HW3 Pattern Recognition

2019150445 신백록

1. Download MNIST dataset

```
In [1]:
                                           import numpy as np
                                           import tensorflow as tf
                                           from tensorflow.keras.datasets import mnist
                                           import matplotlib.pyplot as plt
                                           (X,y),(X_test,y_test)=mnist.load_data()
                                           print(X.shape)
                                           print(X_test.shape)
                                           print(y.shape)
                                           print(y_test.shape)
                                        Init Plugin
                                        Init Graph Optimizer
                                        Init Kernel
                                         (60000, 28, 28)
                                         (10000, 28, 28)
                                         (60000,)
                                         (10000,)
In [2]:
                                           from sklearn.model_selection import train_test_split
                                           X train, X val, y train, y val = train_test_split(X, y, test_size=0.1, strain_test_split(X, y, t
In [3]:
                                           print(X_train.shape)
                                           print(X val.shape)
                                         (54000, 28, 28)
                                         (6000, 28, 28)
```

By train_test_split function, I assigned 10% of training set to X_val, y_val.

```
In [4]:
          X_train=X_train.reshape(-1,28*28)
          X_val=X_val.reshape(-1,28*28)
          X_{\text{test=X_test.reshape}(-1,28*28)}
          print(X_train.shape)
          print(X val.shape)
          print(X test.shape)
         (54000, 784)
         (6000, 784)
         (10000, 784)
In [5]:
          from tensorflow.keras.utils import to categorical
          X_train=X_train/255.
          X_val=X_val/255.
          X_{\text{test}} = X_{\text{test}} / 255.
          y_train=to_categorical(y_train)
          y_val=to_categorical(y_val)
          y_test=to_categorical(y_test)
          print(y_train.shape)
         (54000, 10)
```

I reshaped the image data to flatten data to use MLP. And by to_categorical function, I made y to be one-hot encoded.

2. Explain Activation Function

The activation function makes the linear combination w^Tx to $g(w^Tx)$ to make the linear function non-linear. Since linear functions cannot create a non-linear model, activation functions are used. In fact, if each layer is connected only by a linear combination without an activation function, the result will be the same as using a single linear combination even if several hidden layers are created.

For example, the sigmoid function transforms the result of a linear combination non-linearly so that it falls within the range 0 to 1. Therefore, it is often used for the last MLP layer in a binary classification model that classifies 0 or 1.

If the result of the linear combination is less than 0, the ReLU function converts it to 0, and if it is greater than 0, the result is converted as it is. Since the differential value is 0 or 1, gradient vanishing and exploding phenomena that occur when the layer is deep can be prevented. In addition, since the differential calculation is simple, it has the advantage of fast learning speed.

In conclusion, activation functions such as sigmoid and ReLU functions are used to create non-linear models that cannot be expressed as linear combinations.

3. Explain MLP

Let's define input value of unit j as x_j , weight on link from unit j to unit i as θ_{ij} , activation function as g(.), activation value of unit i as a_i

Assume there are 1 input layer and 1 hidden layer with 3 nodes each excluding bias node. Then nodes of input layer is x_0 (actually it is bias term 1), x_1 , x_2 and x_3 . The node for next layer a_i is defined with linear combination of input nodes and activation function. For example, $a_1=g(\theta_{10}x_0+\theta_{11}x_1+\theta_{12}x_2+\theta_{13}x_3)$ and $a_2=g(\theta_{20}x_0+\theta_{21}x_1+\theta_{22}x_2+\theta_{23}x_3)$

Here, our purpose is to find optimal parameter θ_{ij} . So first, we initialize θ_{ij} to any value or something. Then we compute error at last output layer for initialized parameter θ . And compute error for each node at each layer and by optimization algorithm(gradient descent algorithm or something), move θ_{ij} to reduce the error. Then by that θ we obtain, we again do forward propagation and compute error and back propagation again and again until obtain optimal parameter.

4. Training and Evaluation

```
In [6]:
    from tensorflow.keras.models import Sequential
    from tensorflow.keras.layers import Dense
    from tensorflow.keras.utils import plot_model

In [7]:
    model=Sequential()
    model.add(Dense(1024, input_dim=784, activation='relu'))
    model.add(Dense(10, activation='relu'))
    model.summary()
    plot_model(model,show_shapes=True)
```

> Metal device set to: Apple M1 Model: "sequential"

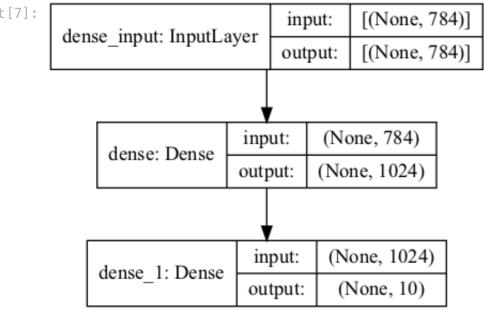
Layer (type)	Output Shape	Param #
dense (Dense)	(None, 1024)	803840
dense_1 (Dense)	(None, 10)	10250
Total params: 814,090		

Trainable params: 814,090 Non-trainable params: 0

2021-12-01 16:42:44.159086: I tensorflow/core/common_runtime/pluggable_devi ce/pluggable device factory.cc:305] Could not identify NUMA node of platfor m GPU ID 0, defaulting to 0. Your kernel may not have been built with NUMA support.

2021-12-01 16:42:44.159170: I tensorflow/core/common runtime/pluggable devi ce/pluggable device factory.cc:271] Created TensorFlow device (/job:localho st/replica:0/task:0/device:GPU:0 with 0 MB memory) -> physical PluggableDev ice (device: 0, name: METAL, pci bus id: <undefined>)





```
In [8]:
         import keras
         test_acc=[]
         class TestCallback(keras.callbacks.Callback):
             def init (self, test data):
                 self.test data = test data
             def on_epoch_end(self, epoch, logs={}):
                 global test acc
                 x, y = self.test data
                 test acc.append(self.model.evaluate(x, y, verbose=0)[1])
```

By callback function, test accuracy for each epoch is calculated and saved in test_acc

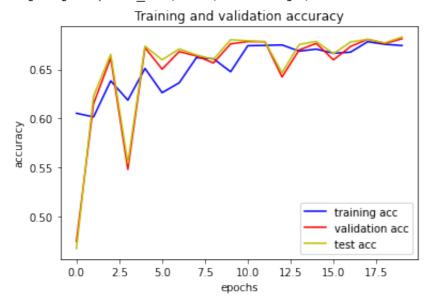
```
In [9]:
               model.compile(loss='categorical crossentropy',optimizer='adam', metrics=[
In [10]:
               history=model.fit(X train, y train, epochs=20, batch size=64, validation delation delta between the between training and training and training are selected as a selected and training are selected as a selected and training are selected as a selected are selected are selected are selected as a selected are selected as a selected are selected are
               history out=history.history
             Epoch 1/20
                1/844 [.....] - ETA: 2:23 - loss: 10.1765 - accu
             racy: 0.0938
              2021-12-01 16:42:46.159026: I tensorflow/compiler/mlir/mlir graph optimizat
              ion pass.cc:176] None of the MLIR Optimization Passes are enabled (register
             ed 2)
              2021-12-01 16:42:46.159177: W tensorflow/core/platform/profile utils/cpu ut
             ils.cc:128] Failed to get CPU frequency: 0 Hz
             2021-12-01 16:42:46.253955: I tensorflow/core/grappler/optimizers/custom_gr
             aph optimizer registry.cc:112] Plugin optimizer for device type GPU is enab
             led.
             y: 0.6053
             2021-12-01 16:42:52.341683: I tensorflow/core/grappler/optimizers/custom_gr
             aph_optimizer_registry.cc:112] Plugin optimizer for device_type GPU is enab
              led.
             uracy: 0.6053 - val loss: 5.2325 - val accuracy: 0.4743
             Epoch 2/20
             uracy: 0.6016 - val loss: 5.0079 - val accuracy: 0.6152
             Epoch 3/20
             uracy: 0.6384 - val_loss: 4.8330 - val_accuracy: 0.6617
             Epoch 4/20
             844/844 [============== ] - 6s 7ms/step - loss: 4.7865 - acc
             uracy: 0.6187 - val_loss: 5.1388 - val_accuracy: 0.5480
             Epoch 5/20
              uracy: 0.6511 - val_loss: 4.8430 - val_accuracy: 0.6723
             Epoch 6/20
             uracy: 0.6263 - val loss: 4.8255 - val accuracy: 0.6503
             Epoch 7/20
              uracy: 0.6364 - val_loss: 4.8310 - val_accuracy: 0.6683
             Epoch 8/20
             uracy: 0.6621 - val_loss: 4.4427 - val_accuracy: 0.6638
             Epoch 9/20
             uracy: 0.6610 - val_loss: 4.7152 - val_accuracy: 0.6567
             Epoch 10/20
              844/844 [==============] - 6s 7ms/step - loss: 4.7627 - acc
             uracy: 0.6477 - val_loss: 4.7909 - val_accuracy: 0.6762
             Epoch 11/20
              uracy: 0.6743 - val_loss: 4.5289 - val_accuracy: 0.6785
```

```
Epoch 12/20
      uracy: 0.6746 - val loss: 4.0436 - val accuracy: 0.6783
      Epoch 13/20
      uracy: 0.6751 - val_loss: 4.8201 - val_accuracy: 0.6423
      Epoch 14/20
      uracy: 0.6688 - val_loss: 4.5122 - val_accuracy: 0.6700
      Epoch 15/20
      844/844 [=============] - 6s 7ms/step - loss: 3.6945 - acc
      uracy: 0.6708 - val_loss: 3.4961 - val_accuracy: 0.6767
      Epoch 16/20
      uracy: 0.6666 - val loss: 2.5915 - val accuracy: 0.6598
      Epoch 17/20
      844/844 [============] - 6s 7ms/step - loss: 3.6029 - acc
      uracy: 0.6678 - val_loss: 4.0397 - val_accuracy: 0.6735
      Epoch 18/20
      844/844 [============] - 6s 7ms/step - loss: 3.8680 - acc
      uracy: 0.6784 - val loss: 3.7478 - val accuracy: 0.6808
      Epoch 19/20
      uracy: 0.6757 - val_loss: 3.6131 - val_accuracy: 0.6765
      Epoch 20/20
      uracy: 0.6745 - val_loss: 3.6157 - val_accuracy: 0.6813
In [11]:
       import matplotlib.pyplot as plt
       accuracy=history out['accuracy']
       accuracy_val=history_out['val_accuracy']
       plt.clf()
       plt.plot(accuracy, 'b', label='training acc')
       plt.plot(accuracy_val, 'b', color='r', label='validation acc')
       plt.plot(test_acc, 'b', color='y', label='test acc')
       plt.title('Training and validation accuracy')
       plt.xlabel('epochs')
       plt.ylabel('accuracy')
       plt.legend()
       plt.show()
```

/var/folders/9r/7f1bw3q15yz7435178lsgb5w0000gp/T/ipykernel_3430/2521518520. py:8: UserWarning: color is redundantly defined by the 'color' keyword argu ment and the fmt string "b" (-> color=(0.0, 0.0, 1.0, 1)). The keyword argu ment will take precedence.

plt.plot(accuracy_val,'b', color='r', label='validation acc') /var/folders/9r/7f1bw3q15yz7435178lsgb5w0000gp/T/ipykernel_3430/2521518520. py:9: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "b" (-> color=(0.0, 0.0, 1.0, 1)). The keyword argument will take precedence.

plt.plot(test_acc, 'b', color='y', label='test acc')



We can see there are no convergences occur for train, validation, test set for first 12 epochs. But after 12 epoch, we can see some convergence for train, validation, test data set. But accuracy is too low which is underfitted.

```
from tensorflow.keras.models import Sequential
    from tensorflow.keras.layers import Dense, Activation, Dropout, BatchNormal
    from tensorflow.keras.utils import plot_model

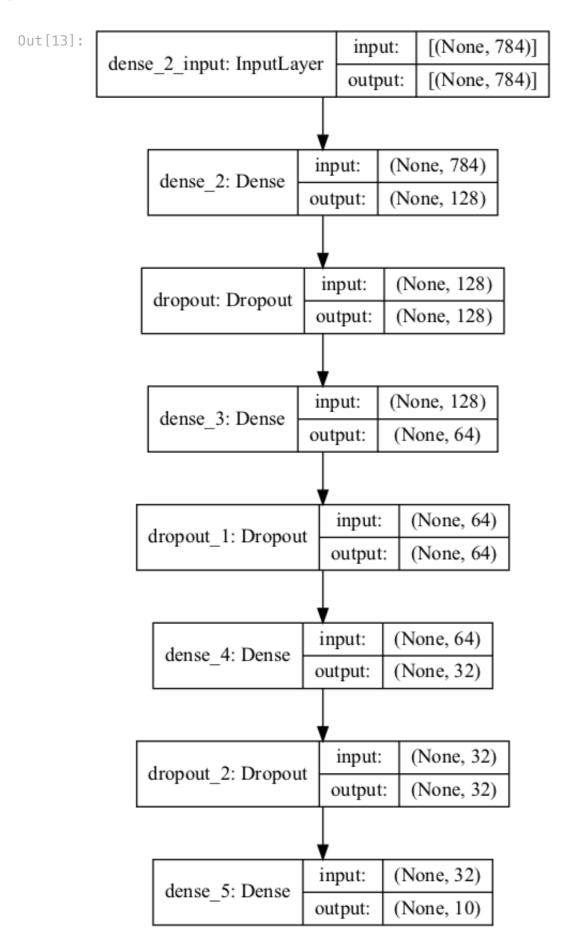
    model=Sequential()
    model.add(Dense(128, input_dim=784, activation='relu'))
    model.add(Dropout(0.4))
    model.add(Dropout(0.4))
    model.add(Dropout(0.3))
    model.add(Dropout(0.3))
    model.add(Dropout(0.2))
    model.add(Dropout(0.2))
    model.add(Dense(10,activation='softmax'))
    model.summary()
    plot_model(model,show_shapes=True)
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_2 (Dense)	(None, 128)	100480
dropout (Dropout)	(None, 128)	0

dense_3 (Dense)	(None, 64)	8256
dropout_1 (Dropout)	(None, 64)	0
dense_4 (Dense)	(None, 32)	2080
dropout_2 (Dropout)	(None, 32)	0
dense_5 (Dense)	(None, 10)	330

Total params: 111,146
Trainable params: 111,146
Non-trainable params: 0



Input dim is set to 784 because there are 784 characteristic variables.

The first Dense layer was fitted with dimension 128 and the activation function was relu.

Dropout was given to prevent overfitting, so that each node had a value of 0 with a 40% probability.

The second Dense layer is set to dimension 64, and the activation function is relu as above, and gave a dropout of 0.3.

The third Dense layer is set to dimension 32, activation function relu, and dropout 0.2.

The last Dense layer has to extract the probability for 10 labels, so dimension=10, activation='softmax' was given.

In order to prevent the bottleneck phenomenon, the dimension gradually decreases from 128, and finally at the last layer, 10 nodes are estimated from 32 nodes.

```
In [14]: test_acc=[]
#initialize test_acc list.

In [15]: from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
```

Earlystopping and model checkpoint were called to give callback, and to prevent overfitting, learning was stopped if validation_accuracy did not improve for 4 epochs, and the model was saved when val accuracy was improved.

callback list=[TestCallback((X test, y test)), EarlyStopping(monitor='val ac

```
In [16]:
    model.compile(loss='categorical_crossentropy',optimizer='adam', metrics=['a
    history=model.fit(X_train, y_train, epochs=30, batch_size=64, callbacks=call
    history_out=history.history
    history_out.keys()
```

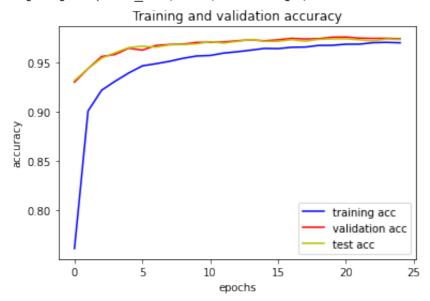
```
Epoch 3/30
uracy: 0.9216 - val_loss: 0.1555 - val_accuracy: 0.9557
Epoch 4/30
uracy: 0.9308 - val_loss: 0.1460 - val_accuracy: 0.9578
Epoch 5/30
uracy: 0.9391 - val_loss: 0.1252 - val_accuracy: 0.9641
Epoch 6/30
uracy: 0.9463 - val_loss: 0.1308 - val_accuracy: 0.9622
Epoch 7/30
uracy: 0.9484 - val_loss: 0.1158 - val_accuracy: 0.9669
Epoch 8/30
591/591 [============= ] - 5s 8ms/step - loss: 0.1798 - acc
uracy: 0.9508 - val_loss: 0.1171 - val_accuracy: 0.9678
Epoch 9/30
591/591 [============= ] - 5s 8ms/step - loss: 0.1649 - acc
uracy: 0.9539 - val loss: 0.1161 - val accuracy: 0.9682
Epoch 10/30
uracy: 0.9562 - val_loss: 0.1071 - val_accuracy: 0.9700
Epoch 11/30
uracy: 0.9568 - val_loss: 0.1053 - val_accuracy: 0.9701
Epoch 12/30
uracy: 0.9592 - val_loss: 0.1041 - val_accuracy: 0.9704
Epoch 13/30
591/591 [============= ] - 5s 8ms/step - loss: 0.1405 - acc
uracy: 0.9606 - val_loss: 0.1038 - val_accuracy: 0.9717
Epoch 14/30
uracy: 0.9621 - val loss: 0.1015 - val accuracy: 0.9726
Epoch 15/30
uracy: 0.9639 - val_loss: 0.1012 - val_accuracy: 0.9715
Epoch 16/30
591/591 [=============] - 5s 8ms/step - loss: 0.1288 - acc
uracy: 0.9637 - val loss: 0.1022 - val accuracy: 0.9727
Epoch 17/30
591/591 [============== ] - 5s 8ms/step - loss: 0.1202 - acc
uracy: 0.9651 - val_loss: 0.0953 - val_accuracy: 0.9741
Epoch 18/30
591/591 [============= ] - 5s 8ms/step - loss: 0.1202 - acc
uracy: 0.9653 - val_loss: 0.1007 - val_accuracy: 0.9735
Epoch 19/30
uracy: 0.9669 - val_loss: 0.0989 - val_accuracy: 0.9738
Epoch 20/30
uracy: 0.9670 - val loss: 0.0929 - val accuracy: 0.9752
Epoch 21/30
uracy: 0.9681 - val loss: 0.0938 - val accuracy: 0.9754
```

```
Epoch 22/30
      uracy: 0.9682 - val loss: 0.0946 - val accuracy: 0.9743
      Epoch 23/30
      uracy: 0.9697 - val_loss: 0.0973 - val_accuracy: 0.9740
      Epoch 24/30
      uracy: 0.9700 - val_loss: 0.1036 - val_accuracy: 0.9741
      Epoch 25/30
      uracy: 0.9696 - val loss: 0.1004 - val accuracy: 0.9736
      dict keys(['loss', 'accuracy', 'val loss', 'val accuracy'])
Out[16]:
In [17]:
       import matplotlib.pyplot as plt
       accuracy=history out['accuracy']
       accuracy_val=history_out['val_accuracy']
       plt.clf()
       plt.plot(accuracy, 'b', label='training acc')
       plt.plot(accuracy_val, 'b', color='r', label='validation acc')
       plt.plot(test_acc, 'b', color='y', label='test acc')
       plt.title('Training and validation accuracy')
       plt.xlabel('epochs')
       plt.ylabel('accuracy')
       plt.legend()
       plt.show()
```

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plt.plot(accuracy_val,'b', color='r', label='validation acc')
/var/folders/9r/7f1bw3q15yz7435178lsgb5w0000gp/T/ipykernel_3430/2521518520.
py:9: UserWarning: color is redundantly defined by the 'color' keyword argu ment and the fmt string "b" (-> color=(0.0, 0.0, 1.0, 1)). The keyword argu ment will take precedence.

plt.plot(test_acc, 'b', color='y', label='test acc')



It converges neatly without any vibration.