MNIST 분류 모델 만들기 - 신경망

학습 내용

- 데이터 전처리 후, 딥러닝 모델 돌려보기
  - 데이터 차원 조정
  - 데이터의 값의 범위 변경(0 ~ 255 -> 0 ~ 1)

환경

- google colab
  - tensorflow 2.8.0
  - keras 2.8.0
  - python 3.7.13

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01 라이브러리 임포트 및 데이터 준비

In [ ]:
```
from keras.datasets import mnist
from keras.utils import np_utils
```

In [ ]:
```
import numpy
import sys
import tensorflow as tf
```

In [ ]:
```
# 난수 생성기의 패턴이 지정되지 않았을때,
print( numpy.random.rand(4) )
print( numpy.random.rand(4) )
```

```
[0.58876587 0.23991335 0.72467289 0.63857356]
[0.14204534 0.26480378 0.22780786 0.79339815]
```

In [ ]:
```
# 난수 생성기 패턴 지정
numpy.random.seed(0)
print( numpy.random.rand(4) )
numpy.random.seed(0)
print( numpy.random.rand(4) )
```

```
[0.5488135  0.71518937 0.60276338 0.54488318]
[0.5488135  0.71518937 0.60276338 0.54488318]
```

- 난수 패턴기의 패턴이 지정이 되면 같은 난수가 발생된다.

데이터 다운로드

In [ ]:
```
# 처음 다운일 경우, 데이터 다운로드 시간이 걸릴 수 있음.
(X_train, y_train), (X_test, y_test) = mnist.load_data()
print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)
```

```
(60000, 28, 28) (60000,)
(10000, 28, 28) (10000,)
```

In [ ]:

```
import matplotlib.pyplot as plt
```

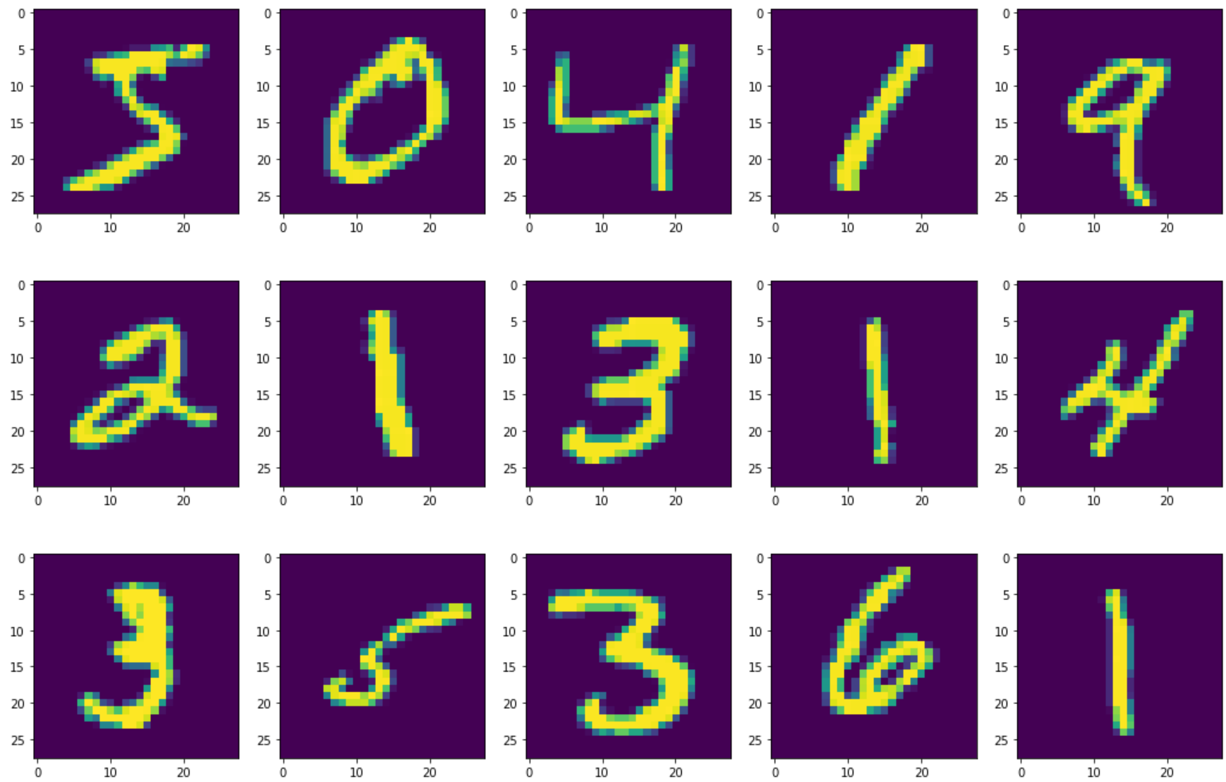
In [ ]:

```
fig, axes = plt.subplots(3, 5, figsize=(18,12) )

print("label={}".format(y_train[0:15]))   # x데이터 0~14개 가져오기

for image, ax in zip( X_train, axes.ravel() ):
    ax.imshow(image) # 이미지 표시
```

```
label=[5 0 4 1 9 2 1 3 1 4 3 5 3 6 1]
```



X_train의 데이터 정보를 하나 보기

In [ ]:

```
print(X_train.shape)  # 60000 만개, 28행, 28열
X_train[0].shape
```

```
(60000, 28, 28)
```

Out[ ]:

```
(28, 28)
```

02 데이터 전처리

신경망에 맞추어 주기 위한 데이터 전처리

- 학습 데이터
- 테스트 데이터

입력 데이터의 텐서형 변경 및 값의 범위 조정

In [ ]:

```
X_train = X_train.reshape(X_train.shape[0],784)   # 60000, 28, 28 -> 60000, 7
# 데이터 값의 범위 0~255 -> 0~1
X_train.astype('float64')
X_train = X_train/255
```

```
# 한줄 표현 - 이렇게도 가능
# X_train = X_train.reshape(X_train.shape[0],784).astype('float64') / 255
```

In [ ]:
```
import numpy as np
```

In [ ]:
```
print(X_train.shape)                    # 데이터 크기
print("데이터의 최대, 최소 :", np.min(X_train), np.max(X_train) )   # 값의 범위
```

```
(60000, 784)
데이터의 최대, 최소 : 0.0 1.0
```

In [ ]:
```
# 테스트 데이터 전처리
X_test = X_test.reshape(X_test.shape[0],784)
X_test.astype('float64')
X_test = X_test/255
```

In [ ]:
```
print(X_test.shape)                    # 데이터 크기
np.min(X_test), np.max(X_test)         # 값의 범위
```

```
(10000, 784)
```

Out[ ]:
```
(0.0, 1.0)
```

출력데이터 검증을 위해 10진수의 값을 One-Hot Encoding을 수행

In [ ]:
```
# OneHotEncoding - 10진수의 값을 0, 1의 값을 갖는 벡터로 표현
y_train_1D = np_utils.to_categorical(y_train, 10)
y_test_1D = np_utils.to_categorical(y_test, 10)
```

변환 전과 후

In [ ]:
```
y_train[0:4]
```

Out[ ]:
```
array([5, 0, 4, 1], dtype=uint8)
```

In [ ]:
```
y_train_1D[0:4]
```

Out[ ]:
```
array([[0., 0., 0., 0., 0., 1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 1., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.]], dtype=float32)
```

03 딥러닝 모델 구축하기

In [ ]:
```
from keras.models import Sequential
from keras.layers import Dense
```

In [ ]:
```
m = Sequential()
m.add(Dense(512,input_dim=784, activation='relu'))
m.add(Dense(128, activation='relu') )
m.add(Dense(10,activation='softmax'))   #softmax
```

오차함수 :categorical_crossentropy, 최적화 함수 : adam

In [ ]:
```
m.compile(loss="categorical_crossentropy",
          optimizer='adam',
          metrics=['accuracy'])
```

In [ ]:
```
### 배치 사이즈 200, epochs 30회 실행,
history = m.fit(X_train, y_train_1D, validation_data=(X_test, y_test_1D),
                epochs=30,
                batch_size=200,
                verbose=1)
```

```
Epoch 1/30
300/300 [==============================] - 4s 12ms/step - loss: 0.2652 - accur
acy: 0.9247 - val_loss: 0.1228 - val_accuracy: 0.9615
Epoch 2/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0961 - accur
acy: 0.9710 - val_loss: 0.0843 - val_accuracy: 0.9738
Epoch 3/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0625 - accur
acy: 0.9806 - val_loss: 0.0727 - val_accuracy: 0.9777
Epoch 4/30
300/300 [==============================] - 4s 15ms/step - loss: 0.0430 - accur
acy: 0.9865 - val_loss: 0.0670 - val_accuracy: 0.9808
Epoch 5/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0307 - accur
acy: 0.9907 - val_loss: 0.0665 - val_accuracy: 0.9800
Epoch 6/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0235 - accur
acy: 0.9928 - val_loss: 0.0688 - val_accuracy: 0.9799
Epoch 7/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0184 - accur
acy: 0.9944 - val_loss: 0.0646 - val_accuracy: 0.9828
Epoch 8/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0142 - accur
acy: 0.9955 - val_loss: 0.0699 - val_accuracy: 0.9804
Epoch 9/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0109 - accur
acy: 0.9966 - val_loss: 0.0766 - val_accuracy: 0.9798
Epoch 10/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0137 - accur
acy: 0.9954 - val_loss: 0.0803 - val_accuracy: 0.9780
Epoch 11/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0104 - accur
acy: 0.9967 - val_loss: 0.0735 - val_accuracy: 0.9821
Epoch 12/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0092 - accur
acy: 0.9970 - val_loss: 0.0780 - val_accuracy: 0.9798
Epoch 13/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0108 - accur
acy: 0.9964 - val_loss: 0.0756 - val_accuracy: 0.9813
Epoch 14/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0075 - accur
acy: 0.9975 - val_loss: 0.0783 - val_accuracy: 0.9818
Epoch 15/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0059 - accur
acy: 0.9982 - val_loss: 0.0822 - val_accuracy: 0.9806
Epoch 16/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0053 - accur
acy: 0.9984 - val_loss: 0.1060 - val_accuracy: 0.9767
Epoch 17/30
300/300 [==============================] - 3s 12ms/step - loss: 0.0056 - accur
acy: 0.9983 - val_loss: 0.0778 - val_accuracy: 0.9836
Epoch 18/30
300/300 [==============================] - 3s 12ms/step - loss: 0.0054 - accur
acy: 0.9983 - val_loss: 0.0902 - val_accuracy: 0.9804
Epoch 19/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0066 - accur
acy: 0.9978 - val_loss: 0.0964 - val_accuracy: 0.9794
Epoch 20/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0067 - accur
acy: 0.9980 - val_loss: 0.0878 - val_accuracy: 0.9805
Epoch 21/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0048 - accur
acy: 0.9985 - val_loss: 0.0935 - val_accuracy: 0.9811
```

```
Epoch 22/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0062 - accur
acy: 0.9984 - val_loss: 0.0934 - val_accuracy: 0.9825
Epoch 23/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0078 - accur
acy: 0.9976 - val_loss: 0.0867 - val_accuracy: 0.9825
Epoch 24/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0052 - accur
acy: 0.9984 - val_loss: 0.0926 - val_accuracy: 0.9829
Epoch 25/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0038 - accur
acy: 0.9987 - val_loss: 0.0972 - val_accuracy: 0.9821
Epoch 26/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0056 - accur
acy: 0.9984 - val_loss: 0.0992 - val_accuracy: 0.9811
Epoch 27/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0031 - accur
acy: 0.9991 - val_loss: 0.0905 - val_accuracy: 0.9833
Epoch 28/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0030 - accur
acy: 0.9990 - val_loss: 0.0970 - val_accuracy: 0.9823
Epoch 29/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0066 - accur
acy: 0.9979 - val_loss: 0.1049 - val_accuracy: 0.9820
Epoch 30/30
300/300 [==============================] - 3s 11ms/step - loss: 0.0046 - accur
acy: 0.9985 - val_loss: 0.1087 - val_accuracy: 0.9807
```

In [ ]:

```
print("학습용 데이터 셋 Accuracy : %.4f" %(m.evaluate(X_train, y_train_1D)[1]))
print("테스트용 데이터 셋 Accuracy : %.4f" %(m.evaluate(X_test, y_test_1D)[1]))
```

```
1875/1875 [==============================] - 5s 3ms/step - loss: 0.0045 - accu
racy: 0.9985
학습용 데이터 셋 Accuracy : 0.9985
313/313 [==============================] - 1s 3ms/step - loss: 0.1087 - accura
cy: 0.9807
테스트용 데이터 셋 Accuracy : 0.9807
```

In [ ]:

```
pred = m.predict(X_test)
```

In [ ]:

```
print( pred.shape )
print( "예측값 : ", pred[1] )
print( "예측값 중 가장 높은 값의 위치 : ", np.argmax(pred[1]) )
```

```
(10000, 10)
예측값 :  [9.3413454e-17 1.6887590e-16 1.0000000e+00 4.6736043e-16 1.1535825e-2
9
 6.4255561e-22 1.9321864e-17 7.5378626e-24 9.8010006e-14 9.5771777e-25]
예측값 중 가장 높은 값의 위치 :  2
```