[2],
             img_array_train.shape[3])    # row, col, channel
```

```
>>> img_shape
(28, 28, 1)
```

## 2. GAN

- 판별자(discriminator) 만들기

```
discriminator = Sequential()  
discriminator.add(Conv2D(64, kernel_size=(5, 5),  
                        input_shape=img_shape,  
                        strides=2, padding='same',  
                        activation=LeakyReLU(alpha=0.2)))  
discriminator.add(Dropout(rate=0.4))  
discriminator.add(Conv2D(64, kernel_size=(5, 5),  
                        strides=2, padding='same',  
                        activation=LeakyReLU(alpha=0.2)))  
discriminator.add(Dropout(rate=0.4))  
discriminator.add(Conv2D(128, kernel_size=(5, 5),  
                        strides=2, padding='same',  
                        activation=LeakyReLU(alpha=0.2)))  
discriminator.add(Dropout(rate=0.4))  
discriminator.add(Flatten())  
discriminator.add(Dense(units=1, activation='sigmoid' ))  
  
discriminator.summary()
```

## 2. GAN

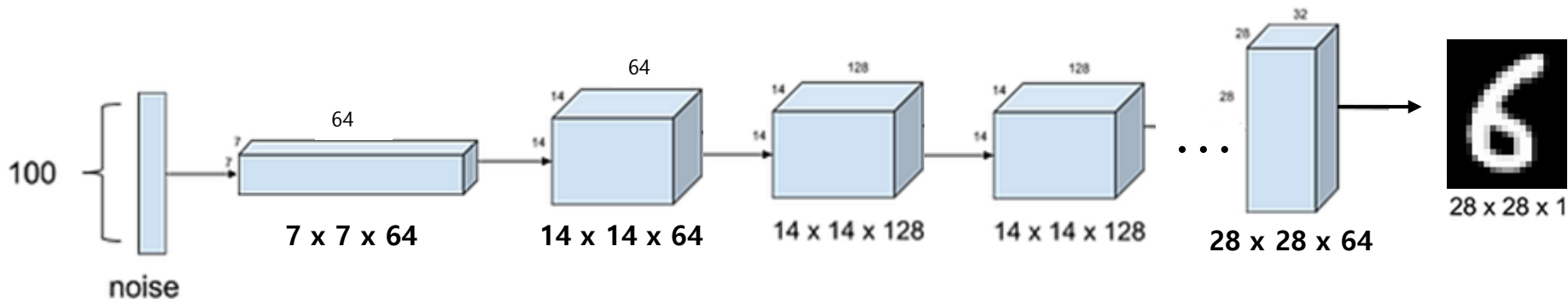
```
>>> discriminator.summary()  
Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 14, 14, 64)	1,664
dropout (Dropout) conv2d_1 (Conv2D)	(None, 14, 14, 64) (None, 7, 7, 64)	0 102,464
dropout_1 (Dropout)	(None, 7, 7, 64)	0
conv2d_2 (Conv2D)	(None, 4, 4, 128)	204,928
dropout_2 (Dropout)	(None, 4, 4, 128)	0
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 1)	2,049

```
Total params: 311,105 (1.19 MB)  
Trainable params: 311,105 (1.19 MB)  
Non-trainable params: 0 (0.00 B)
```

## 2. GAN

- 생성자 구조



[BatchNormalization]

- 딥러닝 모델에서 학습을 안정화하는 데 사용되는 Keras 레이어
- 그래디언트 소실 문제를 완화, 모델의 가중치 초기화에 덜 민감, 상대적으로 큰 학습률 사용으로 학습 속도가 빨라짐, 정규화를 통해 과적합(overfitting) 문제를 방지

## 2. GAN

- 생성자 만들기

```
gen_dense_size=(7, 7, 64)

generator = Sequential()
generator.add(Dense(units=np.prod(gen_dense_size),
                        input_shape=(100,)))
generator.add(BatchNormalization())
generator.add(Activation('relu'))
generator.add(Reshape(gen_dense_size))

generator.add(UpSampling2D())           # 이미지 사이즈를 2배로
generator.add(Conv2D(filters = 128, kernel_size=5,
                        padding='same', strides=1))
generator.add(BatchNormalization(momentum=0.9))
generator.add(Activation('relu'))
```



## 2. GAN

```
generator.add(UpSampling2D())
generator.add(Conv2D(filters = 64, kernel_size=5,
                    padding='same', strides=1))
generator.add(BatchNormalization(momentum=0.9))
generator.add(Activation('relu'))

generator.add(Conv2D(filters = 64, kernel_size=5,
                    padding='same', strides=1))
generator.add(BatchNormalization(momentum=0.9))
generator.add(Activation('relu'))

generator.add(Conv2D(filters = 1, kernel_size=5,
                    padding='same', strides=1))
generator.add(Activation('sigmoid'))

generator.summary()
```

```
>>> generator.summary()  
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 3136)	316,736
batch_normalization (BatchNormalization)	(None, 3136)	12,544
activation (Activation)	(None, 3136)	0
reshape (Reshape)	(None, 7, 7, 64)	0
up_sampling2d (UpSampling2D)	(None, 14, 14, 64)	0
conv2d_3 (Conv2D)	(None, 14, 14, 128)	204,928
batch_normalization_1 (BatchNormalization)	(None, 14, 14, 128)	512
activation_1 (Activation) up_sampling2d_1 (UpSampling2D)	(None, 14, 14, 128) (None, 28, 28, 128)	0 0
conv2d_4 (Conv2D)	(None, 28, 28, 64)	204,864
batch_normalization_2 (BatchNormalization)	(None, 28, 28, 64)	256
activation_2 (Activation)	(None, 28, 28, 64)	0
conv2d_5 (Conv2D)	(None, 28, 28, 64)	102,464
batch_normalization_3 (BatchNormalization)	(None, 28, 28, 64)	256
activation_3 (Activation)	(None, 28, 28, 64)	0
conv2d_6 (Conv2D)	(None, 28, 28, 1)	1,601
activation_4 (Activation)	(None, 28, 28, 1)	0

Total params: 844,161 (3.22 MB)  
Trainable params: 837,377 (3.19 MB)  
Non-trainable params: 6,784 (26.50 KB)

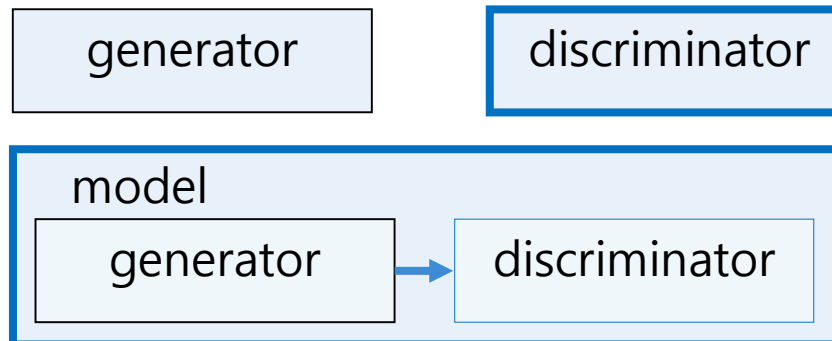
## 2. GAN

- Model compile

```
discriminator.compile(optimizer=RMSprop(learning_rate=0.0008),  
                      loss='binary_crossentropy',  
                      metrics=['accuracy'])
```


```
model = Sequential()  
model.add(generator)  
model.add(discriminator)
```

```
model.compile(optimizer=RMSprop(learning_rate=0.0004),  
              loss='binary_crossentropy',  
              metrics=['accuracy'])
```



## 2. GAN

- Fitting

```
def train_discriminator(x_train, batch_size):  
    valid = np.ones((batch_size, 1))  
    fake = np.zeros((batch_size, 1))  
  
    idx = np.random.randint(0, len(x_train), batch_size)   
    true_imgs = x_train[idx]  
    discriminator.fit(true_imgs, valid, verbose=0)  
  
    noise = np.random.normal(0, 1, (batch_size, 100))  
    gen_imgs = generator.predict(noise)  
  
    discriminator.fit(gen_imgs, fake, verbose=0)  
  
def train_generator(batch_size):  
    valid = np.ones((batch_size, 1))  
    noise = np.random.normal(0, 1, (batch_size, 100))  
    model.fit(noise, valid, verbose=1)
```

## 2. GAN

```
for epoch in tqdm(range(500)):                                # Try 2000
    train_discriminator(Xtrain, 64)
    train_generator(64)
```

```
2/2 [=====] - 0s 195ms/step - loss: 1.5415 - accuracy: 0.3281
2/2 [=====] - 0s 57ms/step [redacted] | 293/300 [04:09<00:05, 1.19it/s]
2/2 [=====] - 0s 197ms/step - loss: 1.5356 - accuracy: 0.0625
2/2 [=====] - 0s 56ms/step [redacted] | 294/300 [04:10<00:04, 1.21it/s]
2/2 [=====] - 0s 272ms/step - loss: 2.5275 - accuracy: 0.1406
2/2 [=====] - 0s 59ms/step [redacted] | 295/300 [04:11<00:04, 1.19it/s]
2/2 [=====] - 1s 293ms/step - loss: 1.9715 - accuracy: 0.0781
2/2 [=====] - 0s 67ms/step [redacted] | 296/300 [04:12<00:03, 1.10it/s]
2/2 [=====] - 0s 190ms/step - loss: 1.7042 - accuracy: 0.3750
2/2 [=====] - 0s 64ms/step [redacted] | 297/300 [04:13<00:02, 1.10it/s]
2/2 [=====] - 0s 224ms/step - loss: 1.8096 - accuracy: 0.1719
2/2 [=====] - 0s 56ms/step [redacted] | 298/300 [04:14<00:01, 1.13it/s]
2/2 [=====] - 0s 196ms/step - loss: 1.5157 - accuracy: 0.3125
2/2 [=====] - 0s 57ms/step [redacted] | 299/300 [04:14<00:00, 1.16it/s]
2/2 [=====] - 0s 184ms/step - loss: 1.7288 - accuracy: 0.1406
100% [redacted] | 300/300 [04:15<00:00, 1.17it/s]
```

## 2. GAN

```
for epoch in tqdm(range(300)):  
    train_discriminator(Xtrain, 64)  
    train_generator(64)
```

```
def train_discriminator(x_train, batch_size):  
    valid = np.ones((batch_size, 1))  
    fake = np.zeros((batch_size, 1))  
  
    {  
        idx = np.random.randint(0, len(Xtrain), batch_size)  
        true_imgs = Xtrain[idx]  
        discriminator.fit(true_imgs, valid, verbose=0)  
    }  
  
    {  
        noise = np.random.normal(0, 1, (batch_size, 100))  
        gen_imgs = generator.predict(noise)  
    }  
  
    {  
        discriminator.fit(gen_imgs, fake, verbose=0)  
    }  
  
def train_generator(batch_size):  
    valid = np.ones((batch_size, 1))  
    noise = np.random.normal(0, 1, (batch_size, 100))  
    model.fit(noise, valid, verbose=1)
```

true\_image valid (1)

discriminator

fit

noise

generator

predict

gen\_image

fake (0)

fit

discriminator

noise valid (1)

fit

model

generator

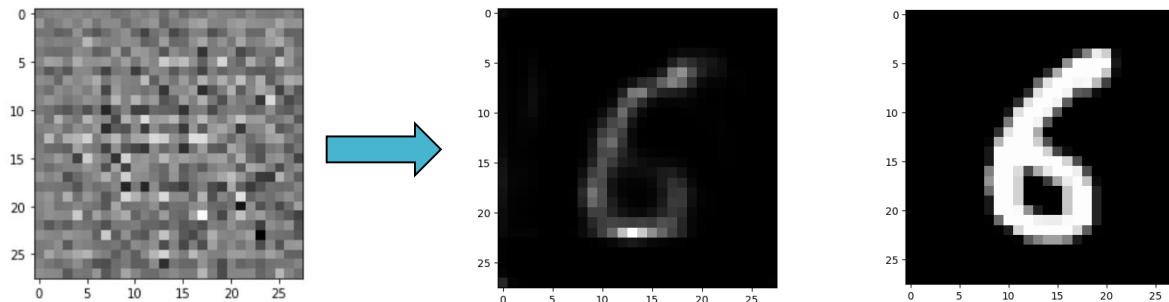
discriminator

generator 를 훈련

## 2. GAN

- Test

```
original=array_to_img(Xtrain[0])  
plt.imshow(original, cmap='gray')  
plt.show()  
  
np.random.seed(123)  
random_noise=np.random.normal(0, 1, (1, 100)) # source of fake image  
gen_result = generator.predict(random_noise)  
gen_img = array_to_img(gen_result[0])  
plt.imshow(gen_img, cmap='gray')  
plt.show()
```



## [실습]

- 1. 주어진 코드를 이용하여 진짜 이미지와 비슷한 가짜 이미지를 생성해 보자. (진짜 이미지는 각자 선택)
  - 진짜 이미지와 가짜이미지를 보인다
- Note. 주어진 코드는 28x28 이미지 학습에 맞도록 숫자들이 지정되어 있다. 선택한 이미지가 28x28 가 아니어도 코드가 작동하도록 코드를 수정하여 테스트 하시오

```
# load data  
img = image.load_img('d:/data/6_img.png', target_size=(28,28))
```

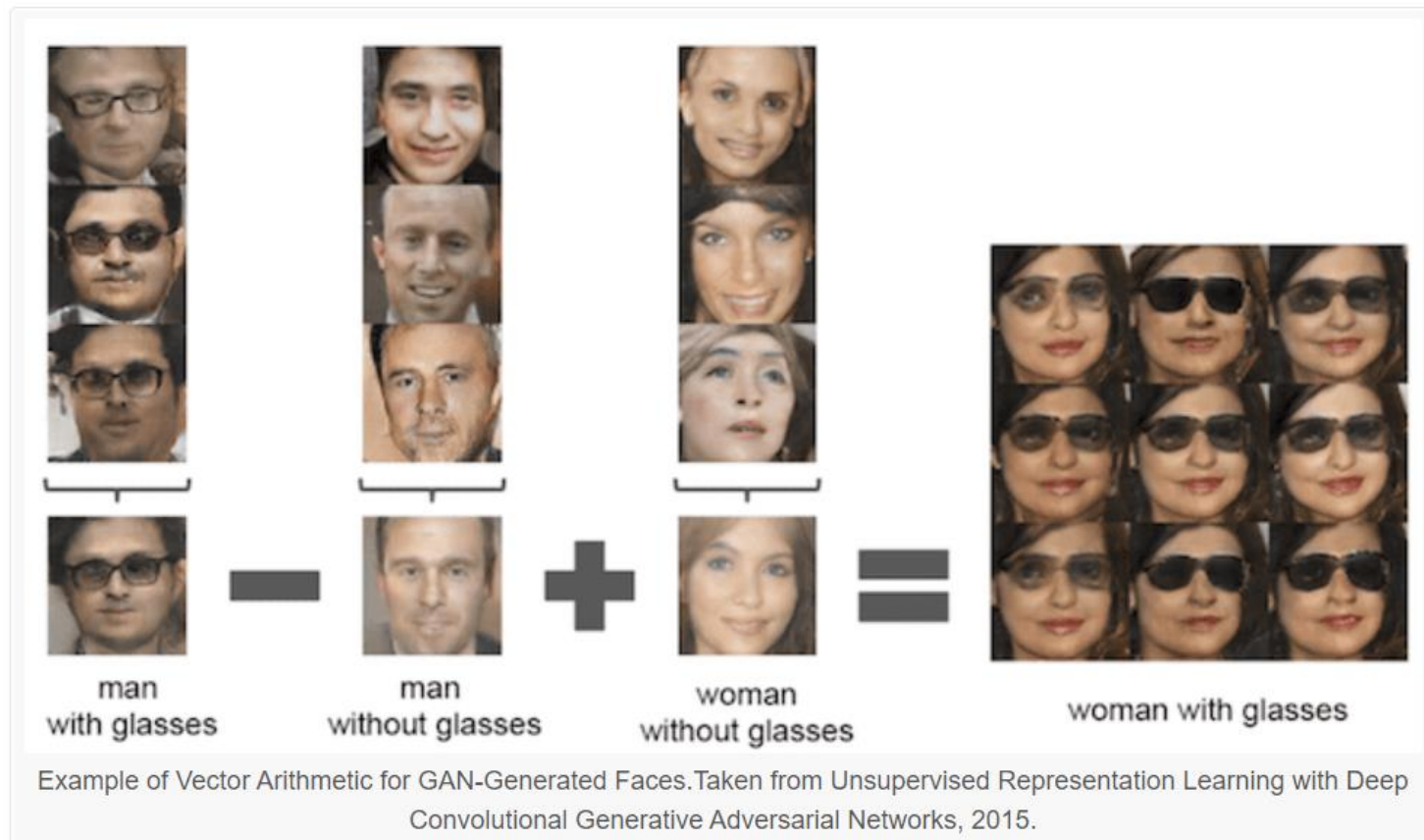
여기를 바꾸어도 작동하도록



# 3. Applications of GAN

- <https://machinelearningmastery.com/impressive-applications-of-generative-adversarial-networks/>

## 18 Impressive Applications of Generative Adversarial Networks (GANs)



# 3. Applications of GAN

- Sketches to Color Photographs



Example of Sketches to Color Photographs With pix2pix. Taken from Image-to-Image Translation with Conditional Adversarial Networks, 2016.

# 3. Applications of GAN

- Text to image translation

