

케라스, 텐서플로우 버전 확인

```
In [20]: 1 import keras
         2 keras.__version__

Out[20]: '2.3.1'

In [21]: 1 import tensorflow as tf
         2 tf.__version__

Out[21]: '2.0.0'
```

사용 라이브러리 및 이미지 불러오기

```
In [3]: 1 import warnings
        2 warnings.filterwarnings('ignore')
        3
        4 from keras import models, layers
        5 from keras.callbacks import ModelCheckpoint, EarlyStopping
        6 import cv2
        7 from glob import glob
        8 import os
        9 import numpy as np
       10 from IPython.display import SVG
       11 from keras.utils.vis_utils import model_to_dot
       12 import tensorflow as tf
       13 from tensorflow import keras
       14
       15 from keras import regularizers
       16 from sklearn.model_selection import train_test_split
       17 from tensorflow.keras.utils import to_categorical
       18 from keras.models import Sequential
       19 from keras.layers import Dense, Activation, Dropout, Flatten, Conv2D, MaxPooling2D, BatchNormalization
       20 from keras.callbacks import ModelCheckpoint, EarlyStopping
       21 import matplotlib.pyplot as plt

Using TensorFlow backend.

In [4]: 1 img_data = glob('C:\\\\Users\\WW82106\\Desktop\\sw_0601\\pokemon_\\*.*.jpg')
        2 class_name = ['Charmander', 'Gastly', 'Goldeen', 'Gyarados', 'Horsea', 'Mew', 'Mewtwo', 'Pikachu', 'Poliwag', 'Squirtle']
        3 dic = {'Charmander':0, 'Gastly':1, 'Goldeen':2, 'Gyarados':3, 'Horsea':4, 'Mew':5, 'Mewtwo':6, 'Pikachu':7, 'Poliwag':8, 'Squirtle':9}
        4 dic2 = {0:'Charmander', 1:'Gastly', 2:'Goldeen', 3:'Gyarados', 4:'Horsea', 5:'Mew', 6:'Mewtwo', 7:'Pikachu', 8:'Poliwag', 9:'Squirtle'}
```

이미지, 레이블들을 저장

In [5]:

```
1 #데이터들을 담을 리스트 정의
2 X_all = list()
3 #레이블들을 담을 리스트 정의
4 Y_all = list()
5
6
7 for imagename in img_data:
8     try:
9         img = cv2.imread(imagename)
10        img = cv2.resize(img, dsize=(32, 32))
11        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
12
13        image = np.array(img)
14        X_all.append(img)
15
16        label = imagename.split('WW')
17        label = label[6]
18        label = label.split('.')
19        label = str(label[0])
20        label = dic[label]
21        Y_all.append(label)
22    except :
23        pass # 예외
24
25
26 # X, Y리스트들을 NP형식의 배열로 생성
27 X_all = np.array(X_all)
28 Y_all = np.array(Y_all)
29
30 print(X_all)
31 print(Y_all)
32 print('X_all shape: ', X_all.shape)
33 print('Y_all shape: ', Y_all.shape)
```

```
...
[[ 0  0  0]
 [ 0  0  0]
 [ 0  0  0]]

[[ 0  0  0]
 [ 0  0  0]
 [ 0  0  0]

...
[[ 0  0  0]
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[[ 0  0  0]
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 [ 0  0  0]

...
[[ 0  0  0]
 [ 0  0  0]
 [ 0  0  0]]]
```

train, test 데이터셋 분리

In [6]:

```
1 X_train,X_test,Y_train,Y_test = train_test_split(X_all, Y_all, test_size = 0.2, shuffle=True, random_state=44)
2 print(X_train.shape)
3 print(X_test.shape)
4 print(Y_train.shape)
5 print(Y_test.shape)
```

```
(16127, 32, 32, 3)
(4032, 32, 32, 3)
(16127,)
(4032,)
```

정규화 및 원핫인코딩

```
In [7]: 1 X_train = X_train.reshape(X_train.shape[0], 32, 32, 3)
2 X_test = X_test.reshape(X_test.shape[0], 32, 32, 3)
3 X_train = X_train.astype('float') / 255
4 X_test = X_test.astype('float') / 255
5
6 print('X_train_shape: ', X_train.shape)
7 print('X_test_shape: ', X_test.shape)
8 print(X_train[:5])
9 print(X_test[:5])
```

```
...
[[1. 1. 1. ]
 [1. 1. 1. ]
 [1. 1. 1. ]]

[[1. 1. 1. ]
 [1. 1. 1. ]
 [1. 1. 1. ]

...
[[1. 1. 1. ]
 [1. 1. 1. ]
 [1. 1. 1. ]]

[[1. 1. 1. ]
 [1. 1. 1. ]
 [1. 1. 1. ]

...
[[1. 1. 1. ]
 [1. 1. 1. ]
 [1. 1. 1. ]]]
```

```
In [8]: 1 Y_train = to_categorical(Y_train, 10)
2 Y_test = to_categorical(Y_test, 10)
3 print('Y_train_shape:', Y_train.shape)
4 print('Y_test_shape', Y_test.shape)
```

Y_train_shape: (16127, 10)
Y_test_shape (4032, 10)

CNN 인공지능 모델 설계

```
In [9]: 1 model = Sequential()
2 model.add(Conv2D(64, kernel_size=(5, 5), strides=(1, 1), padding='same',
3                 activation='relu',
4                 input_shape=(32, 32, 3)))
5 model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
6 model.add(Conv2D(32, (2, 2), activation='relu', padding='same'))
7 model.add(MaxPooling2D(pool_size=(2, 2)))
8 model.add(Dropout(0.25))
9 model.add(Flatten())
10 model.add(Dense(1000, activation='relu'))
11 model.add(Dropout(0.5))
12 model.add(Dense(10, activation='softmax'))
13 model.summary()
```

Model: "sequential_1"

| Layer (type) | Output Shape | Param # |
|------------------------------|--------------------|---------|
| ===== | | |
| conv2d_1 (Conv2D) | (None, 32, 32, 64) | 4864 |
| max_pooling2d_1 (MaxPooling2 | (None, 16, 16, 64) | 0 |
| conv2d_2 (Conv2D) | (None, 16, 16, 32) | 8224 |
| max_pooling2d_2 (MaxPooling2 | (None, 8, 8, 32) | 0 |
| dropout_1 (Dropout) | (None, 8, 8, 32) | 0 |
| flatten_1 (Flatten) | (None, 2048) | 0 |
| dense_1 (Dense) | (None, 1000) | 2049000 |
| dropout_2 (Dropout) | (None, 1000) | 0 |
| dense_2 (Dense) | (None, 10) | 10010 |
| ===== | | |
| Total params: 2,072,098 | | |
| Trainable params: 2,072,098 | | |
| Non-trainable params: 0 | | |

모델 학습시키기

```
In [10]: 1 early_stopping = EarlyStopping(monitor = 'val_loss', patience=5, verbose=1)
2
3 model.compile(loss='categorical_crossentropy', optimizer='Adam', metrics=['accuracy'])
4 model.fit(X_train, Y_train, batch_size=40, epochs=40, verbose=1, callbacks = [early_stopping])
```

Epoch 1/40
16127/16127 [=====] - 15s 939us/step - loss: 1.3446 - accuracy: 0.5264
Epoch 2/40
16127/16127 [=====] - 15s 933us/step - loss: 0.6275 - accuracy: 0.7885
Epoch 3/40
16127/16127 [=====] - 15s 953us/step - loss: 0.3556 - accuracy: 0.8815
Epoch 4/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.2393 - accuracy: 0.9240
Epoch 5/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.1640 - accuracy: 0.9470
Epoch 6/40
16127/16127 [=====] - 16s 1ms/step - loss: 0.1218 - accuracy: 0.9615
Epoch 7/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.1012 - accuracy: 0.9684
Epoch 8/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.1023 - accuracy: 0.9670
Epoch 9/40
16127/16127 [=====] - 16s 1ms/step - loss: 0.0809 - accuracy: 0.9741
Epoch 10/40
16127/16127 [=====] - 16s 1ms/step - loss: 0.0776 - accuracy: 0.9753
Epoch 11/40
16127/16127 [=====] - 16s 1ms/step - loss: 0.0759 - accuracy: 0.9751
Epoch 12/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0543 - accuracy: 0.9829
Epoch 13/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0650 - accuracy: 0.9785
Epoch 14/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0474 - accuracy: 0.9857
Epoch 15/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0690 - accuracy: 0.9789
Epoch 16/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0534 - accuracy: 0.9833
Epoch 17/40
16127/16127 [=====] - 16s 1ms/step - loss: 0.0652 - accuracy: 0.9788
Epoch 18/40
16127/16127 [=====] - 16s 1ms/step - loss: 0.0467 - accuracy: 0.9849
Epoch 19/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0436 - accuracy: 0.9874
Epoch 20/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0454 - accuracy: 0.9858
Epoch 21/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0452 - accuracy: 0.9870
Epoch 22/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0444 - accuracy: 0.9862
Epoch 23/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0460 - accuracy: 0.9860
Epoch 24/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0466 - accuracy: 0.9860
Epoch 25/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0530 - accuracy: 0.9845
Epoch 26/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0426 - accuracy: 0.9877
Epoch 27/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0372 - accuracy: 0.9876
Epoch 28/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0457 - accuracy: 0.9865
Epoch 29/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0493 - accuracy: 0.9852
Epoch 30/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0286 - accuracy: 0.9911
Epoch 31/40
16127/16127 [=====] - 16s 1ms/step - loss: 0.0302 - accuracy: 0.9902
Epoch 32/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0339 - accuracy: 0.9904
Epoch 33/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0406 - accuracy: 0.9880
Epoch 34/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0399 - accuracy: 0.9883
Epoch 35/40
16127/16127 [=====] - 18s 1ms/step - loss: 0.0409 - accuracy: 0.9888
Epoch 36/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0307 - accuracy: 0.9913
Epoch 37/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0304 - accuracy: 0.9915
Epoch 38/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0279 - accuracy: 0.9918
Epoch 39/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0277 - accuracy: 0.9926
Epoch 40/40
16127/16127 [=====] - 17s 1ms/step - loss: 0.0266 - accuracy: 0.9924

Out[10]: <keras.callbacks.callbacks.History at 0x17025eee630>

CNN 모델 평가

In [11]:

1 score = model.evaluate(X_test, Y_test)

2 print('Test score:', score[0])

3 print('Test accuracy:', score[1])

4032/4032 [=====] - 1s 269us/step
Test score: 0.043170154354246704
Test accuracy: 0.9908233880996704

VGG16 - Transfer Learning

In [12]:

1 from tensorflow.keras import Input, models, layers, optimizers, metrics

2 from tensorflow.keras.layers import Dense, Flatten

3 from tensorflow.keras.applications import VGG16

VGG 모델 설계

```
In [13]: 1 transfer_model = VGG16(weights='imagenet', include_top=False, input_shape=(32, 32, 3))
2 transfer_model.trainable = False
3 transfer_model.summary()
4
5 finetune_model = models.Sequential()
6 finetune_model.add(transfer_model)
7 finetune_model.add(Flatten())
8 finetune_model.add(Dense(64, activation='relu'))
9 finetune_model.add(Dense(10, activation='softmax'))
10 finetune_model.summary()
```

| Model: "vgg16" | | |
|----------------------------------|---------------------|----------|
| Layer (type) | Output Shape | Param # |
| ===== | | |
| input_1 (InputLayer) | [(None, 32, 32, 3)] | 0 |
| block1_conv1 (Conv2D) | (None, 32, 32, 64) | 1792 |
| block1_conv2 (Conv2D) | (None, 32, 32, 64) | 36928 |
| block1_pool (MaxPooling2D) | (None, 16, 16, 64) | 0 |
| block2_conv1 (Conv2D) | (None, 16, 16, 128) | 73856 |
| block2_conv2 (Conv2D) | (None, 16, 16, 128) | 147584 |
| block2_pool (MaxPooling2D) | (None, 8, 8, 128) | 0 |
| block3_conv1 (Conv2D) | (None, 8, 8, 256) | 295168 |
| block3_conv2 (Conv2D) | (None, 8, 8, 256) | 590080 |
| block3_conv3 (Conv2D) | (None, 8, 8, 256) | 590080 |
| block3_pool (MaxPooling2D) | (None, 4, 4, 256) | 0 |
| block4_conv1 (Conv2D) | (None, 4, 4, 512) | 1180160 |
| block4_conv2 (Conv2D) | (None, 4, 4, 512) | 2359808 |
| block4_conv3 (Conv2D) | (None, 4, 4, 512) | 2359808 |
| block4_pool (MaxPooling2D) | (None, 2, 2, 512) | 0 |
| block5_conv1 (Conv2D) | (None, 2, 2, 512) | 2359808 |
| block5_conv2 (Conv2D) | (None, 2, 2, 512) | 2359808 |
| block5_conv3 (Conv2D) | (None, 2, 2, 512) | 2359808 |
| block5_pool (MaxPooling2D) | (None, 1, 1, 512) | 0 |
| ===== | | |
| Total params: 14,714,688 | | |
| Trainable params: 0 | | |
| Non-trainable params: 14,714,688 | | |
| Model: "sequential" | | |
| Layer (type) | Output Shape | Param # |
| ===== | | |
| vgg16 (Model) | (None, 1, 1, 512) | 14714688 |
| flatten (Flatten) | (None, 512) | 0 |
| dense (Dense) | (None, 64) | 32832 |
| dense_1 (Dense) | (None, 10) | 650 |
| ===== | | |
| Total params: 14,748,170 | | |
| Trainable params: 33,482 | | |
| Non-trainable params: 14,714,688 | | |

모델 학습시키기

```
In [26]: 1 finetune_model.compile(loss='categorical_crossentropy', optimizer=optimizers.Adam(learning_rate=0.0002), metrics=['accuracy']
2 t_history = finetune_model.fit(X_train, Y_train, batch_size=1000, epochs=20, validation_data=(X_test, Y_test))
```

Train on 16127 samples, validate on 4032 samples

Epoch 1/20
16127/16127 [=====] - 42s 3ms/sample - loss: 0.2793 - accuracy: 0.9327 - val_loss: 0.3689 - val_accuracy: 0.8991

Epoch 2/20
16127/16127 [=====] - 46s 3ms/sample - loss: 0.2768 - accuracy: 0.9333 - val_loss: 0.3667 - val_accuracy: 0.8976

Epoch 3/20
16127/16127 [=====] - 47s 3ms/sample - loss: 0.2745 - accuracy: 0.9347 - val_loss: 0.3644 - val_accuracy: 0.8988

Epoch 4/20
16127/16127 [=====] - 48s 3ms/sample - loss: 0.2725 - accuracy: 0.9341 - val_loss: 0.3634 - val_accuracy: 0.9020

Epoch 5/20
16127/16127 [=====] - 48s 3ms/sample - loss: 0.2709 - accuracy: 0.9353 - val_loss: 0.3607 - val_accuracy: 0.9023

Epoch 6/20
16127/16127 [=====] - 48s 3ms/sample - loss: 0.2691 - accuracy: 0.9360 - val_loss: 0.3598 - val_accuracy: 0.9010

Epoch 7/20
16127/16127 [=====] - 49s 3ms/sample - loss: 0.2677 - accuracy: 0.9367 - val_loss: 0.3596 - val_accuracy: 0.9005

Epoch 8/20
16127/16127 [=====] - 51s 3ms/sample - loss: 0.2661 - accuracy: 0.9382 - val_loss: 0.3576 - val_accuracy: 0.9010

Epoch 9/20
16127/16127 [=====] - 50s 3ms/sample - loss: 0.2644 - accuracy: 0.9371 - val_loss: 0.3562 - val_accuracy: 0.9030

Epoch 10/20
16127/16127 [=====] - 50s 3ms/sample - loss: 0.2627 - accuracy: 0.9372 - val_loss: 0.3536 - val_accuracy: 0.9043

Epoch 11/20
16127/16127 [=====] - 50s 3ms/sample - loss: 0.2610 - accuracy: 0.9397 - val_loss: 0.3531 - val_accuracy: 0.9035

Epoch 12/20
16127/16127 [=====] - 50s 3ms/sample - loss: 0.2593 - accuracy: 0.9392 - val_loss: 0.3518 - val_accuracy: 0.9040

Epoch 13/20
16127/16127 [=====] - 50s 3ms/sample - loss: 0.2580 - accuracy: 0.9398 - val_loss: 0.3508 - val_accuracy: 0.9062

Epoch 14/20
16127/16127 [=====] - 50s 3ms/sample - loss: 0.2564 - accuracy: 0.9403 - val_loss: 0.3493 - val_accuracy: 0.9038

Epoch 15/20
16127/16127 [=====] - 50s 3ms/sample - loss: 0.2549 - accuracy: 0.9406 - val_loss: 0.3467 - val_accuracy: 0.9075

Epoch 16/20
16127/16127 [=====] - 50s 3ms/sample - loss: 0.2534 - accuracy: 0.9421 - val_loss: 0.3469 - val_accuracy: 0.9055

Epoch 17/20
16127/16127 [=====] - 50s 3ms/sample - loss: 0.2526 - accuracy: 0.9415 - val_loss: 0.3444 - val_accuracy: 0.9070

Epoch 18/20
16127/16127 [=====] - 52s 3ms/sample - loss: 0.2510 - accuracy: 0.9425 - val_loss: 0.3434 - val_accuracy: 0.9065

Epoch 19/20
16127/16127 [=====] - 51s 3ms/sample - loss: 0.2489 - accuracy: 0.9420 - val_loss: 0.3428 - val_accuracy: 0.9053

Epoch 20/20
16127/16127 [=====] - 53s 3ms/sample - loss: 0.2473 - accuracy: 0.9435 - val_loss: 0.3410 - val_accuracy: 0.9080

VGG16 모델 평가

```
In [27]: 1 score = finetune_model.evaluate(X_test, Y_test)
2 print('Test score:', score[0])
3 print('Test accuracy:', score[1])

=====
=====
=====
=====
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=====
=====
=====
=====] - 11s 3ms/sample - loss: 0.281
4 - accuracy: 0.9080

Test score: 0.34101119495573495
Test accuracy: 0.9079861
```

Autoencoder - Unsupervised Learning

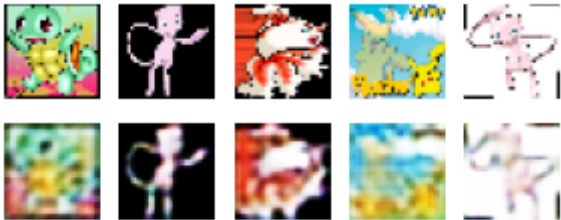
```
In [96]: 1 from tensorflow.keras.models import Sequential, Model
2 from tensorflow.keras.layers import Input, Dense, Conv2D, MaxPooling2D, UpSampling2D, Flatten, Reshape
3
4 autoencoder = Sequential()
5
6 # 인코딩 부분입니다.
7 autoencoder.add(Conv2D(16, kernel_size=3, padding='same', input_shape=(32,32,3), activation='relu'))
8 #autoencoder.add(MaxPooling2D(pool_size=2, padding='same'))
9 autoencoder.add(Conv2D(8, kernel_size=3, activation='relu', padding='same'))
10 autoencoder.add(MaxPooling2D(pool_size=2, padding='same'))
11 autoencoder.add(Conv2D(8, kernel_size=3, strides=2, padding='same', activation='relu'))
12
13 # 디코딩 부분이 이어집니다.
14 autoencoder.add(Conv2D(8, kernel_size=3, padding='same', activation='relu'))
15 autoencoder.add(UpSampling2D())
16 autoencoder.add(Conv2D(3, kernel_size=3, padding='same', activation='relu'))
17 autoencoder.add(UpSampling2D())
18 #autoencoder.add(Conv2D(3, kernel_size=3, padding='same', activation='relu'))
19 #autoencoder.add(UpSampling2D())
20 autoencoder.add(Conv2D(3, kernel_size=3, padding='same', activation='sigmoid'))
21
22 # 전체 구조를 확인해 봅니다.
23 autoencoder.summary()
24
25 # 컴파일 및 학습을 하는 부분입니다.
26 autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
27 autoencoder.fit(X_train, X_train, epochs=100, batch_size=50, validation_data=(X_test, X_test))

16127/16127 [=====] - 14s 890us/sample - loss: 0.3776 - val_loss: 0.3745
Epoch 87/100
16127/16127 [=====] - 14s 890us/sample - loss: 0.3778 - val_loss: 0.3751
Epoch 88/100
16127/16127 [=====] - 14s 889us/sample - loss: 0.3778 - val_loss: 0.3745
Epoch 89/100
16127/16127 [=====] - 14s 888us/sample - loss: 0.3776 - val_loss: 0.3743
Epoch 90/100
16127/16127 [=====] - 14s 889us/sample - loss: 0.3779 - val_loss: 0.3744
Epoch 91/100
16127/16127 [=====] - 14s 881us/sample - loss: 0.3774 - val_loss: 0.3745
Epoch 92/100
16127/16127 [=====] - 14s 872us/sample - loss: 0.3776 - val_loss: 0.3743
Epoch 93/100
16127/16127 [=====] - 14s 890us/sample - loss: 0.3775 - val_loss: 0.3745
Epoch 94/100
16127/16127 [=====] - 14s 895us/sample - loss: 0.3774 - val_loss: 0.3747
Epoch 95/100
16127/16127 [=====] - 14s 886us/sample - loss: 0.3775 - val_loss: 0.3742
Epoch 96/100
```

결과 출력 ¶

In [97]:

```
1 #학습된 결과를 출력하는 부분입니다.
2 random_test = np.random.randint(X_test.shape[0], size=5) #테스트할 이미지를 랜덤하게 불러옵니다.
3 ae_imgs = autoencoder.predict(X_test) #앞서 만든 오토인코더 모델에 집어 넣습니다.
4
5 plt.figure(figsize=(7, 2)) #출력될 이미지의 크기
6
7 for i, image_idx in enumerate(random_test): #랜덤하게 뽑은 이미지를 차례로 나열
8     ax = plt.subplot(2, 7, i + 1) ### VGG16 - Transfer Learning
9     plt.imshow(X_test[image_idx].reshape(32, 32, 3)) #테스트할 이미지
10    ax.axis('off')
11    ax = plt.subplot(2, 7, 7 + i + 1)
12    plt.imshow(ae_imgs[image_idx].reshape(32, 32, 3)) #오토인코딩 결과를 다음열에 출력
13    ax.axis('off')
14
15 plt.show()
```



In [98]:

```
1 #학습된 결과를 출력하는 부분입니다.
2 random_test = np.random.randint(X_test.shape[0], size=5) #테스트할 이미지를 랜덤하게 불러옵니다.
3 ae_imgs = autoencoder.predict(X_test) #앞서 만든 오토인코더 모델에 집어 넣습니다.
4
5 plt.figure(figsize=(7, 2)) #출력될 이미지의 크기
6
7 for i, image_idx in enumerate(random_test): #랜덤하게 뽑은 이미지를 차례로 나열
8     ax = plt.subplot(2, 7, i + 1)
9     plt.imshow(X_test[image_idx].reshape(32, 32, 3)) #테스트할 이미지
10    ax.axis('off')
11    ax = plt.subplot(2, 7, 7 + i + 1)
12    plt.imshow(ae_imgs[image_idx].reshape(32, 32, 3)) #오토인코딩 결과를 다음열에 출력
13    ax.axis('off')
14
15 plt.show()
```

