In [29]:
```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import itertools
from functools import partial

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, ConfusionMatrixDisplay,

import tensorflow as tf
from tensorflow import keras
```

In [2]:
```python
%load_ext watermark
%watermark -v -n -m -p numpy,sklearn,pandas,seaborn,tensorflow
```

```
Python implementation: CPython
Python version       : 3.8.8
IPython version      : 7.22.0

numpy     : 1.23.5
sklearn   : 1.2.0
pandas    : 1.4.3
seaborn   : 0.12.2
tensorflow: 2.11.0

Compiler    : MSC v.1916 64 bit (AMD64)
OS          : Windows
Release     : 10
Machine     : AMD64
Processor   : Intel64 Family 6 Model 140 Stepping 1, GenuineIntel
CPU cores   : 8
Architecture: 64bit
```

Identify a Deep Learning Problem

Neural Networks are the standard for image classification given their complexity. This project is an exploration of different types of NN's learned in the Introduction to Deep Learning course and their ability to classify simple images (fashion-MINST) compared to simpler machine learning algorithm such as KNN.

The Fashion MINST dataset is collection of fashion article images, it consists of 70,000 examples in total and is a popular benchmarking dataset of machine learning algorithms as it is more complicated than the regular MINST dataset.

In [185…
```python
fashion_mnist = keras.datasets.fashion_mnist
(X_train, y_train), (X_test, y_test) = fashion_mnist.load_data()
```

In [133…
```python
class_names = ["T-shirt/top", "Trouser", "Pullover", "Dress", "Coat",
               "Sandal", "Shirt", "Sneaker", "Bag", "Ankle boot"]
```

Exploratory Data Analysis (EDA)

There are a total of 60,000 training and images and a total of 10,000 testing images.The dataframe train_labels contains the labels for the training images.

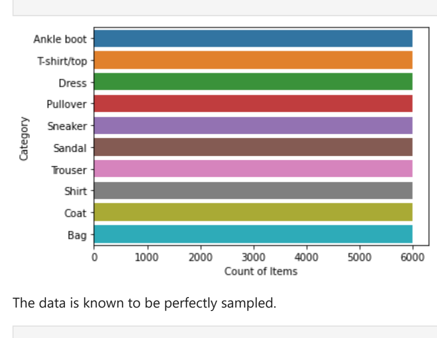
The images are 28x28 and are GrayScale images, giving us an input array of 96 by 96 by 1

In [134…
```python
print(X_train.shape, X_test.shape)
```

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

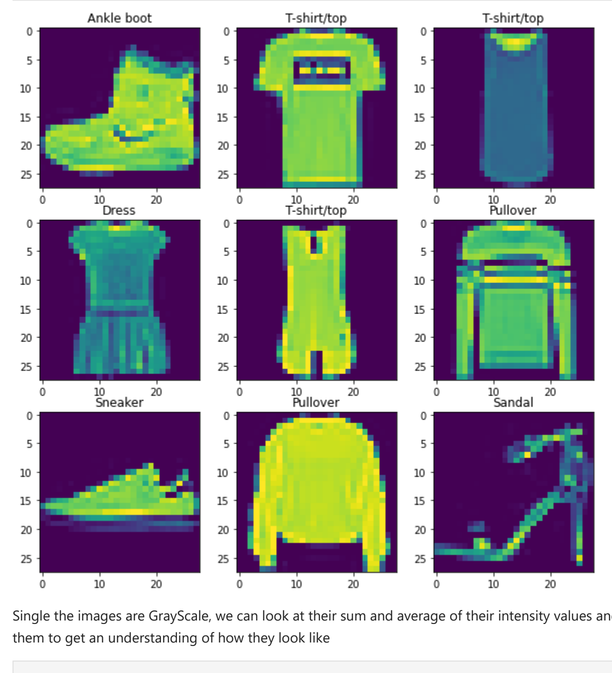
In [205…
```python
images_df = pd.DataFrame(np.array(class_names)[y_train], columns=['labels'])
```

In [206…
```python
sns.barplot(data=images_df['labels'].value_counts().to_frame().reset_index(),
            x='labels',
            y='index')
plt.ylabel('Category')
plt.xlabel('Count of Items')
plt.show()
```



The data is known to be perfectly sampled.

In [207…
```python
fig, axs = plt.subplots(3, 3, figsize=(10, 10))
axs = axs.flatten()
for image, prediction, axis in zip(X_train[:9], np.array(class_names)[y_train[:9]], ax
    axis.imshow(image)
    axis.set_title(prediction)
```



Single the images are GrayScale, we can look at their sum and average of their intensity values and plot them to get an understanding of how they look like

In [228…
```python
images_df['TotalIntensity'] = X_train.reshape((60000, -1)).sum(axis=1)
images_df['MeanIntensity'] = np.mean(X_train.reshape((60000, -1)), axis=1)
```

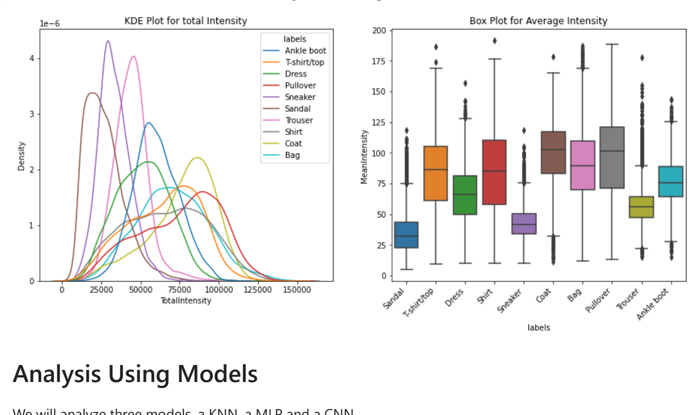
In [239…
```python
figs, axs = plt.subplots(ncols=2,
                         figsize=(15,6))

g1 = sns.kdeplot(data=images_df,
            x='TotalIntensity',
            hue='labels',
            ax=axs[0]).set(title='KDE Plot for total Intensity')

g2 = sns.boxplot(data=images_df,
                 y=images_df['MeanIntensity'],
                 x='labels',
                 ax=axs[1])

g2.set_xticklabels(g2.get_xticklabels(), rotation=45, ha='right')
g2.set(title='Box Plot for Average Intensity')
```

Out[239… `[Text(0.5, 1.0, 'Box Plot for Average Intensity')]`



Analysis Using Models

We will analyze three models, a KNN, a MLP and a CNN

k Nearest Neighbors

We need to reshape the input data for the KNN model (images are 3D, need 2D data)

In [240…
```python
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train.reshape((60000, -1)), y_train)
```

Out[240…
```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

In [241…
```python
knn_predictions = knn.predict(X_test.reshape((10000, -1)))
```

In [242…
```python
knn_predictions
```

Out[242… `array([9, 2, 1, ..., 8, 1, 7], dtype=uint8)`

Results

In [243…
```python
print("Accuracy ->", accuracy_score(knn_predictions, y_test))
print(classification_report(mlp_predicted_classes, y_test))
```

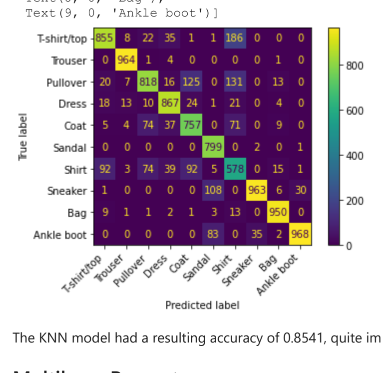
```
Accuracy -> 0.8541
              precision    recall  f1-score   support

           0       0.82      0.81      0.82      1011
           1       0.96      0.99      0.98       967
           2       0.90      0.62      0.73      1451
           3       0.89      0.87      0.88      1017
           4       0.64      0.85      0.73       749
           5       0.95      0.98      0.97       973
           6       0.58      0.71      0.64       826
           7       0.96      0.93      0.95      1038
           8       0.96      0.98      0.97       973
           9       0.95      0.96      0.95       995

    accuracy                           0.86     10000
   macro avg       0.86      0.87      0.86     10000
weighted avg       0.87      0.86      0.86     10000
```

In [198…
```python
cf_matrix = ConfusionMatrixDisplay(confusion_matrix(knn_predictions,
                                                    y_test,
                                                    labels=np.arange(0,10)),
                                   display_labels=class_names)
cf_matrix.plot()
cf_matrix.ax_.set_xticklabels(cf_matrix.ax_.get_xticklabels(), rotation=45, ha='right
```

Out[198…
```
[Text(0, 0, 'T-shirt/top'),
 Text(1, 0, 'Trouser'),
 Text(2, 0, 'Pullover'),
 Text(3, 0, 'Dress'),
 Text(4, 0, 'Coat'),
 Text(5, 0, 'Sandal'),
 Text(6, 0, 'Shirt'),
 Text(7, 0, 'Sneaker'),
 Text(8, 0, 'Bag'),
 Text(9, 0, 'Ankle boot')]
```



The KNN model had a resulting accuracy of 0.8541, quite impressive.

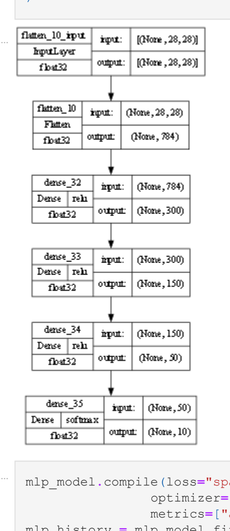
Multilayer Perceptrons

In [151…
```python
# Get a validation dataset from the training dataset
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train
                                                      ,test_size=.2)
```

In [179…
```python
# Using a simple MLP
mlp_model = keras.models.Sequential([
                            keras.layers.Flatten(input_shape=[28, 28]),
                            keras.layers.Dense(400, activation="relu"),
                            keras.layers.Dense(200, activation="relu"),
                            keras.layers.Dropout(0.2),
                            keras.layers.Dense(100, activation="relu"),
                            keras.layers.Dropout(0.2),
                            keras.layers.Dense(10, activation="softmax")
                        ])
```

In [247…
```python
# Get a visual view of the architecture
keras.utils.plot_model(mlp_model, show_shapes=True, show_dtype=True,
                       show_layer_names=True, expand_nested=True,
                        dpi=50, show_layer_activations=True,
)
```

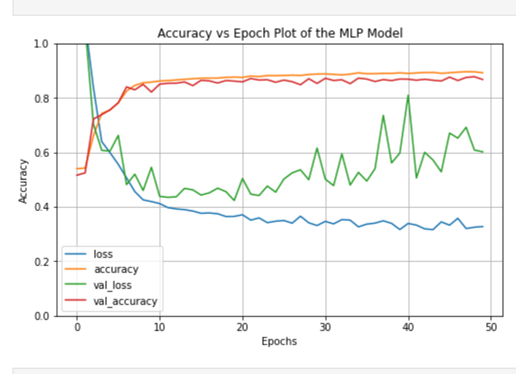
Out[247…



In [181…
```python
mlp_model.compile(loss="sparse_categorical_crossentropy", # Loss function
                  optimizer="adam", # Gradient Descent
                  metrics=["accuracy"])
mlp_history = mlp_model.fit(X_train, y_train,
                            epochs=50,
                            validation_data=(X_valid, y_valid),
                            batch_size = 10)
```

```
Epoch 1/50
4800/4800 [==============================] - 13s 3ms/step - loss: 1.7572 - accuracy:
0.5403 - val_loss: 1.1754 - val_accuracy: 0.5163
Epoch 2/50
4800/4800 [==============================] - 13s 3ms/step - loss: 1.0797 - accuracy:
0.5426 - val_loss: 1.0644 - val_accuracy: 0.5249
Epoch 3/50
4800/4800 [==============================] - 12s 2ms/step - loss: 0.8380 - accuracy:
0.6609 - val_loss: 0.7041 - val_accuracy: 0.7230
Epoch 4/50
4800/4800 [==============================] - 12s 2ms/step - loss: 0.6399 - accuracy:
0.7433 - val_loss: 0.6079 - val_accuracy: 0.7386
Epoch 5/50
4800/4800 [==============================] - 13s 3ms/step - loss: 0.5993 - accuracy:
0.7555 - val_loss: 0.6046 - val_accuracy: 0.7565
Epoch 6/50
4800/4800 [==============================] - 13s 3ms/step - loss: 0.5562 - accuracy:
0.7819 - val_loss: 0.6626 - val_accuracy: 0.7825
Epoch 7/50
4800/4800 [==============================] - 13s 3ms/step - loss: 0.5065 - accuracy:
0.8254 - val_loss: 0.4816 - val_accuracy: 0.8408
Epoch 8/50
4800/4800 [==============================] - 13s 3ms/step - loss: 0.4561 - accuracy:
0.8461 - val_loss: 0.5200 - val_accuracy: 0.8300
Epoch 9/50
4800/4800 [==============================] - 12s 3ms/step - loss: 0.4258 - accuracy:
0.8557 - val_loss: 0.4602 - val_accuracy: 0.8499
Epoch 10/50
4800/4800 [==============================] - 14s 3ms/step - loss: 0.4194 - accuracy:
0.8584 - val_loss: 0.5452 - val_accuracy: 0.8218
Epoch 11/50
4800/4800 [==============================] - 22s 5ms/step - loss: 0.4121 - accuracy:
0.8625 - val_loss: 0.4386 - val_accuracy: 0.8508
Epoch 12/50
4800/4800 [==============================] - 15s 3ms/step - loss: 0.3972 - accuracy:
0.8639 - val_loss: 0.4350 - val_accuracy: 0.8542
Epoch 13/50
4800/4800 [==============================] - 13s 3ms/step - loss: 0.3924 - accuracy:
0.8662 - val_loss: 0.4369 - val_accuracy: 0.8544
Epoch 14/50
4800/4800 [==============================] - 12s 2ms/step - loss: 0.3899 - accuracy:
0.8686 - val_loss: 0.4679 - val_accuracy: 0.8589
Epoch 15/50
4800/4800 [==============================] - 13s 3ms/step - loss: 0.3846 - accuracy:
0.8706 - val_loss: 0.4624 - val_accuracy: 0.8454
Epoch 16/50
4800/4800 [==============================] - 15s 3ms/step - loss: 0.3764 - accuracy:
0.8728 - val_loss: 0.4433 - val_accuracy: 0.8649
Epoch 17/50
4800/4800 [==============================] - 14s 3ms/step - loss: 0.3776 - accuracy:
0.8730 - val_loss: 0.4516 - val_accuracy: 0.8627
Epoch 18/50
4800/4800 [==============================] - 14s 3ms/step - loss: 0.3746 - accuracy:
0.8730 - val_loss: 0.4687 - val_accuracy: 0.8550
Epoch 19/50
4800/4800 [==============================] - 14s 3ms/step - loss: 0.3645 - accuracy:
0.8758 - val_loss: 0.4559 - val_accuracy: 0.8641
Epoch 20/50
4800/4800 [==============================] - 13s 3ms/step - loss: 0.3649 - accuracy:
0.8767 - val_loss: 0.4234 - val_accuracy: 0.8619
Epoch 21/50
4800/4800 [==============================] - 18s 4ms/step - loss: 0.3710 - accuracy:
0.8757 - val_loss: 0.5043 - val_accuracy: 0.8593
Epoch 22/50
4800/4800 [==============================] - 19s 4ms/step - loss: 0.3512 - accuracy:
0.8806 - val_loss: 0.4468 - val_accuracy: 0.8714
Epoch 23/50
4800/4800 [==============================] - 19s 4ms/step - loss: 0.3594 - accuracy:
0.8789 - val_loss: 0.4416 - val_accuracy: 0.8659
Epoch 24/50
4800/4800 [==============================] - 15s 3ms/step - loss: 0.3420 - accuracy:
0.8822 - val_loss: 0.4765 - val_accuracy: 0.8669
Epoch 25/50
4800/4800 [==============================] - 19s 4ms/step - loss: 0.3473 - accuracy:
0.8820 - val_loss: 0.4540 - val_accuracy: 0.8577
Epoch 26/50
4800/4800 [==============================] - 21s 4ms/step - loss: 0.3499 - accuracy:
0.8828 - val_loss: 0.5024 - val_accuracy: 0.8658
Epoch 27/50
4800/4800 [==============================] - 20s 4ms/step - loss: 0.3401 - accuracy:
0.8839 - val_loss: 0.5250 - val_accuracy: 0.8598
Epoch 28/50
4800/4800 [==============================] - 19s 4ms/step - loss: 0.3657 - accuracy:
0.8829 - val_loss: 0.5362 - val_accuracy: 0.8486
Epoch 29/50
4800/4800 [==============================] - 16s 3ms/step - loss: 0.3415 - accuracy:
0.8864 - val_loss: 0.4996 - val_accuracy: 0.8708
Epoch 30/50
4800/4800 [==============================] - 16s 3ms/step - loss: 0.3314 - accuracy:
0.8878 - val_loss: 0.6161 - val_accuracy: 0.8534
Epoch 31/50
4800/4800 [==============================] - 18s 4ms/step - loss: 0.3467 - accuracy:
0.8884 - val_loss: 0.5020 - val_accuracy: 0.8722
Epoch 32/50
4800/4800 [==============================] - 17s 4ms/step - loss: 0.3375 - accuracy:
0.8867 - val_loss: 0.4780 - val_accuracy: 0.8644
Epoch 33/50
4800/4800 [==============================] - 19s 4ms/step - loss: 0.3533 - accuracy:
0.8848 - val_loss: 0.5948 - val_accuracy: 0.8668
Epoch 34/50
4800/4800 [==============================] - 19s 4ms/step - loss: 0.3512 - accuracy:
0.8876 - val_loss: 0.4802 - val_accuracy: 0.8526
Epoch 35/50
4800/4800 [==============================] - 17s 4ms/step - loss: 0.3265 - accuracy:
0.8925 - val_loss: 0.5267 - val_accuracy: 0.8731
Epoch 36/50
4800/4800 [==============================] - 17s 3ms/step - loss: 0.3365 - accuracy:
0.8890 - val_loss: 0.4948 - val_accuracy: 0.8695
Epoch 37/50
4800/4800 [==============================] - 17s 4ms/step - loss: 0.3403 - accuracy:
0.8894 - val_loss: 0.5402 - val_accuracy: 0.8606
Epoch 38/50
4800/4800 [==============================] - 21s 4ms/step - loss: 0.3488 - accuracy:
0.8906 - val_loss: 0.7362 - val_accuracy: 0.8674
Epoch 39/50
4800/4800 [==============================] - 19s 4ms/step - loss: 0.3393 - accuracy:
0.8904 - val_loss: 0.5613 - val_accuracy: 0.8640
Epoch 40/50
4800/4800 [==============================] - 18s 4ms/step - loss: 0.3167 - accuracy:
0.8923 - val_loss: 0.5977 - val_accuracy: 0.8696
Epoch 41/50
4800/4800 [==============================] - 16s 3ms/step - loss: 0.3391 - accuracy:
0.8903 - val_loss: 0.8100 - val_accuracy: 0.8691
Epoch 42/50
4800/4800 [==============================] - 15s 3ms/step - loss: 0.3330 - accuracy:
0.8920 - val_loss: 0.5061 - val_accuracy: 0.8652
Epoch 43/50
4800/4800 [==============================] - 17s 4ms/step - loss: 0.3192 - accuracy:
0.8934 - val_loss: 0.6005 - val_accuracy: 0.8687
Epoch 44/50
4800/4800 [==============================] - 17s 4ms/step - loss: 0.3163 - accuracy:
0.8938 - val_loss: 0.5722 - val_accuracy: 0.8652
Epoch 45/50
4800/4800 [==============================] - 18s 4ms/step - loss: 0.3448 - accuracy:
0.8907 - val_loss: 0.5286 - val_accuracy: 0.8623
Epoch 46/50
4800/4800 [==============================] - 22s 5ms/step - loss: 0.3328 - accuracy:
0.8926 - val_loss: 0.6711 - val_accuracy: 0.8766
Epoch 47/50
4800/4800 [==============================] - 17s 4ms/step - loss: 0.3579 - accuracy:
0.8950 - val_loss: 0.6525 - val_accuracy: 0.8642
Epoch 48/50
4800/4800 [==============================] - 18s 4ms/step - loss: 0.3203 - accuracy:
0.8964 - val_loss: 0.6923 - val_accuracy: 0.8754
Epoch 49/50
4800/4800 [==============================] - 18s 4ms/step - loss: 0.3252 - accuracy:
0.8961 - val_loss: 0.6087 - val_accuracy: 0.8781
Epoch 50/50
4800/4800 [==============================] - 17s 3ms/step - loss: 0.3277 - accuracy:
0.8927 - val_loss: 0.6024 - val_accuracy: 0.8678
```

In [182…
```python
pd.DataFrame(mlp_history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.gca().set_ylim(0, 1)
plt.title('Accuracy vs Epoch Plot of the MLP Model')
plt.show()
```



In [183…
```python
mlp_predicted_classes = np.argmax(mlp_model.predict(X_test), axis=1)
```

```
313/313 [==============================] - 1s 2ms/step
```

Results

In [184…
```python
print("Accuracy ->", accuracy_score(mlp_predicted_classes, y_test))
print(classification_report(mlp_predicted_classes, y_test))
```

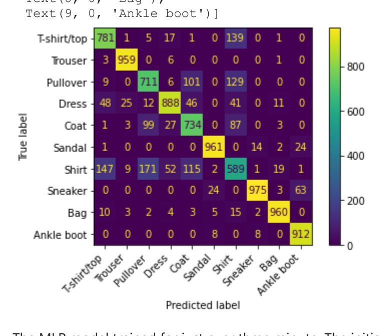
```
Accuracy -> 0.8612
              precision    recall  f1-score   support

           0       0.82      0.81      0.82      1011
           1       0.96      0.99      0.98       967
           2       0.90      0.62      0.73      1451
           3       0.89      0.87      0.88      1017
           4       0.64      0.85      0.73       749
           5       0.95      0.98      0.97       973
           6       0.58      0.71      0.64       826
           7       0.96      0.93      0.95      1038
           8       0.96      0.98      0.97       973
           9       0.95      0.96      0.95       995

    accuracy                           0.86     10000
   macro avg       0.86      0.87      0.86     10000
weighted avg       0.87      0.86      0.86     10000
```

In [178…
```python
cf_matrix = ConfusionMatrixDisplay(confusion_matrix(mlp_predicted_classes,
                                                    y_test,
                                                    labels=np.arange(0,10)),
                                   display_labels=class_names)
cf_matrix.plot()
cf_matrix.ax_.set_xticklabels(cf_matrix.ax_.get_xticklabels(), rotation=45, ha='right
```

Out[178…
```
[Text(0, 0, 'T-shirt/top'),
 Text(1, 0, 'Trouser'),
 Text(2, 0, 'Pullover'),
 Text(3, 0, 'Dress'),
 Text(4, 0, 'Coat'),
 Text(5, 0, 'Sandal'),
 Text(6, 0, 'Shirt'),
 Text(7, 0, 'Sneaker'),
 Text(8, 0, 'Bag'),
 Text(9, 0, 'Ankle boot')]
```



The MLP model trained for just over three minute. The initial results with just two layers was 0.851. After adding another layer along with dropout layers it improved to 0.862 but the training time increased to over 12 minutes. Its resulting accuracy is slightly higher than the KNN model but not significantly.

Based on the confusion matrix we can see that the model struggles to identify Shirts, frequently misclassifying them as T-shirts/tops, Pullovers and Coats. The reverse is also a pattern where these are classified as shirts.

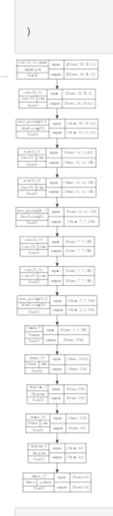
Convolutional Neural Network

In [119…
```python
DefaultConv2D = partial(keras.layers.Conv2D, kernel_size=3, activation='relu', paddin
```

In [120…
```python
cnn_model = keras.models.Sequential([
                    DefaultConv2D(filters=64, kernel_size=6, input_shape=[28, 28, 1]),
                    keras.layers.MaxPooling2D(pool_size=2), # Pool
                    DefaultConv2D(filters=128),
                    DefaultConv2D(filters=128),
                    keras.layers.MaxPooling2D(pool_size=2), # Pool
                    DefaultConv2D(filters=256),
                    DefaultConv2D(filters=256),
                    keras.layers.MaxPooling2D(pool_size=2), # Pool
                    keras.layers.Flatten(),
                    keras.layers.Dense(units=128, activation='relu'),
                    keras.layers.Dropout(0.2),
                    keras.layers.Dense(units=64, activation='relu'),
                    keras.layers.Dropout(0.2),
                    keras.layers.Dense(units=10, activation='softmax'),
                ])
```

In [248…
```python
# Get a visual view of the architecture
keras.utils.plot_model(cnn_model, show_shapes=True, show_dtype=True,
                       show_layer_names=True, expand_nested=True,
                        dpi=20, show_layer_activations=True,
)
```

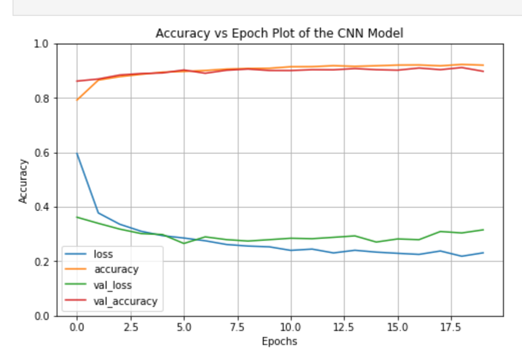
Out[248…



In [123…
```python
cnn_model.compile(loss="sparse_categorical_crossentropy", # Loss function
                  optimizer="adam", # Gradient Descent
                  metrics=["accuracy"])
cnn_model_history = cnn_model.fit(X_train, y_train,
                        epochs=20,
                        validation_data=(X_valid, y_valid))
```

```
Epoch 1/20
1500/1500 [==============================] - 210s 139ms/step - loss: 0.5960 - accurac
y: 0.7924 - val_loss: 0.3620 - val_accuracy: 0.8620
Epoch 2/20
1500/1500 [==============================] - 245s 163ms/step - loss: 0.3777 - accurac
y: 0.8656 - val_loss: 0.3395 - val_accuracy: 0.8697
Epoch 3/20
1500/1500 [==============================] - 284s 189ms/step - loss: 0.3362 - accurac
y: 0.8784 - val_loss: 0.3184 - val_accuracy: 0.8843
Epoch 4/20
1500/1500 [==============================] - 275s 183ms/step - loss: 0.3105 - accurac
y: 0.8868 - val_loss: 0.3019 - val_accuracy: 0.8897
Epoch 5/20
1500/1500 [==============================] - 269s 179ms/step - loss: 0.2943 - accurac
y: 0.8948 - val_loss: 0.2984 - val_accuracy: 0.8921
Epoch 6/20
1500/1500 [==============================] - 266s 177ms/step - loss: 0.2856 - accurac
y: 0.8975 - val_loss: 0.2655 - val_accuracy: 0.9028
Epoch 7/20
1500/1500 [==============================] - 258s 172ms/step - loss: 0.2754 - accurac
y: 0.9010 - val_loss: 0.2897 - val_accuracy: 0.8908
Epoch 8/20
1500/1500 [==============================] - 270s 180ms/step - loss: 0.2617 - accurac
y: 0.9061 - val_loss: 0.2796 - val_accuracy: 0.9020
Epoch 9/20
1500/1500 [==============================] - 266s 177ms/step - loss: 0.2560 - accurac
y: 0.9084 - val_loss: 0.2744 - val_accuracy: 0.9062
Epoch 10/20
1500/1500 [==============================] - 297s 198ms/step - loss: 0.2532 - accurac
y: 0.9091 - val_loss: 0.2794 - val_accuracy: 0.9011
Epoch 11/20
1500/1500 [==============================] - 278s 185ms/step - loss: 0.2401 - accurac
y: 0.9147 - val_loss: 0.2847 - val_accuracy: 0.9008
Epoch 12/20
1500/1500 [==============================] - 286s 190ms/step - loss: 0.2448 - accurac
y: 0.9151 - val_loss: 0.2830 - val_accuracy: 0.9039
Epoch 13/20
1500/1500 [==============================] - 271s 181ms/step - loss: 0.2308 - accurac
y: 0.9186 - val_loss: 0.2881 - val_accuracy: 0.9035
Epoch 14/20
1500/1500 [==============================] - 249s 166ms/step - loss: 0.2405 - accurac
y: 0.9163 - val_loss: 0.2934 - val_accuracy: 0.9081
Epoch 15/20
1500/1500 [==============================] - 248s 166ms/step - loss: 0.2337 - accurac
y: 0.9184 - val_loss: 0.2707 - val_accuracy: 0.9039
Epoch 16/20
1500/1500 [==============================] - 241s 160ms/step - loss: 0.2293 - accurac
y: 0.9209 - val_loss: 0.2821 - val_accuracy: 0.9022
Epoch 17/20
1500/1500 [==============================] - 248s 166ms/step - loss: 0.2253 - accurac
y: 0.9214 - val_loss: 0.2794 - val_accuracy: 0.9101
Epoch 18/20
1500/1500 [==============================] - 238s 159ms/step - loss: 0.2379 - accurac
y: 0.9181 - val_loss: 0.3095 - val_accuracy: 0.9040
Epoch 19/20
1500/1500 [==============================] - 238s 159ms/step - loss: 0.2186 - accurac
y: 0.9232 - val_loss: 0.3042 - val_accuracy: 0.9118
Epoch 20/20
1500/1500 [==============================] - 246s 164ms/step - loss: 0.2311 - accurac
y: 0.9206 - val_loss: 0.3155 - val_accuracy: 0.8980
```

In [125…
```python
pd.DataFrame(cnn_model_history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.gca().set_ylim(0, 1)
plt.title('Accuracy vs Epoch Plot of the CNN Model')
plt.show()
```



In [126…
```python
cnn_model_classes = np.argmax(cnn_model.predict(X_test), axis=1)
```

```
313/313 [==============================] - 24s 75ms/step
```

Results

In [127…
```python
print("Accuracy ->", accuracy_score(cnn_model_classes, y_test))
print(classification_report(cnn_model_classes, y_test))
```

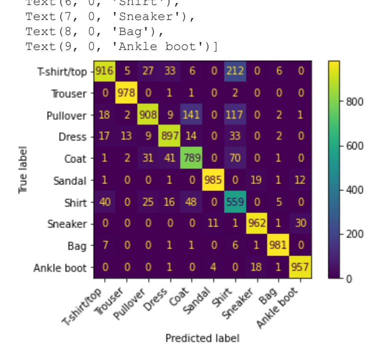
```
Accuracy -> 0.8932
              precision    recall  f1-score   support

           0       0.92      0.76      0.83      1205
           1       0.98      1.00      0.99       982
           2       0.91      0.76      0.83      1198
           3       0.90      0.91      0.90       985
           4       0.79      0.84      0.82       935
           5       0.98      0.97      0.98      1019
           6       0.56      0.81      0.66       693
           7       0.96      0.96      0.96      1005
           8       0.98      0.98      0.98       997
           9       0.96      0.98      0.97       981

    accuracy                           0.89     10000
   macro avg       0.89      0.90      0.89     10000
weighted avg       0.90      0.89      0.90     10000
```

In [128…
```python
cf_matrix = ConfusionMatrixDisplay(confusion_matrix(cnn_model_classes,
                                                    y_test,
                                                    labels=np.arange(0,10)),
                                   display_labels=class_names)
cf_matrix.plot()
cf_matrix.ax_.set_xticklabels(cf_matrix.ax_.get_xticklabels(), rotation=45, ha='right
```

Out[128…
```
[Text(0, 0, 'T-shirt/top'),
 Text(1, 0, 'Trouser'),
 Text(2, 0, 'Pullover'),
 Text(3, 0, 'Dress'),
 Text(4, 0, 'Coat'),
 Text(5, 0, 'Sandal'),
 Text(6, 0, 'Shirt'),
 Text(7, 0, 'Sneaker'),
 Text(8, 0, 'Bag'),
 Text(9, 0, 'Ankle boot')]
```



Results and Conclusion

The CNN model performs a lot better, with an accuracy of 0.893. It took a lot longer to train (around 40 minutes) but the inference time wasn't significantly longer and the accuracy, precision and recall scores are a lot better.

Based on the confusion matrix we can see that the model continues to struggles for Shirts, T-shirts/tops, Pullovers and Coats. This is somewhat easy to understand because of the similarity between these products. The KDE plot during the EDA has similar, larger intensity values for these categories that occupy a similar range of intensity and overall shape.

If the images were actually in the RGB scale, we know the KNN model would not be able to preform as well while the convolution model would have a better score. Future projects based off of this could be to replicate similar findings for a different dataset or focus on a better classifier using CNNs.

References

Fashion MINST https://github.com/zalandoresearch/fashion-mnist

ML Book https://github.com/rasbt/machine-learning-book