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MNIST Handwritten Digit Classification

Summary Abstract: This past winter break, I decided to explore machine learning (ML). After completing a ML w/ Python bootcamp from Udemy, I was prepared to undertake my first technical project with Tensorflow: Implementing an artificial neural network to classify handwritten digits from the MNIST data set. This is common for beginners to ML. **A final accuracy of 96% was reported**.

Background: In a nutshell, artificial neural networks (ANNs) are a collection of interconnected perceptrons, (mathematical representations of biological neurons). These perceptrons take in inputs, multiply them by weights and add them to biases. An activation function takes in that product and sets boundaries on the output of that perceptron. Which then becomes the input for the next perceptron(s).

The output of the ANN is then evaluated with a loss function, which compares the model's predictions to the correct labels of the training data. The more incorrect predictions, the higher the loss. The goal is to minimize loss, so an ANN "learns" by going back and adjusting the weights and biases in the ANN. The model would then traverse the training data, make new predictions & be reevaluated. This is back propagation. The mathematics involved in minimizing loss is known as gradient descent.

Implementation & Thought Process:

```python
import numpy as np # for data manipulation
import pandas as pd # for data manipulation

import matplotlib.pyplot as plt # for data visualization
%matplotlib inline # Allows us to print in Jupyter.

import tensorflow as tf # machine learning library.
```

Tensorflow (& the accompanying Keras API) greatly abstract the process behind implementing an ANN in python.

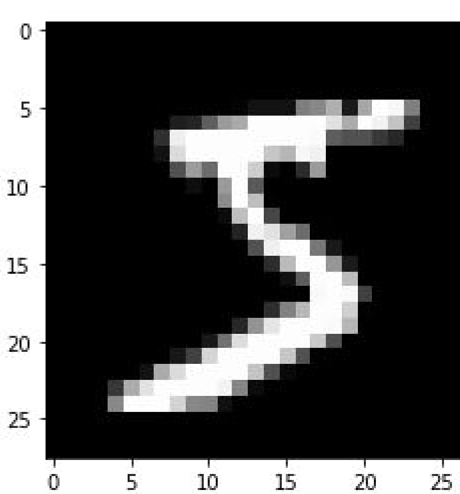
```python
MNIST = tf.keras.datasets.mnist # import our data

(X_train, y_train), (x_test, y_test) = MNIST.load_data()
''' We split our data into a training set to fit the model
onto, and a testing set to evaluate the model with. '''
```

X is the image.
Y is the number represented.

```python
plt.imshow(X_train[0],cmap='gist_gray')
```

```
<matplotlib.image.AxesImage at 0x15ff8e1f0>
```



The MNIST data set is a collection of 28x28 pixel images of handwritten digits ranging from 0 to 9. Each image is represented by a large array of numbers. Each value in said array represents how luminous an individual pixel is, values range from (0-255).

Here is the 1st image in the training set visualized using matplotlib.

```
''' Normalizing our data: pixel values in each array
will now range from 0-1. This is a common practice.'''
X_train = tf.keras.utils.normalize(X_train, axis=1)
x_test = tf.keras.utils.normalize(x_test, axis=1)
```

```
#Defining our model using Tensorflow / Keras:

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten

model = Sequential() # defining model object as a sequence of layers.

#input layer of ANN:
model.add(Flatten()) ''' The "Flatten" layer converts the 2D
array of pixel values (the "image") into a one dimensional series.'''

# hidden layers of ANN:
'''hidden layers: "Dense" meaning each neuron in one layer is
connected to every neuron in the next layer.
A recitified linear unit is a common activation function '''

model.add(Dense(64, activation='relu')) # 64 neurons
model.add(Dense(32, activation='relu')) # 32 neurons

#output layer of ANN:
''' We are preforming multi class classfication, therefore we
need an output neuron for each number an image could represent, 10.

Each class is mutually exclusive, therefore we use softmax as our
activation function. Each output neuron will represent the
probability that an image was the number ranging from 0-9. '''

model.add(Dense(10, activation='softmax')) # 10 neurons

'''We will optimize gradient descent with the adam optimizer.
Cross entropy is a common loss function for classfication.
We will keep track of the accuracy metric whilst parsing data'''

model.compile(optimizer='adam',loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

```
model.fit(X_train, y_train, epochs = 3)
```

```
Epoch 1/3
1875/1875 [==============================]
Epoch 2/3
1875/1875 [==============================]
Epoch 3/3
```

Here we "fit" the training data onto the model, parsing through the data 3 times / epochs. We then pass in unlabeled data test data. The model's predictions are based on the output neuron with the highest probability calculated.

```
predictions = np.argmax(model.predict(x_test), axis=-1)
```

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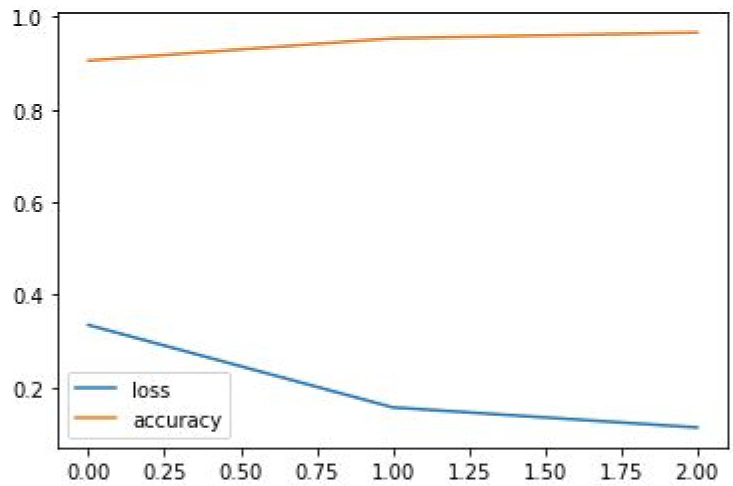
Results:

```
losses = pd.DataFrame(model.history.history)
losses.plot()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1
```



We can see that loss decreases and accuracy increases as the model "learns" via backpropagation.

One could definitely tinker with an ANN's architecture much further.

We want to make sure the model can actually recognize patterns in data, and not just memorize this specific training set. Parsing through the training data for a greater number of epochs increases this risk. This is known as overfitting. One could combat this by adding a dropout layer in our ANN architecture, which deactivates neurons as loss increases.

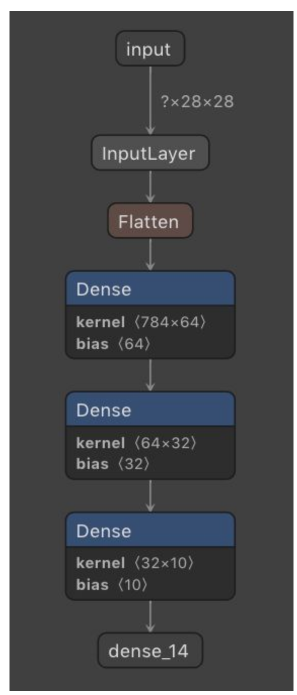
```
from sklearn.metrics import classification_report
print(classification_report(y_test,predictions))
```

```
              precision    recall  f1-score   support

           0       0.97      0.98      0.98       980
           1       0.98      0.98      0.98      1135
           2       0.96      0.97      0.96      1032
           3       0.95      0.96      0.95      1010
           4       0.96      0.96      0.96       982
           5       0.96      0.96      0.96       892
           6       0.96      0.97      0.97       958
           7       0.97      0.97      0.97      1028
           8       0.94      0.95      0.95       974
           9       0.98      0.92      0.95      1009

    accuracy                           0.96     10000
   macro avg       0.96      0.96      0.96     10000
weighted avg       0.96      0.96      0.96     10000
```

Although there are multiple metrics to gauge an ANN's performance at classification, accuracy is the most relevant to us in this context. (Percentage of correct predictions)

Visualization and Summary:

I used *Netron*, an open source neural network visualization tool to describe our ANN's architecture.



I definitely enjoyed this project. The field of AI is multifaceted but I'm ready to keep exploring!! I would love to hone in on the subfield of deep learning next!!