Introduction

Welcome to : Image Classification!

The aim of this project is to create, train and evaluate a neural network in TensorFlow, understand the basics of neural networks and solve classification problems with neural networks.

In [1]:

```
import tensorflow as tf

print("Using TensorFlow version", tf.__version__)
```

```
/srv/conda/envs/notebook/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:526: FutureWarning: Passing (typ
e, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) /
'(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/srv/conda/envs/notebook/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:527: FutureWarning: Passing (typ
e, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) /
'(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/srv/conda/envs/notebook/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:528: FutureWarning: Passing (typ
e, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) /
'(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/srv/conda/envs/notebook/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:529: FutureWarning: Passing (typ
e, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) /
'(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/srv/conda/envs/notebook/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:530: FutureWarning: Passing (typ
e, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) /
'(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
/srv/conda/envs/notebook/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:535: FutureWarning: Passing (typ
e, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) /
'(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])

Using TensorFlow version 1.13.1
```

The Dataset

In order to understand the problem better, we will first import the data that we'd be working with and take a closer look at it. We are going to use the popular MNIST dataset which has lots of images of hand-written digits along with their labels.

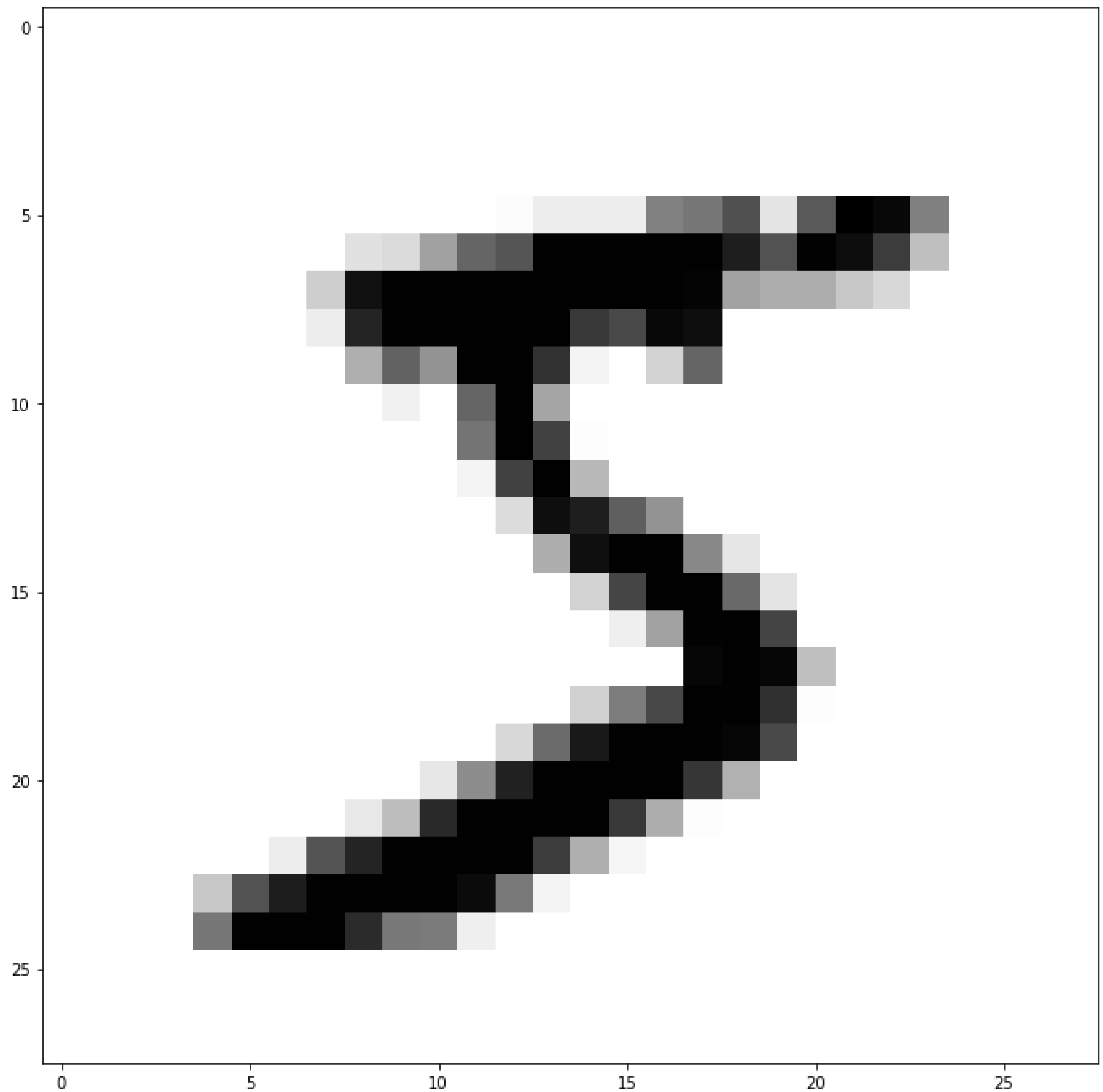
In [2]:
```
from tensorflow.keras.datasets import mnist

(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

In [3]:
```
print("x_train shape: ", x_train.shape)
print("y_train shape: ", y_train.shape)
print("x_test shape: ", x_test.shape)
print("y_test shape: ", y_test.shape)
```

```
x_train shape:  (60000, 28, 28)
y_train shape:  (60000,)
x_test shape:  (10000, 28, 28)
y_test shape:  (10000,)
```

In [4]:
```
import matplotlib.pyplot as plt
%matplotlib inline
plt.figure(figsize = (12, 12))
plt.imshow(x_train[0], cmap = "binary")
plt.show()
```



In [5]:
```
y_train[0]
```

Out[5]: 5

In [6]:
```
y_train[:10]
```

Out[6]: array([5, 0, 4, 1, 9, 2, 1, 3, 1, 4], dtype=uint8)

One Hot Encoding

Change the way this label is represented from a class name or number to a list of all possible classes with all the classes set to 0 except the one which this example belongs to - which will be set to 1. For example:

original label	one-hot encoded label
5	[0, 0, 0, 0, 0, 1, 0, 0, 0, 0]
7	[0, 0, 0, 0, 0, 0, 0, 1, 0, 0]
1	[0, 1, 0, 0, 0, 0, 0, 0, 0, 0]

In [7]:
```
from tensorflow.python.keras.utils import to_categorical

y_train_encoded = to_categorical(y_train)
y_test_encoded = to_categorical(y_test)
```

To make sure the encoding worked, let's check the shape of the encoded labels.

In [8]:
```
print("y_train shape: ", y_train_encoded.shape)
print("y_test shape: ", y_test_encoded.shape)
```

```
y_train shape:  (60000, 10)
y_test shape:  (10000, 10)
```

Let's also take a look at the first label and make sure that encoding is correct:

In [9]:
```
y_train_encoded[0]
```

Out[9]: array([0., 0., 0., 0., 0., 1., 0., 0., 0., 0.], dtype=float32)

Neural Networks

$$y = w1 * x1 + w2 * x2 + w3 * x3 + b$$

Where the `w1, w2, w3` are called the weights and `b` is an intercept term called bias. The graph above, therefore, is simply a graphical representation of a simple linear equation. The equation can also be *vectorised* like this:

$$y = W.X + b$$

Where `X = [x1, x2, x3]` and `W = [w1, w2, w3].T`. The .T means *transpose*. This is because we want the dot product to give us the result we want i.e. `w1 * x1 + w2 * x2 + w3 * x3`. This gives us the vectorised version of our linear equation.

By taking the observed data and a proposed model, we want to write an algorithm to learn the values for W and b which best fit the data and ultimately, by doing that, we learn an approximate function which maps the inputs to outputs of our data. This type of algorithm is called an *optimization* algorithm and there are a few different optimization algorithms that are typically used in training neural networks.

In the problem, the examples are of shape`(60000, 28, 28)`. The first dimension is simply the number of examples we have, so each example is of the shape `(28, 28)`. If we unroll this array into a single dimension, it will become a `28 * 28 = 784` dimensional vector. Given features from `x1` to `x784`, we get an output y. Here, each pixel value is a feature in our examples.

We can learn much more complex functions by simply *cascading* the linear functions one after the other. The only additional thing that a node in a neural network does (as opposed to a node in a linear equation shown above) is that an activation function is applied to each linear output. The purpose of an activation functions is to help the neural network find non-linear patterns in the data because if we just cascaded the neurons or nodes like the ones described above, even with many layers of cascaded linear functions, the result will still be a linear function which means that, after training the mode, it will learn a linear function that best fit the data. This is a problem because in many, if not most cases, the input to output map is going to be much more complex than a linear function. So, the activation gives the model more flexibility, and allows the model to be able to learn non-linear patterns.

Now, instead of setting y to a weighted sum of our input features, we can get a few hidden outputs which are weighted sums of our input features passed through an activation function and then get the weighted sums of those hidden outputs and so on. We do this a few times, and then get to our output y. This type of model gives our algorithm a much greater chance of learning a complex function.

In our neural network, we have two *hidden layers*. The first layer with all the X features is called the input layer and the output y is called the output layer. In this example, the output has only one **node**. The hidden layer can have a lot of nodes or a very few nodes depending on how complex the problem may be. Here, both the hidden layer have 2 nodes each. Each node gives the output of a linear function after the linear output passes through an activation function, and takes inputs from each node of the preceding layer. All the W's and all the b's associated with all of these functions will have to be "learned" by the algorithm as it attempts to optimize those values in order to best fit the given data. The total number of learnable parameters in any layer depend on the number of nodes in that layer as well as on the number of nodes in the preceding layer. For example, learnable parameters for **hidden layer 1** can be calculated as: (number of nodes of the layer) *(number of nodes of preceding layer) + (number of nodes of the layer). Also, the **bias** from previous layer would be connected to each node in the layer as well - that gives us the second term. So, for **hidden layer 1**, we get:* `2 2 + 2 = 6` learnable parameters.

In the hand-written digit classification problem, we will have 128 nodes for two hidden layers, we will have 10 nodes for the output layer with each node corresponding to one output class, and of course we already know that the input is a 784 dimensional vector.

Preprocessing the Examples

We will create a Neural Network which will take 784 dimensional vectors as inputs (28 rows * 28 columns) and will output a 10 dimensional vector (For the 10 classes). We have already converted the outputs to 10 dimensional, one-hot encoded vectors. We will use numpy to easily unroll the examples from `(28, 28)` arrays to `(784, 1)` vectors.

In [10]:
```
import numpy as np

x_train_reshaped = np.reshape(x_train, (60000, 784))
x_test_reshaped = np.reshape(x_test, (10000, 784))

print("x_train_reshaped shape: ", x_train_reshaped.shape)
print("x_test_reshaped shape: ", x_test_reshaped.shape)
```

```
x_train_reshaped shape:  (60000, 784)
x_test_reshaped shape:  (10000, 784)
```

Each element in each example is a pixel value.

In [11]:
```
print(set(x_train_reshaped[0]))
```

```
{0, 1, 2, 3, 9, 11, 14, 16, 18, 23, 24, 25, 26, 27, 30, 35, 36, 39, 43, 45, 46, 49, 55, 56, 64, 66, 70, 78, 80, 81, 82, 90,
93, 94, 107, 108, 114, 119, 126, 127, 130, 132, 133, 135, 136, 139, 148, 150, 154, 156, 160, 166, 170, 171, 172, 175, 182,
183, 186, 187, 190, 195, 198, 201, 205, 207, 212, 213, 219, 221, 225, 226, 229, 238, 240, 241, 242, 244, 247, 249, 250, 25
1, 252, 253, 255}
```

Pixel values, in this dataset, range from 0 to 255. That's fine if we want to display our images, but for the neural network to learn the weights and biases for different layers, computations will be simply much more effective and fast if we *normalized* these values. In order to normalize the data, we can calculate the mean and standard deviation for each example.

In [12]:
```
x_mean = np.mean(x_train_reshaped)
x_std = np.std(x_train_reshaped)

print("mean: ", x_mean)
print("std: ", x_std)
```

```
mean:  33.318421449829934
std:  78.56748998339798
```

Now we will normalise both the training and test set using the mean and standard deviation.

In [13]:
```
epsilon = 1e-10
x_train_norm = (x_train_reshaped - x_mean)/(x_std + epsilon)
x_test_norm = (x_test_reshaped - x_mean)/(x_std + epsilon)
```

In [14]:
```
print(set(x_train_norm[0]))
```

```
{-0.38589016215482896, 1.306921966983251, 1.17964285952926, 1.803310486053816, 1.6887592893452241, 2.8215433456857437, 2.71
9720059722551, 1.1923707702746593, 1.7396709323268205, 2.057868700961798, 2.3633385588513764, 2.096052433197995, 1.76512675
38176187, 2.7960875241949457, 2.7451758812133495, 2.45243393406917, 0.02140298169794222, -0.22042732246464067, 1.2305545025
108566, 0.2759611966059242, 2.210603629906587, 2.6560805059955555, 2.6051688630139593, -0.4240738943910262, 0.4668798577869
107, 0.1486820891519332, 0.3905123933145161, 1.0905474843114664, -0.09314821501064967, 1.4851127174188385, 2.75790379195874
86, 1.5360243604004349, 0.07231462467953861, -0.13133194724684696, 1.294194056237852, 0.03413089244334132, 1.34510569921944
83, 2.274243183633583, -0.24588314395543887, 0.772349715676489, 0.75962180493109, 0.7214380726948927, 0.1995937321335296, -
0.41134598364562713, 0.5687031437501034, 0.5941589652409017, 0.9378125553666773, 0.9505404661120763, 0.6068868759863008, 0.
4159682148053143, -0.042236572029053274, 2.7706317027041476, 2.1342361654341926, 0.12322626766113501, -0.08042030426525057,
0.16140999989733232, 1.8924058612716097, 1.2560103240016547, 2.185147808415789, 0.6196147867316999, 1.943317504253206, -0.1
1860403650144787, -0.30952269768243434, 1.9942291472348024, -0.2840668761916362, 2.6306246845047574, 2.286971094378982, -0.
19497150097384247, -0.39861807290022805, 0.2886891073513233, 1.7523988430722195, 2.3887943803421745, 2.681536327486354, 1.4
596568959280403, 2.439706023323771, 2.7833596134495466, 2.490617666305367, -0.10587612575604877, 1.5614801818912332, 1.9051
337720170087, 1.6123918248728295, 1.268738234747054, 1.9560454149986053, 2.6433525952501564, 1.026907930584471}
```

Creating a Model

We use a Sequential class defined in Keras to create our model. All the layers are going to be Dense layers. This means, like our examples above, all the nodes of a layer would be connected to all the nodes of the preceding layer i.e. densely connected.

In [15]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

model = Sequential([
    Dense(128, activation = "relu", input_shape = (784,)),
    Dense(128, activation = "relu"),
    Dense(10, activation = "softmax")
])
```

```
WARNING:tensorflow:From /srv/conda/envs/notebook/lib/python3.7/site-packages/tensorflow/python/ops/resource_variable_ops.p
y:435: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.
Instructions for updating:
Colocations handled automatically by placer.
```

We are instantiating a Sequential model. We pass on a list of layers that we want in our model, in the order that we want them. So, we have two hidden layers with 128 nodes each and one output layer with 10 nodes. We set the input shape on the first hidden layer to correspond to the shape of a single example from our reshaped training and test sets - we know each example is a 784 dimensional vector for the 784 pixels of the images.

First step is the weighted sum, Z:

$$Z = W.X + b$$

The second step in the node is the activation function output, A:

$$A = f(Z)$$

There are various types of activation functions used in Neural Networks. One of the more common ones is a rectified linear unit of ReLU function. It's a linear function for all the positive values and is simply set to `0` for all the negative values. Something like this:

Another activation function we are using is called *softmax*. This function gives us probability scores for various nodes, in this case 10 nodes of the output layer, which sum upto 1. This activation gives us the probabilities for various classes given the input. The class with the highest probability gives us our prediction.

In addition to setting up our model architecture, we also need to define which algorithm should the model use in order to optimize the weights and biases as per the given data. We will use stochastic gradient descent.

We also need to define a loss function. Loss function is difference between the predicted outputs and the actual outputs given in the dataset. This loss needs to be minimised in order to have a higher model accuracy. That's what the optimasation algorithm essentially does - it minimises the loss during model training. For multi-class classification problem, *categorical cross entropy* is commonly used.

Finally, we will use the accuracy during training as a metric to keep track of as the model trains.

In [16]:
```
model.compile(
    optimizer = "sgd",
    loss = "categorical_crossentropy",
    metrics = ["accuracy"]
)

model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense (Dense)                (None, 128)               100480    
_________________________________________________________________
dense_1 (Dense)              (None, 128)               16512     
_________________________________________________________________
dense_2 (Dense)              (None, 10)                1290      
=================================================================
Total params: 118,282
Trainable params: 118,282
Non-trainable params: 0
_________________________________________________________________
```

In order to get the approximation of our function, we just need to fit the model to our data. We will use only training set to do this learning and will reserve the test set for later when we want to check the accuracy of our model. This is because, if we used only one set for both training and testing, the results may be biased and our model may have simply memorized all the examples instead of learning the relationship between features and label.

Training the Model

We are going to train the model for 3 epochs. Epoch is like an iteration of all the examples going through the model. So, by setting the epochs to 3, we will go through all the training examples 3 times.

In [17]:
```
h = model.fit(
    x_train_norm,
    y_train_encoded,
    epochs = 3
)
```

```
WARNING:tensorflow:From /srv/conda/envs/notebook/lib/python3.7/site-packages/tensorflow/python/ops/math_ops.py:3066: to_int
32 (from tensorflow.python.ops.math_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/3
60000/60000 [==============================] - 14s 235us/sample - loss: 0.3821 - acc: 0.8896
Epoch 2/3
60000/60000 [==============================] - 14s 234us/sample - loss: 0.1858 - acc: 0.9457
Epoch 3/3
60000/60000 [==============================] - 14s 230us/sample - loss: 0.1409 - acc: 0.9588 - loss:
```

In order to ensure that this is not a simple "memorization" by the machine, we should evaluate the performance on the test set. To do this, we simply use the `evaluate` method on our model.

In [18]:
```
accuracy = model.evaluate(x_test_norm, y_test_encoded)

print("test set accuracy: ", accuracy * 100)
```

```
10000/10000 [==============================] - 1s 89us/sample - loss: 0.1286 - acc: 0.9612
test set accuracy:  [0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.1286108784422
2785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785,
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0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612,
0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.12861
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22785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785,
0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612,
0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612, 0.12861087844222785, 0.9612]
```

Predictions

In [19]:
```
preds = model.predict(x_test_norm)

print("shape of preds: ", preds.shape)
```

```
shape of preds:  (10000, 10)
```

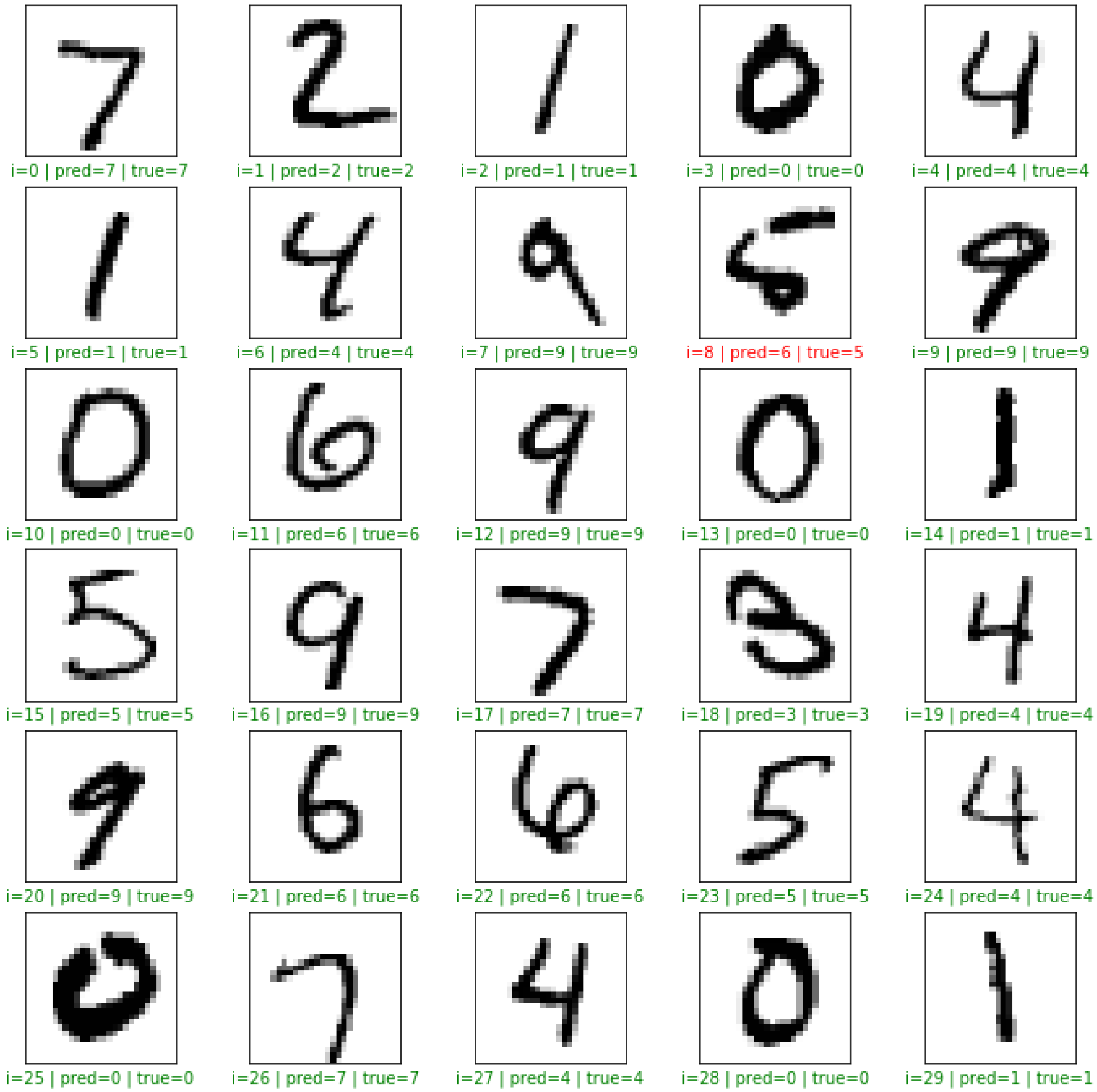
Let's plot the first few test set images along with their predicted and actual labels and see how the trained model actually performed.

In [20]:
```
plt.figure(figsize = (12, 12))

start_index = 0

for i in range(30):
    plt.subplot(6, 5, i + 1)
    plt.grid(False)
    plt.xticks([])
    plt.yticks([])
    pred = np.argmax(preds[start_index + i])
    actual = np.argmax(y_test_encoded[start_index + i])
    col = "g"
    if pred != actual:
        col = "r"
    plt.xlabel("i={} | pred={} | true={}".format(start_index + i, pred, actual), color = col)
    plt.imshow(x_test[start_index + i], cmap = "binary")

plt.show()
```



It gets most of the predictions right!

In [21]:
```
plt.figure(figsize = (12, 12))
plt.plot(preds[8])
plt.show()
```