

Neural Networks for Classifying Fashion MNIST

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Abstract

The application of neural networks and convolutional neural network is applied to build a classifier for a data set called Fashion-MNIST, native from the TensorFlow Library.

1 Introduction and Overview

Similar to the the popular MNIST data set, which consisted of hand-written datasets, the Fashion-MNIST dataset contains images of 10 different classes of fashion items. The dataset, consisting of several thousand images are split into training and testing data sets where each set contains a list of images and their associated labels. The labels are as follows:

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

2 Theoretical Background

2.1 Neural Network

A neural network, also called an artificial neural network, is based on a collection of nodes called artificial neurons which are loosely modeled after a biological brain. A neural network is a combination of many layers where a linear combination is performed between the previous layer's output and the current layer's weight before passing the data to the next layer through an activation function.

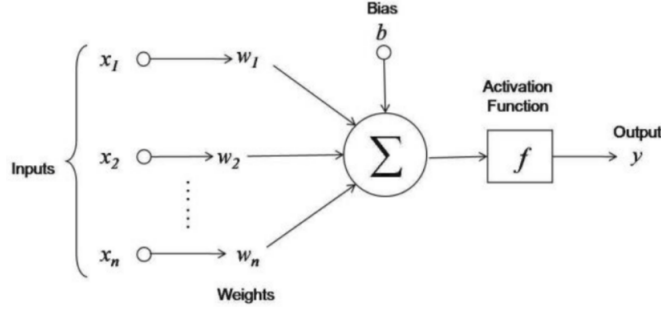


Figure 1: Test 1/3: Layer of a Neural Network

2.2 Convolutional Neural Networks

A Convolutional Neural Network(CNN) is a type of neural network that is mainly used to analyze visual imagery. One of the defining aspects of it is that it has one or more layers of convolution units. The layers of a CNN consists of an input layer, an output layer, and a hidden layer that includes multiple convolution layers, pooling layers, fully connected layers and normalization layers.

3 Algorithm Implementation and Development

The data set consisting of 10 different classes of fashion items are loaded from TensorFlow.

1. The dataset is then split into training and test data.
2. The training data is then split into training and validation data and also normalized and converted to float from uint8.
3. A model is constructed with varying number of layers and density. The best result is selected through trial and error.
4. The model is fitted to the training data and accuracy of the training and validation data is determined. If the training data is higher than the validation data, the model is adjusted.
5. The accuracy and loss is plotted and a confusion matrix is displayed.
6. This process is repeated with a convolutional neural network with the addition of a convolutional layer where the hyper-parameters are adjusted based on trial and error.

4 Computational Results

4.1 Fully Connected Neural Network

The Fully Connected Neural Network ran over 40 epochs, with the best validation accuracy at 86.36% and training accuracy at 86.31% at the 27th epoch. At a greater epoch, there are signs of over fitting as the training accuracy is larger than the validation accuracy. A training accuracy greater than 90% was possible but there would be severe over fitting issues.

The Fully Connected Neural Network had the most trouble identifying Shirt(0) and T-Shirts(6) in both the prediction and test data as seen in figure 4 and 5.

4.2 Convolutional Neural Network

The CNN ran for 10 epochs due to time and memory constraints as many convolution layers were defined. The model best performed at its 7th epoch where the validation accuracy was at 90.02 % and the training accuracy was at 90.47%. Any greater epochs showed signs of overfitting.

Similarly, the CNN had the most trouble identifying Shirt(0) and T-Shirts(6) in both the prediction and test data as seen in figure 6 and 7.

Accuracy and Loss of Fully Connected NN

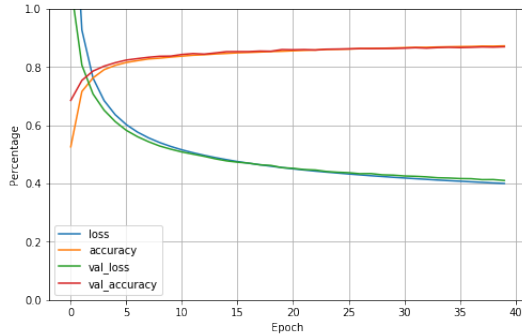


Figure 2: Fully Connected Neural Network

Accuracy and Loss of Convoluted NN

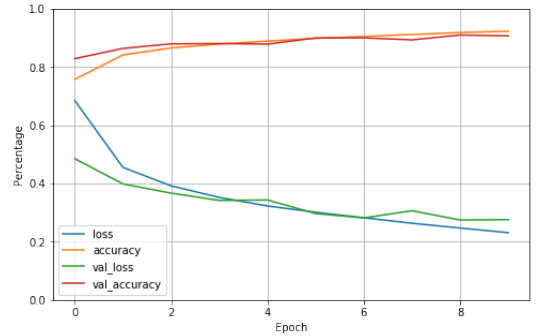


Figure 3: Convolutional Neural Network

```

[[4663 27 76 215 14 7 492 0 49 0]
 [ 14 5270 25 111 8 1 13 0 2 0]
 [ 56 13 4400 47 582 0 372 0 26 0]
 [ 172 62 53 4863 208 0 122 0 18 1]
 [ 11 4 514 150 4414 0 399 0 19 1]
 [ 4 0 0 3 0 5207 1 197 18 77]
 [ 743 15 560 142 415 0 3574 1 57 0]
 [ 0 0 0 0 0 149 0 5146 9 184]
 [ 28 3 30 30 20 16 69 21 5292 1]
 [ 2 1 1 1 0 54 1 192 2 5240]]

```

Figure 4: Confusion Matrix for Fully Connected NN (Training)

```

[[811 3 12 46 5 1 109 0 13 0]
 [ 4 957 6 24 5 0 3 0 1 0]
 [ 17 3 774 10 124 1 68 0 3 0]
 [ 30 13 12 867 35 1 39 0 3 0]
 [ 0 1 118 35 767 0 72 0 7 0]
 [ 0 0 0 1 0 932 0 45 2 20]
 [139 2 117 38 85 0 603 0 16 0]
 [ 0 0 0 0 0 27 0 936 0 37]
 [ 4 1 6 7 3 3 15 6 955 0]
 [ 0 0 0 0 0 7 1 42 0 950]]

```

Figure 5: Confusion Matrix for Fully Connected NN (Test)

```

[[5027 0 42 58 12 2 391 0 11 0]
 [ 3 5343 6 75 4 0 11 0 2 0]
 [ 54 0 4789 22 378 0 243 0 10 0]
 [ 123 0 29 5017 201 0 128 0 1 0]
 [ 12 2 166 98 5024 0 206 0 4 0]
 [ 0 0 0 0 0 5433 0 56 0 18]
 [ 475 1 253 58 294 1 4412 0 13 0]
 [ 0 0 0 0 0 39 0 5314 0 135]
 [ 9 0 11 3 14 11 12 0 5450 0]
 [ 0 0 0 0 0 8 0 105 1 5380]]

```

Figure 6: Confusion Matrix for CNN (Training)

```

[[848 0 12 15 4 1 111 0 9 0]
 [ 0 909 2 22 1 0 5 0 1 0]
 [ 14 0 820 7 88 0 68 0 3 0]
 [ 26 2 12 878 42 0 36 0 4 0]
 [ 1 0 48 21 876 0 54 0 0 0]
 [ 0 0 0 0 0 977 0 12 0 11]
 [129 0 55 19 83 0 706 0 8 0]
 [ 0 0 0 0 0 11 0 965 0 24]
 [ 0 0 4 2 4 7 2 2 978 1]
 [ 1 0 0 0 0 3 0 22 0 974]]

```

Figure 7: Confusion Matrix for CNN (Test)

5 Summary & Conclusion

A fully connected neural network and a convolutional neural network was built to classify categories from the Fashion-MNIST dataset. The CNN performed slightly better compared to the fully connected neural network but in time performance, the fully connected neural network performed better. Both networks had issues in identifying a shirt or a t-shirt, possibly due to similarities.

6 Appendix A.

- `tf.keras.datasets` = a public API for datasets
- `functool.partial` = returns a new partial object when called and behaves like a func with arguments
- `tf.keras.layers.Sequential` = a linear stack of layers
- `tf.keras.layers.Dense` = a regular densely connected NN layer
- `tf.keras.layers.Conv2D` = a 2D convolution layer

7 Appendix B.

```
#!/usr/bin/env python
# coding: utf-8
```

```
# In [1]:
```

```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.metrics import confusion_matrix
```

```
# In [2]:
```

```
fashion_mnist = tf.keras.datasets.fashion_mnist
(X_train_full, y_train_full), (X_test, y_test) = fashion_mnist.load_data
```

```
# In [3]:
```

```
plt.figure()
for k in range(10):
    plt.subplot(3,4,k+1)
    plt.imshow(X_train_full[k], cmap="gray")
    plt.axis('off')
plt.show()
```

```
# In [4]:
```

```
X_valid = X_train_full[:5000] / 255.0
X_train = X_train_full[5000:] / 255.0
X_test = X_test / 255.0
```

```
y_valid = y_train_full[:5000]
y_train = y_train_full[5000:]
```

```
# In [5]:
```

```
from functools import partial
```

```
my_dense_layer = partial(tf.keras.layers.Dense, activation="relu", ker
```

```
model = tf.keras.models.Sequential([
    tf.keras.layers.Flatten(input_shape=[28, 28]),
```

```
    my_dense_layer(128),
    #my_dense_layer(64),
    my_dense_layer(32),
    #my_dense_layer(128),
```

```
    #my_dense_layer(400),
    # my_dense_layer(100),
    # my_dense_layer(100),
```

```
    #my_dense_layer(600),
    #my_dense_layer(400),
    #my_dense_layer(200),
    my_dense_layer(10, activation="softmax")
```

```
])
```

```
# In [6]:
```

```
model.compile(loss="sparse_categorical_crossentropy",
              optimizer=tf.keras.optimizers.Adam(learning_rate=0.00001),
              metrics=["accuracy"])
```

```
# validation below training -> not overfitting. validation go down wh
```

```
# In [7]:
```

```
history = model.fit(X_train, y_train, epochs=40, validation_data=(X_va
```

```
# In [8]:
```

```
pd.DataFrame(history.history).plot(figsize=(8,5))  
plt.grid(True)  
plt.gca().set_ylim(0,1)  
plt.ylabel("Percentage")  
plt.xlabel("Epoch")  
plt.show()
```

```
# In [9]:
```

```
model.evaluate(X_test, y_test)
```

```
# In [10]:
```

```
y_pred = model.predict_classes(X_train)  
conf_train = confusion_matrix(y_train, y_pred)  
print(conf_train)
```

```
# In [11]:
```

```
y_pred = model.predict_classes(X_test)  
conf_test = confusion_matrix(y_test, y_pred)  
print(conf_test)
```

```
# CNN
```



```
# In [12]:
```

```
fashion_mnist = tf.keras.datasets.fashion_mnist
(X_train_full, y_train_full), (X_test, y_test) = fashion_mnist.load_data()
X_valid = X_train_full[:5000] / 255.0
X_train = X_train_full[5000:] / 255.0
X_test = X_test / 255.0

y_valid = y_train_full[:5000]
y_train = y_train_full[5000:]
```

```
# In [29]:
```

```
plt.figure()
for k in range(10):
    plt.subplot(3,4,k+1)
    plt.imshow(X_train_full[k], cmap="gray")
    plt.axis('off')
    plt.title(y_train_full[k])
plt.show()
```

```
# In [13]:
```

```
X_train = X_train[..., np.newaxis]
X_valid = X_valid[..., np.newaxis]
X_test = X_test[..., np.newaxis]
```

```
# In [14]:
```

```
my_dense_layer = partial(tf.keras.layers.Dense, activation="relu", kernel_initializer="he_normal")
my_conv_layer = partial(tf.keras.layers.Conv2D, activation="relu", padding="same", kernel_initializer="he_normal")

model = tf.keras.models.Sequential([
    my_conv_layer(6, 5, padding="same", input_shape=[28, 28, 1]),
```

```

        tf.keras.layers.AveragePooling2D(2),
# my_conv_layer(8,5),
#tf.keras.layers.AveragePooling2D(2),
        my_conv_layer(32,3),
        my_conv_layer(64,3),
        my_conv_layer(128,3),
        my_conv_layer(256,3),
        my_conv_layer(512,3),
        tf.keras.layers.Flatten(),
        my_dense_layer(256),
#my_dense_layer(32),
#my_dense_layer(8),
        my_dense_layer(10, activation="softmax")
])

```

In [15]:

```

model.compile(loss="sparse_categorical_crossentropy",
              optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001),
              metrics=["accuracy"])

```

In [16]:

```

history = model.fit(X_train, y_train, epochs=10, validation_data=(X_val, y_val))

```

In [17]:

```

pd.DataFrame(history.history).plot(figsize=(8,5))
plt.grid(True)
plt.gca().set_ylim(0,1)
plt.ylabel("Percentage")
plt.xlabel("Epoch")
plt.show()

```

```
# In [18]:
```

```
y_pred = model.predict_classes(X_train)
conf_train = confusion_matrix(y_train , y_pred)
print(conf_train)
```

```
# In [19]:
```

```
model.evaluate(X_test , y_test)
```

```
# In [20]:
```

```
y_pred = model.predict_classes(X_test)
conf_test = confusion_matrix(y_test , y_pred)
print(conf_test)
```

```
# In [ ]:
```