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POSTECH Institute of Artificial Intelligence

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Keras Additional Functions

GyeongYeong Kim

ML/DL Lab 3rd Day

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- Keras Additional Functions
  - CIFAR10 Introduction
  - Model Summation
  - Data Augmentation
  - Transfer Learning
  - LSTM
  - GAN
- Pytorch Additional Functions
  - CIFAR10 Introduction
  - Data Augmentation
  - Transfer Learning
  - Training Customized Dataset
  - GAN

CNN – CIFAR 10

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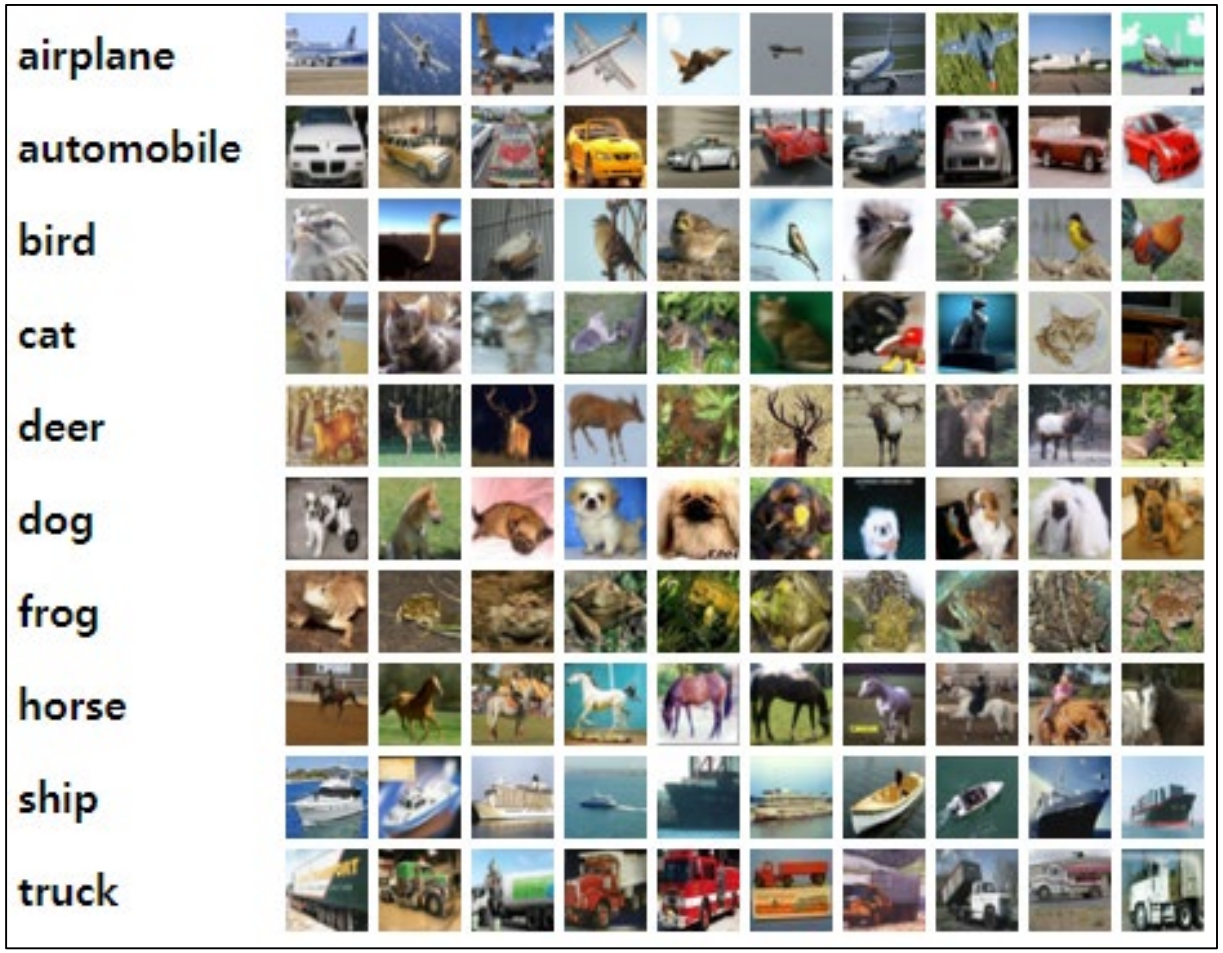
- **데이터셋 소개 – CIFAR 10**



- CIFAR-10은 열 가지의 class로 이루어진 공인 Dataset
- 비행기, 자동차, 새, 고양이, 사슴, 개, 개구리, 말, 배, 트럭으로 구성
- 32 × 32 픽셀의 3채널 RGB 이미지
- Class당 6,000개의 이미지로 이루어져 있으며 총 60,000장
- 5만장이 Train / 1만장이 Test
- 머신러닝 / 딥러닝 챌린징 분야에서 널리 사용되는 데이터셋

데이터셋 다운로드 링크: https://www.cs.toronto.edu/~kriz/cifar.html

Model Summation

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```python
def conv_maxpool_layers(n_in):
    # Coding Time
    model = Sequential()
    model.add(Conv2D(16, kernel_size=(3, 3), padding='same', activation='relu', input_shape=(n_in)))
    model.add(Conv2D(32, kernel_size=(3, 3), padding='same', strides=(2, 2), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Flatten())
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

def fc_layers(n_out):
    # Coding Time
    model = Sequential()
    model.add(Dense(units =128, input_shape=(2048,), activation='relu'))
    model.add(Dense(units =n_out, activation='softmax'))
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model
```

```python
def CNN_sum(n_in, n_out):
    feature_extractor=conv_maxpool_layers(n_in)
    feature_extractor.trainable=True
    ann_classifier = fc_layers(n_out)
    ann_classifier.trainable=True

    x = Input(shape=n_in)
    feature = feature_extractor(x)
    y = ann_classifier(feature)
    model = Model(inputs = x, outputs = y)
```

- trainable 특정 layer 중심으로 학습 여부를 설정할 수 있음 -> Fine Tuning 같은 역할을 할 수 있음
- Feature_extractor, ann_classifier이 customized layer같은 성격을 가질 수 있게 됨
- VGG / ResNet / InceptionNet에 있는 layer block 역할처럼도 쓰임!

Data Augmentation & Transfer Learning

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Collecting data is the most difficult thing

Data Augmentation & Transfer Learning

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Collecting data is
the most difficult thing

How to solve?

- Data Augmentation
- Transfer Learning
- Self-supervised Learning
- Semi-supervised Learning
- …

Data Augmentation

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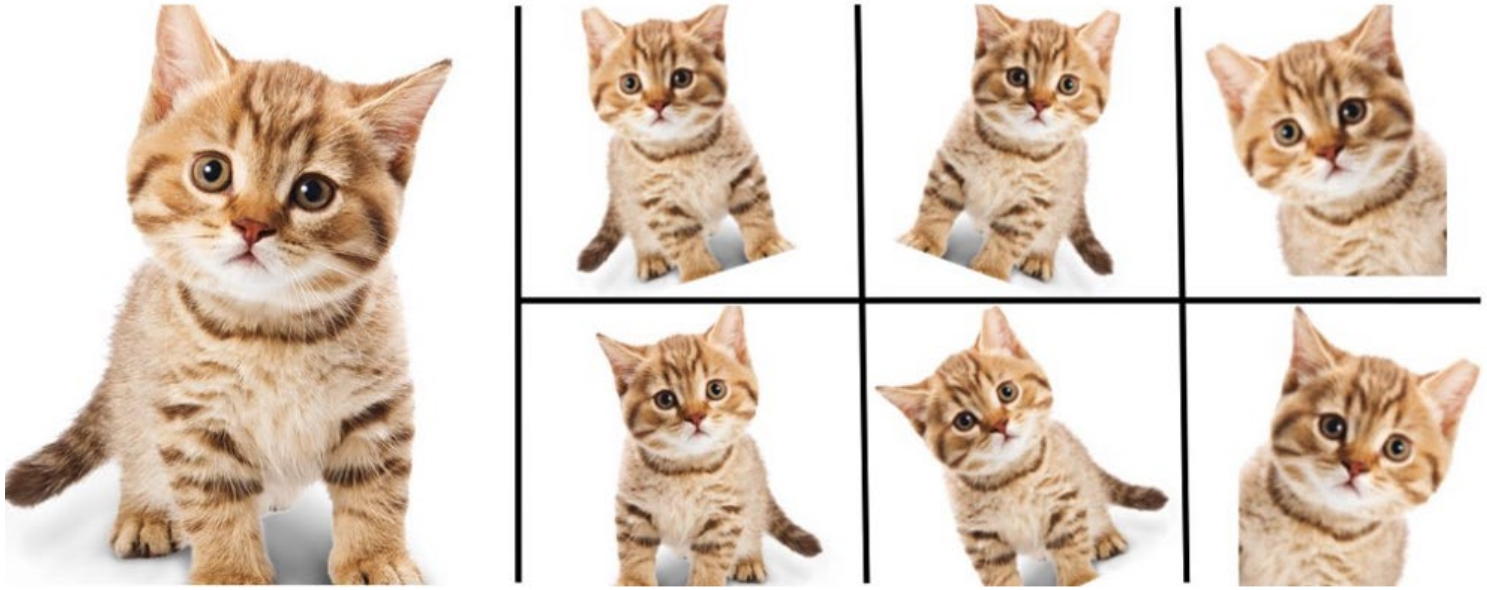

Enlarge your Dataset

Keras ImageDataGenerator

```
datagen = ImageDataGenerator(
    featurewise_center = False,
    samplewise_center = False,
    featurewise_std_normalization = False,
    samplewise_std_normalization = False,
    zca_whitening = False,
    rotation_range = 2, # 회전
    zoom_range = 0.1, # 확대 축소
    width_shift_range = 0.1, # 수평 이동
    height_shift_range = 0.1, # 수직 이동
    horizontal_flip = True, # 수평 반전
    vertical_flip = False # 수직 반전
)

datagen.fit(X_train)
```

```
model.fit(X_train, Y_train,
```

```
model.fit(datagen.flow(X_train[:-10000], Y_train[:-10000], batch_size = 1000),
```

Transfer Learning

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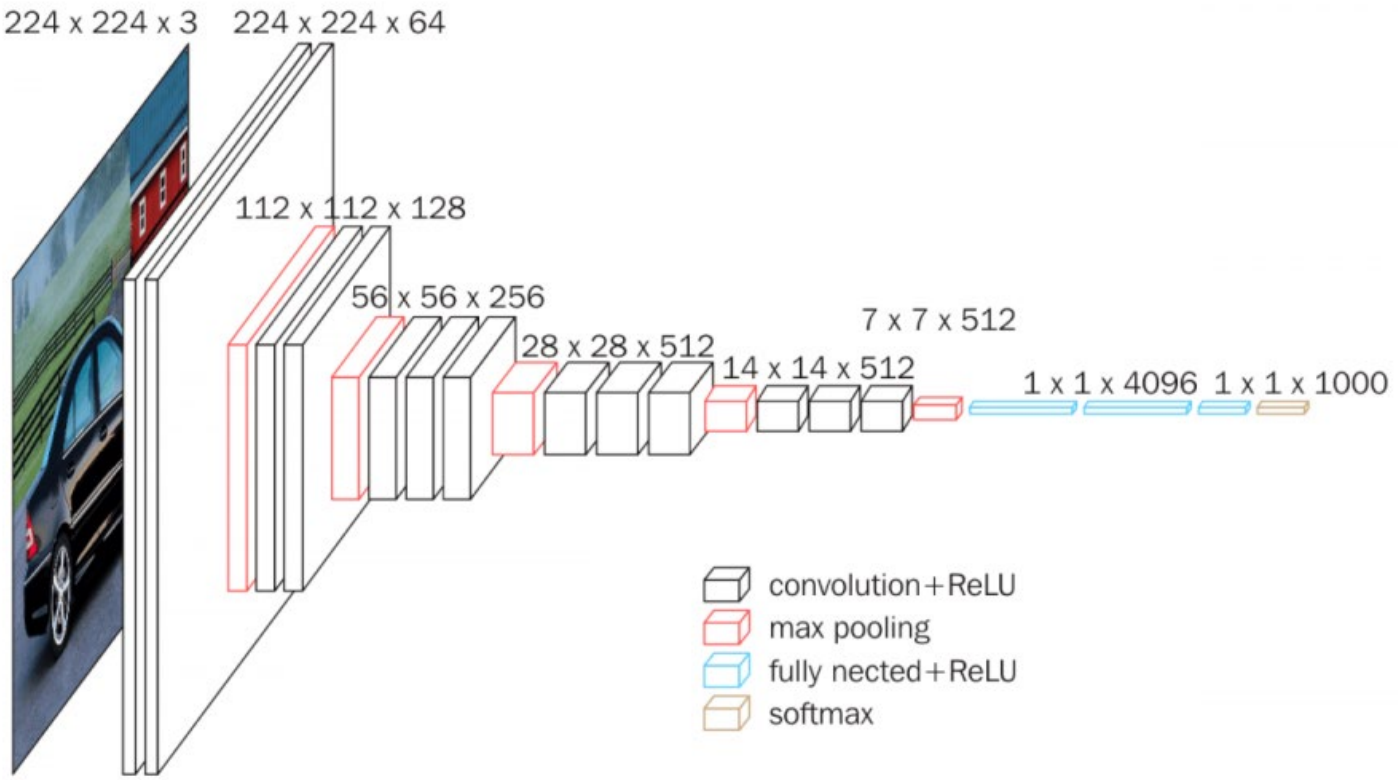
VGGNet



처음부터 모델을 구성하는 것이 아니라 기존에 존재하는 성능 좋은 모델을 가져와 학습하는 기법

Transfer Learning

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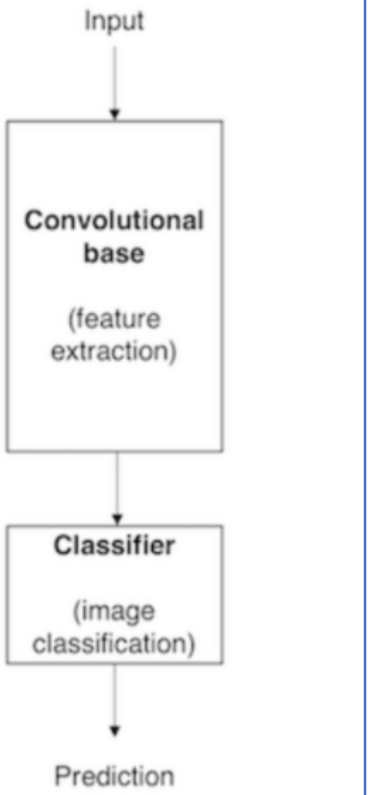
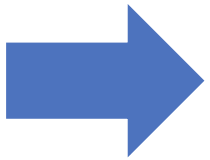
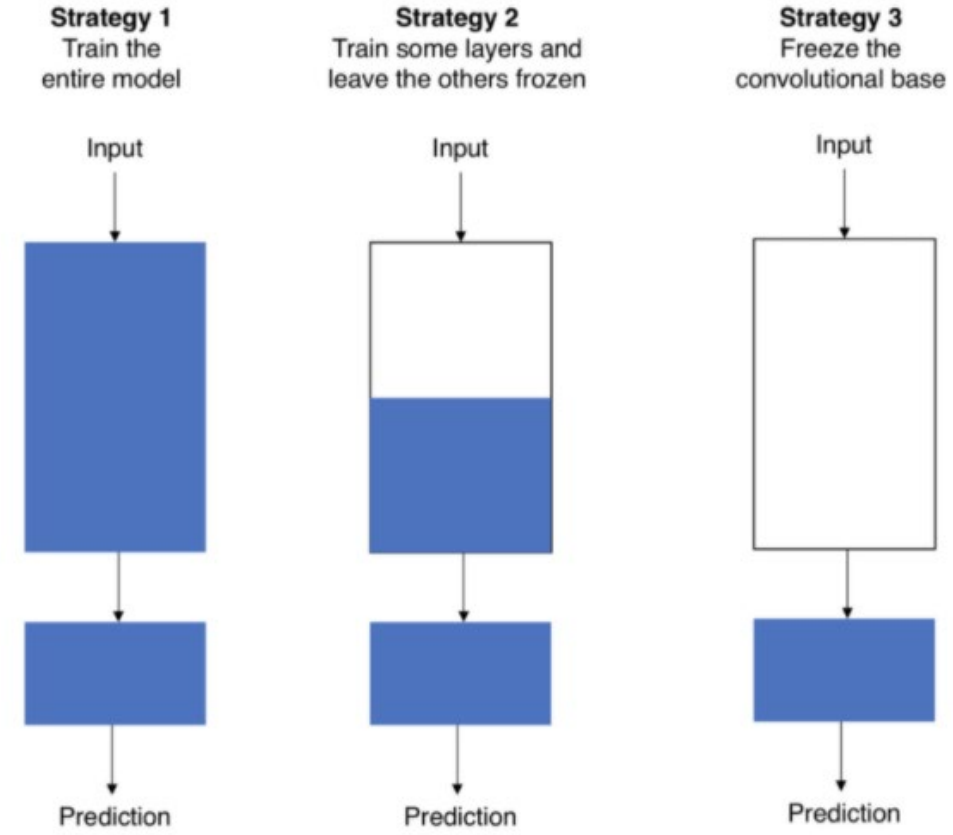
Pretrained model







Fine Tuning

Transfer Learning

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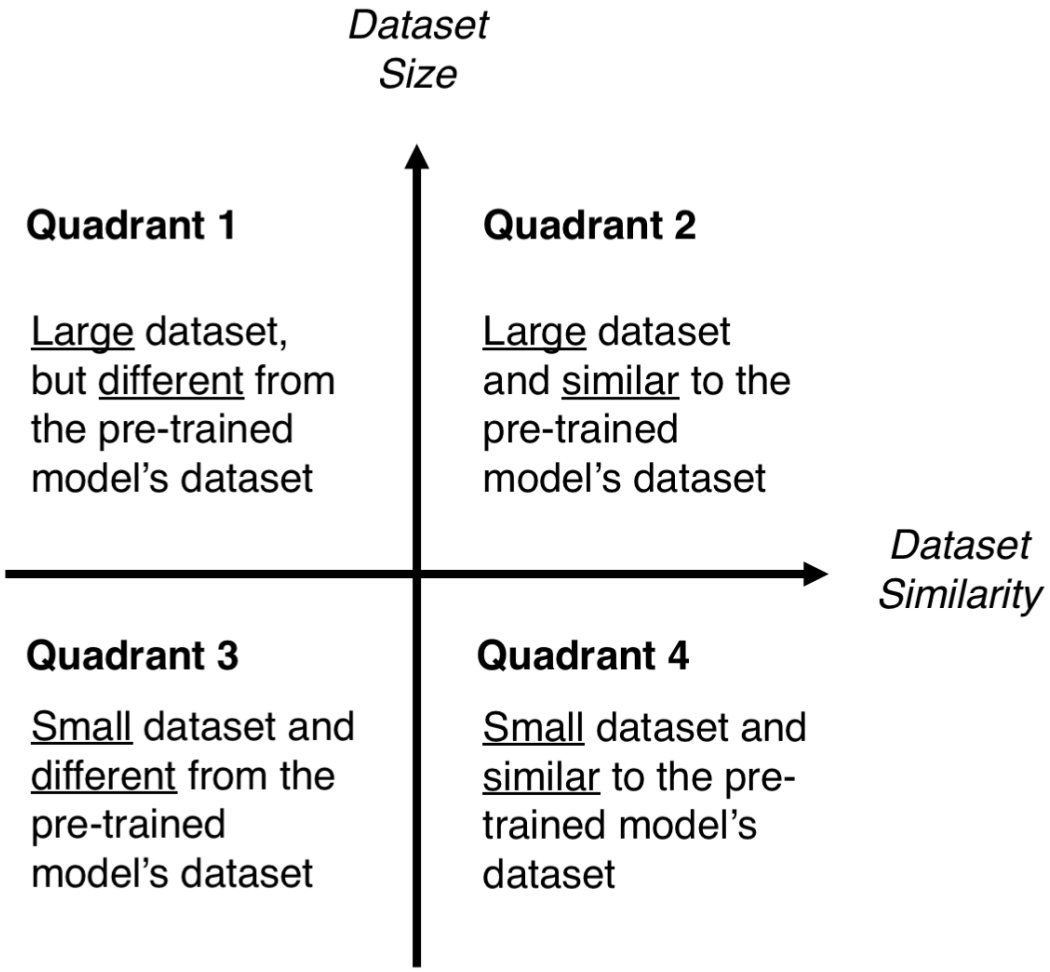

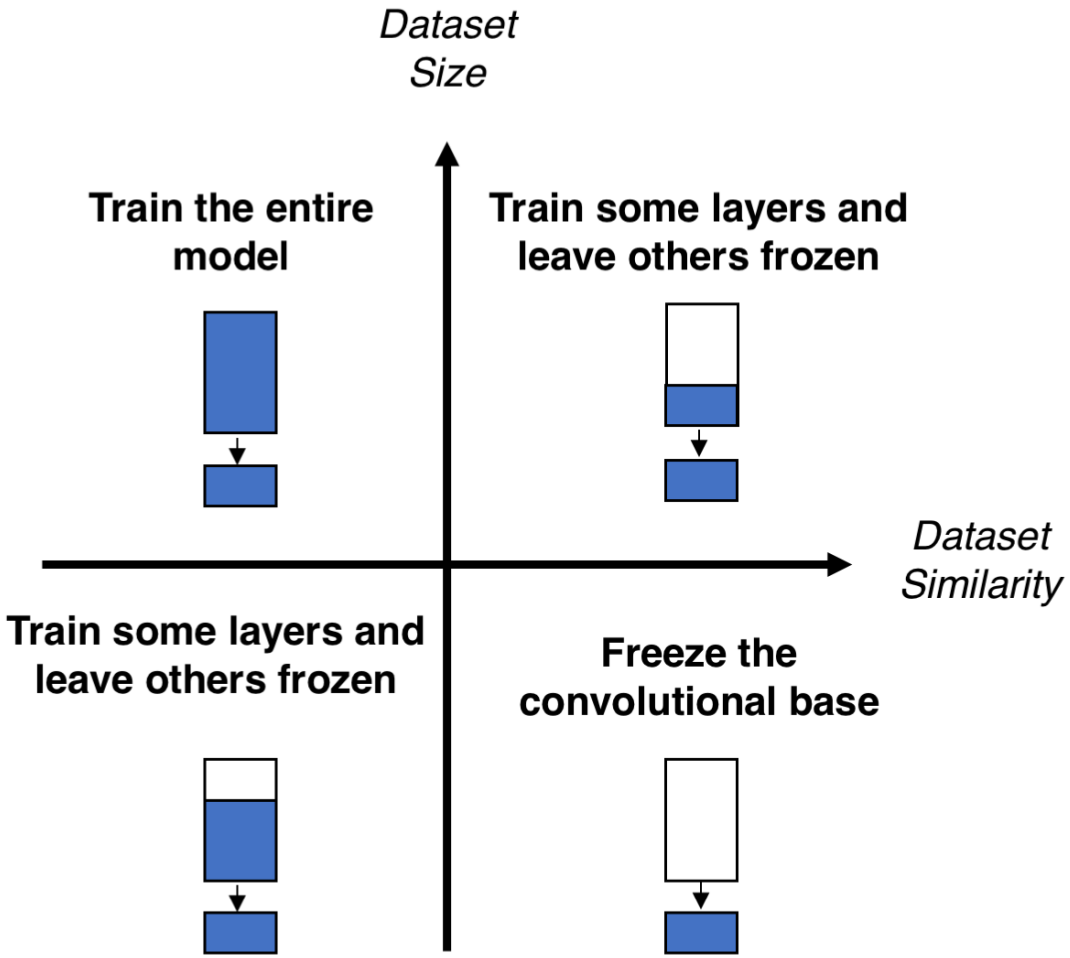

LSTM

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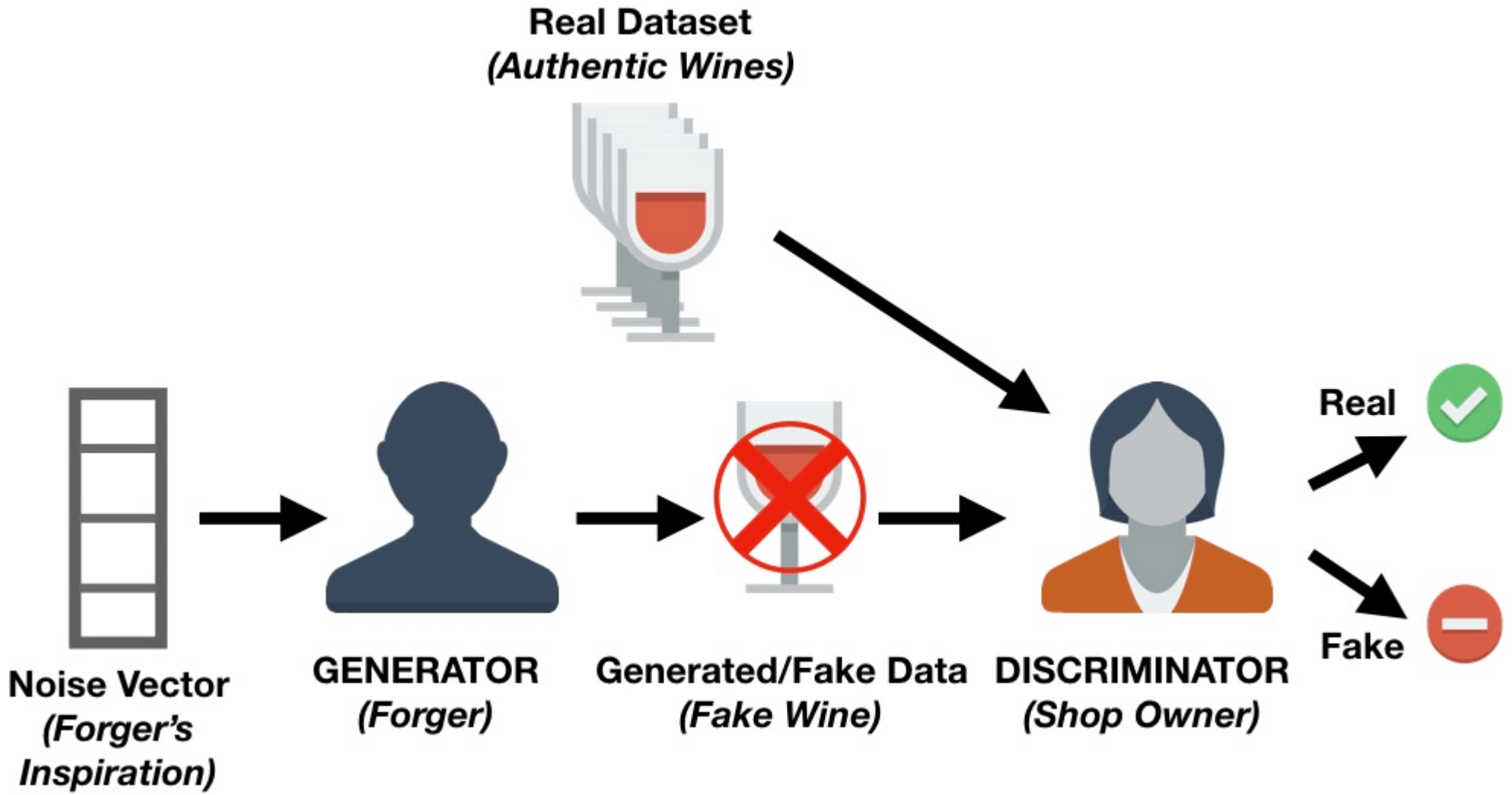
```
def lstm(n_in, n_out):
    # Coding Time
    model = Sequential()
    model.add(LSTM(30, input_shape=(28,28)))
    model.add(Dense(n_out, activation='softmax'))
    return model

model = lstm(n_in, n_out)
```

종류

- **RNN (MinimalRNNCell)**
- **SimpleRNN (SimpleRNNCell)**
- **GRU (GRUCell) (CuDNNGRU)**
- **LSTM (LSTMCell) (CuDNNLSTM)**
- **ConvLSTM2D**
- **Bidirectional**

(https://keras.io/ko/layers/recurrent/)

GAN


Real Dataset
(Authentic Wines)
Noise Vector
(Forger's
Inspiration)
GENERATOR
(Forger)
Generated/Fake Data
(Fake Wine)
DISCRIMINATOR
(Shop Owner)
Real
Fake

GAN

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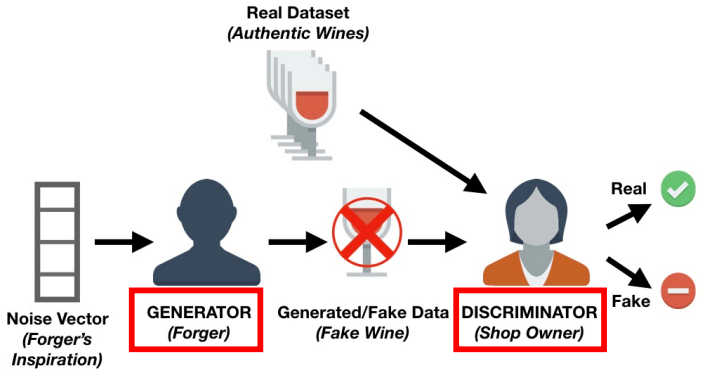
```
def get_generator(optimizer):
    generator = Sequential()
    generator.add(Dense(256, input_dim=random_dim, kernel_initializer=initializers.RandomNormal(stddev=0.02)))
    generator.add(LeakyReLU(0.2))

    generator.add(Dense(512))
    generator.add(LeakyReLU(0.2))

    generator.add(Dense(1024))
    generator.add(LeakyReLU(0.2))

    generator.add(Dense(784, activation='tanh'))
    generator.compile(loss='binary_crossentropy', optimizer=optimizer)
    return generator


def get_discriminator(optimizer):
    discriminator = Sequential()
    discriminator.add(Dense(1024, input_dim=784, kernel_initializer=initializers.RandomNormal(stddev=0.02)))
    discriminator.add(LeakyReLU(0.2))
    discriminator.add(Dropout(0.3))

    discriminator.add(Dense(512))
    discriminator.add(LeakyReLU(0.2))
    discriminator.add(Dropout(0.3))

    discriminator.add(Dense(256))
    discriminator.add(LeakyReLU(0.2))
    discriminator.add(Dropout(0.3))

    discriminator.add(Dense(1, activation='sigmoid'))
    discriminator.compile(loss='binary_crossentropy', optimizer=optimizer)
    return discriminator
```



GAN

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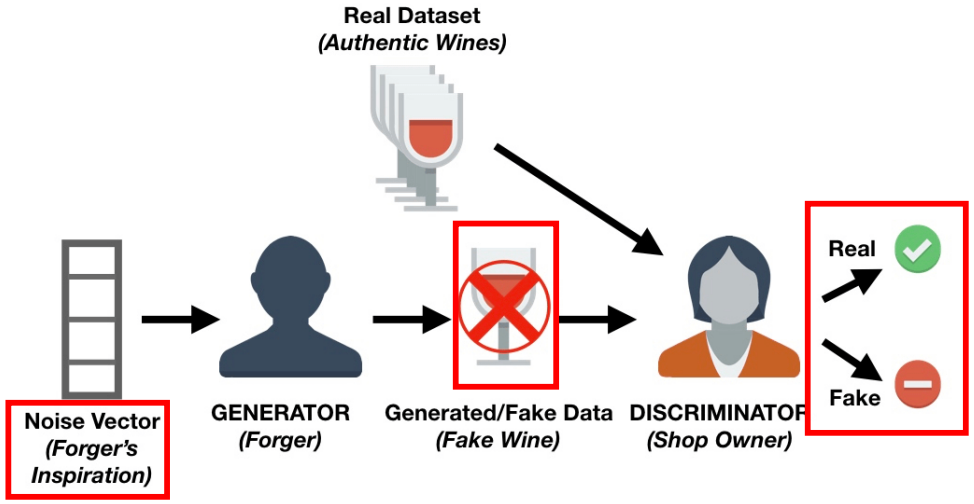


```
def get_gan_network(discriminator, random_dim, generator, optimizer):

    discriminator.trainable = False # Generator와 Discriminator를 동시에 학습시 trainable을 False로 설정

    gan_input = Input(shape=(random_dim,)) # gan_input : 노이즈(100 차원)

    x = generator(gan_input) # X:이미지

    gan_output = discriminator(x) # gan_output : 이미지가 진짜인지 아닌지에 대한 확률

    gan = Model(inputs=gan_input, outputs=gan_output)
    gan.compile(loss='binary_crossentropy', optimizer=optimizer)
    return gan
```

GAN

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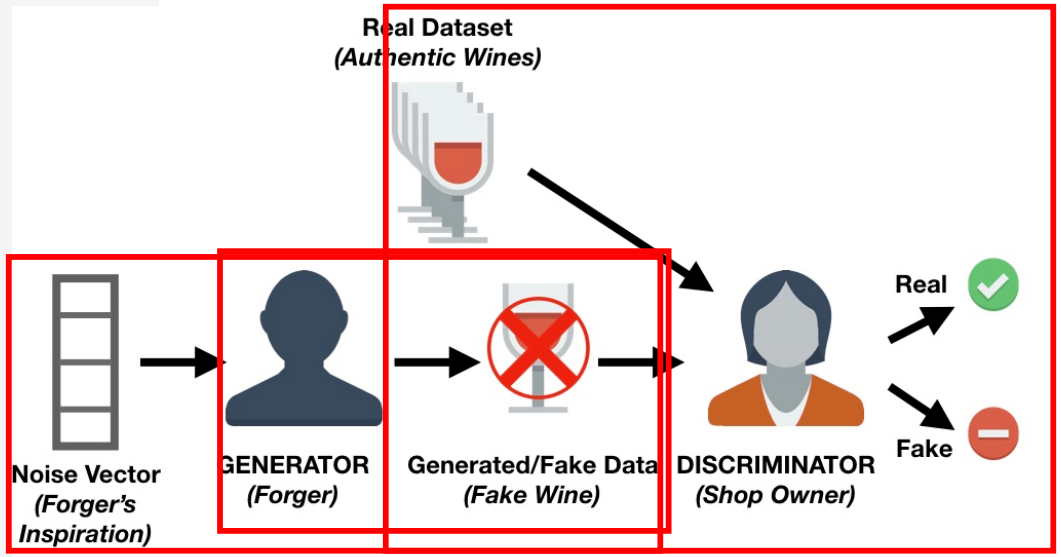
```python
# Generator를 통해 MNIST 이미지를 생성
generated_images = generator.predict(noise, verbose =0)
X = np.concatenate([image_batch, generated_images])
```

```python
# Discriminator 학습
y_dis = np.zeros(2*batch_size)
y_dis[:batch_size] = 0.9
discriminator.trainable = True
discriminator.train_on_batch(X, y_dis)
```

```python
# Generator 학습
noise = np.random.normal(0, 1, size=[batch_size, random_dim])
y_gen = np.ones(batch_size)
discriminator.trainable = False
gan.train_on_batch(noise, y_gen)
```



GAN

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1 Epoch

20 Epoch

GAN

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100 Epoch

400 Epoch

GAN – Another Data Augmentation?!

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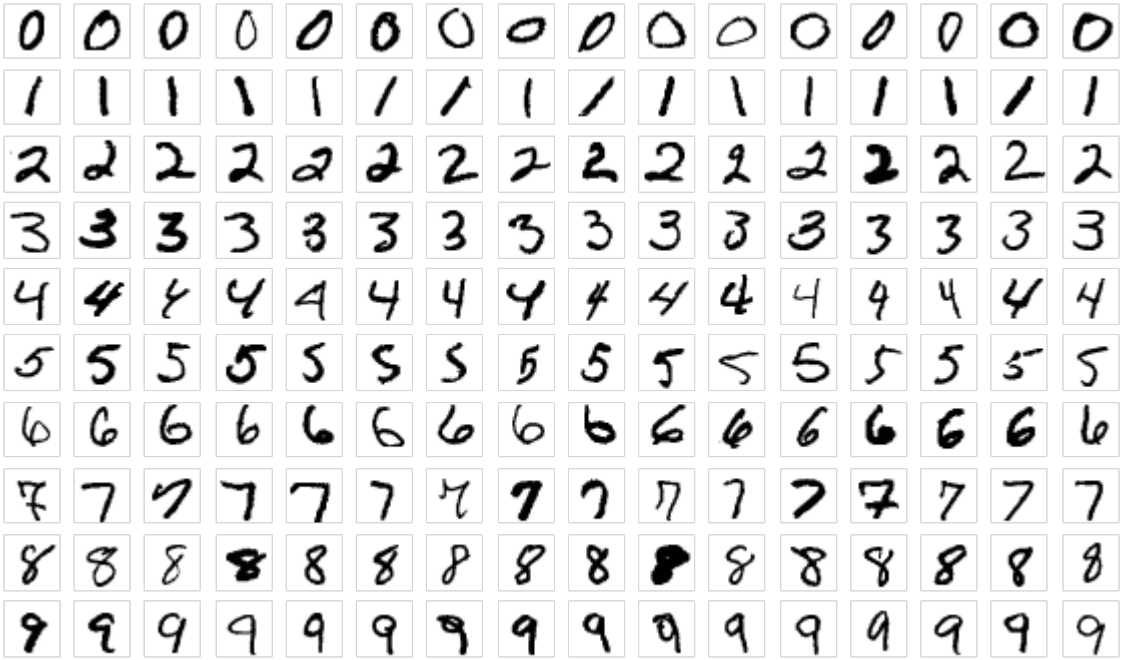

Ground Truth

400 Epoch

Code Running

3. Keras CNN – Additional Functions

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Machine Learning Analysis

Machine Learning Analysis

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- 머신 러닝 분석 이슈

데이터

학습

성능

서비스

데이터

포맷 : 학습하기에 적정한 포맷인가?

규모 : 모델을 학습할 수 있을만큼 충분한 양인가? (Quantity / Level)

품질 : Outlier가 학습에 악영향을 끼칠만큼 있는가?

- 데이터 Outlier : 저품질이거나 대표성이 모호한 Outlier, 중복되는 데이터 (Noise Ratio)
- 데이터-라벨 Outlier : 데이터와 라벨에 대한 매칭이 잘못된 Outlier
- 학습/검증 Outlier : 학습과 검증하는 데이터의 편차 여부(10-fold validation)

구성 : 학습에 적정한 구성을 가지는가? (Imbalance / Bias / Breadth / Depth / 클래스 별 similarity)

라벨링 특성 : 데이터와 라벨의 구성이 합당한가? (성별 / 나이 / 표정)

학습

학습 방법 : 어떤 머신러닝 방식을 쓰는 것이 합당한가? (지도학습 / 비지도 학습 / …)

데이터 연계 : 학습/ 평가하기에 적합한 전처리가 잘 진행되었는가?

네트워크 구조 :

- Layer나 Activation이 잘 설정 되었는가?(층 수, 종류, Input/Output 크기 등)
- 학습할 Parameter 수가 적정한가?

하이퍼 파라미터 : activation, loss, optimizer, learning_rate, metric들을 잘 조정했는가?

학습 방법 : learning rate schedule, batch_size, epoch, validation 구성이 적정한가?

학습 효율 : loss나 정확도가 충분히 수렴되었는가?

성능

Metric : 모델의 성능을 확인하기에 적절한 metric인가? (정량 성능과 실제 성능의 괴리)

예상치 : 모델의 성능이 예상되는 값의 범주에 속하는가? (모델의 성능 한계 예측)

Bias : 모델이 편향되도록 분류하거나 하진 않는가?

에러 패턴 : 결과 에러 중 흔하게 발생하는 경우가 있는가?

개선 방향성 : 네트워크? 학습 방법? 데이터 개선?

서비스

도메인 적합성 : 학습되는 데이터와 실제 사용될 데이터와의 차이가 없는가?

호환성 : 개발 모델이 실제 환경에 호환이 가능한 환경인가?(GPU, 이미지 크기 등)

속도 : 해당 모델이 필요한 서비스에 적용가능한 속도인가? (Speed / Accuracy TradeOff)

백엔드 여부 : 모델 내 나타는 문제를 보완할 백엔드 기술이 필요한가?

적용성 : 쉬운 문제를 어렵게 푼건 아닐까..? (End-To-End / Process System)

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PyTorch Additional Functions

I-Eon, Na

CNN – 공인 데이터셋

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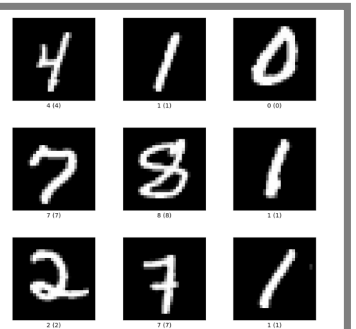
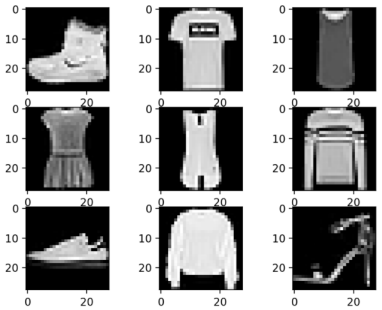
이전 수업에서 사용



MNIST



Fashion MNIST

EMNIST

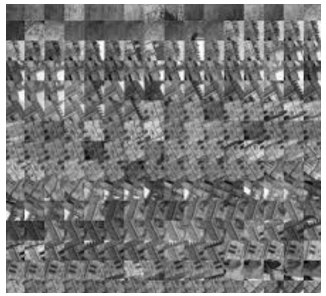
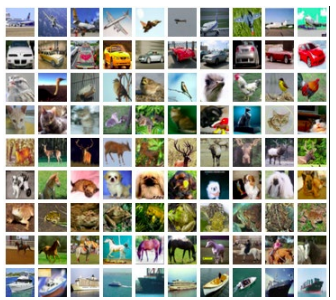


Photo tour

Flickr



CIFAR-10

- 머신러닝/딥러닝 모델을 평가하기 위한 다양한 공인 데이터셋
- MNIST와 다르게 RGB 3채널인 CIFAR-10
- 기타 PyTorch 데이터셋:

  https://teddylee777.github.io/pytorch/pytorch-mnist-dataloader-loading%ED%95%98%EA%B8%B0

CIFAR-10 다운로드 링크: https://www.cs.toronto.edu/~kriz/cifar.html

CNN – Data Augmentation

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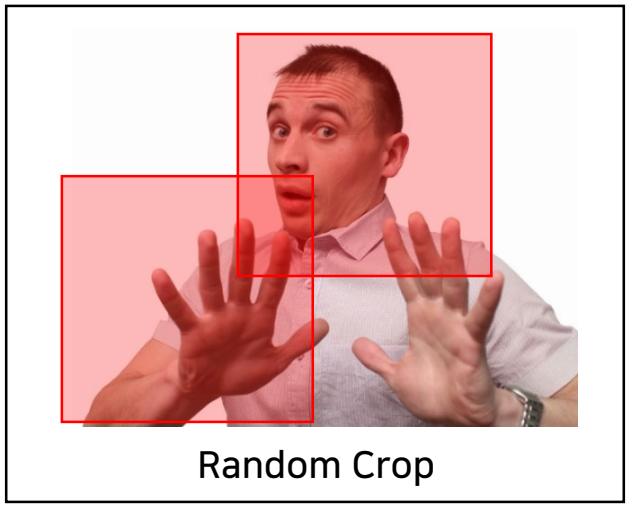
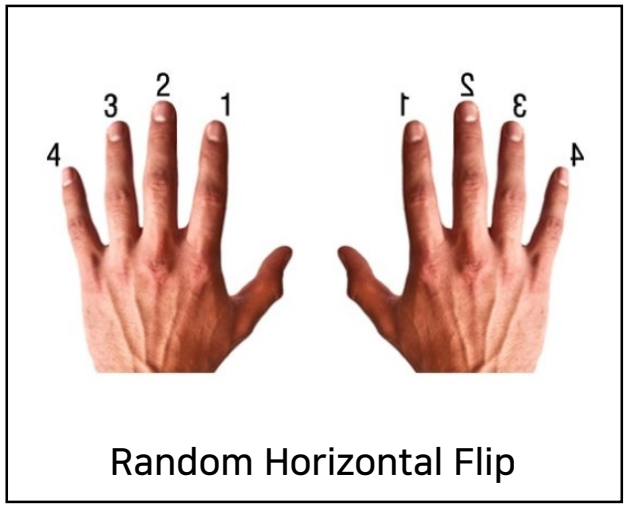
- **데이터 증강 기법**

```
# Load dataset into python variable
input_transform = transforms.Compose([
  Resize(56),
  RandomCrop(56, padding=6),
  RandomHorizontalFlip(),
  ToTensor(),
])
```



Random Crop

출처: https://bonlivre.tistory.com/833



Random Horizontal Flip

출처: https://part2-what-do-we-want.tistory.com/11

- 한정된 데이터로 더 정확도 높은 예측을 하기 위한 데이터 증강 기법

- Random Crop
- Random Horizontal Flip
- Image Rotation
- Brightness
- Contrast
- Saturation
- Hue
- Gaussian Noise
- Random Erasing

- 코드 사용 안내:
  https://androidkt.com/pytorch-image-augmentation-using-transforms/

PyTorch 공식 홈페이지 명령어 안내: https://pytorch.org/vision/stable/transforms.html

Transfer Learning – Custom Dataset Train

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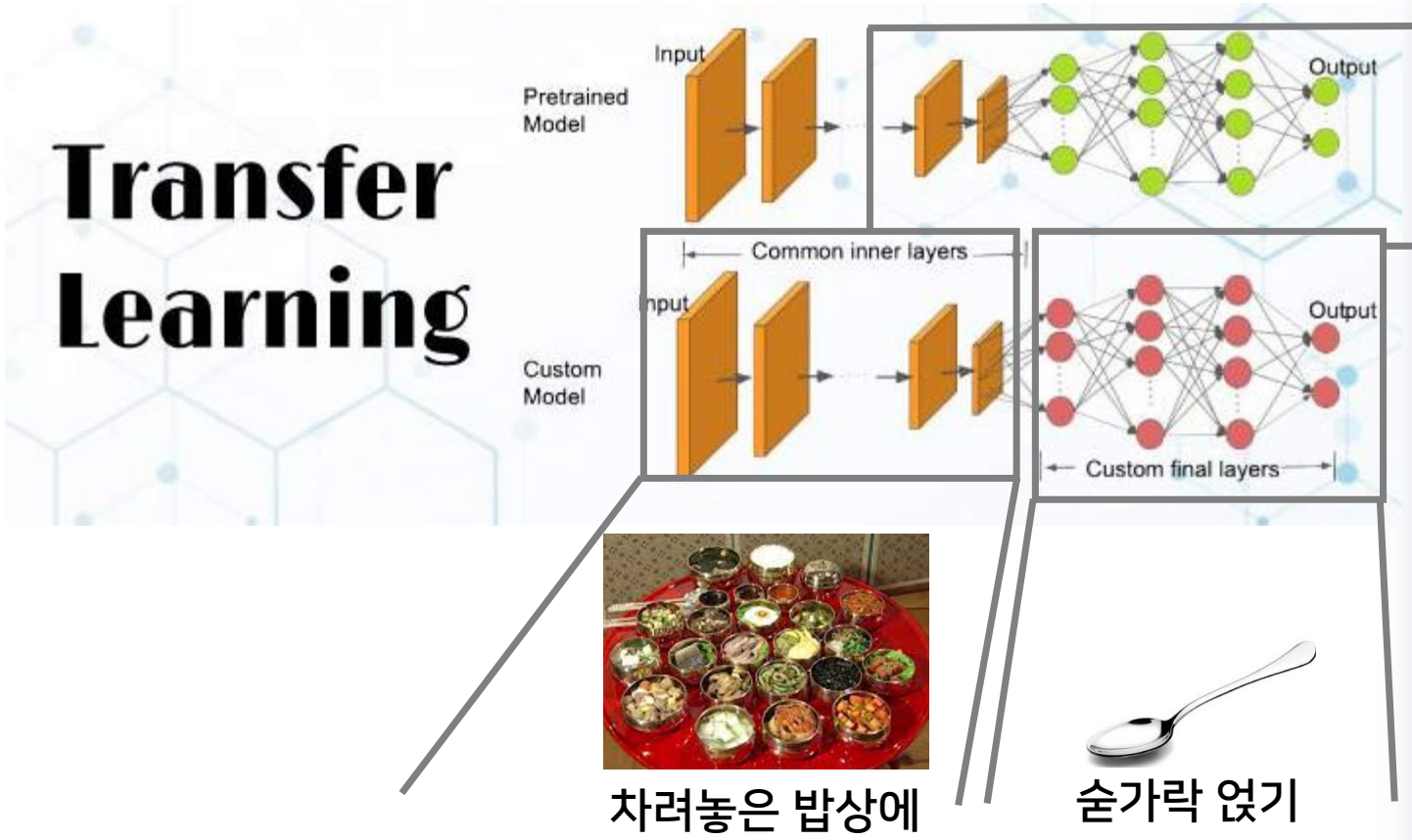
- **Save Time by training only few layers**



- 학습 시간을 효과적으로 줄이기 위하여 이미 학습이 완료된 Pre-Trained 모델을 이용
- Pre-Trained 모델의 끝단 레이어만 학습
- 학습 시 필요한 데이터의 양과 학습 시간을 효율적으로 절약

출처: https://www.analyticsvidhya.com/blog/2021/10/understanding-transfer-learning-for-deep-learning/

Transfer Learning – Custom Dataset Train

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- **Save Time by training only few layers**

  - AlexNet
  - ConvNeXt
  - DenseNet
  - EfficientNet
  - EfficientNetV2
  - GoogLeNet
  - Inception V3
  - MNASNet
  - MobileNet V2
  - MobileNet V3
  - RegNet
  - ResNet
  - ResNeXt
  - ShuffleNet V2
  - SqueezeNet
  - SwinTransformer
  - VGG
  - VisionTransformer
  - Wide ResNet

이번에 사용할 모델(ResNet 18)

`resnet18` (*[, weights, progress])	ResNet-18 from Deep Residual Learning for Image Recognition.
`resnet34` (*[, weights, progress])	ResNet-34 from Deep Residual Learning for Image Recognition.
`resnet50` (*[, weights, progress])	ResNet-50 from Deep Residual Learning for Image Recognition.
`resnet101` (*[, weights, progress])	ResNet-101 from Deep Residual Learning for Image Recognition.
`resnet152` (*[, weights, progress])	ResNet-152 from Deep Residual Learning for Image Recognition.

출처: https://pytorch.org/vision/stable/models.html

Transfer Learning – Custom Dataset Train

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- **데이터셋 준비 – 원숭이와 사람 구분하기**

원숭이 100장

사람 100장

- 분류하기 원하는 사진을 class 당 개수가 동일하도록 준비
- 데이터셋의 양은 class당 최대 1,000장

How Do You Know You Have Enough Training Data?

2019. 4. 22. — Computer Vision: For image classification using deep learning, a **rule of thumb** is **1,000** images **per class**, where this number can go down ...

Transfer Learning – Custom Dataset Train

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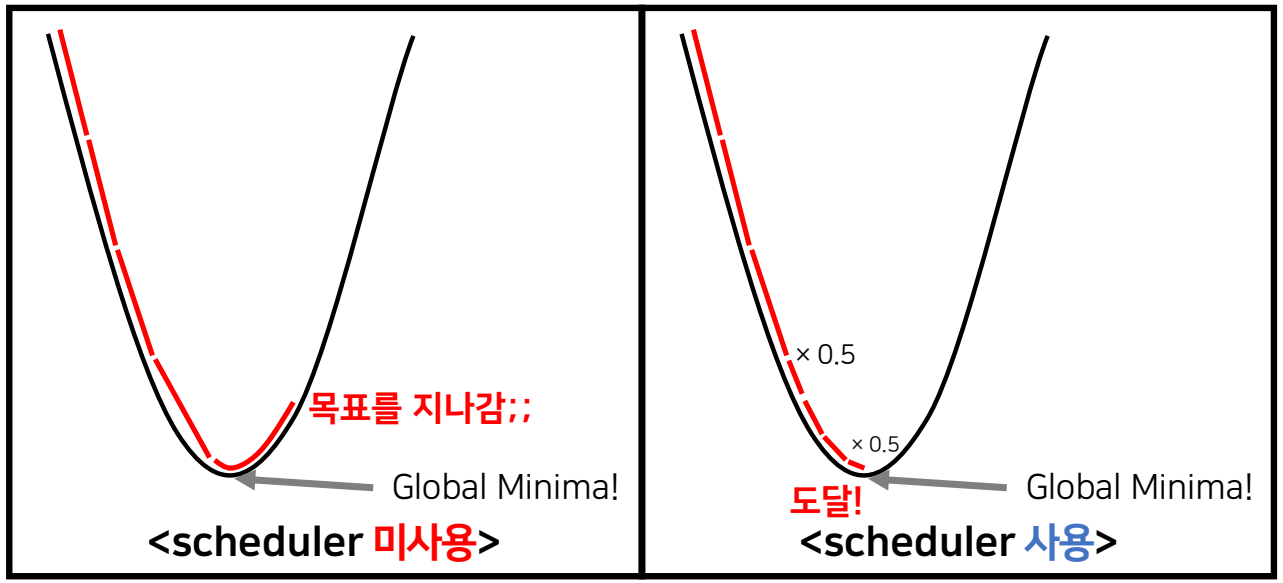
- **Pre-Train Model – ResNet 18 이용**

```
from torchvision import models
model_resnet = models.resnet18(pretrained = True)
```

```
num_ftrs = model_resnet.fc.in_features
model_resnet.fc = nn.Linear(num_ftrs, 2)
net = model_resnet.to(device)
```

```
maximum_epoch = 10
loss_fn = nn.CrossEntropyLoss()
optim = Adam(net.parameters(), lr=0.00001)
from torch.optim import lr_scheduler
lr_scheduler = lr_scheduler.StepLR(optim, step_size = 3, gamma = 0.5)
```

- 모델을 선언하고, pretrained 모드 설정
- 마지막 *FC 레이어의 입, 출력 개수를 변경
- 하이퍼 파라미터 설정
- 학습 추이에 따라 Learning Rate가 줄어들어 학습에 유리한 Schedular 설정



FC레이어: Fully Connected Layer

Transfer Learning – Custom Dataset Train

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- **Pre-trained 모델 전이 학습 결과**


```
Iter:   10 >> T_loss 0.24788    T_acc 0.90714    V_loss 0.06752    V_acc 1.00000    4.119s
Iter:    9 >> T_loss 0.26694    T_acc 0.85714    V_loss 0.05087    V_acc 1.00000    3.900s
Iter:    8 >> T_loss 0.23141    T_acc 0.93571    V_loss 0.04966    V_acc 1.00000    3.961s
Iter:    7 >> T_loss 0.20230    T_acc 0.94286    V_loss 0.05406    V_acc 1.00000    4.053s
Iter:    6 >> T_loss 0.26257    T_acc 0.88571    V_loss 0.06644    V_acc 1.00000    4.012s
Iter:    5 >> T_loss 0.20305    T_acc 0.96429    V_loss 0.07678    V_acc 1.00000    3.990s
Iter:    4 >> T_loss 0.27384    T_acc 0.89286    V_loss 0.09413    V_acc 1.00000    3.985s
Iter:    3 >> T_loss 0.26819    T_acc 0.92857    V_loss 0.12793    V_acc 1.00000    3.947s
Iter:    2 >> T_loss 0.36696    T_acc 0.87857    V_loss 0.19387    V_acc 0.97500    4.015s
Iter:    1 >> T_loss 0.56073    T_acc 0.70000    V_loss 0.41837    V_acc 0.77500    4.255s

Best val Acc: 1.000000
```

- 3 epoch부터 Validation 분류 정확도 100% 달성
- [Weakly To Do]
  직접 설계한 모델과 Transfer Learning의 성능을 CIFAR-10 데이터셋 기준으로 비교해보자

Transfer Learning – Custom Dataset Train

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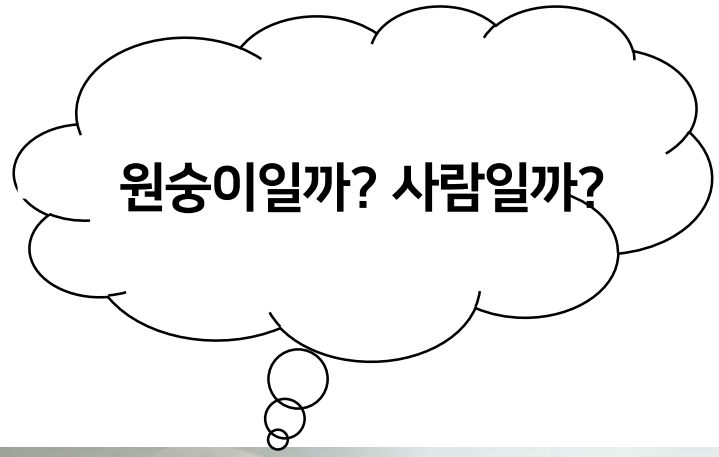

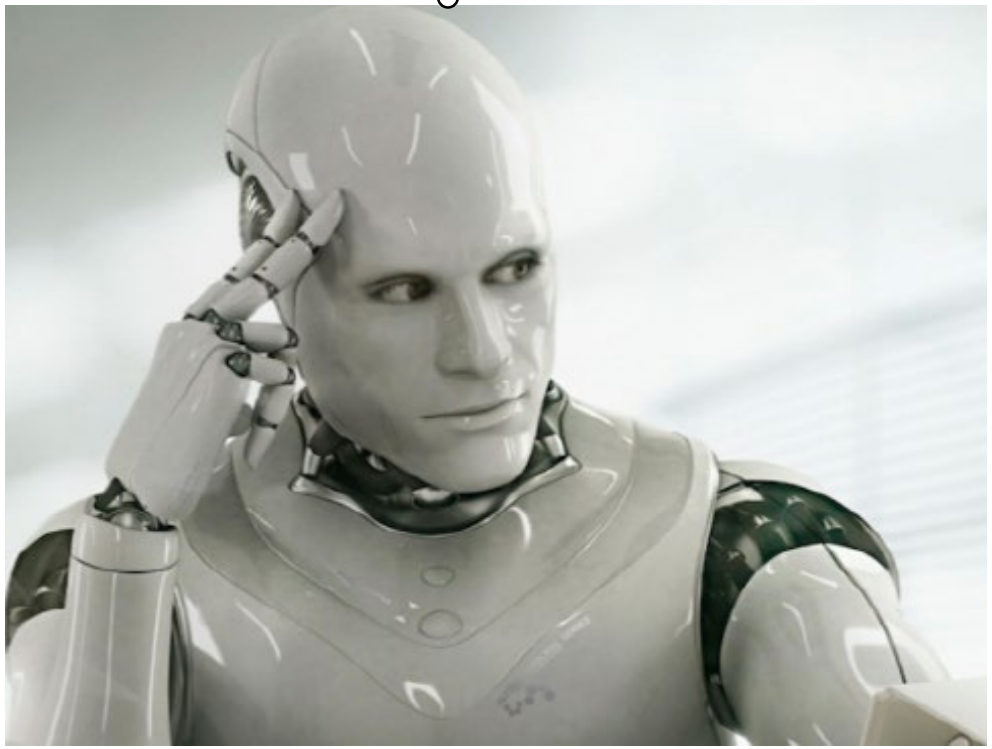

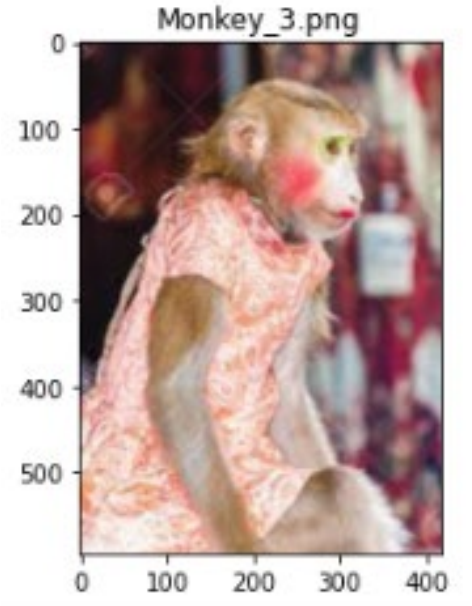

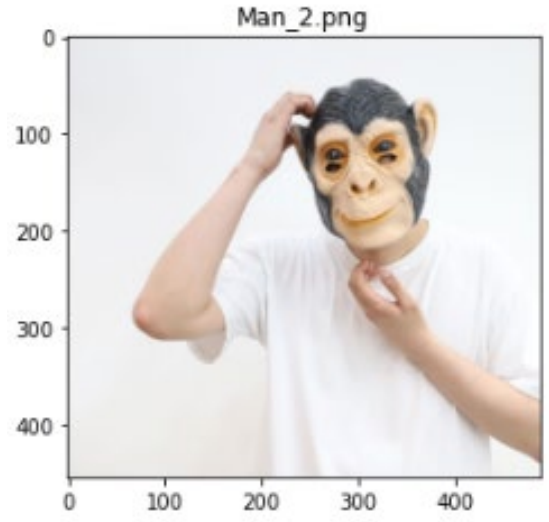

- 원숭이 탈을 쓴 사람과, 사람의 옷을 입은 원숭이를 모델이 제대로 분류할 수 있을까?
- 구분한다면 원리가 무엇일까?

GAN – with MNIST

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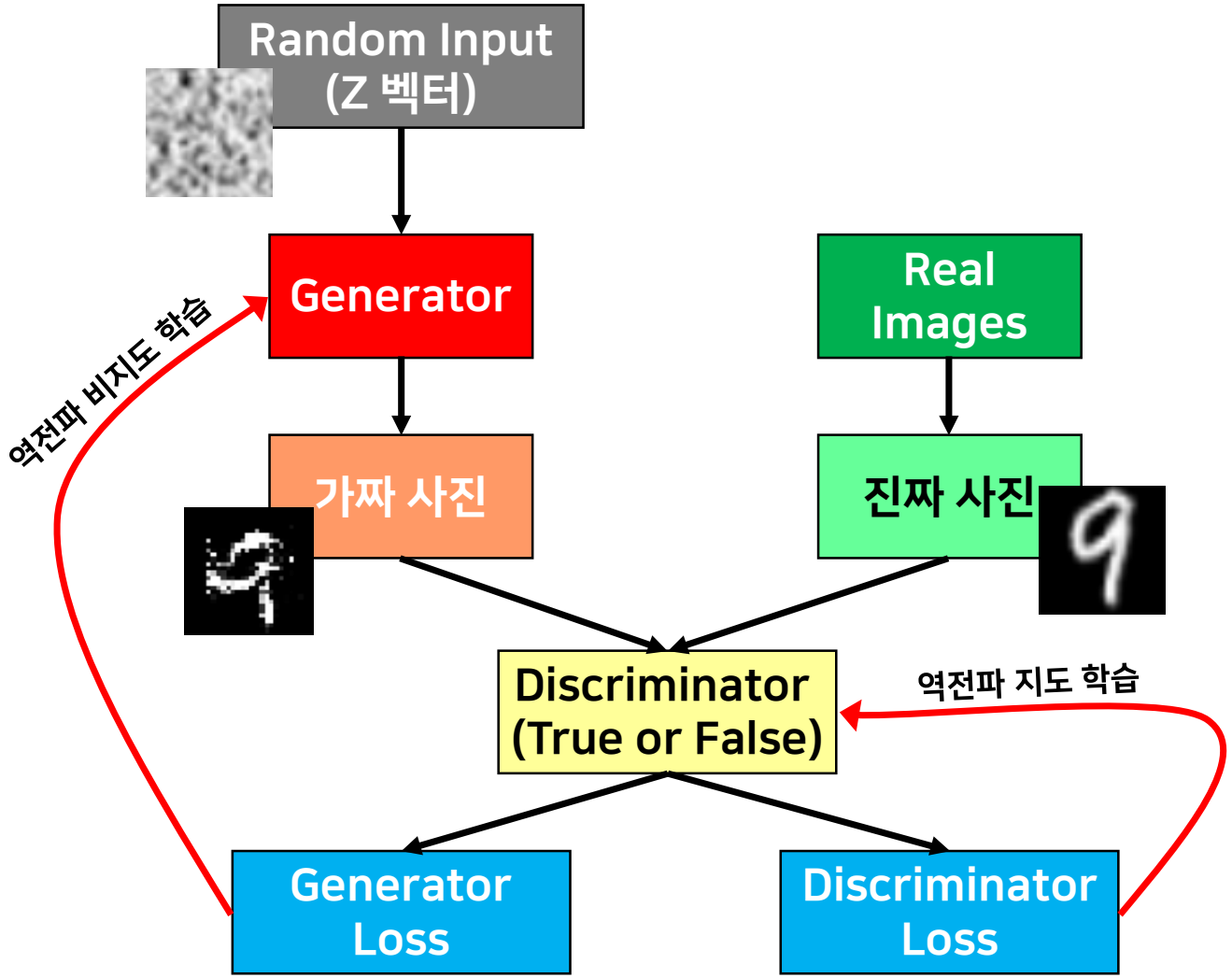

- GAN(Generative Adversarial Networks)
- 생성적 적대 신경망이라는 의미
- 비지도 학습에 사용되는 머신러닝
- 기존에 없는 새로운 데이터를 생성
- Generator와 Discriminator가 서로 경쟁하며 발전

GAN – with MNIST

- **Generator 아키텍처**

-1 ~ 1 사이로 정규화

```
# MNIST Dataset
transform = transforms.Compose([ToTensor(), Normalize(mean=(0.5,), std=(0.5,))])
```

```
# 진짜같은 가짜 생성기
class Generator(nn.Module):
    def __init__(self, g_input_dim, g_output_dim):
        super(Generator, self).__init__()
        self.fc1 = nn.Linear(g_input_dim, 256)
        self.fc2 = nn.Linear(self.fc1.out_features, self.fc1.out_features*2)
        self.fc3 = nn.Linear(self.fc2.out_features, self.fc2.out_features*2)
        self.fc4 = nn.Linear(self.fc3.out_features, g_output_dim)

    # forward method
    def forward(self, x):
        x = F.leaky_relu(self.fc1(x), 0.2)
        x = F.leaky_relu(self.fc2(x), 0.2)
        x = F.leaky_relu(self.fc3(x), 0.2)
        return torch.tanh(self.fc4(x))
```

- 가짜 데이터를 생성하는 Generator 아키텍처 설계
- 입력으로 난수 입력
- 출력으로 28 * 28 이미지 생성
- -1 ~ 1 사이의 값으로 출력하기 위하여 Tanh Activation Function 사용

GAN – with MNIST

- **Generator 학습 알고리즘**

```
z_dim = 100
mnist_dim = train_dataset.train_data.size(1) * train_dataset.train_data.size(2)

G = Generator(g_input_dim = z_dim, g_output_dim = mnist_dim).to(device)
D = Discriminator(mnist_dim).to(device)
```

```
def G_train(x):

    G.zero_grad()

    z = torch.randn(batch_size, z_dim).to(device)
    y = torch.ones(batch_size, 1).to(device)

    G_output = G(z)
    D_output = D(G_output)
    G_loss = criterion(D_output, y)

    G_loss.backward()
    G_optimizer.step()

    return G_loss.data.item()
```

Binary Cross Entropy Loss

- G를 Generator 모델로 선언
- 난수로 가짜 이미지 생성
- 가짜 이미지를 Discriminator 투입
- Discriminator의 예측 값과 1 사이의 loss 산정
- 계산된 loss로 Generator 학습
- 결국 진짜에 가까운 이미지를 만들도록 학습됨

GAN – with MNIST

- **Discriminator 아키텍처**

```
class Discriminator(nn.Module):
    def __init__(self, d_input_dim):
        super(Discriminator, self).__init__()
        self.fc1 = nn.Linear(d_input_dim, 1024)
        self.fc2 = nn.Linear(self.fc1.out_features, self.fc1.out_features//2)
        self.fc3 = nn.Linear(self.fc2.out_features, self.fc2.out_features//2)
        self.fc4 = nn.Linear(self.fc3.out_features, 1)

    # forward method
    def forward(self, x):
        x = F.leaky_relu(self.fc1(x), 0.2)
        x = F.dropout(x, 0.3)
        x = F.leaky_relu(self.fc2(x), 0.2)
        x = F.dropout(x, 0.3)
        x = F.leaky_relu(self.fc3(x), 0.2)
        x = F.dropout(x, 0.3)
        return torch.sigmoid(self.fc4(x))
```

진짜일 확률값을 출력

- 진짜와 가짜를 판별하는 Discriminator 아키텍처 설계
- 입력 28×28 이미지
- 출력으로 1 or 0 (진짜 or 가짜)

GAN – with MNIST

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- **Discriminator 학습 알고리즘**

```
def D_train(x):

    D.zero_grad()

    x_real = x.view(-1, mnist_dim)
    y_real = torch.ones(batch_size, 1)

    x_real, y_real = x_real.to(device), y_real.to(device)

    D_output = D(x_real)
    D_real_loss = criterion(D_output, y_real)
    D_real_score = D_output

    z = torch.randn(batch_size, z_dim).to(device)
    x_fake, y_fake = G(z), torch.zeros(batch_size, 1).to(device)

    D_output = D(x_fake)
    D_fake_loss = criterion(D_output, y_fake)

    D_loss = D_real_loss + D_fake_loss
    D_loss.backward()
    D_optimizer.step()

    return  D_loss.data.item()
```

- 실제 데이터셋 로드
- 진짜를 구별하도록 Loss 산정
- G로 가짜 데이터 생성
- 가짜를 구별하도록 Loss 산정
- 진짜와 가짜를 모두 구별하도록 학습

GAN – with MNIST

- **GAN (G + D) 학습 알고리즘**

```
for epoch in range(1, n_epoch+1):
    D_losses, G_losses = [], []
    for batch_idx, (x, _) in enumerate(train_loader):
        D_losses.append(D_train(x))
        G_losses.append(G_train(x))
```

- G와 D를 번갈아 가며 학습

GAN – with MNIST

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1 epochs　　100 epochs　　200 epochs

- MNIST 데이터를 학습하여 세상에 없던 손 글씨를 생성
- MNIST 데이터 증강이 가능할지도..?

n epochs

출처: https://debuggercafe.com/generating-mnist-digit-images-using-vanilla-gan-with-pytorch/

Code Running

3. Pytorch CNN – Additional Functions