Capstone Project on Image Classification - Fashion Industry

This is a dataset of 60,000 28x28 grayscale images of 10 fashion categories, along with a test set of 10,000 images.

Data Set -

Domain: Image classification Data: https://keras.io/api/datasets/fashion_mnist/

Label Description 0: T-shirt/top

1: Trouser

2: Pullover

3: Dress

4: Coat

5: Sandal

6: Shirt

7: Sneaker

8: Bag

9: Ankle boot

Objective

Classify the image into different classes, using the values of 784 pixels as features

Question 1

Collect Fashion mnist data from tf.keras.datasets

- Check the shape of the data

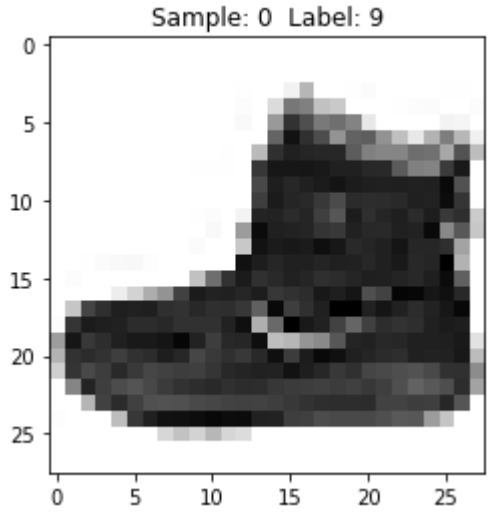
```
import pandas as pd
import tensorflow as tf

#Loading the dataset into training and tests sets
```

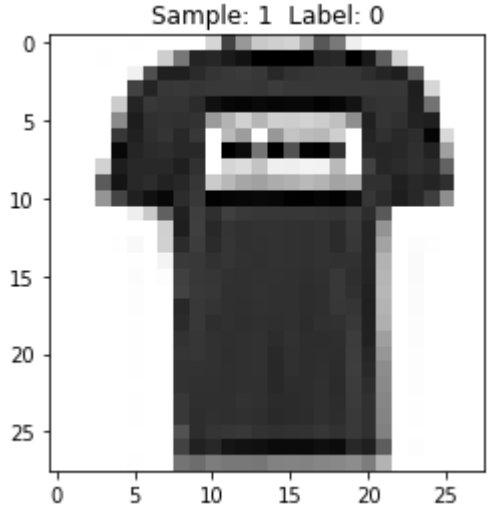
```
(x_train,y_train),(x_test,y_test) = tf.keras.datasets.fashion_mnist.load_data()

#Shape of sets
print("x_train: ",x_train.shape)
print("y_train: ",y_train.shape)
print("x_test: ",x_test.shape)
print("y_test: ",y_test.shape)
```

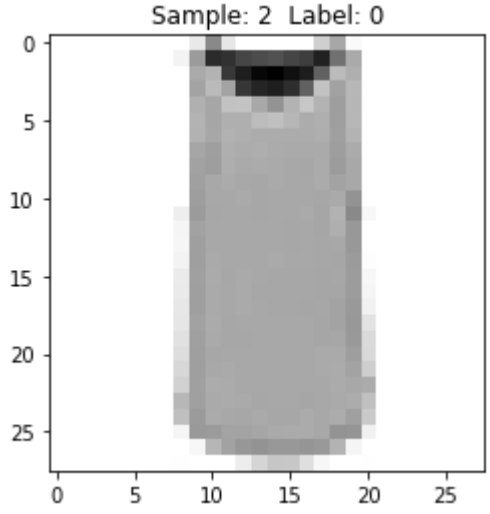
```
x_train:  (60000, 28, 28)
y_train:  (60000,)
x_test:  (10000, 28, 28)
y_test:  (10000,)
```

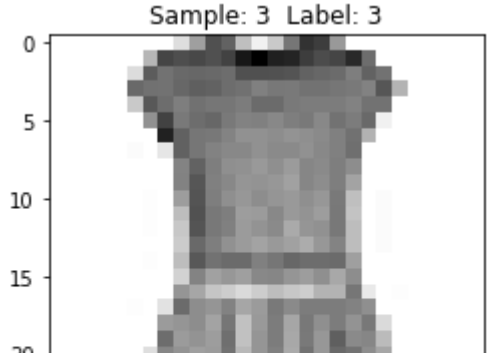
Display first 10 images along with their labels

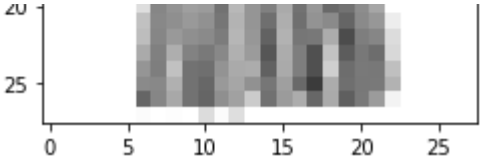
```
%matplotlib inline
#First 10 Images with their labels
import matplotlib.pyplot as plt
for num in range(0,10):

    #Print this sample's label
    label = y_train[num]

    #Reshape the 784 values to a 28x28 image
    image = x_train[num]

    # show the gray scale
    plt.title('Sample: %d  Label: %d' % (num, label))
    plt.imshow(image, cmap=plt.get_cmap('gray_r'))
    plt.show()
```

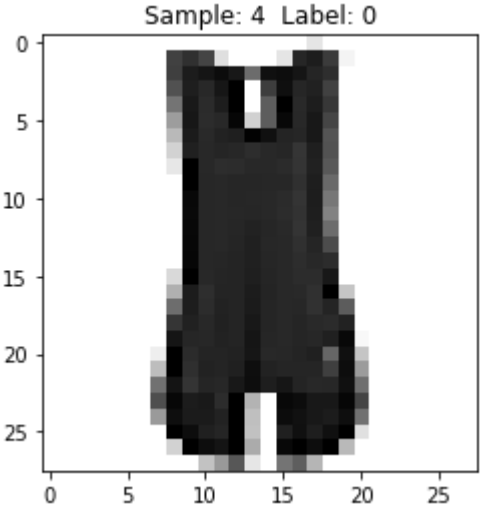

Sample: 0 Label: 9

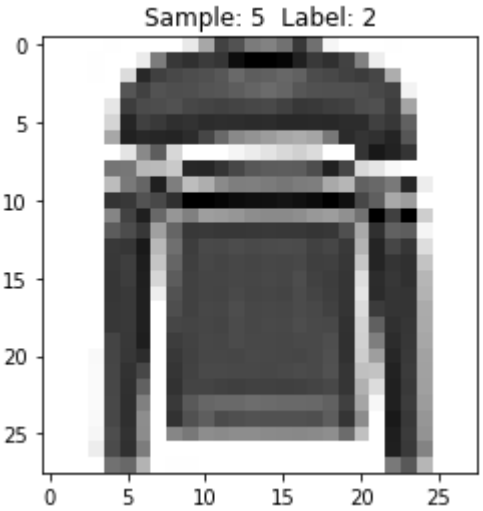

Sample: 1 Label: 0

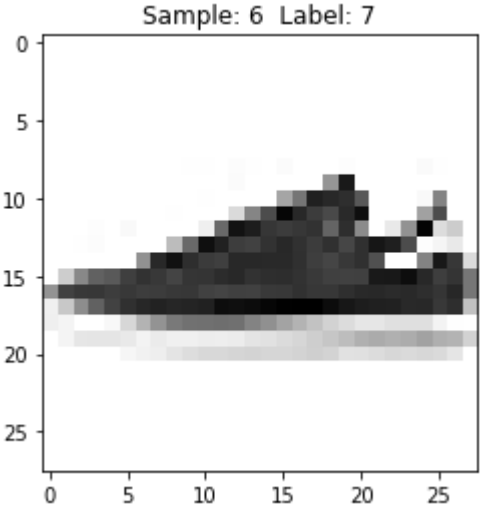

Sample: 2 Label: 0


Sample: 3 Label: 3

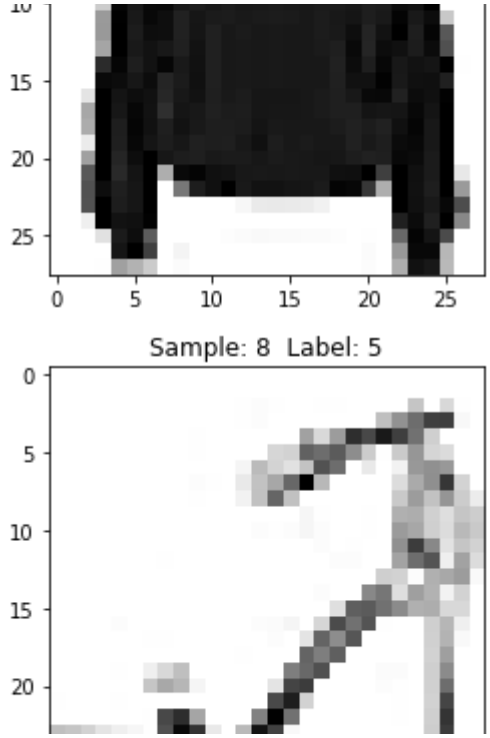



Sample: 4 Label: 0


Sample: 5 Label: 2


Sample: 6 Label: 7


Sample: 7 Label: 2



Question 2

Change train and test labels into one-hot vectors

- Check the shape of labels after one hot encoding

```
import numpy as np

num_classes = 10

x_train = np.expand_dims(x_train, -1)
x_test = np.expand_dims(x_test, -1)

y_train = tf.keras.utils.to_categorical(y_train,num_classes)
y_test = tf.keras.utils.to_categorical(y_test, num_classes)



print(x_train.shape,x_test.shape)
print(y_train.shape,y_test.shape)
```

```
(60000, 28, 28, 1) (10000, 28, 28, 1)
(60000, 10) (10000, 10)
```

Normalize the pixel values

```
#Normalizing pixel values in float
x_train=x_train/255.0
```

```
x_test=x_test/255.0
```

Question 3

Create a Deep Neural Network Model for Classification

- Initialize a Sequential model
- Reshape the 28X28 images into 1d array with 784 features
- Add 3 hidden layer with activation relu
- Add dropout layer after each hidden layer
- Add a Dense layer with 10 neuron as output, use activation softmax

The output layer has **number of neurons = number of classes** if activation is softmax.

Softmax is used for multi-class classification

Initialize model and reshape the data for the input layer

```
from keras.layers import Dense,Input,Dropout

#Reshaping 28x28 into 784 features of 1 array
num_features = 784
x_train = tf.reshape(x_train,[-1,num_features])
x_test = tf.reshape(x_test,[-1,num_features])

#Initialization of Model and input layer
model = tf.keras.Sequential()
model.add(tf.keras.Input(shape=(num_features,)))
```

Add hidden layers

- Add 3 fully-connected layers with 300, 200, and 100 neurons respectively with `relu` activations. Add a dropout layer with `p=0.15` after each hidden layer

```
#3 Hidden layers with required specifications
model.add(Dense(300,activation='relu'))
model.add(Dropout(0.15))
model.add(Dense(200,activation='relu'))
model.add(Dropout(0.15))
```

```
model.add(Dense(100,activation='relu'))
model.add(Dropout(0.15))
```

Add the output layer

- Use a fully connected layer with 10 neurons with `softmax` activation.
- Use `categorical_crossentropy` loss
- Use `adam` optimizer with learning rate = 0.002 and train the network.

Also add callback,

- such that if validation loss doesn't decreases consecutively 2 times, stop the training

```
from keras.callbacks import EarlyStopping

#Outer Layer with 10 neurons for 10 outputs
model.add(Dense(10,activation='softmax'))

#Model compilation using Adam optimizer and categorical_crossentropy
opt = tf.keras.optimizers.Adam(learning_rate=0.002)
model.compile(optimizer=opt,loss='categorical_crossentropy',metrics=['accuracy'])

#Callback to stop epochs for said condition
stop_here = EarlyStopping(patience=2)
```

Print model summary

```
#Model Summary
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_4 (Dense)             (None, 300)               235500

 dropout_3 (Dropout)         (None, 300)               0

 dense_5 (Dense)             (None, 200)               60200

 dropout_4 (Dropout)         (None, 200)               0

 dense_6 (Dense)             (None, 100)               20100

 dropout_5 (Dropout)         (None, 100)               0
```

```
 dense_7 (Dense)             (None, 10)                1010

=================================================================
Total params: 316,810
Trainable params: 316,810
Non-trainable params: 0
_________________________________________________________________
```

Question 4

Train your model, use test data as validation set

- epochs = 20
- batch size = 32

```
#Training Model
history = model.fit(x_train,y_train,batch_size=32,epochs=20,validation_data=(x_test,y_test),s

Epoch 1/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.5559 - accuracy: 0.79
Epoch 2/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.4362 - accuracy: 0.84
Epoch 3/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.4044 - accuracy: 0.85
Epoch 4/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.3833 - accuracy: 0.86
Epoch 5/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.3727 - accuracy: 0.86
Epoch 6/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.3593 - accuracy: 0.87
Epoch 7/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.3513 - accuracy: 0.87
Epoch 8/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.3448 - accuracy: 0.87
Epoch 9/20
1875/1875 [==============================] - 8s 4ms/step - loss: 0.3412 - accuracy: 0.87
Epoch 10/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.3364 - accuracy: 0.87
Epoch 11/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.3313 - accuracy: 0.88
Epoch 12/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.3231 - accuracy: 0.88
Epoch 13/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.3221 - accuracy: 0.88
Epoch 14/20
1875/1875 [==============================] - 8s 4ms/step - loss: 0.3131 - accuracy: 0.88
Epoch 15/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.3142 - accuracy: 0.88
Epoch 16/20
1875/1875 [==============================] - 8s 4ms/step - loss: 0.3034 - accuracy: 0.88
```

```
Epoch 17/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.3101 - accuracy: 0.88
Epoch 18/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.3035 - accuracy: 0.88
Epoch 19/20
1875/1875 [==============================] - 9s 5ms/step - loss: 0.3018 - accuracy: 0.89
Epoch 20/20
1875/1875 [==============================] - 8s 4ms/step - loss: 0.3027 - accuracy: 0.89
```

Evaluate the model on the test data

```
score = model.evaluate(x_test,y_test,verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])
```

```
Test loss: 0.3647908568382263
Test accuracy: 0.880299985408783
```

Question 5

Predict Labels of test data

```
y_pred= model.predict(x_test)
y_pred
```

```
array([[1.3649205e-13, 3.4128298e-15, 9.4117636e-17, ..., 3.4147798e-04,
        7.7537116e-10, 9.9964809e-01],
       [6.4450924e-06, 3.5540462e-14, 9.9952400e-01, ..., 3.1614008e-26,
        9.3240910e-12, 4.6281187e-31],
       [8.9872954e-23, 1.0000000e+00, 3.2098906e-30, ..., 0.0000000e+00,
        5.0013486e-36, 0.0000000e+00],
       ...,
       [3.1777156e-06, 1.0363660e-15, 5.4042513e-09, ..., 2.7365864e-19,
        9.9999189e-01, 1.9710648e-21],
       [3.7504394e-22, 1.0000000e+00, 2.8541328e-28, ..., 0.0000000e+00,
        6.5332618e-32, 0.0000000e+00],
       [4.7018713e-17, 1.2564215e-29, 1.1730180e-22, ..., 5.1925758e-07,
        5.4064790e-16, 1.5893713e-07]], dtype=float32)
```

Print Confusion matrix of test data

```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

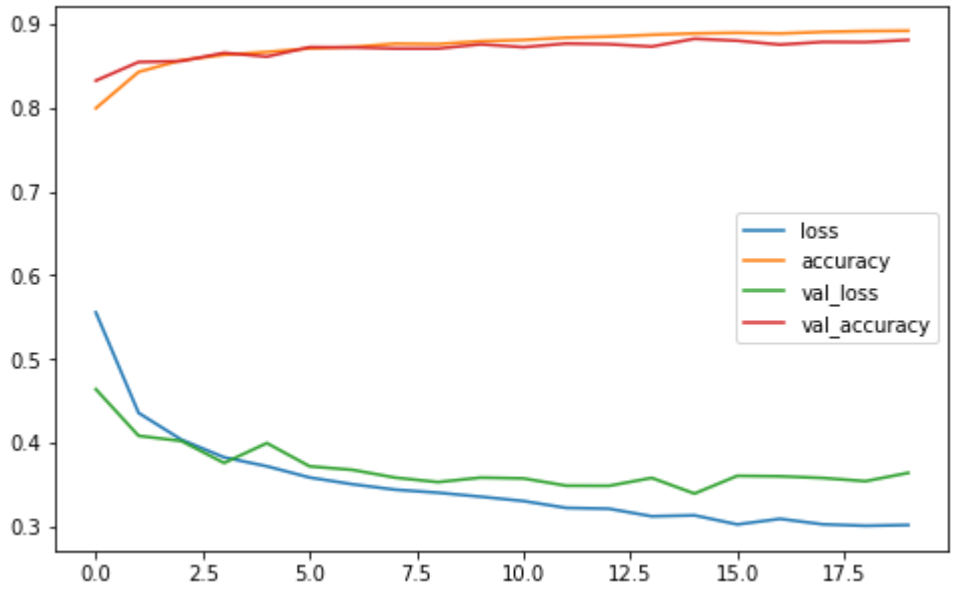
```
y_pred=np.argmax(y_pred, axis=1)
y_test=np.argmax(y_test, axis=1)
cm = confusion_matrix(y_pred,y_test)

columns = ['T-Shirt','Trouser','Pullover','Dress','Coat','Sandal','Shirt','Sneaker','Bag','An
pd.DataFrame(cm,columns=columns,index=columns)
```

	T-Shirt	Trouser	Pullover	Dress	Coat	Sandal	Shirt	Sneaker	Bag	Ankle
T-Shirt	870	4	18	31	0	0	156	0	0	
Trouser	2	969	0	2	1	0	0	0	0	
Pullover	15	2	796	13	95	0	113	0	5	
Dress	20	21	5	877	21	1	24	0	3	
Coat	2	2	126	51	804	0	56	0	6	
Sandal	1	0	0	0	0	959	0	12	2	
Shirt	82	1	55	22	77	0	638	0	7	
Sneaker	0	0	0	0	0	24	0	959	2	
Bag	8	1	0	4	2	0	13	0	975	
Ankle Boot	0	0	0	0	0	16	0	29	0	

Plot training accuracy vs validation accuracy

Plot training loss vs validation loss

```
pd.DataFrame(history.history).plot(figsize=(8,5))
plt.show()
```



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