image

September 26, 2021

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[ ]:
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```

1 Introduction to Image Classification

We have learned about binary and multiclass classification, and we've done so using datasets consisting of feature columns that contain numeric and string values. The numbers could be continuous or categorical. The strings we have used so far were all categorical features.

In this lab we will perform another type of classification: **image classification**.

Image classification can be binary: "*Is this an image of a dog?*"
It can also be multiclass: "*Is this an image of a cat, dog, horse, or cow?*"

The questions above assume there is only one item in an image. There is an even more advanced form of multiclass classification that answers the following question: What are all of the classes in an image and where are they located? For example: "*Where are all of the cats, dogs, horses, and cows in this image?*".

In this introduction to image classification, we'll focus on classification where there is only one item depicted in each image. In future labs we'll learn about the more advanced forms of image classification.

1.1 The Dataset

The dataset we'll use for this Colab is the Fashion-MNIST dataset, which contains 70,000 grayscale images labeled with one of ten categories.

The categories are:

Label	Class
0	T-shirt/top
1	Trouser
2	Pullover
3	Dress
4	Coat
5	Sandal
6	Shirt
7	Sneaker
8	Bag
9	Ankle boot

The images show individual articles of clothing at low resolution (28 by 28 pixels), as seen here:

Figure 1. Fashion-MNIST samples (by Zalando, MIT License).

1.1.1 Load the Data

Now that we have a rough understanding of the data we're going to use in our model, let's load the data into this lab. The Fashion MNIST dataset is conveniently available from the Keras Datasets repository along with a utility function for downloading and loading the data into NumPy arrays.

In the code cell below, we import TensorFlow and download the Fashion-MNIST data.

[ ]:
```
import tensorflow as tf

(train_images, train_labels), (test_images, test_labels) = \
    tf.keras.datasets.fashion_mnist.load_data()

print(train_images.shape)
print(train_labels.shape)
print(test_images.shape)
print(test_labels.shape)
```

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

`load_data()` returns two tuples, one for the training dataset and the other for the testing dataset. As you can see from the output of the code cell above, we have `60,000` training samples and `10,000` testing samples. This makes for a `14%` holdout of the data.

You might be wondering what that `28, 28` is in the image data. That is a two-dimensional representation of the image. This is our feature data. Each pixel of the image is a feature. A `28` by `28` image has `784` pixels.

As you can see, even a tiny image generates quite a few features. If we were processing 4k-resolution images, which are often `3840` by `2160` pixels, then we would have `8,294,400` features! Over eight million features is quite a bit. In later labs we'll address some strategies for working with this massive amount of data.

1.1.2 Exploratory Data Analysis

It is always a good idea to look at your data before diving in to building your model. Remember that our data is divided across four NumPy arrays, two of which are three-dimensional arrays:

[ ]:
```
print('Training images:', train_images.shape)
print('Training labels:', train_labels.shape)
print('Test images:', test_images.shape)
print('Test labels:', test_labels.shape)
```

```
Training images: (60000, 28, 28)
Training labels: (60000,)
Test images: (10000, 28, 28)
Test labels: (10000,)
```

To make our exploration tasks a little easier, let's put the data into a Pandas `DataFrame`. One way to do this is to flatten the 28 by 28 image into a flat array of 784 pixels, with the pixel number being the column name. We then add the labels to a `target` column.

[ ]:
```
import numpy as np
import pandas as pd

train_df = pd.DataFrame(
    np.array([x.flatten() for x in train_images]),
    columns=[i for i in range(784)]
)
train_df['target'] = train_labels

train_df.describe()
```

[ ]:
```
                  0             1             2             3             4  \
count  60000.000000  60000.000000  60000.000000  60000.000000  60000.000000
mean       0.000800      0.005783      0.030083      0.103800      0.249683
std        0.092554      0.249033      0.767868      2.512017      4.331376
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000      0.000000      0.000000
75%        0.000000      0.000000      0.000000      0.000000      0.000000
max       16.000000     36.000000    119.000000    164.000000    224.000000

                  5             6             7             8             9  \
count  60000.000000  60000.000000  60000.000000  60000.000000  60000.000000
mean       0.414717      0.821667      2.224733      5.698667     14.434650
std        5.827394      8.309935     14.201820     23.835980     38.204702
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000      0.000000      0.000000
```

```
50%         0.000000      0.000000      0.000000      0.000000      0.000000
75%         0.000000      0.000000      0.000000      0.000000      0.000000
max       230.000000    221.000000    221.000000    254.000000    255.000000

       …           775           776           777           778  \
count  …  60000.000000  60000.000000  60000.000000  60000.000000
mean   …     23.208633     16.576250     17.831967     22.918850
std    …     48.881430     42.044318     43.911297     51.928401
min    …      0.000000      0.000000      0.000000      0.000000
25%    …      0.000000      0.000000      0.000000      0.000000
50%    …      0.000000      0.000000      0.000000      0.000000
75%    …      8.000000      0.000000      0.000000      0.000000
max    …    255.000000    255.000000    255.000000    255.000000

                779           780           781           782           783  \
count  60000.000000  60000.000000  60000.000000  60000.000000  60000.000000
mean      17.916900      8.485717      2.706333      0.819000      0.070883
std       45.173634     29.448614     17.258682      9.133252      2.075829
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000      0.000000      0.000000
75%        0.000000      0.000000      0.000000      0.000000      0.000000
max      255.000000    255.000000    255.000000    255.000000    170.000000

             target
count  60000.000000
mean       4.500000
std        2.872305
min        0.000000
25%        2.000000
50%        4.500000
75%        7.000000
max        9.000000

[8 rows x 785 columns]
```

With so many columns, reading the output of `describe()` is nearly impossible. Let's instead do our analysis a little differently.

To begin, we will find the minimum value of every pixel column and output the sorted list of unique values.

[ ]:
```
FEATURES = train_df.columns[:-1]

sorted(train_df.loc[:, FEATURES].min().unique())
```

[ ]:
```
[0]
```

All of the values were `0`.

Let's do the same for the maximum values.

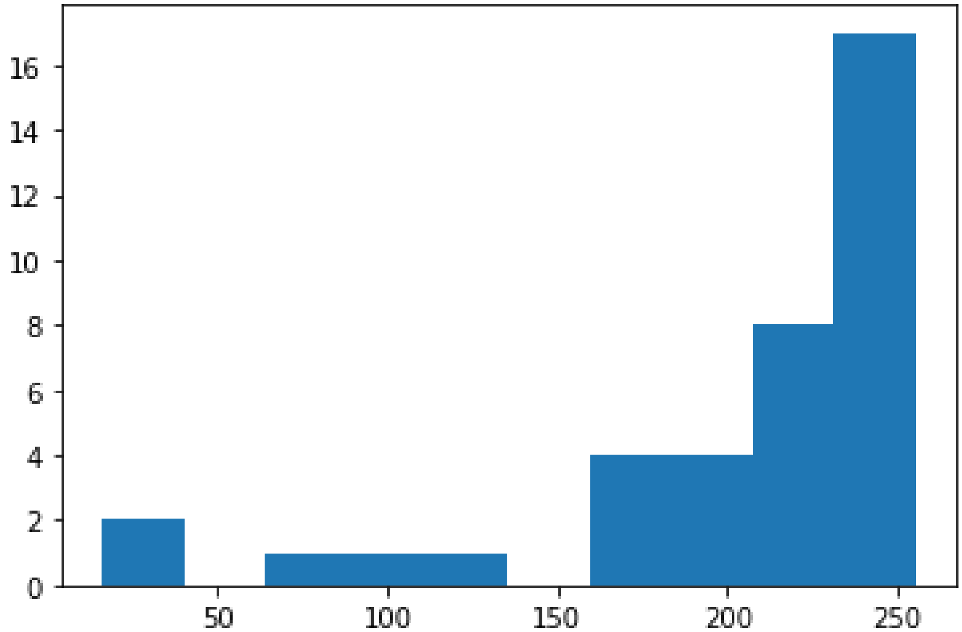
```
[ ]: sorted(train_df.loc[:, FEATURES].max().unique())
```

```
[ ]: [16,
      36,
      83,
      105,
      119,
      164,
      167,
      170,
      180,
      188,
      189,
      202,
      206,
      211,
      212,
      219,
      221,
      224,
      225,
      227,
      230,
      232,
      233,
      235,
      237,
      239,
      242,
      243,
      244,
      245,
      247,
      249,
      250,
      251,
      252,
      253,
      254,
      255]
```

That is more interesting. We seem to have values ranging from `16` through `255`. These values represent color intensities for grayscale images. `0`, which we saw as a minimum value, maps to black in the color map that we will use, while `255` is white.

Let's see a histogram distribution of our max pixel values.

[ ]:
```python
import matplotlib.pyplot as plt

_ = plt.hist(train_df.loc[:, FEATURES].max().unique())
```



Unsurprisingly, higher intensity values seem to be more prevalent as maximum pixel values than lower intensity values.

Exercise 1: Charting Pixel Intensities In the example above, we created a histogram containing the maximum pixel intensities. In this exercise you will create a histogram for all pixel intensities in the training dataset.

If some intensities are outliers, remove them to get a more meaningful histogram.

Hint: The NumPy `where` and `flatten` can come in handy for this exercise.

Student Solution

[ ]:
```python
train_df.loc[FEATURES]
```

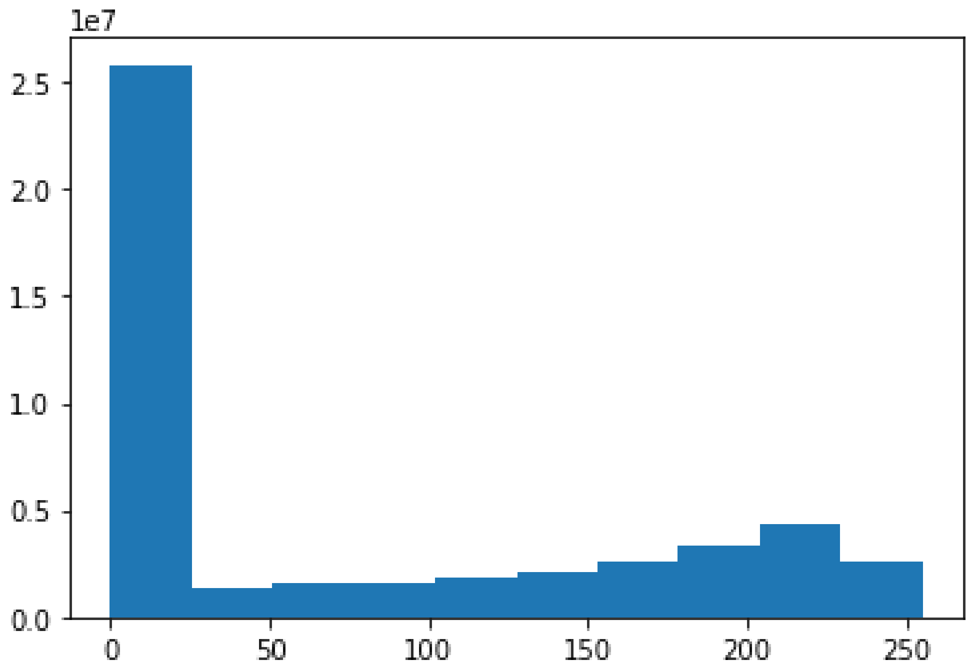
[ ]:

	0	1	2	3	4	5	6	7	8	9	…	775	776	777	778	779	780	\
0	0	0	0	0	0	0	0	0	0	0	…	0	0	0	0	0	0	
1	0	0	0	0	0	1	0	0	0	0	…	114	130	76	0	0	0	
2	0	0	0	0	0	0	0	0	0	22	…	0	1	0	0	0	0	
3	0	0	0	0	0	0	0	0	33	96	…	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	…	0	0	0	0	0	0	
..	..	..	..	..	..	..	..	..	..	…	…	…	…	…	…	…	…	
779	0	0	0	0	0	0	0	0	1	0	…	0	0	0	139	163	58	
780	0	0	0	0	0	0	0	3	1	0	…	19	0	0	0	0	0	

```
781  0  0  0  0  0  0  38  72  75   91  …    0    0    0    0    0    0
782  0  0  0  0  0  0   0   0   3  113  …    3    0    0    0    0    0
783  0  0  0  0  0  0   0   0   0    0  …    0    0    0    0    0    0

     781  782  783  target
0      0    0    0       9
1      0    0    0       0
2      0    0    0       0
3      0    0    0       3
4      0    0    0       0
..   …  …  …       …
779    0    0    0       6
780    0    0    0       0
781    9    0    0       6
782    0    0    0       1
783    0    0    0       1

[784 rows x 785 columns]
```

[ ]:
```
inten = train_df.loc[:, FEATURES].to_numpy().flatten()
plt.hist(inten)
```

[ ]:
```
(array([25790964.,  1344502.,  1582733.,  1643562.,  1876736.,  2034790.,
         2606932.,  3303752.,  4306392.,  2549637.]),
 array([  0. ,  25.5,  51. ,  76.5, 102. , 127.5, 153. , 178.5, 204. ,
        229.5, 255. ]),
 <BarContainer object of 10 artists>)
```



Continuing on With EDA Now that we have a basic idea of the values in our dataset, let's see if any are missing.

[ ]:
```
train_df.isna().any().any()
#train_df.isna().any().any()
```

[ ]:
```
False
```

Good. We now know we aren't missing any values, and our pixel values range from `0` through `255`.

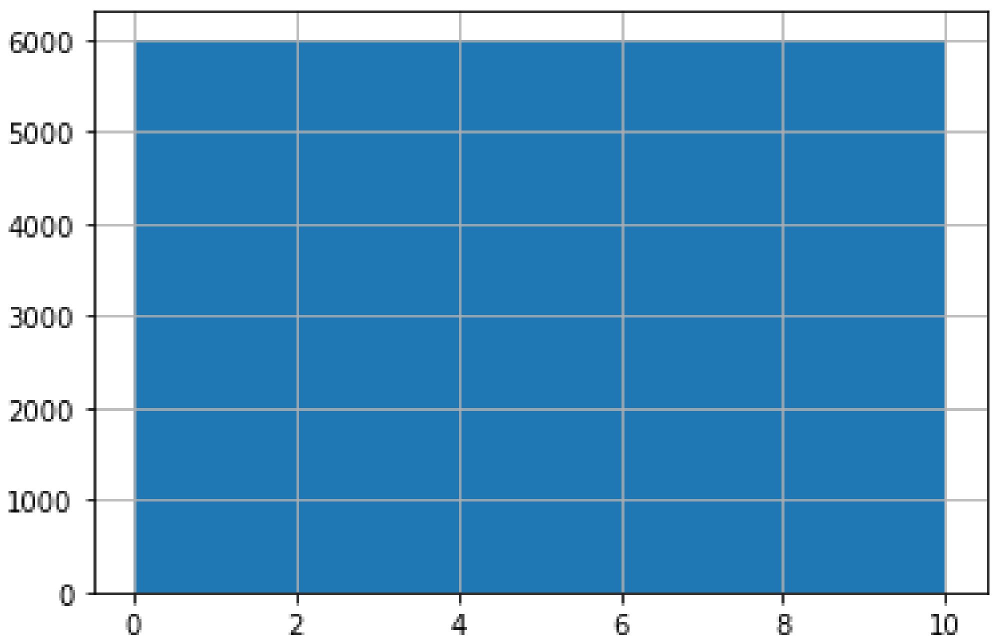
Let's now see if our target values are what we expect.

[ ]:
```
sorted(train_df['target'].unique())
```

[ ]:
```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

Let's see the distribution.

[ ]:
```
_ = train_df['target'].hist(bins=[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10])
```



The class types seem evenly distributed. We have `6,000` of each.

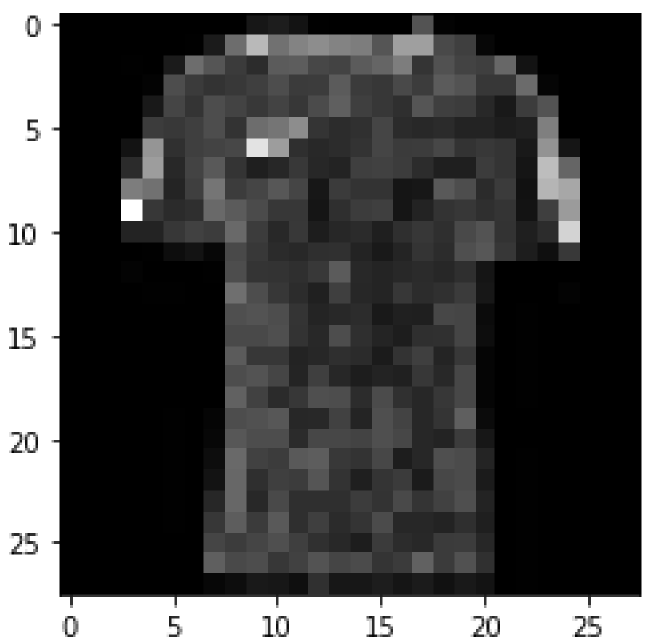
The numeric values should map to these clothing types:

Label	Class
0	T-shirt/top
1	Trouser
2	Pullover
3	Dress
4	Coat
5	Sandal
6	Shirt
7	Sneaker
8	Bag
9	Ankle boot

We can spot check this by looking at some of the images. Let's check a random 'T-shirt/top'.

To do this we select a random index from the 'T-shirt/top' items (`target = 0`). We then reshape the pixel columns back into a `28` by `28` two-dimensional array, which are the dimensions of the image. We then use `imshow()` to display the image.

[ ]:
```
index = np.random.choice(train_df[train_df['target'] == 0].index.values)

pixels = train_df.loc[index, FEATURES].to_numpy().reshape(28, 28)

_ = plt.imshow(pixels, cmap='gray')
```



In our sample we got an image that looked like a very low resolution t-shirt. You should see the same. Note: every time you rerun the above cell, a new random index will be chosen, so feel free to cycle through some of the values to see the different types of t-shirt/top images included in the dataset.

This single image spot checking is okay, but it doesn't scale well.

We can view multiple images at a time using the `GridSpec` class from Matplotlib.

In the code below, we build a visualization with a `10` by `10` grid of images in our t-shirt class.

The code imports `gridspec`, sets the number of rows and columns, and then sets the figure size so the image is large enough for us to actually see different samples.

After that bit of setup, we create a `10` by `10` `GridSpec`. The other parameters to the constructor are there to ensure the images are tightly packed into the grid. Try experimenting with some other values.

Next we randomly choose `100` indexes from items labelled with class `0` our training data.

The remainder of the code should look pretty familiar. We used similar code above to show a single image. The difference in this code is that we are adding `100` subplots using the `GridSpec`.

Label	Class
0	T-shirt/top
1	Trouser
2	Pullover
3	Dress
4	Coat
5	Sandal
6	Shirt
7	Sneaker
8	Bag
9	Ankle boot

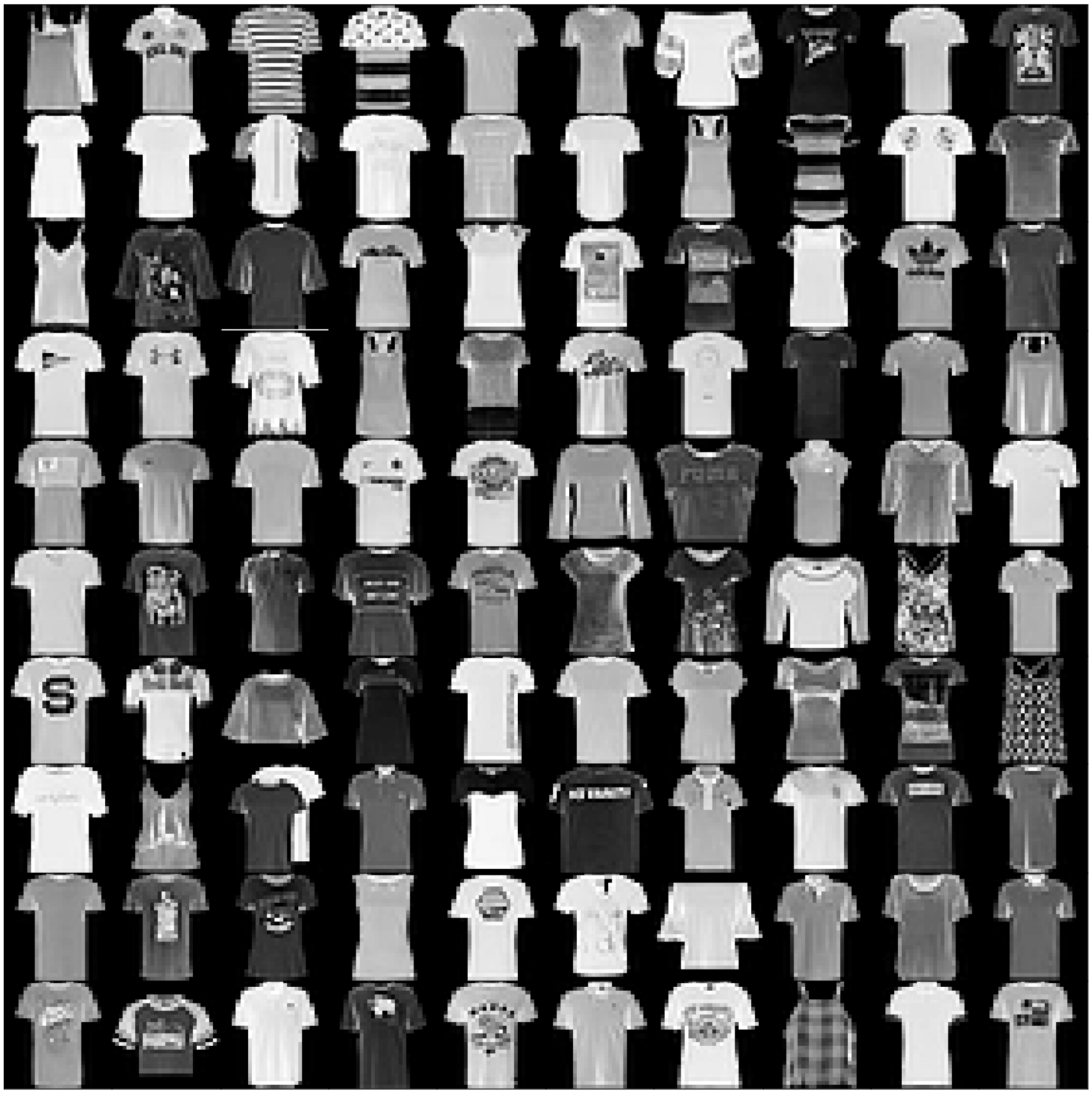
[ ]:

```

```

[ ]:

```
from matplotlib import gridspec

# Row and column count (100 samples)
rows = 10
cols = 10

# Size of the final output image
plt.figure(figsize=(12, 12))

# Grid that will be used to organize our samples
gspec = gridspec.GridSpec(
    rows,
    cols,
    wspace = 0.0,
    hspace = 0.0,
```

```python
    top = 1.0,
    bottom = 0.0,
    left = 0.00,
    right = 1.0,
)

# Randomly choose a sample of t-shirts
T_SHIRTS = 0
indexes = np.random.choice(
    train_df[train_df['target'] == T_SHIRTS].index.values,
    rows*cols
)


# Add each sample to a plot using the GridSpec
cnt = 0
for r in range(rows):
  for c in range(cols):
    row = train_df.loc[indexes[cnt], FEATURES]
    img = row.to_numpy().reshape((28, 28))

    ax = plt.subplot(gspec[r, c])
    ax.imshow(img, cmap='gray')
    ax.xaxis.set_visible(False)
    ax.yaxis.set_visible(False)
    cnt = cnt + 1

plt.show()
```



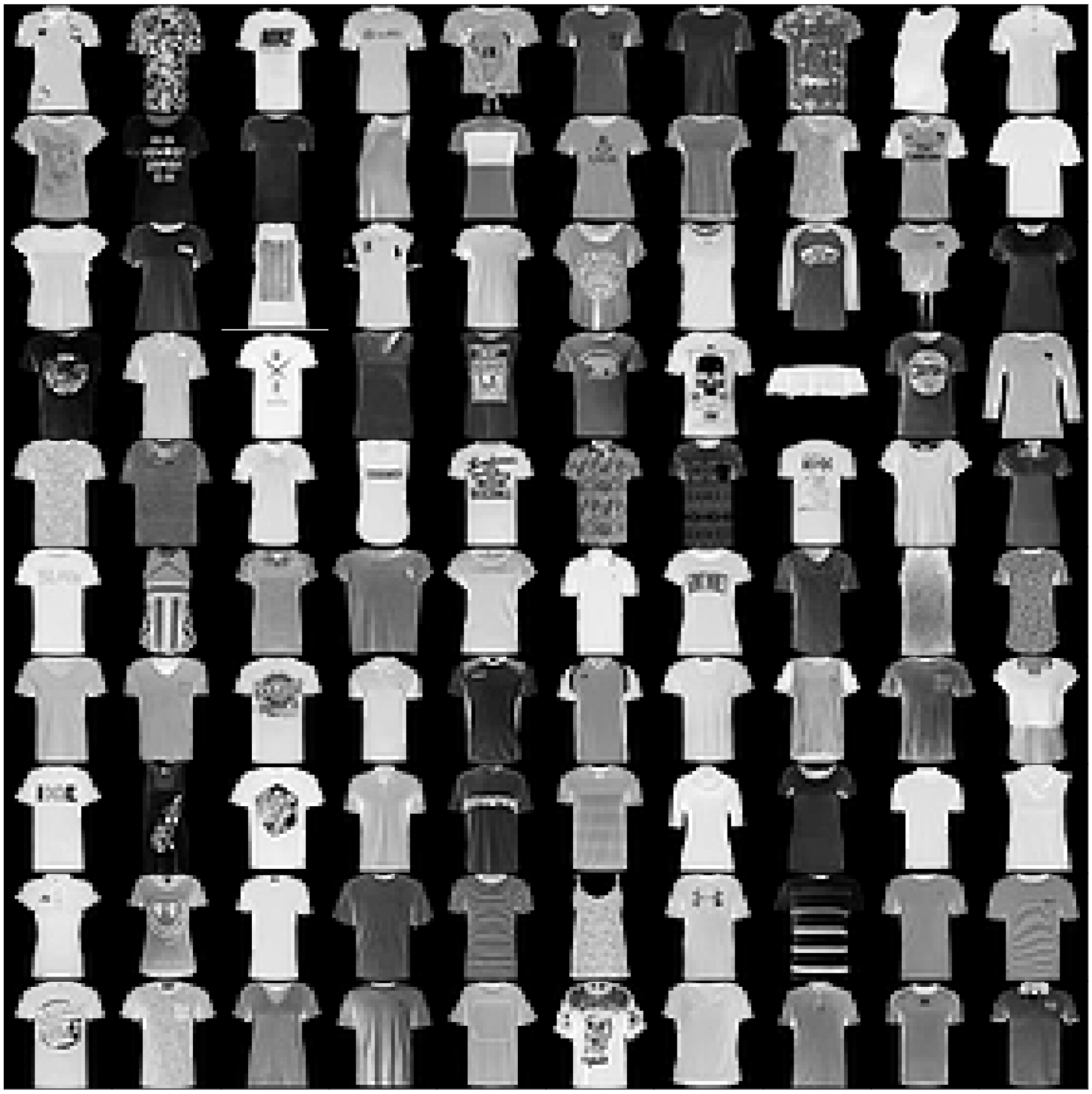
Exercise 2: Visualizing Every Class In this exercise, you'll take the code that we used above to visualize t-shirts and use it to visualize every class represented in our dataset. You'll need to print out the class name and then show a `10` by `10` grid of samples from that class. Try to minimize the amount of repeated code in your solution.

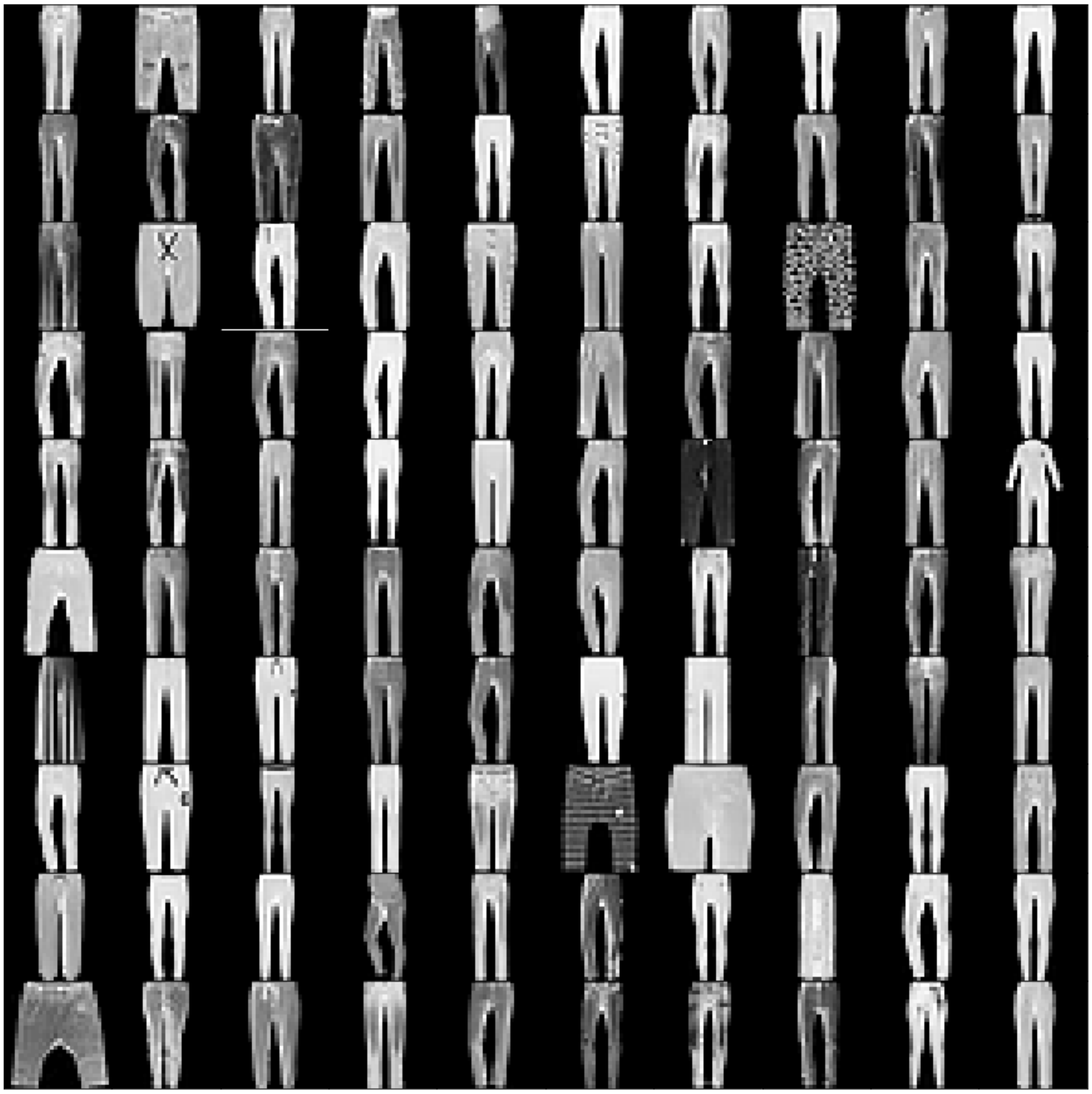
Student Solution **Defining a function to pass in a particular class**

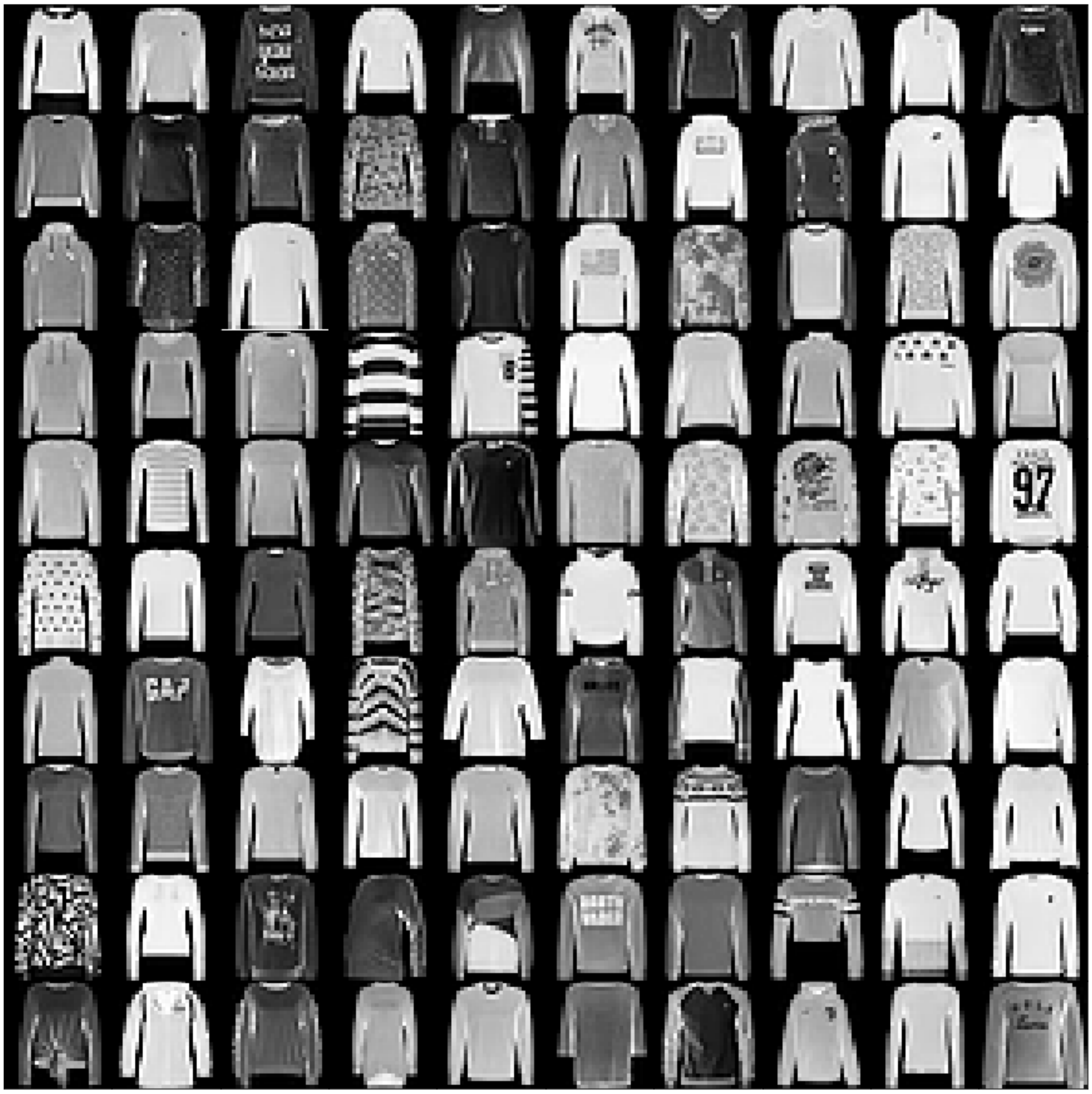
[ ]:
```
def function(classer):
    rows = 10
    cols = 10

    # Size of the final output image
```

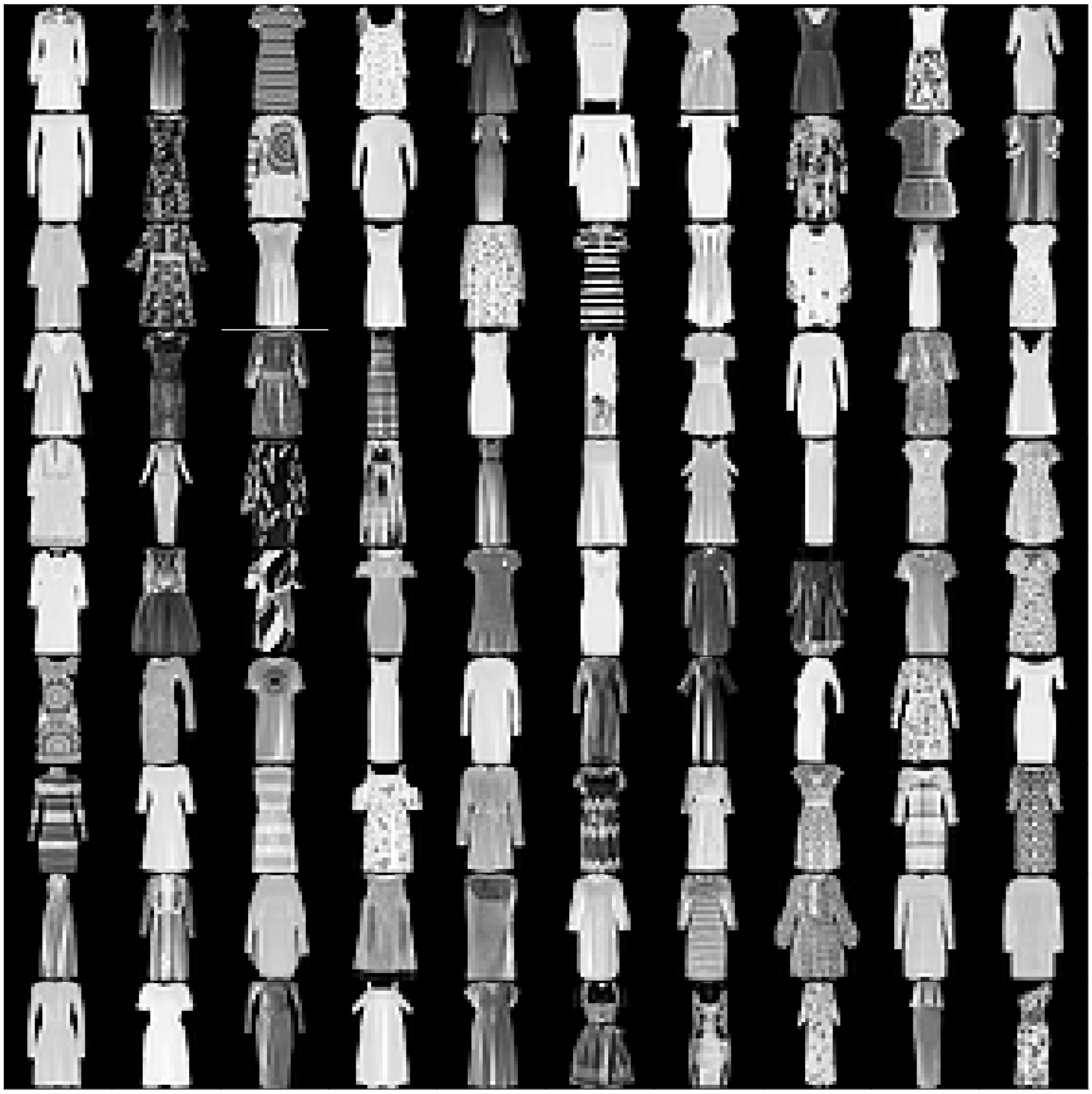
```
    plt.figure(figsize=(12, 12))

    # Grid that will be used to organize our samples
    gspec = gridspec.GridSpec(
        rows,
        cols,
        wspace = 0.0,
        hspace = 0.0,
        top = 1.0,
        bottom = 0.0,
        left = 0.00,
        right = 1.0,
    )

    # Randomly choose a sample of t-shirts

    indexes = np.random.choice(
        train_df[train_df['target'] == classer].index.values,
        rows*cols
    )
    cnt = 0
    for r in range(rows):
        for c in range(cols):
            row = train_df.loc[indexes[cnt], FEATURES]
            img = row.to_numpy().reshape((28, 28))
            ax = plt.subplot(gspec[r, c])
            ax.imshow(img, cmap='gray')
            ax.xaxis.set_visible(False)
            ax.yaxis.set_visible(False)
            cnt = cnt + 1

    plt.show()
```

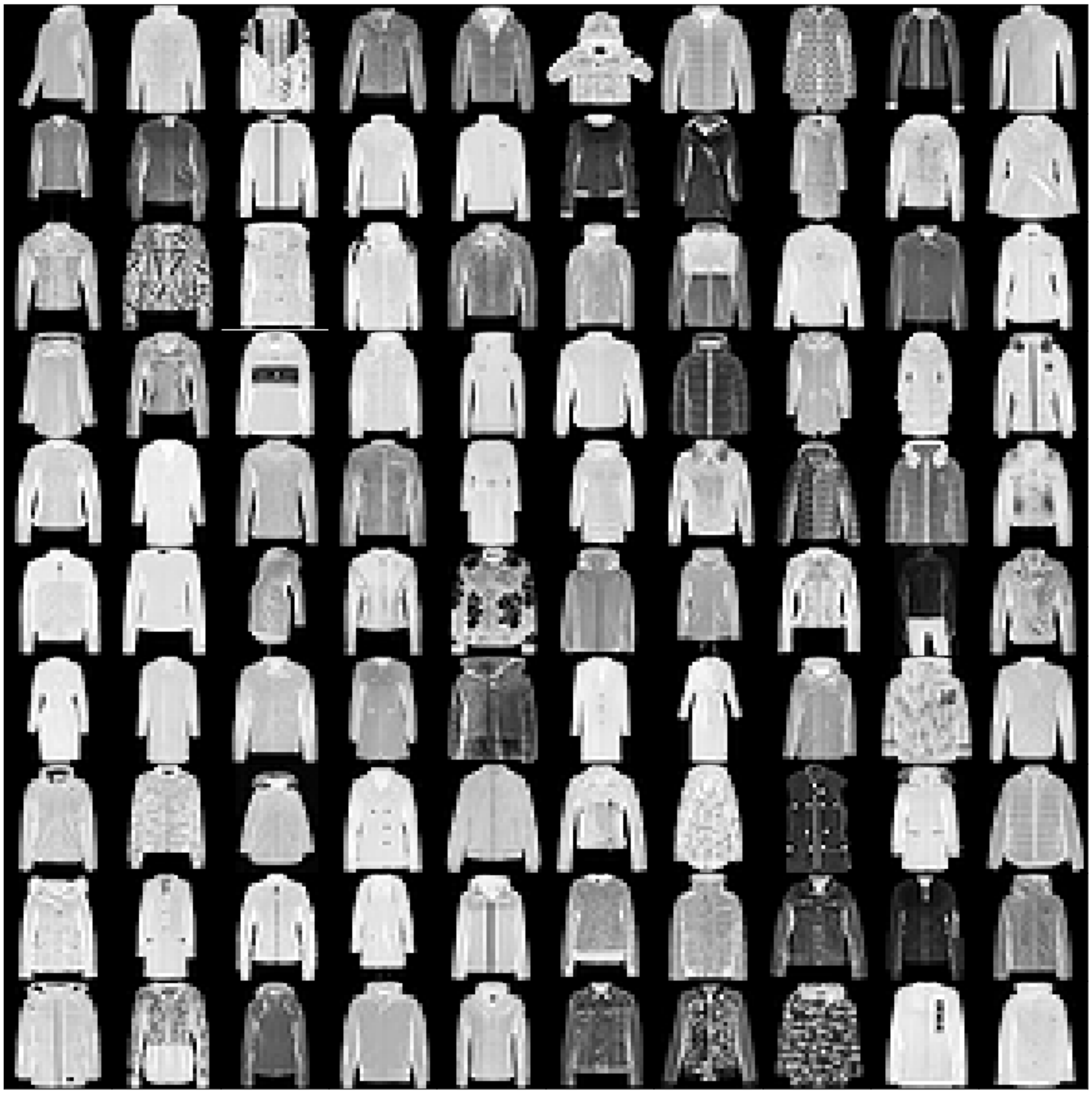
[ ]:
```
classes = [0,1,2,3,4,5,6,7]
for i in classes:
    function(i)
```

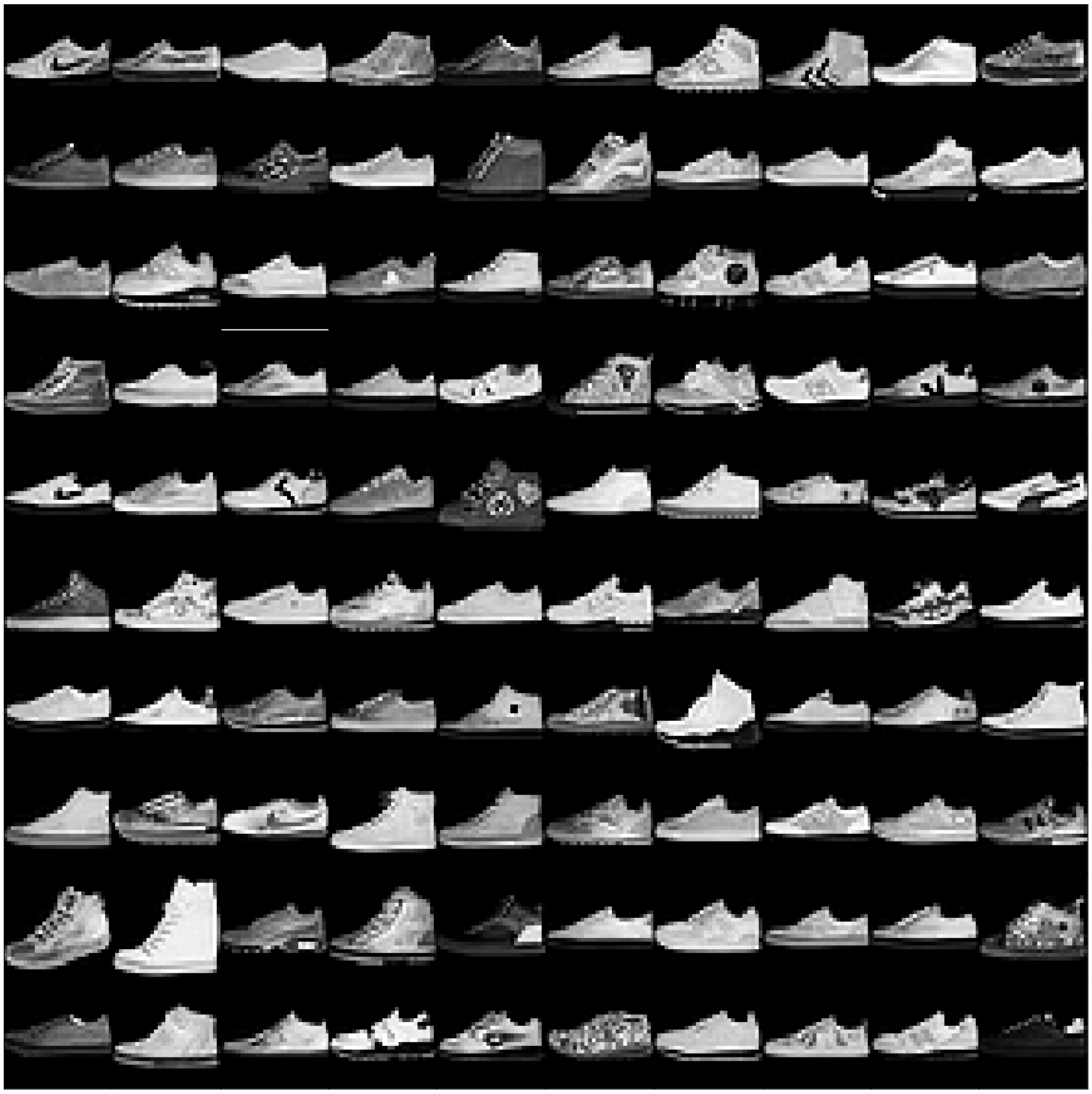












Wrapping Up EDA From our visual analysis, our samples seem reasonable.

First off, class names seem to match pictures. This can give us some confidence that our data is labelled correctly.

Another nice thing is that all of the clothing items seem to be oriented in the same direction for the most part. If shoes were pointing in different directions, or if any images were rotated, then we would have had a lot more processing to do.

And finally, all of our images are the same dimensions and are encoded with a single numeric grayscale intensity. In the real world, you'll likely not get so lucky. Images are acquired in different sizes and with different color encodings. We'll get to some examples of this in future labs.

Based on our analysis so far, we can end our EDA and move on to model building.

1.2 Modeling

We have many options for building a multiclass classification model for images. In this lab we will build a deep neural network using TensorFlow Keras.

1.2.1 Preparing the Data

Our feature data is on a scale from `0` to `255`, and our target data is categorically encoded. Fortunately, all of the features are on the same scale, so we don't have to worry about standardizing scale. However, we'll need to do a little data preprocessing in order to get our data ready for modeling.

The first bit of data preprocessing we'll do is bring the feature values into the range of `0.0` and `1.0`. We could perform normalization to do this, but normalization actually isn't the only solution in this case.

We know that all of our features are pixel values in the range of `0` to `255`. We also know from our EDA that every feature has a minimum value of `0`, but that the max values have a pretty wide range. It is possible we would make our model worse by normalizing, since we'd be making the same values across pixels not map to the same color.

Instead of normalizing, we can just divide every feature by `255.0`. This keeps the relative values the same across pixels.

[ ]:
```
train_df[FEATURES] = train_df[FEATURES] / 255.0

train_df[FEATURES].describe()
```

[ ]:
```
                 0             1             2             3             4  \
count  60000.000000  60000.000000  60000.000000  60000.000000  60000.000000
mean       0.000003      0.000023      0.000118      0.000407      0.000979
std        0.000363      0.000977      0.003011      0.009851      0.016986
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000      0.000000      0.000000
75%        0.000000      0.000000      0.000000      0.000000      0.000000
max        0.062745      0.141176      0.466667      0.643137      0.878431

                 5             6             7             8             9  \
count  60000.000000  60000.000000  60000.000000  60000.000000  60000.000000
mean       0.001626      0.003222      0.008724      0.022348      0.056606
std        0.022853      0.032588      0.055693      0.093474      0.149822
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000      0.000000      0.000000
75%        0.000000      0.000000      0.000000      0.000000      0.000000
max        0.901961      0.866667      0.866667      0.996078      1.000000
```

```
       …            774           775           776           777  \
count  …  60000.000000  60000.000000  60000.000000  60000.000000
mean   …      0.135547      0.091014      0.065005      0.069929
std    …      0.225717      0.191692      0.164880      0.172201
min    …      0.000000      0.000000      0.000000      0.000000
25%    …      0.000000      0.000000      0.000000      0.000000
50%    …      0.000000      0.000000      0.000000      0.000000
75%    …      0.223529      0.031373      0.000000      0.000000
max    …      1.000000      1.000000      1.000000      1.000000

                778           779           780           781           782  \
count  60000.000000  60000.000000  60000.000000  60000.000000  60000.000000
mean       0.089878      0.070262      0.033277      0.010613      0.003212
std        0.203641      0.177152      0.115485      0.067681      0.035817
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000      0.000000      0.000000
75%        0.000000      0.000000      0.000000      0.000000      0.000000
max        1.000000      1.000000      1.000000      1.000000      1.000000

                783
count  60000.000000
mean       0.000278
std        0.008141
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        0.666667

[8 rows x 784 columns]
```

Exercise 3: One-Hot Encoding Our target values are categorical values in a column named `target`. In this exercise, you will one-hot encode the target values. Your code should:

1. Create ten new columns named `target_0` through `target_9`.
2. Create a variable called `TARGETS` that contains the `10` target column names.
3. `describe()` the ten new target column values to ensure that they have values between 0 and 1 and that the one-hot encoding looks evenly distributed.

Student Solution **Getting one hot encoding dataframe**

[ ]:
```python
from sklearn.preprocessing import OneHotEncoder
```

```
target_columns =␣
↪['target_0','target_1','target_2','target_3','target_4','target_5','target_6','target_7','t
TARGETS = target_columns
key = ['target']
ohe = OneHotEncoder(sparse=False)


encodedTargets = ohe.fit_transform(train_df[['target']])
print(type(encodedTargets))


encodedTargets_df = pd.DataFrame(encodedTargets)
encodedTargets_df.columns =target_columns
```

```
<class 'numpy.ndarray'>
```

Dropping Target Column

[ ]:
```
train_df = train_df.drop('target',axis =1 )

train_df
```

[ ]:
```
         0    1    2    3    4         5    6    7         8         9  ...  \
0      0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.000000  ...
1      0.0  0.0  0.0  0.0  0.0  0.003922  0.0  0.0  0.000000  0.000000  ...
2      0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.086275  ...
3      0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.129412  0.376471  ...
4      0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.000000  ...
…      …    …    …    …    …         …    …    …       …         …  …
59995  0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.000000  ...
59996  0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.000000  ...
59997  0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.019608  ...
59998  0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.000000  ...
59999  0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.000000  ...

            774       775       776       777  778       779  780  781  782  \
0      0.000000  0.000000  0.000000  0.000000  0.0  0.000000  0.0  0.0  0.0
1      0.466667  0.447059  0.509804  0.298039  0.0  0.000000  0.0  0.0  0.0
2      0.000000  0.000000  0.003922  0.000000  0.0  0.000000  0.0  0.0  0.0
3      0.000000  0.000000  0.000000  0.000000  0.0  0.000000  0.0  0.0  0.0
4      0.000000  0.000000  0.000000  0.000000  0.0  0.000000  0.0  0.0  0.0
…           …        …        …         …    …         …    …    …    …
59995  0.000000  0.000000  0.000000  0.000000  0.0  0.000000  0.0  0.0  0.0
59996  0.000000  0.000000  0.000000  0.000000  0.0  0.000000  0.0  0.0  0.0
59997  0.000000  0.000000  0.000000  0.000000  0.0  0.000000  0.0  0.0  0.0
59998  0.258824  0.211765  0.196078  0.019608  0.0  0.003922  0.0  0.0  0.0
59999  0.000000  0.000000  0.000000  0.000000  0.0  0.000000  0.0  0.0  0.0
```

```
       783
0      0.0
1      0.0
2      0.0
3      0.0
4      0.0
…    …
59995  0.0
59996  0.0
59997  0.0
59998  0.0
59999  0.0

[60000 rows x 784 columns]
```

Combining DataFrames

[ ]:
```python
encodedTargets_df
train_df
frames = [train_df,encodedTargets_df]

train_df = train_df.join(encodedTargets_df)

train_df
#new_target_df = pd.merge(train_df,encodedTargets_df)
```

[ ]:
```
         0    1    2    3    4         5    6    7         8         9  …  \
0      0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.000000  …
1      0.0  0.0  0.0  0.0  0.0  0.003922  0.0  0.0  0.000000  0.000000  …
2      0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.086275  …
3      0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.129412  0.376471  …
4      0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.000000  …
…    …  …  …  …  …       …  …  …       …       …  …
59995  0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.000000  …
59996  0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.000000  …
59997  0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.019608  …
59998  0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.000000  …
59999  0.0  0.0  0.0  0.0  0.0  0.000000  0.0  0.0  0.000000  0.000000  …

       target_0  target_1  target_2  target_3  target_4  target_5  target_6  \
0           0.0       0.0       0.0       0.0       0.0       0.0       0.0
1           1.0       0.0       0.0       0.0       0.0       0.0       0.0
2           1.0       0.0       0.0       0.0       0.0       0.0       0.0
3           0.0       0.0       0.0       1.0       0.0       0.0       0.0
4           1.0       0.0       0.0       0.0       0.0       0.0       0.0
…         …       …       …       …       …       …       …
```

```
59995        0.0        0.0        0.0        0.0        0.0        1.0        0.0
59996        0.0        1.0        0.0        0.0        0.0        0.0        0.0
59997        0.0        0.0        0.0        1.0        0.0        0.0        0.0
59998        1.0        0.0        0.0        0.0        0.0        0.0        0.0
59999        0.0        0.0        0.0        0.0        0.0        1.0        0.0

       target_7  target_8  target_9
0           0.0       0.0       1.0
1           0.0       0.0       0.0
2           0.0       0.0       0.0
3           0.0       0.0       0.0
4           0.0       0.0       0.0
…          …        …        …
59995       0.0       0.0       0.0
59996       0.0       0.0       0.0
59997       0.0       0.0       0.0
59998       0.0       0.0       0.0
59999       0.0       0.0       0.0

[60000 rows x 794 columns]
```

1.2.2 Configure and Compile the Model

We'll be relying on the TensorFlow Keras `Sequential` model and `Dense` layers that we used in previous labs.

In this case our input shape needs to be the size of our feature count. We'll then add a few hidden layers and then use a softmax layer the same width as our target count. This layer should output the probability that a given set of input features maps to each of our targets. The sum of the probabilities will equal `1.0`.

[ ]:
```
model = tf.keras.Sequential([
    tf.keras.layers.Dense(128, input_shape=(len(FEATURES),)),
    tf.keras.layers.Dense(64, activation=tf.nn.relu),
    tf.keras.layers.Dense(32, activation=tf.nn.relu),
    tf.keras.layers.Dense(len(TARGETS), activation=tf.nn.softmax)
])

model.summary()
```

```
Model: "sequential"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 128)               100480

_________________________________________________________________
dense_1 (Dense)              (None, 64)                8256

_________________________________________________________________
dense_2 (Dense)              (None, 32)                2080
```

```
_________________________________________________________________
dense_3 (Dense)              (None, 10)                330
=================================================================
Total params: 111,146
Trainable params: 111,146
Non-trainable params: 0
_________________________________________________________________
2021-09-26 13:10:07.675669: I tensorflow/core/platform/cpu_feature_guard.cc:142]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  SSE4.1 SSE4.2
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
```

Note that our images are actually 28 by 28 images. We flattened the images when we loaded them into a dataframe for EDA. However, flattening outside of the model isn't necessary. TensorFlow works in many dimensions. If we wanted to keep our images as 28 by 28 matrices, we could have added a `Flatten` layer as shown below.

```
model = tf.keras.Sequential([
    tf.keras.layers.Flatten(input_shape=(28, 28)),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
    tf.keras.layers.Dense(64, activation=tf.nn.relu),
    tf.keras.layers.Dense(32, activation=tf.nn.relu),
    tf.keras.layers.Dense(len(TARGETS), activation=tf.nn.softmax)
])

model.summary()
```

```
Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten_5 (Flatten)          (None, 784)               0
_________________________________________________________________
dense_28 (Dense)             (None, 128)               100480
_________________________________________________________________
dense_29 (Dense)             (None, 64)                8256
_________________________________________________________________
dense_30 (Dense)             (None, 32)                2080
_________________________________________________________________
dense_31 (Dense)             (None, 10)                330
=================================================================
Total params: 111,146
Trainable params: 111,146
Non-trainable params: 0
_________________________________________________________________
```

This model results in the same number of trainable parameters as our pre-flattened model; it just saves us from having to flatten the images outside of TensorFlow.

Before the model is ready for training, it needs a few more settings. These are added during the model's *compile* step:

- *Loss function* — This measures how well the model is doing during training. We want to minimize this function to "steer" the model in the right direction. A large loss would indicate the model is performing poorly in classification tasks, meaning it is not matching input images to the correct class names. (It might classify a boot as a coat, for example.)
- *Optimizer* — This is how the model is updated based on the data it sees and its loss function.
- *Metrics* — This is used to monitor the training and testing steps. The following example uses *accuracy*, the fraction of the images that are correctly classified.

[ ]:
```
model.compile(
    loss='categorical_crossentropy',
    optimizer='Adam',
    metrics=['accuracy'],
)

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 128)               100480
_________________________________________________________________
dense_1 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_2 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_3 (Dense)              (None, 10)                330
=================================================================
Total params: 111,146
Trainable params: 111,146
Non-trainable params: 0
_________________________________________________________________
```

1.3 Train the Model

Training a Keras API neural network model to classify images looks just like all of the other Keras models we have worked with so far. We call this the `model.fit` method, passing it our training data and any other parameters we'd like to use.

[ ]:
```
callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=5)

history = model.fit(
    train_df[FEATURES],
    train_df[TARGETS],
```

```
    epochs=500,
    callbacks=[callback]
)
```

```
Epoch 1/500
1875/1875 [==============================] - 2s 1ms/step - loss: 0.1560 -
accuracy: 0.9416
Epoch 2/500
1875/1875 [==============================] - 2s 1ms/step - loss: 0.1503 -
accuracy: 0.9427
Epoch 3/500
1875/1875 [==============================] - 2s 1ms/step - loss: 0.1543 -
accuracy: 0.9427
Epoch 4/500
1875/1875 [==============================] - 2s 1ms/step - loss: 0.1499 -
accuracy: 0.9423
Epoch 5/500
1875/1875 [==============================] - 2s 993us/step - loss: 0.1462 -
accuracy: 0.9446
Epoch 6/500
1875/1875 [==============================] - 2s 1ms/step - loss: 0.1504 -
accuracy: 0.9435
Epoch 7/500
1875/1875 [==============================] - 2s 1ms/step - loss: 0.1481 -
accuracy: 0.9440
Epoch 8/500
1875/1875 [==============================] - 2s 1ms/step - loss: 0.1468 -
accuracy: 0.9445
Epoch 9/500
1875/1875 [==============================] - 2s 1ms/step - loss: 0.1473 -
accuracy: 0.9441
Epoch 10/500
1875/1875 [==============================] - 2s 1ms/step - loss: 0.1445 -
accuracy: 0.9445
Epoch 11/500
1875/1875 [==============================] - 2s 1ms/step - loss: 0.1436 -
accuracy: 0.9453
Epoch 12/500
 801/1875 [===========>…] - ETA: 1s - loss: 0.1356 - accuracy:
0.9488
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
/var/folders/q7/wrxzkb515gqcskvhd38dwx6h0000gn/T/ipykernel_72421/2811613906.py␣
 ↪in <module>
      1 callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=5)
      2
```

```
----> 3 history = model.fit(
      4     train_df[FEATURES],
      5     train_df[TARGETS],

~/opt/anaconda3/envs/data/lib/python3.9/site-packages/tensorflow/python/keras/
↪engine/training.py in fit(self, x, y, batch_size, epochs, verbose, callbacks,␣
↪validation_split, validation_data, shuffle, class_weight, sample_weight,␣
↪initial_epoch, steps_per_epoch, validation_steps, validation_batch_size,␣
↪validation_freq, max_queue_size, workers, use_multiprocessing)
   1098                 _r=1):
   1099               callbacks.on_train_batch_begin(step)
-> 1100               tmp_logs = self.train_function(iterator)
   1101               if data_handler.should_sync:
   1102                 context.async_wait()

~/opt/anaconda3/envs/data/lib/python3.9/site-packages/tensorflow/python/eager/
↪def_function.py in __call__(self, *args, **kwds)
    826     tracing_count = self.experimental_get_tracing_count()
    827     with trace.Trace(self._name) as tm:
--> 828       result = self._call(*args, **kwds)
    829       compiler = "xla" if self._experimental_compile else "nonXla"
    830       new_tracing_count = self.experimental_get_tracing_count()

~/opt/anaconda3/envs/data/lib/python3.9/site-packages/tensorflow/python/eager/
↪def_function.py in _call(self, *args, **kwds)
    853       # In this case we have created variables on the first call, so we␣
↪run the
    854       # defunned version which is guaranteed to never create variables.
--> 855       return self._stateless_fn(*args, **kwds)  # pylint:␣
↪disable=not-callable
    856     elif self._stateful_fn is not None:
    857       # Release the lock early so that multiple threads can perform the␣
↪call

~/opt/anaconda3/envs/data/lib/python3.9/site-packages/tensorflow/python/eager/
↪function.py in __call__(self, *args, **kwargs)
   2940       (graph_function,
   2941        filtered_flat_args) = self._maybe_define_function(args, kwargs)
-> 2942     return graph_function._call_flat(
   2943         filtered_flat_args, captured_inputs=graph_function.
↪captured_inputs)  # pylint: disable=protected-access
   2944

~/opt/anaconda3/envs/data/lib/python3.9/site-packages/tensorflow/python/eager/
↪function.py in _call_flat(self, args, captured_inputs, cancellation_manager)
   1916         and executing_eagerly):
   1917       # No tape is watching; skip to running the function.
```

```
-> 1918        return self._build_call_outputs(self._inference_function.call(

   1919            ctx, args, cancellation_manager=cancellation_manager))
   1920      forward_backward = self._select_forward_and_backward_functions(

~/opt/anaconda3/envs/data/lib/python3.9/site-packages/tensorflow/python/eager/
↪function.py in call(self, ctx, args, cancellation_manager)
    553        with _InterpolateFunctionError(self):
    554          if cancellation_manager is None:
--> 555            outputs = execute.execute(

    556                str(self.signature.name),
    557                num_outputs=self._num_outputs,

~/opt/anaconda3/envs/data/lib/python3.9/site-packages/tensorflow/python/eager/
↪execute.py in quick_execute(op_name, num_outputs, inputs, attrs, ctx, name)
     57   try:
     58     ctx.ensure_initialized()
---> 59     tensors = pywrap_tfe.TFE_Py_Execute(ctx._handle, device_name,␣
↪op_name,

     60                                         inputs, attrs, num_outputs)
     61   except core._NotOkStatusException as e:

KeyboardInterrupt:
```

As the model trains, the loss and accuracy metrics are displayed. We also store the progression in history.

You'll notice that this took longer to train per epoch than many of the models we've built previously in this course. That's because of the large number of features. Even with these tiny 28 by 28 grayscale images, we are still dealing with 784 features. This is orders of magnitude larger than the 10 or so features we are used to using.

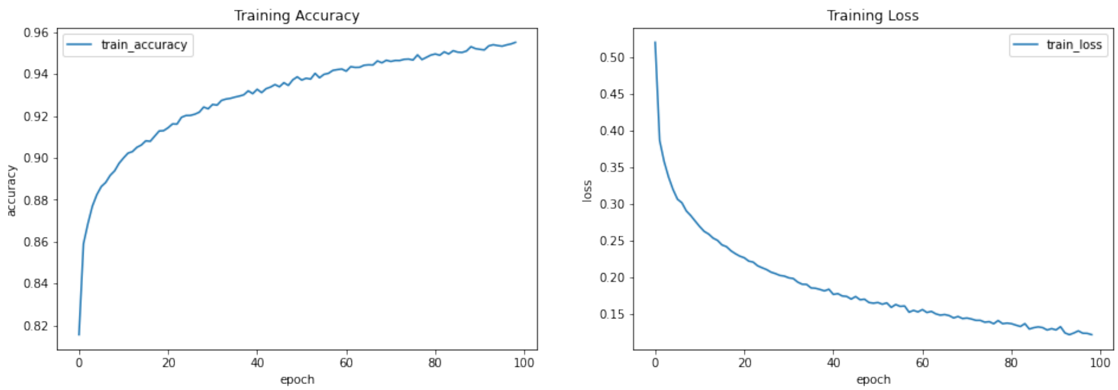
1.3.1 Exercise 4: Graph Model Progress

In this exercise you'll create two graphs. The first will show the model loss over each epoch. The second will show the model accuracy over each epoch. Feel free to use any graphical toolkit we have used so far.

[ ]:
```python
import matplotlib.pyplot as plt

plt.figure(figsize=(16,5))

plt.subplot(1,2,2)
plt.plot(history.history['loss'])
plt.title('Training Loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train_loss'], loc='best')
```

```
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'])
plt.title('Training Accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train_accuracy'], loc='best')
```

```
[ ]: <matplotlib.legend.Legend at 0x7f95ace62dd0>
```



1.4 Evaluate the Model

Now that our model is trained, let's evaluate it using an independent test data set. Then let's see if the model quality holds up. We'll use `model.evaluate()` and pass in the test dataset. `model.evaluate()` returns a `test_loss` and `test_accuracy`.

Also note that we need to apply the same feature preprocessing to the test data that we did to the train data.

```
[ ]: test_df = pd.DataFrame(
         np.array([x.flatten() for x in test_images]),
         columns=[i for i in range(784)]
     )
     test_df['target'] = test_labels

     test_df[FEATURES] = test_df[FEATURES] / 255.0

     for class_i in sorted(test_df['target'].unique()):
       column_name = f'target_{class_i}'
       test_df[column_name] = (test_df['target'] == class_i).astype(int)

     train_loss = history.history['loss'][-1]
```

```python
train_accuracy = history.history['accuracy'][-1]
(test_loss, test_accuracy) = model.evaluate(test_df[FEATURES], test_df[TARGETS])

print('Training loss:', train_loss)
print('Training accuracy:', train_accuracy)

print('Test loss:', test_loss)
print('Test accuracy:', test_accuracy)
```

```
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find
data adapter that can handle input: <class 'pandas.core.frame.DataFrame'>,
<class 'NoneType'>
10000/10000 [==============================] - 1s 65us/sample - loss: 0.5598 -
accuracy: 0.8761
Training loss: 0.12142243753870328
Training accuracy: 0.9551833
Test loss: 0.5598000788092613
Test accuracy: 0.8761
```

The accuracy on the test dataset is noticeably less than the accuracy on the training dataset. This gap between training accuracy and test accuracy is an example of **overfitting**. Overfitting is when a machine learning model tends to perform worse on new data than on the training data. The trained model is unable to **generalize** to data that it has not seen before.

There are many ways to try to reduce overfitting. One that we have seen is **early stopping**. This causes training to stop when loss stops changing significantly for a model. Without early stopping, the model would continue training, becoming more and more tailored to the training data and likely less to be able to generalize across new data.

Another method for reducing overfitting in deep neural networks is **dropout**. A dropout layer is a layer that sits between two regular layers (in our case, dense layers) and randomly sets some of the values passed between layers to `0`.

In TensorFlow the `Dropout` class is capable of doing this. To use `Dropout` you simply add a `Dropout` layer between other layers of the model. Each dropout layer has a percentage of values that it will set to `0`.

```python
model = tf.keras.Sequential([
    ...
    tf.keras.layers.Dense(name='L14', 431, activation=tf.nn.relu),
    # Randomly sets 15% of values between L14 and L15 to 0
    tf.keras.layers.Dropout(rate=0.15),
    tf.keras.layers.Dense(name='L15', 257, activation=tf.nn.relu),
    # Randomly sets 1% of values between L15 and L16 to 0
    tf.keras.layers.Dropout(rate=0.01),
    tf.keras.layers.Dense(name='L16', 57, activation=tf.nn.relu),
    ...
])
```

1.4.1 Exercise 5: Dropout Layers

In this exercise take the model from above and add a `Dropout` layer or layers between the `Dense` layers. See if you can find a configuration that reduces the gap between the training loss and accuracy and the test loss and accuracy. Document your findings.

Student Solution

[ ]:
```
model = tf.keras.Sequential([
    tf.keras.layers.Dense(128, input_shape=(len(FEATURES),)),
    tf.keras.layers.Dropout(rate=0.25),
    tf.keras.layers.Dense(64, activation=tf.nn.relu),
    tf.keras.layers.Dropout(rate=0.15),
    tf.keras.layers.Dense(32, activation=tf.nn.relu),
    tf.keras.layers.Dropout(rate=0.01),
    tf.keras.layers.Dense(len(TARGETS), activation=tf.nn.softmax)
])

model.summary()

model.compile(
    loss='categorical_crossentropy',
    optimizer='Adam',
    metrics=['accuracy'],
)

model.summary()

callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=5)

history = model.fit(
    train_df[FEATURES],
    train_df[TARGETS],
    epochs=500,
    callbacks=[callback]
)
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_16 (Dense)             (None, 128)               100480
_________________________________________________________________
dropout (Dropout)            (None, 128)               0
_________________________________________________________________
dense_17 (Dense)             (None, 64)                8256
_________________________________________________________________
dropout_1 (Dropout)          (None, 64)                0
_________________________________________________________________
```

```
dense_18 (Dense)             (None, 32)               2080
_________________________________________________________________
dropout_2 (Dropout)          (None, 32)               0
_________________________________________________________________
dense_19 (Dense)             (None, 10)               330
=================================================================
Total params: 111,146
Trainable params: 111,146
Non-trainable params: 0
_________________________________________________________________
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape             Param #
=================================================================
dense_16 (Dense)             (None, 128)              100480
_________________________________________________________________
dropout (Dropout)            (None, 128)              0
_________________________________________________________________
dense_17 (Dense)             (None, 64)               8256
_________________________________________________________________
dropout_1 (Dropout)          (None, 64)               0
_________________________________________________________________
dense_18 (Dense)             (None, 32)               2080
_________________________________________________________________
dropout_2 (Dropout)          (None, 32)               0
_________________________________________________________________
dense_19 (Dense)             (None, 10)               330
=================================================================
Total params: 111,146
Trainable params: 111,146
Non-trainable params: 0
_________________________________________________________________
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find
data adapter that can handle input: <class 'pandas.core.frame.DataFrame'>,
<class 'NoneType'>
Train on 60000 samples
Epoch 1/500
60000/60000 [==============================] - 12s 196us/sample - loss: 0.6168 -
accuracy: 0.7790
Epoch 2/500
60000/60000 [==============================] - 11s 186us/sample - loss: 0.4657 -
accuracy: 0.8296
Epoch 3/500
60000/60000 [==============================] - 12s 193us/sample - loss: 0.4312 -
accuracy: 0.8445
Epoch 4/500
60000/60000 [==============================] - 12s 195us/sample - loss: 0.4138 -
accuracy: 0.8480
```

```
Epoch 5/500
60000/60000 [==============================] - 12s 193us/sample - loss: 0.3985 -
accuracy: 0.8544
Epoch 6/500
60000/60000 [==============================] - 11s 188us/sample - loss: 0.3900 -
accuracy: 0.8561
Epoch 7/500
60000/60000 [==============================] - 11s 186us/sample - loss: 0.3781 -
accuracy: 0.8606
Epoch 8/500
60000/60000 [==============================] - 11s 187us/sample - loss: 0.3724 -
accuracy: 0.8619
Epoch 9/500
60000/60000 [==============================] - 11s 188us/sample - loss: 0.3690 -
accuracy: 0.8649
Epoch 10/500
60000/60000 [==============================] - 11s 187us/sample - loss: 0.3579 -
accuracy: 0.8695
Epoch 11/500
60000/60000 [==============================] - 11s 189us/sample - loss: 0.3563 -
accuracy: 0.8683
Epoch 12/500
60000/60000 [==============================] - 11s 188us/sample - loss: 0.3542 -
accuracy: 0.8688
Epoch 13/500
60000/60000 [==============================] - 11s 189us/sample - loss: 0.3520 -
accuracy: 0.8713
Epoch 14/500
60000/60000 [==============================] - 11s 190us/sample - loss: 0.3474 -
accuracy: 0.8732
Epoch 15/500
60000/60000 [==============================] - 12s 197us/sample - loss: 0.3420 -
accuracy: 0.8743
Epoch 16/500
60000/60000 [==============================] - 12s 199us/sample - loss: 0.3398 -
accuracy: 0.8739
Epoch 17/500
60000/60000 [==============================] - 12s 201us/sample - loss: 0.3375 -
accuracy: 0.8744
Epoch 18/500
60000/60000 [==============================] - 11s 191us/sample - loss: 0.3355 -
accuracy: 0.8762
Epoch 19/500
60000/60000 [==============================] - 11s 190us/sample - loss: 0.3334 -
accuracy: 0.8757
Epoch 20/500
60000/60000 [==============================] - 12s 197us/sample - loss: 0.3314 -
accuracy: 0.8779
```

```
Epoch 21/500
60000/60000 [==============================] - 11s 189us/sample - loss: 0.3280 -
accuracy: 0.8776
Epoch 22/500
60000/60000 [==============================] - 12s 198us/sample - loss: 0.3262 -
accuracy: 0.8784
Epoch 23/500
60000/60000 [==============================] - 12s 194us/sample - loss: 0.3272 -
accuracy: 0.8781
Epoch 24/500
60000/60000 [==============================] - 11s 191us/sample - loss: 0.3222 -
accuracy: 0.8809
Epoch 25/500
60000/60000 [==============================] - 12s 200us/sample - loss: 0.3218 -
accuracy: 0.8807
Epoch 26/500
60000/60000 [==============================] - 12s 198us/sample - loss: 0.3198 -
accuracy: 0.8815
Epoch 27/500
60000/60000 [==============================] - 11s 187us/sample - loss: 0.3186 -
accuracy: 0.8817
Epoch 28/500
60000/60000 [==============================] - 11s 188us/sample - loss: 0.3188 -
accuracy: 0.8815
Epoch 29/500
60000/60000 [==============================] - 11s 190us/sample - loss: 0.3134 -
accuracy: 0.8842
Epoch 30/500
60000/60000 [==============================] - 11s 190us/sample - loss: 0.3148 -
accuracy: 0.8844
Epoch 31/500
60000/60000 [==============================] - 11s 187us/sample - loss: 0.3146 -
accuracy: 0.8833
Epoch 32/500
60000/60000 [==============================] - 12s 192us/sample - loss: 0.3119 -
accuracy: 0.8839
Epoch 33/500
60000/60000 [==============================] - 12s 208us/sample - loss: 0.3111 -
accuracy: 0.8853
Epoch 34/500
60000/60000 [==============================] - 12s 199us/sample - loss: 0.3120 -
accuracy: 0.8852
Epoch 35/500
60000/60000 [==============================] - 12s 204us/sample - loss: 0.3116 -
accuracy: 0.8834
Epoch 36/500
60000/60000 [==============================] - 11s 185us/sample - loss: 0.3057 -
accuracy: 0.8862
```

```
Epoch 37/500
60000/60000 [==============================] - 11s 185us/sample - loss: 0.3107 -
accuracy: 0.8863
Epoch 38/500
60000/60000 [==============================] - 12s 204us/sample - loss: 0.3059 -
accuracy: 0.8859
Epoch 39/500
60000/60000 [==============================] - 12s 193us/sample - loss: 0.3075 -
accuracy: 0.8859
Epoch 40/500
60000/60000 [==============================] - 12s 194us/sample - loss: 0.3065 -
accuracy: 0.8868
Epoch 41/500
60000/60000 [==============================] - 12s 200us/sample - loss: 0.3046 -
accuracy: 0.8867
Epoch 42/500
60000/60000 [==============================] - 12s 205us/sample - loss: 0.3045 -
accuracy: 0.8870
Epoch 43/500
60000/60000 [==============================] - 11s 184us/sample - loss: 0.2986 -
accuracy: 0.8887
Epoch 44/500
60000/60000 [==============================] - 13s 211us/sample - loss: 0.2999 -
accuracy: 0.8895
Epoch 45/500
60000/60000 [==============================] - 11s 190us/sample - loss: 0.3026 -
accuracy: 0.8872
Epoch 46/500
60000/60000 [==============================] - 11s 186us/sample - loss: 0.3021 -
accuracy: 0.8878
Epoch 47/500
60000/60000 [==============================] - 11s 181us/sample - loss: 0.3005 -
accuracy: 0.8870
Epoch 48/500
60000/60000 [==============================] - 11s 182us/sample - loss: 0.2984 -
accuracy: 0.8889
Epoch 49/500
60000/60000 [==============================] - 11s 181us/sample - loss: 0.2979 -
accuracy: 0.8892
Epoch 50/500
60000/60000 [==============================] - 11s 187us/sample - loss: 0.2944 -
accuracy: 0.8911
Epoch 51/500
60000/60000 [==============================] - 12s 200us/sample - loss: 0.2948 -
accuracy: 0.8899
Epoch 52/500
60000/60000 [==============================] - 12s 193us/sample - loss: 0.2978 -
accuracy: 0.8906
```

```
Epoch 53/500
60000/60000 [==============================] - 12s 199us/sample - loss: 0.2960 -
accuracy: 0.8907
Epoch 54/500
60000/60000 [==============================] - 12s 192us/sample - loss: 0.2937 -
accuracy: 0.8904
Epoch 55/500
60000/60000 [==============================] - 11s 190us/sample - loss: 0.2951 -
accuracy: 0.8906
Epoch 56/500
60000/60000 [==============================] - 12s 205us/sample - loss: 0.2934 -
accuracy: 0.8900
Epoch 57/500
60000/60000 [==============================] - 11s 190us/sample - loss: 0.2929 -
accuracy: 0.8913
Epoch 58/500
60000/60000 [==============================] - 12s 192us/sample - loss: 0.2906 -
accuracy: 0.8924
Epoch 59/500
60000/60000 [==============================] - 11s 190us/sample - loss: 0.2905 -
accuracy: 0.8919
Epoch 60/500
60000/60000 [==============================] - 12s 193us/sample - loss: 0.2892 -
accuracy: 0.8927
Epoch 61/500
60000/60000 [==============================] - 12s 192us/sample - loss: 0.2925 -
accuracy: 0.8912
Epoch 62/500
60000/60000 [==============================] - 12s 193us/sample - loss: 0.2868 -
accuracy: 0.8935
Epoch 63/500
60000/60000 [==============================] - 12s 192us/sample - loss: 0.2924 -
accuracy: 0.8911
Epoch 64/500
60000/60000 [==============================] - 12s 194us/sample - loss: 0.2904 -
accuracy: 0.8925
Epoch 65/500
60000/60000 [==============================] - 12s 193us/sample - loss: 0.2887 -
accuracy: 0.8939
Epoch 66/500
60000/60000 [==============================] - 12s 195us/sample - loss: 0.2895 -
accuracy: 0.8924
Epoch 67/500
60000/60000 [==============================] - 12s 193us/sample - loss: 0.2854 -
accuracy: 0.8929
Epoch 68/500
60000/60000 [==============================] - 12s 195us/sample - loss: 0.2819 -
accuracy: 0.8947
```

```
Epoch 69/500
60000/60000 [==============================] - 12s 195us/sample - loss: 0.2869 -
accuracy: 0.8941
Epoch 70/500
60000/60000 [==============================] - 12s 198us/sample - loss: 0.2855 -
accuracy: 0.8952
Epoch 71/500
60000/60000 [==============================] - 12s 193us/sample - loss: 0.2846 -
accuracy: 0.8937
Epoch 72/500
60000/60000 [==============================] - 12s 195us/sample - loss: 0.2845 -
accuracy: 0.8940
Epoch 73/500
60000/60000 [==============================] - 12s 194us/sample - loss: 0.2837 -
accuracy: 0.8952
```

[ ]:

Iterate a few times and find a dropout model that seems to bring the testing and training numbers closer together. When you are done, document your findings in the table below. The ?s are placeholders for accuracy and loss values.

Dropout (Y/N)	Train/Test	Accuracy	Loss
N	Train	*.95*	*.1*
N	Test	*.87*	*.5*
Y	Train	*.89*	*.28*
Y	Test	*.87*	*.35*

[ ]:

```python
train_loss = history.history['loss'][-1]
train_accuracy = history.history['accuracy'][-1]
(test_loss, test_accuracy) = model.evaluate(test_df[FEATURES], test_df[TARGETS])

print('Training loss:', train_loss)
print('Training accuracy:', train_accuracy)

print('Test loss:', test_loss)
print('Test accuracy:', test_accuracy)
```

```
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find
data adapter that can handle input: <class 'pandas.core.frame.DataFrame'>,
<class 'NoneType'>
10000/10000 [==============================] - 1s 68us/sample - loss: 0.3501 -
accuracy: 0.8751
Training loss: 0.2836518274118503
Training accuracy: 0.8952
Test loss: 0.3500618842363358
```

```
Test accuracy: 0.8751
```

1.5 Make Predictions

We have now trained the model while trying to reduce overfitting. Let's say we're happy with our numbers and are ready to deploy the model. Now it is time to make predictions.

We could now snap an image of a clothing item, resize it to 28 by 28, and grayscale it. But that is a lot of work and outside the scope of this class. For simplicity, let's use the test images as input to the model and see what predictions we get.

We'll use the `model.predict()` function to do this. Let's make our predictions and peek at the first result.

[ ]:
```
predictions = model.predict(test_df[FEATURES])

predictions[0]
```

```
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find
data adapter that can handle input: <class 'pandas.core.frame.DataFrame'>,
<class 'NoneType'>
```

[ ]:
```
array([3.2000608e-10, 5.1018556e-12, 1.2096562e-09, 1.9276606e-11,
       2.5907356e-11, 1.1488260e-03, 9.3423907e-11, 3.7617382e-02,
       1.1600423e-09, 9.6123374e-01], dtype=float32)
```

What are those numbers?

For each image: * the prediction result is in the form of 10 numbers, one for each possible label * each number represents the level of confidence that a label is the correct label for the particular image * all 10 numbers should add up to the sum of 1

Let's see if that is true.

[ ]:
```

```

[ ]:
```
sum(predictions[0]), sum(predictions[1])
```

[ ]:
```
(0.9999999455570759, 0.9999999934343045)
```

Well, maybe not `1`, but the result definitely approaches `1`. Floating point math makes summing to exactly `1` a little difficult.

Let's find out which label has the highest predicted number and whether it matches with the actual test label.

To find the highest predicted number we will use Numpy's [argmax](https://docs.scipy.org/doc/numpy/reference/generated/numpy.argmax.html) function which returns the index of the maximum value in an array.

[ ]:
```
import numpy as np

print('Label with the highest confidence: {predicted_label}'.format(
    predicted_label = np.argmax(predictions[0])))
```

```
print('Actual label: {actual_label}'.format(actual_label = test_labels[0]))
```

```
Label with the highest confidence: 9
Actual label: 9
```

With our model the predicted class was class `9`, and the actual class was class `9`. Success!

1.5.1 Exercise 6: Thresholds

When making our predictions, we blindly accepted the output of `argmax` without really understanding what `argmax` was doing.

`argmax` returns the index of the maximum value in an array. What if there are ties? What happens for a 10-element array that looks like:

```
[0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1]
```

In this case it is a virtual tie between all of the classes. `argmax` will return the first value in the case of a tie. This is problematic for a few reasons. In this case we clearly have little confidence in any class, yet an algorithm that relies on `argmax` would naively predict the first class.

For this exercise, discuss ways we can get around relying solely on `argmax`. Are there better ways of finding a prediction algorithm?

Student Solution

> *Argmax is good in cases where classes of labels are discrete and the numerical difference between these values are more apparent. This was was certaintly the case for the model used, where integer values such as 1 and 2 were used to classify certain labels. In cases where this is not apparent, more concrete algorithms that can sort these values and return a maximum value would be better to use*

1.6 Exercise 7: MNIST Digits

Another popular MNIST dataset is the digits dataset. This dataset consists of images of labelled, hand-written digits ranging from `0` through `9`.

In this exercise you will build a model that predicts the class of MNIST digit images.

The dataset is part of scikit-learn.

[ ]:
```
from sklearn import datasets

import pandas as pd

digits_bunch = datasets.load_digits()
digits = pd.DataFrame(digits_bunch.data)
digits['digit'] = digits_bunch.target

#targets
```

```
digits['digit']


#digits.describe()
```

```
[ ]: 0       0
     1       1
     2       2
     3       3
     4       4
            ..
     1792    9
     1793    0
     1794    8
     1795    9
     1796    8
     Name: digit, Length: 1797, dtype: int64
```

You will need to:

- Perform EDA on the data
- Choose a model (or models) to use to predict digits
- Perform any model-specific data manipulation
- Train the model and, if possible, visualize training progression
- Perform a final test of the model on holdout data

Use as many code and text cells as you need to. Explain your work.

1.6.1 Student Solution

EDA

```
[ ]: FEATURES_2 = train_df.columns[:-1]

     #finding target classifications
     print(digits['digit'].unique())




     #loading original dataframe
     og_df = digits

     og_df
```

```
[0 1 2 3 4 5 6 7 8 9]
```

```
[ ]:       0    1    2     3     4    5    6    7    8    9  …   55   56  \
     0    0.0  0.0  5.0  13.0   9.0  1.0  0.0  0.0  0.0  0.0  …  0.0  0.0
     1    0.0  0.0  0.0  12.0  13.0  5.0  0.0  0.0  0.0  0.0  …  0.0  0.0
```

```
2     0.0  0.0   0.0   4.0  15.0  12.0  0.0  0.0  0.0  0.0  …  0.0  0.0
3     0.0  0.0   7.0  15.0  13.0   1.0  0.0  0.0  0.0  8.0  …  0.0  0.0
4     0.0  0.0   0.0   1.0  11.0   0.0  0.0  0.0  0.0  0.0  …  0.0  0.0
…    …  …    …   …    …    …  …   …   …    …   …   …   …
1792  0.0  0.0   4.0  10.0  13.0   6.0  0.0  0.0  0.0  1.0  …  0.0  0.0
1793  0.0  0.0   6.0  16.0  13.0  11.0  1.0  0.0  0.0  0.0  …  0.0  0.0
1794  0.0  0.0   1.0  11.0  15.0   1.0  0.0  0.0  0.0  0.0  …  0.0  0.0
1795  0.0  0.0   2.0  10.0   7.0   0.0  0.0  0.0  0.0  0.0  …  0.0  0.0
1796  0.0  0.0  10.0  14.0   8.0   1.0  0.0  0.0  0.0  2.0  …  0.0  0.0

       57   58    59    60    61   62   63  digit
0     0.0  6.0  13.0  10.0   0.0  0.0  0.0      0
1     0.0  0.0  11.0  16.0  10.0  0.0  0.0      1
2     0.0  0.0   3.0  11.0  16.0  9.0  0.0      2
3     0.0  7.0  13.0  13.0   9.0  0.0  0.0      3
4     0.0  0.0   2.0  16.0   4.0  0.0  0.0      4
…    …  …    …   …    …    …  …     …
1792  0.0  2.0  14.0  15.0   9.0  0.0  0.0      9
1793  0.0  6.0  16.0  14.0   6.0  0.0  0.0      0
1794  0.0  2.0   9.0  13.0   6.0  0.0  0.0      8
1795  0.0  5.0  12.0  16.0  12.0  0.0  0.0      9
1796  1.0  8.0  12.0  14.0  12.0  1.0  0.0      8

[1797 rows x 65 columns]
```

[ ]:
```
#One hot encoding

target_columns =␣
 ↪['target_0','target_1','target_2','target_3','target_4','target_5','target_6','target_7','t
TARGETS = target_columns
ohe = OneHotEncoder(sparse=False)


encodedTargets = ohe.fit_transform(og_df[['digit']])

encodedTargets_df = pd.DataFrame(encodedTargets)
encodedTargets_df.columns =target_columns

og_df = og_df.drop('digit',axis =1 )

og_df = og_df.join(encodedTargets_df)
```

[ ]:
```
og_df
```

```
[ ]:       0    1     2     3     4     5    6    7    8    9  …  target_0  \
     0     0.0  0.0   5.0  13.0   9.0   1.0  0.0  0.0  0.0  0.0  …       1.0
     1     0.0  0.0   0.0  12.0  13.0   5.0  0.0  0.0  0.0  0.0  …       0.0
     2     0.0  0.0   0.0   4.0  15.0  12.0  0.0  0.0  0.0  0.0  …       0.0
     3     0.0  0.0   7.0  15.0  13.0   1.0  0.0  0.0  0.0  8.0  …       0.0
     4     0.0  0.0   0.0   1.0  11.0   0.0  0.0  0.0  0.0  0.0  …       0.0
     …   …   …    …    …    …    …   …   …   …   …   …        …
     1792  0.0  0.0   4.0  10.0  13.0   6.0  0.0  0.0  0.0  1.0  …       0.0
     1793  0.0  0.0   6.0  16.0  13.0  11.0  1.0  0.0  0.0  0.0  …       1.0
     1794  0.0  0.0   1.0  11.0  15.0   1.0  0.0  0.0  0.0  0.0  …       0.0
     1795  0.0  0.0   2.0  10.0   7.0   0.0  0.0  0.0  0.0  0.0  …       0.0
     1796  0.0  0.0  10.0  14.0   8.0   1.0  0.0  0.0  0.0  2.0  …       0.0

           target_1  target_2  target_3  target_4  target_5  target_6  target_7  \
     0          0.0       0.0       0.0       0.0       0.0       0.0       0.0
     1          1.0       0.0       0.0       0.0       0.0       0.0       0.0
     2          0.0       1.0       0.0       0.0       0.0       0.0       0.0
     3          0.0       0.0       1.0       0.0       0.0       0.0       0.0
     4          0.0       0.0       0.0       1.0       0.0       0.0       0.0
     …        …       …       …       …       …       …       …
     1792       0.0       0.0       0.0       0.0       0.0       0.0       0.0
     1793       0.0       0.0       0.0       0.0       0.0       0.0       0.0
     1794       0.0       0.0       0.0       0.0       0.0       0.0       0.0
     1795       0.0       0.0       0.0       0.0       0.0       0.0       0.0
     1796       0.0       0.0       0.0       0.0       0.0       0.0       0.0

           target_8  target_9
     0          0.0       0.0
     1          0.0       0.0
     2          0.0       0.0
     3          0.0       0.0
     4          0.0       0.0
     …        …       …
     1792       0.0       1.0
     1793       0.0       0.0
     1794       1.0       0.0
     1795       0.0       1.0
     1796       1.0       0.0

     [1797 rows x 74 columns]
```

Splitting the data

```
[ ]: from sklearn.model_selection import train_test_split
     X_train, X_test, y_train, y_test = train_test_split(
         og_df[FEATURES_2],
         og_df[TARGETS],
         test_size=0.2,
```

```
random_state=180, shuffle=True)

train_df = X_train.join(y_train)
test_df = X_test.join(y_test)
```

Building the Model

Training set

[ ]:
```
model = tf.keras.Sequential([
    tf.keras.layers.Dense(128, input_shape=(len(FEATURES_2),)),
    tf.keras.layers.Dropout(rate=0.25),
    tf.keras.layers.Dense(64, activation=tf.nn.relu),
    tf.keras.layers.Dropout(rate=0.15),
    tf.keras.layers.Dense(32, activation=tf.nn.relu),
    tf.keras.layers.Dropout(rate=0.01),
    tf.keras.layers.Dense(len(TARGETS), activation=tf.nn.softmax)
])



model.compile(
    loss='categorical_crossentropy',
    optimizer='Adam',
    metrics=['accuracy'],
)



callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=5)

history = model.fit(
    train_df[FEATURES_2],
    train_df[TARGETS],
    epochs=500,
    callbacks=[callback]
)
```

```
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find
data adapter that can handle input: <class 'pandas.core.frame.DataFrame'>,
<class 'NoneType'>
Train on 1437 samples
Epoch 1/500
1437/1437 [==============================] - 1s 507us/sample - loss: 3.0616 -
accuracy: 0.2262
Epoch 2/500
1437/1437 [==============================] - 0s 152us/sample - loss: 1.3810 -
accuracy: 0.5463
Epoch 3/500
```

```
1437/1437 [==============================] - 0s 151us/sample - loss: 0.9188 -
accuracy: 0.7119
Epoch 4/500
1437/1437 [==============================] - 0s 154us/sample - loss: 0.6370 -
accuracy: 0.7989
Epoch 5/500
1437/1437 [==============================] - 0s 156us/sample - loss: 0.4558 -
accuracy: 0.8497
Epoch 6/500
1437/1437 [==============================] - 0s 173us/sample - loss: 0.3616 -
accuracy: 0.8817
Epoch 7/500
1437/1437 [==============================] - 0s 165us/sample - loss: 0.2692 -
accuracy: 0.9172
Epoch 8/500
1437/1437 [==============================] - 0s 154us/sample - loss: 0.3099 -
accuracy: 0.9005
Epoch 9/500
1437/1437 [==============================] - 0s 153us/sample - loss: 0.2069 -
accuracy: 0.9318
Epoch 10/500
1437/1437 [==============================] - 0s 153us/sample - loss: 0.1674 -
accuracy: 0.9429
Epoch 11/500
1437/1437 [==============================] - 0s 155us/sample - loss: 0.2061 -
accuracy: 0.9297
Epoch 12/500
1437/1437 [==============================] - 0s 154us/sample - loss: 0.1802 -
accuracy: 0.9402
Epoch 13/500
1437/1437 [==============================] - 0s 152us/sample - loss: 0.1666 -
accuracy: 0.9492
Epoch 14/500
1437/1437 [==============================] - 0s 153us/sample - loss: 0.1578 -
accuracy: 0.9499
Epoch 15/500
1437/1437 [==============================] - 0s 153us/sample - loss: 0.1355 -
accuracy: 0.9527
Epoch 16/500
1437/1437 [==============================] - 0s 152us/sample - loss: 0.1381 -
accuracy: 0.9589
Epoch 17/500
1437/1437 [==============================] - 0s 152us/sample - loss: 0.1181 -
accuracy: 0.9610
Epoch 18/500
1437/1437 [==============================] - 0s 153us/sample - loss: 0.1287 -
accuracy: 0.9624
Epoch 19/500
```

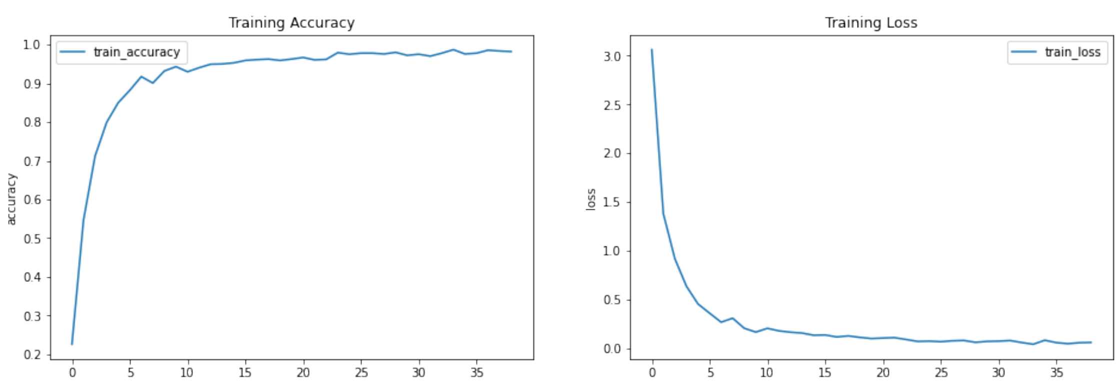
```
1437/1437 [==============================] - 0s 152us/sample - loss: 0.1133 -
accuracy: 0.9589
Epoch 20/500
1437/1437 [==============================] - 0s 150us/sample - loss: 0.1016 -
accuracy: 0.9624
Epoch 21/500
1437/1437 [==============================] - 0s 151us/sample - loss: 0.1066 -
accuracy: 0.9666
Epoch 22/500
1437/1437 [==============================] - 0s 162us/sample - loss: 0.1106 -
accuracy: 0.9603
Epoch 23/500
1437/1437 [==============================] - 0s 152us/sample - loss: 0.0919 -
accuracy: 0.9617
Epoch 24/500
1437/1437 [==============================] - 0s 154us/sample - loss: 0.0720 -
accuracy: 0.9791
Epoch 25/500
1437/1437 [==============================] - 0s 154us/sample - loss: 0.0749 -
accuracy: 0.9749
Epoch 26/500
1437/1437 [==============================] - 0s 152us/sample - loss: 0.0693 -
accuracy: 0.9777
Epoch 27/500
1437/1437 [==============================] - 0s 153us/sample - loss: 0.0783 -
accuracy: 0.9777
Epoch 28/500
1437/1437 [==============================] - 0s 152us/sample - loss: 0.0818 -
accuracy: 0.9756
Epoch 29/500
1437/1437 [==============================] - 0s 157us/sample - loss: 0.0627 -
accuracy: 0.9798
Epoch 30/500
1437/1437 [==============================] - 0s 158us/sample - loss: 0.0723 -
accuracy: 0.9722
Epoch 31/500
1437/1437 [==============================] - 0s 153us/sample - loss: 0.0748 -
accuracy: 0.9749
Epoch 32/500
1437/1437 [==============================] - 0s 151us/sample - loss: 0.0811 -
accuracy: 0.9701
Epoch 33/500
1437/1437 [==============================] - 0s 154us/sample - loss: 0.0605 -
accuracy: 0.9777
Epoch 34/500
1437/1437 [==============================] - 0s 152us/sample - loss: 0.0430 -
accuracy: 0.9868
Epoch 35/500
```

```
1437/1437 [==============================] - 0s 155us/sample - loss: 0.0841 -
accuracy: 0.9756
Epoch 36/500
1437/1437 [==============================] - 0s 153us/sample - loss: 0.0596 -
accuracy: 0.9777
Epoch 37/500
1437/1437 [==============================] - 0s 153us/sample - loss: 0.0488 -
accuracy: 0.9854
Epoch 38/500
1437/1437 [==============================] - 0s 153us/sample - loss: 0.0589 -
accuracy: 0.9833
Epoch 39/500
1437/1437 [==============================] - 0s 152us/sample - loss: 0.0616 -
accuracy: 0.9819
```

Graphing Model Process

[ ]:
```
plt.figure(figsize=(16,5))

plt.subplot(1,2,2)
plt.plot(history.history['loss'])
plt.title('Training Loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train_loss'], loc='best')

plt.subplot(1,2,1)
plt.plot(history.history['accuracy'])
plt.title('Training Accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train_accuracy'], loc='best')
```

[ ]:
```
<matplotlib.legend.Legend at 0x7f954b443e10>
```



Model Evaluation

```
[ ]: train_loss = history.history['loss'][-1]
     train_accuracy = history.history['accuracy'][-1]
     (test_loss, test_accuracy) = model.evaluate(test_df[FEATURES_2],␣
      ↪test_df[TARGETS])

     print('Training loss:', train_loss)
     print('Training accuracy:', train_accuracy)

     print('Test loss:', test_loss)
     print('Test accuracy:', test_accuracy)
```

```
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find
data adapter that can handle input: <class 'pandas.core.frame.DataFrame'>,
<class 'NoneType'>
360/360 [==============================] - 0s 553us/sample - loss: 0.0862 -
accuracy: 0.9861
Training loss: 0.061573891125997905
Training accuracy: 0.9819068
Test loss: 0.08623956021102559
Test accuracy: 0.9861111
```

```
[ ]: predictions = model.predict(test_df[FEATURES_2])

     predictions[0]
```

```
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find
data adapter that can handle input: <class 'pandas.core.frame.DataFrame'>,
<class 'NoneType'>
```

```
[ ]: array([1.6430340e-08, 3.3618651e-08, 3.1002009e-14, 1.9662133e-11,
            1.2574532e-08, 5.4443963e-11, 1.0000000e+00, 3.1500911e-14,
            1.1559946e-08, 1.5749539e-15], dtype=float32)
```