MNIST 분류 모델 만들기 - 신경망

In [1]:

```
from keras.datasets import mnist
from keras.utils import np_utils
```

In [2]:

```
import numpy
import sys
import tensorflow as tf
```

In [4]:

```
seed = 0
numpy.random.seed(seed)
```

데이터 다운로드

In [5]:

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

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

In [6]:

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

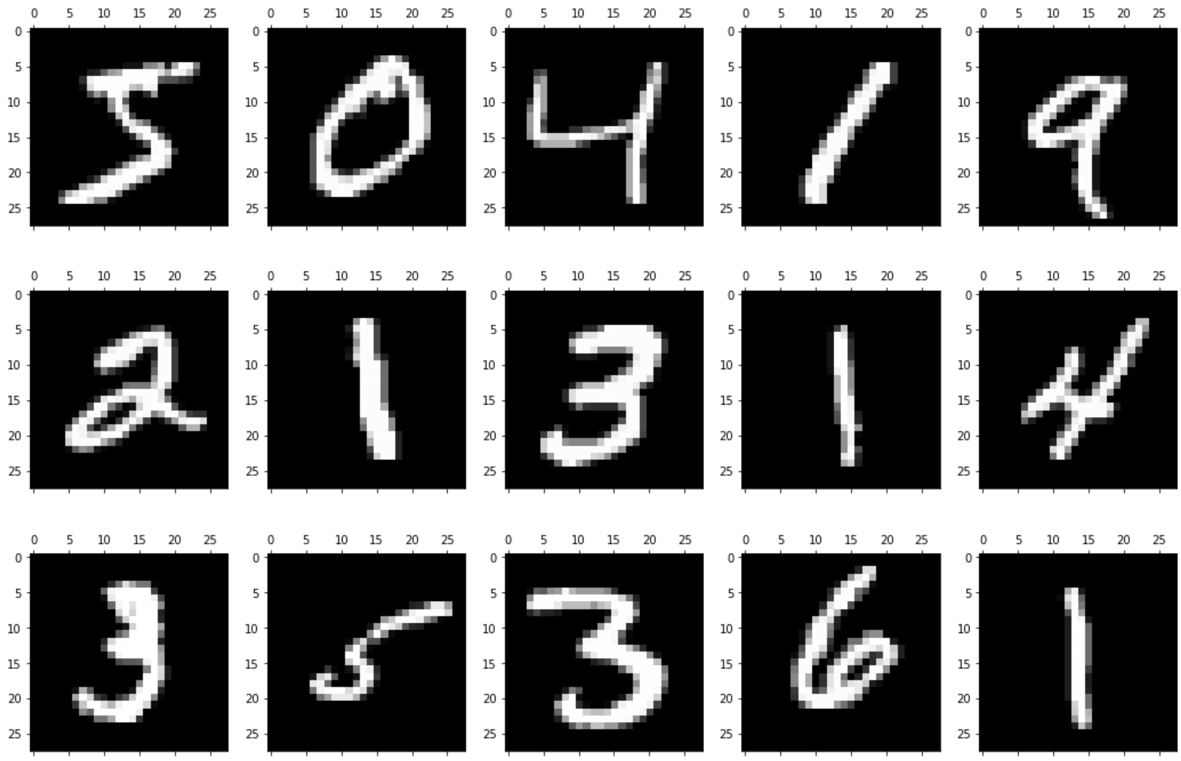
In [7]:

```
figure,axes = plt.subplots(nrows=3, ncols=5)
figure.set_size_inches(18,12)

plt.gray()
print("label={}".format(y_train[0:15]))

col = 0
for row in range(0,3):
    col = row * 5
    axes[row][0].matshow(X_train[col])
    axes[row][1].matshow(X_train[col+1])
    axes[row][2].matshow(X_train[col+2])
    axes[row][3].matshow(X_train[col+3])
    axes[row][4].matshow(X_train[col+4])
```

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



X_train의 데이터 정보를 하나 보기

In [8]:

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

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

Out[8]:

```
(28, 28)
```

신경망에 맞추어 주기 위해 데이터 전처리

- 학습 데이터
- 테스트 데이터

In [9]:

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

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

In [10]:

```
import numpy as np
```

In [11]:

```
print(X_train.shape)            # 데이터 크기
np.min(X_train), np.max(X_train)   # 값의 범위
```

```
(60000, 784)
```

Out[11]:

```
(0.0, 1.0)
```

In [12]:

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

In [13]:

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

```
(10000, 784)
```

Out[13]:

```
(0.0, 1.0)
```

출력데이터 검증을 위해 10진수의 값을 One-Hot Encoding을 수행

In [14]:

```
# OneHotEncoding - 10진수의 값을 0, 1의 값을 갖는 벡터로 표현
Y_train = np_utils.to_categorical(y_train, 10)
Y_test = np_utils.to_categorical(y_test, 10)
```

변환 전과 후

In [15]:

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

Out[15]:

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

In [16]:

```
Y_train[0:4]
```

Out[16]:

```
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)
```

딥러닝 만들어 보기

In [17]:

```
from keras.models import Sequential
from keras.layers import Dense
```

In [18]:

```
m = Sequential()
```

In [19]:

```
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 [20]:

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

In [21]:

```
### 배치 사이즈 200, epochs 30회 실행,
history = m.fit(X_train, Y_train, validation_data=(X_test, Y_test),
                epochs=30,
                batch_size=200,
                verbose=1)
```

```
Epoch 1/30
300/300 [==============================] - 1s 5ms/step - loss: 0.2674 - accuracy: 0.
9245 - val_loss: 0.1346 - val_accuracy: 0.9585
Epoch 2/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0968 - accuracy: 0.
9709 - val_loss: 0.0937 - val_accuracy: 0.9706
Epoch 3/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0614 - accuracy: 0.
9816 - val_loss: 0.0689 - val_accuracy: 0.9780
Epoch 4/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0405 - accuracy: 0.
9874 - val_loss: 0.0718 - val_accuracy: 0.9781
Epoch 5/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0288 - accuracy: 0.
9913 - val_loss: 0.0665 - val_accuracy: 0.9814
Epoch 6/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0226 - accuracy: 0.
9932 - val_loss: 0.0638 - val_accuracy: 0.9796
Epoch 7/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0168 - accuracy: 0.
9950 - val_loss: 0.0818 - val_accuracy: 0.9771
Epoch 8/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0127 - accuracy: 0.
9959 - val_loss: 0.0741 - val_accuracy: 0.9799
Epoch 9/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0118 - accuracy: 0.
9962 - val_loss: 0.0722 - val_accuracy: 0.9801
Epoch 10/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0093 - accuracy: 0.
9970 - val_loss: 0.0811 - val_accuracy: 0.9791
Epoch 11/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0108 - accuracy: 0.
9963 - val_loss: 0.0762 - val_accuracy: 0.9806
Epoch 12/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0088 - accuracy: 0.
9972 - val_loss: 0.0814 - val_accuracy: 0.9781
Epoch 13/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0080 - accuracy: 0.
9973 - val_loss: 0.0814 - val_accuracy: 0.9808
Epoch 14/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0077 - accuracy: 0.
9976 - val_loss: 0.1012 - val_accuracy: 0.9765
Epoch 15/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0068 - accuracy: 0.
9978 - val_loss: 0.0791 - val_accuracy: 0.9824
Epoch 16/30
300/300 [==============================] - 1s 5ms/step - loss: 0.0075 - accuracy: 0.
9976 - val_loss: 0.1116 - val_accuracy: 0.9743
Epoch 17/30
300/300 [==============================] - 1s 5ms/step - loss: 0.0094 - accuracy: 0.
9969 - val_loss: 0.0916 - val_accuracy: 0.9814
Epoch 18/30
```

```
300/300 [==============================] - 1s 4ms/step - loss: 0.0056 - accuracy: 0.
9981 - val_loss: 0.0985 - val_accuracy: 0.9795
Epoch 19/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0034 - accuracy: 0.
9990 - val_loss: 0.0951 - val_accuracy: 0.9826
Epoch 20/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0047 - accuracy: 0.
9984 - val_loss: 0.1212 - val_accuracy: 0.9769
Epoch 21/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0071 - accuracy: 0.
9977 - val_loss: 0.0851 - val_accuracy: 0.9826
Epoch 22/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0038 - accuracy: 0.
9989 - val_loss: 0.1028 - val_accuracy: 0.9804
Epoch 23/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0104 - accuracy: 0.
9965 - val_loss: 0.0933 - val_accuracy: 0.9802
Epoch 24/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0042 - accuracy: 0.
9989 - val_loss: 0.0894 - val_accuracy: 0.9826
Epoch 25/30
300/300 [==============================] - 1s 4ms/step - loss: 0.0022 - accuracy: 0.
9993 - val_loss: 0.0903 - val_accuracy: 0.9837
Epoch 26/30
300/300 [==============================] - 1s 4ms/step - loss: 6.3915e-04 - accurac
y: 0.9999 - val_loss: 0.0901 - val_accuracy: 0.9833
Epoch 27/30
300/300 [==============================] - 1s 4ms/step - loss: 1.1963e-04 - accurac
y: 1.0000 - val_loss: 0.0857 - val_accuracy: 0.9849
Epoch 28/30
300/300 [==============================] - 1s 5ms/step - loss: 4.0693e-05 - accurac
y: 1.0000 - val_loss: 0.0863 - val_accuracy: 0.9848
Epoch 29/30
300/300 [==============================] - 1s 5ms/step - loss: 3.1315e-05 - accurac
y: 1.0000 - val_loss: 0.0874 - val_accuracy: 0.9848
Epoch 30/30
300/300 [==============================] - 2s 5ms/step - loss: 2.5225e-05 - accurac
y: 1.0000 - val_loss: 0.0884 - val_accuracy: 0.9847
```

In [22]:

```python
print("Test Accuracy : %.4f" %(m.evaluate(X_test, Y_test)[1]))
```

```
313/313 [==============================] - 0s 1ms/step - loss: 0.0884 - accuracy: 0.
9847
Test Accuracy : 0.9847
```

In [23]:

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

In [24]:

```
print( pred.shape )
print( pred[1] )
```

```
(10000, 10)
[2.8150371e-18 1.3070420e-12 1.0000000e+00 1.7728102e-17 9.9219194e-30
 1.2918585e-20 2.3182731e-18 6.2873724e-22 6.3510818e-15 9.1639151e-25]
```