

Use MNIST Fashion Dataset and create a classifier to classify fashion clothing into categories.

```
In [1]: 1 import tensorflow as tf
2 import matplotlib.pyplot as plt
3 from tensorflow import keras
4 import numpy as np
5
6 (x_train, y_train), (x_test, y_test) = keras.datasets.fashion_mnist.load_data()
7
8 # There are 10 image classes in this dataset and each class has a mapping correspond
9
10 #0 T-shirt/top
11 #1 Trouser
12 #2 pullover
13 #3 Dress
14 #4 Coat
15 #5 sandals
16 #6 shirt
17 #7 sneaker
18 #8 bag
19 #9 ankle boot
```

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-idx1-ubyte.gz> (<https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-idx1-ubyte.gz>)

29515/29515 [=====] - 0s 4us/step

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-idx3-ubyte.gz> (<https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-idx3-ubyte.gz>)

26421880/26421880 [=====] - 20s 1us/step

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-labels-idx1-ubyte.gz> (<https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-labels-idx1-ubyte.gz>)

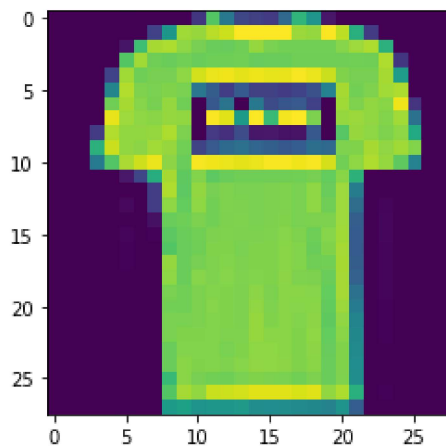
5148/5148 [=====] - 0s 0s/step

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-images-idx3-ubyte.gz> (<https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-images-idx3-ubyte.gz>)

4422102/4422102 [=====] - 2s 0us/step

```
In [2]: 1 plt.imshow(x_train[1])
```

```
Out[2]: <matplotlib.image.AxesImage at 0x16ebe6f2fa0>
```



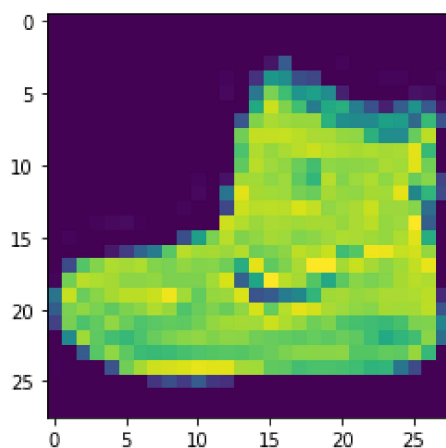
`plt.imshow()`: This is a function from the matplotlib library, specifically used to display images. It takes an array-like object as input and renders it as an image.

`x_train[1]`: This accesses the second element (index 1) of the `x_train` array, which contains the input images from the Fashion MNIST dataset. Each element of `x_train` is a 2D array representing a grayscale image.

So, `plt.imshow(x_train[1])` displays the second image from the training set (`x_train[1]`) as a grayscale image using matplotlib. Since the Fashion MNIST dataset contains grayscale images, `imshow()` will render the image in grayscale by default.

```
In [3]: 1 plt.imshow(x_train[0])
```

```
Out[3]: <matplotlib.image.AxesImage at 0x16ebe720f70>
```



`plt.imshow()`: This function, as before, is used to display images using matplotlib.

`x_train[0]`: This retrieves the first element (index 0) of the `x_train` array, which represents the input image data from the Fashion MNIST dataset. Each element of `x_train` is a 2D array representing a grayscale image.

So, `plt.imshow(x_train[0])` displays the first image from the training set (`x_train[0]`) as a grayscale image using matplotlib. Since the Fashion MNIST dataset contains grayscale images, `imshow()` will render the image in grayscale by default.

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```
In [4]: 1 # Next, we will preprocess the data by scaling the pixel values to be between 0 and 1
2
3 x_train = x_train.astype('float32') / 255.0
4 x_test = x_test.astype('float32') / 255.0
5
6 x_train = x_train.reshape(-1, 28, 28, 1)
7 x_test = x_test.reshape(-1, 28, 28, 1)
8
9 # 28, 28 comes from width, height, 1 comes from the number of channels
10 # -1 means that the length in that dimension is inferred.
11 # This is done based on the constraint that the number of elements in an ndarray or
12 # each image is a row vector (784 elements) and there are lots of such rows (let it
13
14
```

```
In [5]: 1 # converting the training_images array to 4 dimensional array with sizes 60000, 28, 28, 1
2
3 x_train.shape
```

Out[5]: (60000, 28, 28, 1)

```
In [6]: 1 x_test.shape
```

Out[6]: (10000, 28, 28, 1)

```
In [7]: 1 y_train.shape
```

Out[7]: (60000,)

```
In [8]: 1 y_test.shape
```

Out[8]: (10000,)

In [9]:

```
1 # We will use a convolutional neural network (CNN) to classify the fashion items.
2 # The CNN will consist of multiple convolutional layers followed by max pooling,
3 # dropout, and dense layers. Here is the code for the model:
4
5 model = keras.Sequential([
6     keras.layers.Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1)),
7     # 32 filters (default), randomly initialized
8     # 3*3 is Size of Filter
9     # 28,28,1 size of Input Image
10    # No zero-padding: every output 2 pixels less in every dimension
11    # in Parameter shown 320 is value of weights: (3x3 filter weights + 32 bias) * 32
12    # 32*3*3=288(Total)+32(bias)= 320
13
14
15    keras.layers.MaxPooling2D((2,2)),
16    # It shown 13 * 13 size image with 32 channel or filter or depth.
17
18    keras.layers.Dropout(0.25),
19    # Reduce Overfitting of Training sample drop out 25% Neuron
20
21    keras.layers.Conv2D(64, (3,3), activation='relu'),
22    # Deeper layers use 64 filters
23    # 3*3 is Size of Filter
24    # Observe how the input image on 28x28x1 is transformed to a 3x3x64 feature map
25    # 13(Size)-3(Filter Size )+1(bias)=11 Size for Width and Height with 64 Depth or
26    # in Parameter shown 18496 is value of weights: (3x3 filter weights + 64 bias) * 11
27    # 64*3*3=576+1=577*32 + 32(bias)=18496
28
29    keras.layers.MaxPooling2D((2,2)),
30    # It shown 5 * 5 size image with 64 channel or filter or depth.
31
32    keras.layers.Dropout(0.25),
33
34    keras.layers.Conv2D(128, (3,3), activation='relu'),
35    # Deeper layers use 128 filters
36    # 3*3 is Size of Filter
37    # Observe how the input image on 28x28x1 is transformed to a 3x3x128 feature map
38    # It show 5(Size)-3(Filter Size )+1(bias)=3 Size for Width and Height with 64 Depth
39    # 128*3*3=1152+1=1153*64 + 64(bias)= 73856
40
41    # To classify the images, we still need a Dense and Softmax Layer.
42    # We need to flatten the 3x3x128 feature map to a vector of size 1152
43    # https://medium.com/@iamvarman/how-to-calculate-the-number-of-parameters-in-the
44
45    keras.layers.Flatten(),
46    keras.layers.Dense(128, activation='relu'),
47    # 128 Size of Node in Dense Layer
48    # 1152*128 = 147584
49
50    keras.layers.Dropout(0.25),
51    keras.layers.Dense(10, activation='softmax')
52    # 10 Size of Node another Dense Layer
53    # 128*10+10 bias= 1290
54    ])
```

```
In [10]: 1 model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d (MaxPooling2D)	(None, 13, 13, 32)	0
dropout (Dropout)	(None, 13, 13, 32)	0
conv2d_1 (Conv2D)	(None, 11, 11, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 64)	0
dropout_1 (Dropout)	(None, 5, 5, 64)	0
conv2d_2 (Conv2D)	(None, 3, 3, 128)	73856
flatten (Flatten)	(None, 1152)	0
dense (Dense)	(None, 128)	147584
dropout_2 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 10)	1290
=====		
Total params: 241,546		
Trainable params: 241,546		
Non-trainable params: 0		

```
In [11]: 1 # Compile and Train the Model
2 # After defining the model, we will compile it and train it on the training data.
3
4 model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['ac
5
6 history = model.fit(x_train, y_train, epochs=10, validation_data=(x_test, y_test))
7
8 # 1875 is a number of batches. By default batches contain 32 samples. 60000 / 32 = 1875
```

```
Epoch 1/10
1875/1875 [=====] - 54s 27ms/step - loss: 0.5724 - accuracy:
0.7858 - val_loss: 0.3757 - val_accuracy: 0.8620
Epoch 2/10
1875/1875 [=====] - 51s 27ms/step - loss: 0.3712 - accuracy:
0.8638 - val_loss: 0.3395 - val_accuracy: 0.8729
Epoch 3/10
1875/1875 [=====] - 51s 27ms/step - loss: 0.3210 - accuracy:
0.8822 - val_loss: 0.2969 - val_accuracy: 0.8942
Epoch 4/10
1875/1875 [=====] - 51s 27ms/step - loss: 0.2952 - accuracy:
0.8912 - val_loss: 0.2805 - val_accuracy: 0.8947
Epoch 5/10
1875/1875 [=====] - 52s 28ms/step - loss: 0.2742 - accuracy:
0.8981 - val_loss: 0.2626 - val_accuracy: 0.9029
Epoch 6/10
1875/1875 [=====] - 52s 28ms/step - loss: 0.2619 - accuracy:
0.9021 - val_loss: 0.2720 - val_accuracy: 0.9000
Epoch 7/10
1875/1875 [=====] - 53s 28ms/step - loss: 0.2519 - accuracy:
0.9057 - val_loss: 0.2544 - val_accuracy: 0.9089
Epoch 8/10
1875/1875 [=====] - 53s 28ms/step - loss: 0.2420 - accuracy:
0.9088 - val_loss: 0.2545 - val_accuracy: 0.9087
Epoch 9/10
1875/1875 [=====] - 53s 28ms/step - loss: 0.2333 - accuracy:
0.9123 - val_loss: 0.2581 - val_accuracy: 0.9080
Epoch 10/10
1875/1875 [=====] - 54s 29ms/step - loss: 0.2259 - accuracy:
0.9159 - val_loss: 0.2636 - val_accuracy: 0.9076
```

```
In [12]: 1 # Finally, we will evaluate the performance of the model on the test data.
2
3 test_loss, test_acc = model.evaluate(x_test, y_test)
4
5 print('Test accuracy:', test_acc)
```

```
313/313 [=====] - 3s 11ms/step - loss: 0.2636 - accuracy: 0.90
76
Test accuracy: 0.9075999855995178
```