Multilayer Perceptron with Back Propagation

Code an MLP-BP to recognize handwritten digits in MNIST database.

When I creating this project I used Google Colaboratory. A local Python 3 development environment, including pip, a tool for installing Python packages, and venv, for creating virtual environments were needed for this project.

Before I can develop the recognition program, I'll need to install a few dependencies and create a workspace to hold my files. I'll use a Python 3 virtual environment to manage my project's dependencies. Created a new directory for my project and navigated to the new directory:

- `mkdir tensorflow-demo`
- `cd tensorflow-demo`
-

Executed the following commands to set up the virtual environment :

- `python3 -m venv tensorflow-demo`
- `source tensorflow-demo/bin/activate`

Next, installed the libraries I'll use on this project. I'll use specific versions of these libraries by creating a `requirements.txt` file in the project directory which specifies the requirement and the version I need. Created the `requirements.txt` file:

```
touch requirements.txt
```

Opened the file in my text editor and added the following lines to specify the Image, NumPy, and TensorFlow libraries and their versions:

```
image==1.5.20
numpy==1.14.3
tensorflow==1.4.0
```

Saved the file and exit the editor. Then installed these libraries with the following command:

```
pip install -r requirements.txt
```

The dataset I will be using for this project is called the MNIST dataset, and it is a classic in the machine learning community. This dataset is made up of images of handwritten digits, 28x28 pixels in size.
Created a Python program to work with this dataset. I will use one file for all of my work on this project. Created a new file called main.py:

```
touch main.py
```

Opened this file in my text editor of choice and add this line of code to the file to import the TensorFlow library:

```
import tensorflow as tf
```

Added the following lines of code to my file to import the MNIST dataset and store the image data in the variable mnist:

```
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True) # y
labels are oh-encoded
```

When reading in the data, I am using *one-hot-encoding* to represent the labels (the actual digit drawn, e.g. "3") of the images. One-hot-encoding uses a vector of binary values to represent numeric or categorical values. As my labels are for the digits 0-9, the vector contains ten values, one for each possible digit. One of these values is set to 1, to represent the digit at that index of the vector, and the rest are set to 0. For example, the digit 3 is represented using the vector [0, 0, 0, 1, 0, 0, 0, 0, 0, 0]. As the value at index 3 is stored as 1, the vector therefore represents the digit 3.

To represent the actual images themselves, the 28x28 pixels are flattened into a 1D vector which is 784 pixels in size. Each of the 784 pixels making up the image is stored as a value between 0 and 255. This determines the grayscale of the pixel, as my images are presented in black and white only. So a black pixel is represented by 255, and a white pixel by 0, with the various shades of gray somewhere in between.

I can use the mnist variable to find out the size of the dataset I have just imported. Looking at the num_examples for each of the three subsets, I can determine that the dataset has been split into 55,000 images for training, 5000 for validation, and 10,000 for testing. Added the following lines to my file:

```
n_train = mnist.train.num_examples # 55,000
n_validation = mnist.validation.num_examples # 5000
n_test = mnist.test.num_examples # 10,000
```

Now that I have my data imported, it’s time to think about the neural network.

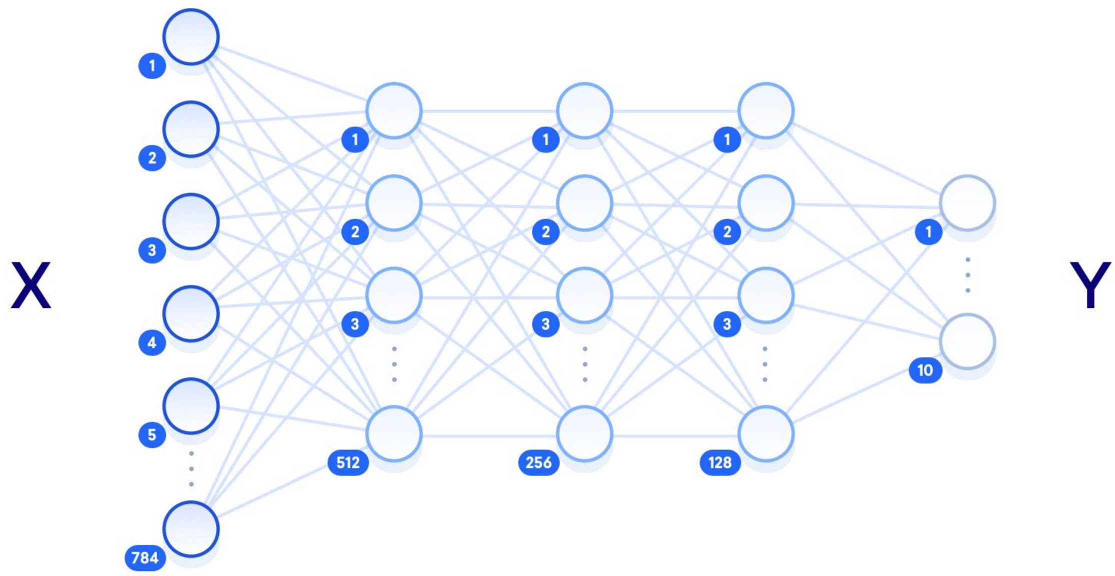
The architecture of the neural network refers to elements such as the number of layers in the network, the number of units in each layer, and how the units are connected between layers. As neural networks are loosely inspired by the workings of the human brain, here the term unit is used to represent what we would biologically think of as a neuron. Like neurons passing signals around the brain, units take some values from previous units as input, perform a computation, and then pass on the new value as output to other units. These units are layered to form the network, starting at a minimum with one layer for inputting values, and one layer to output values. The term *hidden layer* is used for all of the layers in between the input and output layers, i.e. those "hidden" from the real world.

Different architectures can yield drastically different results, as the performance can be thought of as a function of the architecture among other things, such as the parameters, the data, and the duration of training.

Added the following lines of code to my file to store the number of units per layer in global variables. This allows us to alter the network architecture in one place, and at the end of the tutorial I can test for myself how different numbers of layers and units will impact the results of our model:

```
n_input = 784   # input layer (28x28 pixels)
n_hidden1 = 512 # 1st hidden layer
n_hidden2 = 256 # 2nd hidden layer
n_hidden3 = 128 # 3rd hidden layer
n_output = 10   # output layer (0-9 digits)
```

The following diagram shows a visualization of the architecture I've designed, with each layer fully connected to the surrounding layers:



The term "deep neural network" relates to the number of hidden layers, with "shallow" usually meaning just one hidden layer, and "deep" referring to multiple hidden layers. Given enough training data, a shallow neural network with a sufficient number of units should theoretically be able to represent any function that a deep neural network can. But it is often more computationally efficient to use a smaller deep neural network to achieve the same task that would require a shallow network with exponentially more hidden units. Shallow neural networks also often encounter overfitting, where the network essentially memorizes the training data that it has seen, and is not able to generalize the knowledge to new data. This is why deep neural networks are more commonly used: the multiple layers between the raw input data and the output label allow the network to learn features at various levels of abstraction, making the network itself better able to generalize.

Other elements of the neural network that need to be defined here are the hyperparameters. Unlike the parameters that will get updated during training, these values are set initially and remain constant throughout the process. In my file, set the following variables and values:

```
learning_rate = 1e-4
n_iterations = 1000
batch_size = 128
dropout = 0.5
```

The learning rate represents ow much the parameters will adjust at each step of the learning process. These adjustments are a key component of training: after each pass through the network I tune the weights slightly to try and reduce the loss.

Larger learning rates can converge faster, but also have the potential to overshoot the optimal values as they are updated. The number of iterations refers to how many times we go through the training step, and the batch size refers to how many training examples I am using at each step. The dropout variable represents a threshold at which we eliminate some units at random. I will be using dropout in my final hidden layer to give each unit a 50% chance of being eliminated at every training step. This helps prevent overfitting.

I have now defined the architecture of our neural network, and the hyperparameters that impact the learning process. The next step is to build the network as a TensorFlow graph. To build my network, I will set up the network as a computational graph for TensorFlow to execute. The core concept of TensorFlow is the *tensor*, a data structure similar to an array or list. initialized, manipulated as they are passed through the graph, and updated through the learning process.

I'll start by defining three tensors as *placeholders*, which are tensors that I'll feed values into later. Added the following to my file:

```
X = tf.placeholder("float", [None, n_input])
Y = tf.placeholder("float", [None, n_output])
keep_prob = tf.placeholder(tf.float32)
```

The only parameter that needs to be specified at its declaration is the size of the data I will be feeding in. For X I use a shape of [None, 784], where None represents any amount, as I will be feeding in an undefined number of 784-pixel images. The shape of Y is [None, 10] as I will be using it for an undefined number of label outputs, with 10 possible classes. The keep_prob tensor is used to control the dropout rate, and I initialize it as a placeholder rather than an immutable variable because I want to use the same tensor both for training (when dropout is set to 0.5) and testing (when dropout is set to 1.0).

The parameters that the network will update in the training process are the weight and bias values, so for these I need to set an initial value rather than an empty placeholder. These values are essentially where the network does its learning, as they are used in the activation functions of the neurons, representing the strength of the connections between units.

Since the values are optimized during training, I could set them to zero for now. But the initial value actually has a significant impact on the final accuracy of the model. I'll use random values from a truncated normal distribution for the weights. I want them to be close to zero, so they can adjust in either a positive or negative direction, and slightly different, so they generate different errors. This will ensure that the model learns something useful. Added these lines:

```
weights = {
    'w1': tf.Variable(tf.truncated_normal([n_input, n_hidden1],
stddev=0.1)),
    'w2': tf.Variable(tf.truncated_normal([n_hidden1, n_hidden2],
stddev=0.1)),
    'w3': tf.Variable(tf.truncated_normal([n_hidden2, n_hidden3],
stddev=0.1)),
    'out': tf.Variable(tf.truncated_normal([n_hidden3, n_output],
stddev=0.1)),
}
```

For the bias, I use a small constant value to ensure that the tensors activate in the intial stages and therefore contribute to the propagation. The weights and bias tensors are stored in dictionary objects for ease of access. Added this code to my file to define the biases:

```
biases = {
    'b1': tf.Variable(tf.constant(0.1, shape=[n_hidden1])),
    'b2': tf.Variable(tf.constant(0.1, shape=[n_hidden2])),
    'b3': tf.Variable(tf.constant(0.1, shape=[n_hidden3])),
    'out': tf.Variable(tf.constant(0.1, shape=[n_output]))
}
```

Next, set up the layers of the network by defining the operations that will manipulate the tensors. Added these lines to my file:

```
layer_1 = tf.add(tf.matmul(X, weights['w1']), biases['b1'])
layer_2 = tf.add(tf.matmul(layer_1, weights['w2']), biases['b2'])
layer_3 = tf.add(tf.matmul(layer_2, weights['w3']), biases['b3'])
layer_drop = tf.nn.dropout(layer_3, keep_prob)
output_layer = tf.matmul(layer_3, weights['out']) + biases['out']
```

Each hidden layer will execute matrix multiplication on the previous layer's outputs and the current layer's weights, and add the bias to these values. At the last hidden layer, I will apply a dropout operation using our keep_prob value of 0.5.

The final step in building the graph is to define the loss function that I want to optimize. A popular choice of loss function in TensorFlow programs is *cross-entropy*, also known as *log-loss*, which quantifies the difference between two probability distributions (the predictions and the labels). A perfect classification would result in a cross-entropy of 0, with the loss completely minimized.

I also need to choose the optimization algorithm which will be used to minimize the loss function. A process named *gradient descent optimization* is a common method for finding the (local) minimum of a function by taking iterative steps along the gradient in a negative (descending) direction. There are several choices of gradient descent optimization algorithms already implemented in TensorFlow, and in this tutorial I will be using the Adam optimizer. This extends upon gradient descent optimization by using momentum to speed up the process through computing an exponentially weighted average of the gradients and using that in the adjustments. Added the following code to your file:

```
cross_entropy =
tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(labels=Y,
logits=output_layer))
train_step = tf.train.AdamOptimizer(1e-4).minimize(cross_entropy)
```

I've now defined the network and built it out with TensorFlow. The next step is to feed data through the graph to train it, and then test that it has actually learnt something.

The training process involves feeding the training dataset through the graph and optimizing the loss function. Every time the network iterates through a batch of more training images, it updates the parameters to reduce the loss in order to more accurately predict the digits shown. The testing process involves running I testing dataset through the trained graph, and keeping track of the number of images that are correctly predicted, so that I can calculate the accuracy.

Before starting the training process, I will define our method of evaluating the accuracy so I can print it out on mini-batches of data while I train. These printed statements will allow us to check that from the first iteration to the last, loss decreases and accuracy increases; they will also allow us to track whether or not I have ran enough iterations to reach a consistent and optimal result:

```
correct_pred = tf.equal(tf.argmax(output_layer, 1), tf.argmax(Y, 1))
accuracy = tf.reduce_mean(tf.cast(correct_pred, tf.float32))
```

In correct_pred, I use the arg_max function to compare which images are being predicted correctly by looking at the output_layer (predictions) and Y (labels), and I use the equal function to return this as a list of Booleans. I can then cast this list to floats and calculate the mean to get a total accuracy score.

I am now ready to initialize a session for running the graph. In this session I will feed the network with our training examples, and once trained, I feed the same graph with new test examples to determine the accuracy of the model. Added the following lines of code to your file:

```
init = tf.global_variables_initializer()
sess = tf.Session()
sess.run(init)
```

The essence of the training process in deep learning is to optimize the loss function. Here I am aiming to minimize the difference between the predicted labels of the images, and the true labels of the images. The process involves four steps which are repeated for a set number of iterations:

- Propagate values forward through the network
- Compute the loss
- Propagate values backward through the network
- Update the parameters

At each training step, the parameters are adjusted slightly to try and reduce the loss for the next step. As the learning progresses, I should see a reduction in loss, and eventually, I can stop training and use the network as a model for testing my new data.

Added this code to the file:

```
test_accuracy = sess.run(accuracy, feed_dict={X: mnist.test.images, Y:
mnist.test.labels, keep_prob:1.0})
print("\nAccuracy on test set:", test_accuracy)
```

It’s now time to run my program and see how accurately my neural network can recognize these handwritten digits. Saved the main.py file and executed the following command in the terminal to run the script:

```
python3 main.py
```

I'll see an output similar to the following, although individual loss and accuracy results may vary slightly:

```
/usr/lib/python3.6/importlib/_bootstrap.py:219: RuntimeWarning:
compiletime version 3.5 of module
'tensorflow.python.framework.fast_tensor_util' does not match runtime
version 3.6
  return f(*args, **kwds)
Successfully downloaded train-images-idx3-ubyte.gz 9912422 bytes.
Extracting MNIST_data/train-images-idx3-ubyte.gz
Successfully downloaded train-labels-idx1-ubyte.gz 28881 bytes.
Extracting MNIST_data/train-labels-idx1-ubyte.gz
Successfully downloaded t10k-images-idx3-ubyte.gz 1648877 bytes.
Extracting MNIST_data/t10k-images-idx3-ubyte.gz
Successfully downloaded t10k-labels-idx1-ubyte.gz 4542 bytes.
Extracting MNIST_data/t10k-labels-idx1-ubyte.gz
2019-01-10 02:55:07.185148: I
tensorflow/core/platform/cpu_feature_guard.cc:137] Your CPU supports
instructions that this TensorFlow binary was not compiled to use:
SSE4.1 SSE4.2 AVX AVX2 FMA
Iteration 0      | Loss = 3.672276      | Accuracy = 0.1171875
Iteration 100    | Loss = 0.5888463     | Accuracy = 0.8515625
Iteration 200    | Loss = 0.33426428    | Accuracy = 0.90625
Iteration 300    | Loss = 0.41349453    | Accuracy = 0.875
Iteration 400    | Loss = 0.5473601     | Accuracy = 0.8515625
Iteration 500    | Loss = 0.49795425    | Accuracy = 0.8671875
Iteration 600    | Loss = 0.3486076     | Accuracy = 0.8984375
Iteration 700    | Loss = 0.27881935    | Accuracy = 0.90625
Iteration 800    | Loss = 0.399332      | Accuracy = 0.875
Iteration 900    | Loss = 0.2909071     | Accuracy = 0.90625

Accuracy on test set: 0.9187
```

To try and improve the accuracy of my model, or to learn more about the impact of tuning hyperparameters, I can test the effect of changing the learning rate, the dropout threshold, the batch size, and the number of iterations. We can also change the number of units in our hidden layers, and change the amount of hidden layers themselves, to see how different architectures increase or decrease the model accuracy.

To demonstrate that the network is actually recognizing the hand-drawn images, let's test it on a single image of our own.

First either downloaded this sample test image or open up a graphics editor and create my own 28x28 pixel image of a digit.

Opened the main.py file in my editor and added the following lines of code to the top of the file to import two libraries necessary for image manipulation.

```
import numpy as np
from PIL import Image
...
```

Then at the end of the file, added the following line of code to load the test image of the handwritten digit:

```
img = np.invert(Image.open("test_img.png").convert('L')).ravel()
```

The open function of the Image library loads the test image as a 4D array containing the three RGB color channels and the Alpha transparency. This is not the same representation I used previously when reading in the dataset with TensorFlow, so wIll need to do some extra work to match the format.

First, I use the convert function with the L parameter to reduce the 4D RGBA representation to one grayscale color channel. I store this as a numpy array and invert it using np.invert, because the current matrix represents black as 0 and white as 255, whereas I need the opposite. Finally, I call ravel to flatten the array.

Now that the image data is structured correctly,I can run a session in the same way as previously, but this time only feeding in the single image for testing. Ad edethe following code to my file to test the image and print the outputted label.

```
prediction = sess.run(tf.argmax(output_layer,1), feed_dict={X: [img]})
print ("Prediction for test image:", np.squeeze(prediction))
```

The open function of the Image library loads the test image as a 4D array containing the three RGB color channels and the Alpha transparency. This is not the same representation I used previously when reading in the dataset with TensorFlow, so I'll need to do some extra work to match the format.

First, I use the convert function with the L parameter to reduce the 4D RGBA representation to one grayscale color channel. I store this as a numpy array and

invert it using np.invert, because the current matrix represents black as 0 and white as 255, whereas I need the opposite. Finally, I call ravel to flatten the array.

Now that the image data is structured correctly, I can run a session in the same way as previously, but this time only feeding in the single image for testing. Added the following code to my file to test the image and print the outputted label.

The `np.squeeze` function is called on the prediction to return the single integer from the array (i.e. to go from [2] to 2). The resulting output demonstrates that the network has recognized this image as the digit 2.

```
Output

Prediction for test image: 2
```

Output

Prediction for test image: 2

İlk can try testing the network with more complex images — digits that look like other digits, for example, or digits that have been drawn poorly or incorrectly — to see how well it fares.

In this tutorial you successfully trained a neural network to classify the MNIST dataset with around 92% accuracy and tested it on an image of your own. Current state-of-the-art research achieves around 99% on this same problem, using more complex network architectures involving convolutional layers. These use the 2D structure of the image to better represent the contents, unlike our method which flattened all the pixels into one vector of 784 units. You can read more about this topic on the TensorFlow website, and see the research papers detailing the most accurate results on the MNIST website.

Now that you know how to build and train a neural network, you can try and use this implementation on your own data, or test it on other popular datasets such as the Google StreetView House Numbers, or the CIFAR-10 dataset for more general image recognition

In this tutorial, I successfully trained a neural network to classify the MNIST dataset with around 92% accuracy and tested it on an image of my own. Current state-of-the-art research achieves around 99% on this same problem, using more complex network architectures involving convolutional layers. These use the 2D structure of the image to better represent the contents, unlike my method which flattened all the pixels into one vector of 784 units. I can read more about this topic on the TensorFlow website, and see the research papers detailing the most accurate results on the MNIST website.

Now that I know how to build and train a neural network, I can try and use this implementation on my own data, or test it on other popular datasets such as the Google StreetView House Numbers, or the CIFAR-10 dataset for more general image recognition.