

# Deep Learning using Tensor Flow

# Tensor Flow Feedforward NN

```
import numpy as np
# import data
from keras.datasets import mnist
import tensorflow as tf
```

```
mnist_data = mnist.load_data()
```



Load Mnist data

Mnist dataset is a tuple containing training and testing data.

$$\text{Mnist} = ( [\text{training\_data}], [\text{testing\_data}] )$$

[training\_data] and [testing\_data] are both tuple of length 2 which contains the hand written images (X) and labels for each image (y)

$$[\text{training\_data}] = ( [X_{\text{train}}], [y_{\text{train}}] )$$
$$[\text{testing\_data}] = ( [X_{\text{test}}], [y_{\text{test}}] )$$

Then, [X\_train], [y\_train], [X\_test] and [y\_test] are arrays with the following shape:

[X\_train] = (60000, 28, 28)

, which means an array with 60000 images and each image is an matrix of 28x28

$$\left[ \begin{bmatrix} 0 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 0 \end{bmatrix} \quad \begin{bmatrix} 0 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 0 \end{bmatrix} \quad (\dots) \quad \begin{bmatrix} 0 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 0 \end{bmatrix} \right]$$

60000 matrices that represents the hand written images



$$\begin{bmatrix} 0 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 0 \end{bmatrix}$$

A matrix that represents  
one hand written image of  
28x28 pixels

[y\_train] = (60000,)

,which means an array with 10000 labels of the hand written images

$$\left[ 1 \quad 8 \quad 5 \quad 2 \quad 3 \quad 4 \quad (\dots) \quad 7 \quad 0 \right]$$

The same idea is applied for:

```
[X_test] = (10000, 28, 28)  
[y_test] = (10000,)
```

```
# load data  
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

Split the Mnist data  
into training and  
testing sets

We still need to do some data manipulation:

```
np.random.seed(0)
```

```
train_indices = np.random.choice(60000, 50000, replace=False)
valid_indices = [i for i in range(60000) if i not in train_indices]
```

```
X_valid, y_valid = X_train[valid_indices,:,:), y_train[valid_indices]
X_train, y_train = X_train[train_indices,:,:), y_train[train_indices]
```

```
print(X_train.shape, X_valid.shape, X_test.shape)
```

```
# (50000, 28, 28) (10000, 28, 28) (10000, 28, 28)
```

```
image_size = 28
```

```
num_labels = 10
```

```
def reformat(dataset, labels):
```

```
    dataset = dataset.reshape((-1, image_size * image_size)).astype(np.float32)
```

```
    # one hot encoding: Map 1 to [0.0, 1.0, 0.0 ...], 2 to [0.0, 0.0, 1.0 ...]
```

```
    labels = (np.arange(num_labels) == labels[:,None]).astype(np.float32)
```

```
    return dataset, labels
```

```
X_train, y_train = reformat(X_train, y_train)
```

```
X_valid, y_valid = reformat(X_valid, y_valid)
```

```
X_test, y_test = reformat(X_test, y_test)
```

```
print('Training set', X_train.shape, y_train.shape)
```

```
print('Validation set', X_valid.shape, y_valid.shape)
```

```
print('Test set', X_test.shape, y_test.shape)
```

```
# Training set (50000, 784) (50000, 10) # Validation set (10000, 10) (10000, 10) # Test set (10000, 784) (10000, 10)
```

Defining a seed to be able to replicate the results again

We still need to do some data manipulation:

```
np.random.seed(0)
train_indices = np.random.choice(60000, 50000, replace=False)
valid_indices = [i for i in range(60000) if i not in train_indices]

X_valid, y_valid = X_train[valid_indices,:,:), y_train[valid_indices]
X_train, y_train = X_train[train_indices,:,:), y_train[train_indices]
print(X_train.shape, X_valid.shape, X_test.shape)
# (50000, 28, 28) (10000, 28, 28) (10000, 28, 28)

image_size = 28
num_labels = 10

def reformat(dataset, labels):
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    labels = (np.arange(num_labels) == labels[:,None]).astype(np.float32)
    return dataset, labels

X_train, y_train = reformat(X_train, y_train)
X_valid, y_valid = reformat(X_valid, y_valid)
X_test, y_test = reformat(X_test, y_test)
print('Training set', X_train.shape, y_train.shape)
print('Validation set', X_valid.shape, y_valid.shape)
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# Training set (50000, 784) (50000, 10) # Validation set (10000, 10) (10000, 10) # Test set (10000, 784) (10000, 10)
```

Choosing 50000  
numbers without  
repetition between 0  
to 59999

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```
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valid_indices = [i for i in range(60000) if i not in train_indices]

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# (50000, 28, 28) (10000, 28, 28) (10000, 28, 28)

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    labels = (np.arange(num_labels) == labels[:,None]).astype(np.float32)
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X_train, y_train = reformat(X_train, y_train)
X_valid, y_valid = reformat(X_valid, y_valid)
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print('Training set', X_train.shape, y_train.shape)
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```

Choosing 10000  
numbers without  
repetition which  
train\_indices didn't  
pick up



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X_valid, y_valid = X_train[valid_indices,:,:), y_train[valid_indices]
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```



Creating X and y valid arrays by array indices

We still need to do some data manipulation:


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# (50000, 28, 28) (10000, 28, 28) (10000, 28, 28)
```

```
image_size = 28
num_labels = 10
```

Defining some variables which we already know

```
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This part will transform the image's matrix (2-D array) into a 1-D vector and the image's labels into one hot encoding

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The final dimension is expected to be (number\_of\_samples, image\_size\*image\_size)

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The final dimension is expected to be (number\_of\_samples, number\_of\_labels)

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# (50000, 28, 28) (10000, 28, 28) (10000, 28, 28)

image_size = 28
num_labels = 10

def reformat(dataset, labels):
    dataset = dataset.reshape((-1, image_size * image_size)).astype(np.float32)
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X_train, y_train = reformat(X_train, y_train)
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# Training set (50000, 784) (50000, 10) # Validation set (10000, 10) (10000, 10) # Test set (10000, 784) (10000, 10)
```



Reshaping our data

We still need to do some data manipulation:

```
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valid_indices = [i for i in range(60000) if i not in train_indices]

X_valid, y_valid = X_train[valid_indices,:,:), y_train[valid_indices]
X_train, y_train = X_train[train_indices,:,:), y_train[train_indices]
print(X_train.shape, X_valid.shape, X_test.shape)
# (50000, 28, 28) (10000, 28, 28) (10000, 28, 28)

image_size = 28
num_labels = 10

def reformat(dataset, labels):
    dataset = dataset.reshape((-1, image_size * image_size)).astype(np.float32)
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    labels = (np.arange(num_labels) == labels[:,None]).astype(np.float32)
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X_train, y_train = reformat(X_train, y_train)
X_valid, y_valid = reformat(X_valid, y_valid)
X_test, y_test = reformat(X_test, y_test)
print('Training set', X_train.shape, y_train.shape)
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```



Checking dimension

Here should be 784



```
import tensorflow as tf
```

```
def accuracy(predictions, labels):
```

```
    return (100.0 * np.sum(np.argmax(predictions, 1) == np.argmax(labels, 1)) / predictions.shape[0])
```

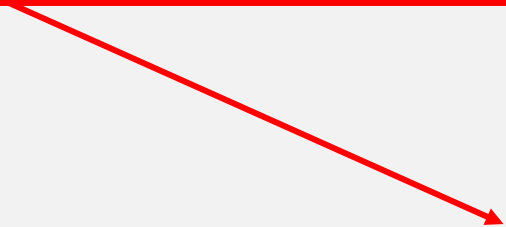
```
batch_size = 256
```

```
num_hidden_units = 1024
```

```
lambda1 = 0.1
```

```
lambda2 = 0.1
```

```
graph = tf.Graph()
```




Calculates the model accuracy

```
import tensorflow as tf

def accuracy(predictions, labels):
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batch_size = 256
num_hidden_units = 1024
lambda1 = 0.1
lambda2 = 0.1

graph = tf.Graph()
```



Counts how many of the predictions is the same from the expected labels


Axis = 1 means to compare along columns

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import tensorflow as tf

def accuracy(predictions, labels):
    return (100.0 * np.sum(np.argmax(predictions, 1) == np.argmax(labels, 1)) / predictions.shape[0])

batch_size = 256
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graph = tf.Graph()
```



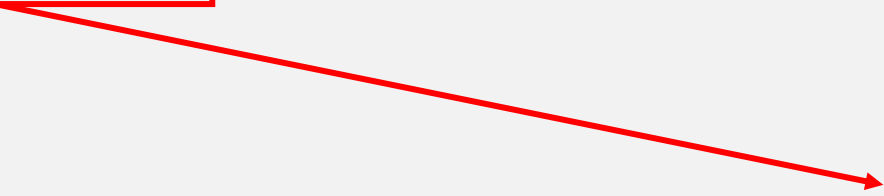
Axis = 1 means to compare  
along columns

```
import tensorflow as tf

def accuracy(predictions, labels):
    return (100.0 * np.sum(np.argmax(predictions, 1) == np.argmax(labels, 1)) / predictions.shape[0])

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An example of how this works

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import tensorflow as tf

def accuracy(predictions, labels):
    return (100.0 * np.sum(np.argmax(predictions, 1) == np.argmax(labels, 1)) / predictions.shape[0])

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lambda1 = 0.1
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graph = tf.Graph()
```

An example of how this works

# Example prediction arrays (probabilities for each class for each sample)

```
predictions = np.array([
    [0.2, 0.5, 0.3], # Sample 1: Probability for Class A, B, and C
    [0.7, 0.1, 0.2], # Sample 2: Probability for Class A, B, and C
    [0.4, 0.3, 0.3], # Sample 3: Probability for Class A, B, and C
    [0.1, 0.2, 0.7], # Sample 4: Probability for Class A, B, and C
])
```

# Find the index of the maximum probability for each sample

```
predicted_classes = np.argmax(predictions, axis=1)
print(predicted_classes)
```

#Returned output

[1 0 0 2]

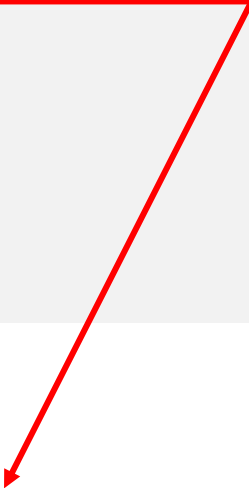
It returns the index of the element from each array that contains the max value

```
import tensorflow as tf

def accuracy(predictions, labels):
    return (100.0 * np.sum(np.argmax(predictions, 1) == np.argmax(labels, 1)) / predictions.shape[0])

batch_size = 256
num_hidden_units = 1024
lambda1 = 0.1
lambda2 = 0.1

graph = tf.Graph()
```




Returns the amount of same  
index matching between this 2  
arrays

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batch_size = 256
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```




Computes the % of accuracy  
when divided by the total  
amount of elements and then  
multiplied by 100

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    return (100.0 * np.sum(np.argmax(predictions, 1) == np.argmax(labels, 1)) / predictions.shape[0])

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Starting to define the neural  
network structure




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```




For each training loop, we will have 256 training sample

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```




For each layer, the neural network will have 1024 hidden units

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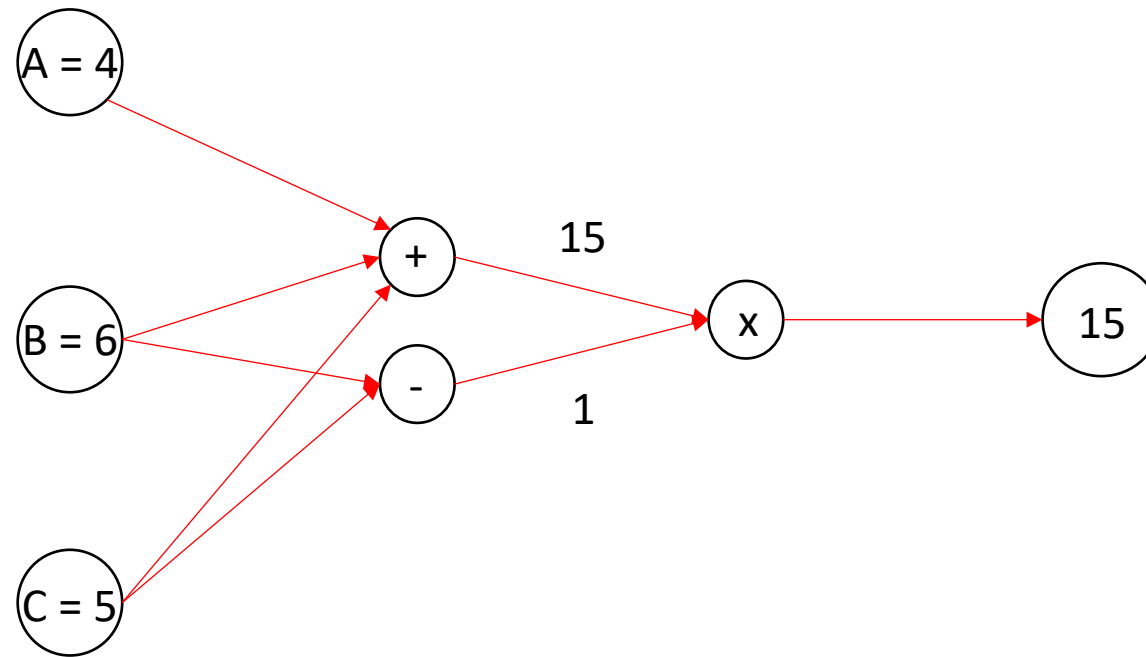
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```



This are the regularization terms by calculating the L2 norm (Euclidian distance) for the first and second hidden layers

About tf.Graph:

- tf.Graph in tensor flow is a method to create a computational graph.
- Computational graphs are directed graphs that represents mathematical expressions.
- Isn't used matrix operation.



Design consideration when building a neural networks:

- How many layers? (Will define the depth of Neural Networks)
- How many layers are connected?
- How many units per layers?
- Activation function will be used in each hidden layer?
- Activation function will be used in output layer?
- Which cost function to use?
- Which optimizer to use?

```

with graph.as_default():
    # Input data placeholders
    tf_train_dataset = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, image_size * image_size))
    tf_train_labels = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, num_labels))
    tf_valid_dataset = tf.constant(X_valid)
    tf_test_dataset = tf.constant(X_test)

    # Variables
    weights1 = tf.Variable(tf.random.truncated_normal([image_size * image_size, num_hidden_units]))
    biases1 = tf.Variable(tf.zeros([num_hidden_units]))
    weights2 = tf.Variable(tf.random.truncated_normal([num_hidden_units, num_labels]))
    biases2 = tf.Variable(tf.zeros([num_labels]))

    # Hidden layer computation with ReLU activation
    hidden_layer_output = tf.nn.relu(tf.matmul(tf_train_dataset, weights1) + biases1

    # Logits computation
    logits = tf.matmul(hidden_layer_output, weights2) + biases2

    # Softmax activation for logits
    softmax_logits = tf.nn.softmax(logits)

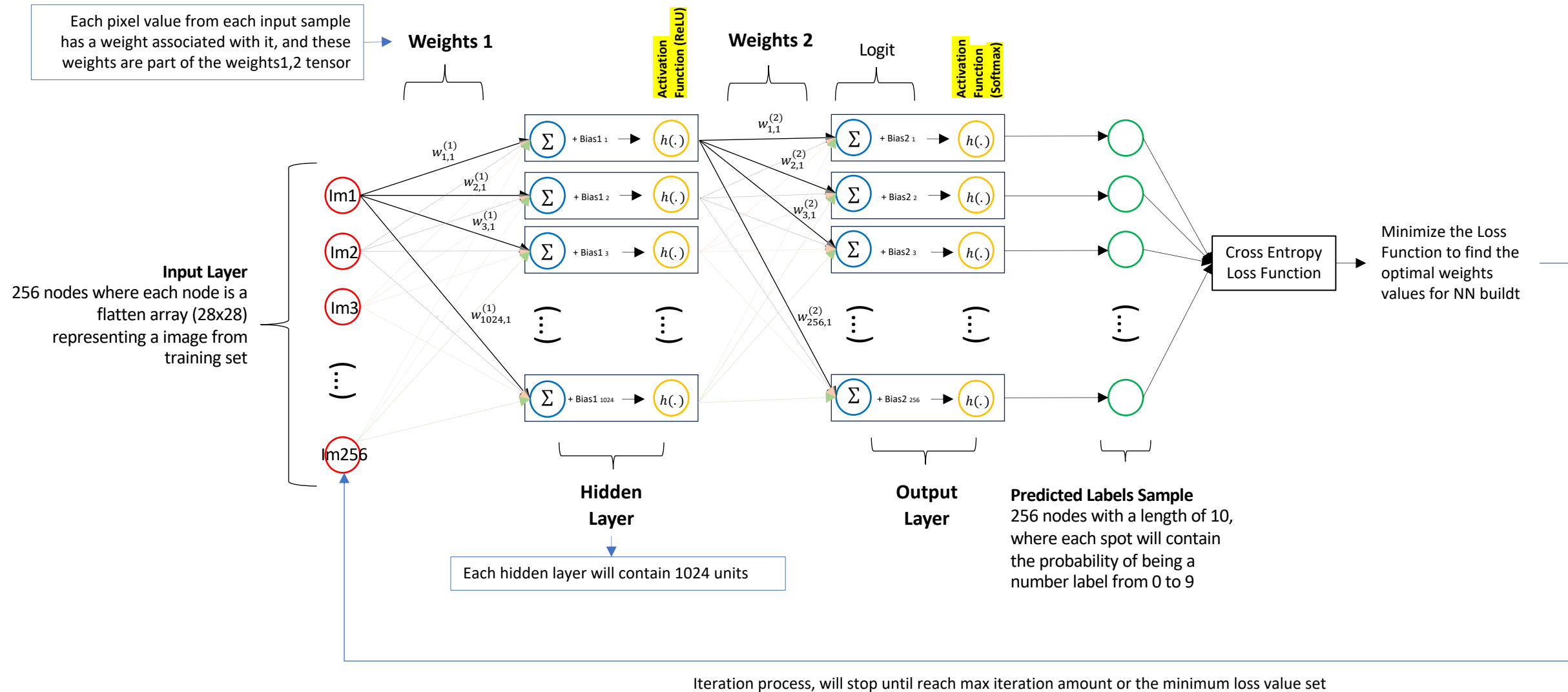
    # Loss computation
    loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(labels=tf_train_labels, logits=softmax_logits) + \
        lambda1 * tf.nn.l2_loss(weights1) + lambda2 * tf.nn.l2_loss(weights2))

    # Optimizer
    optimizer = tf.compat.v1.train.GradientDescentOptimizer(0.008).minimize(loss)

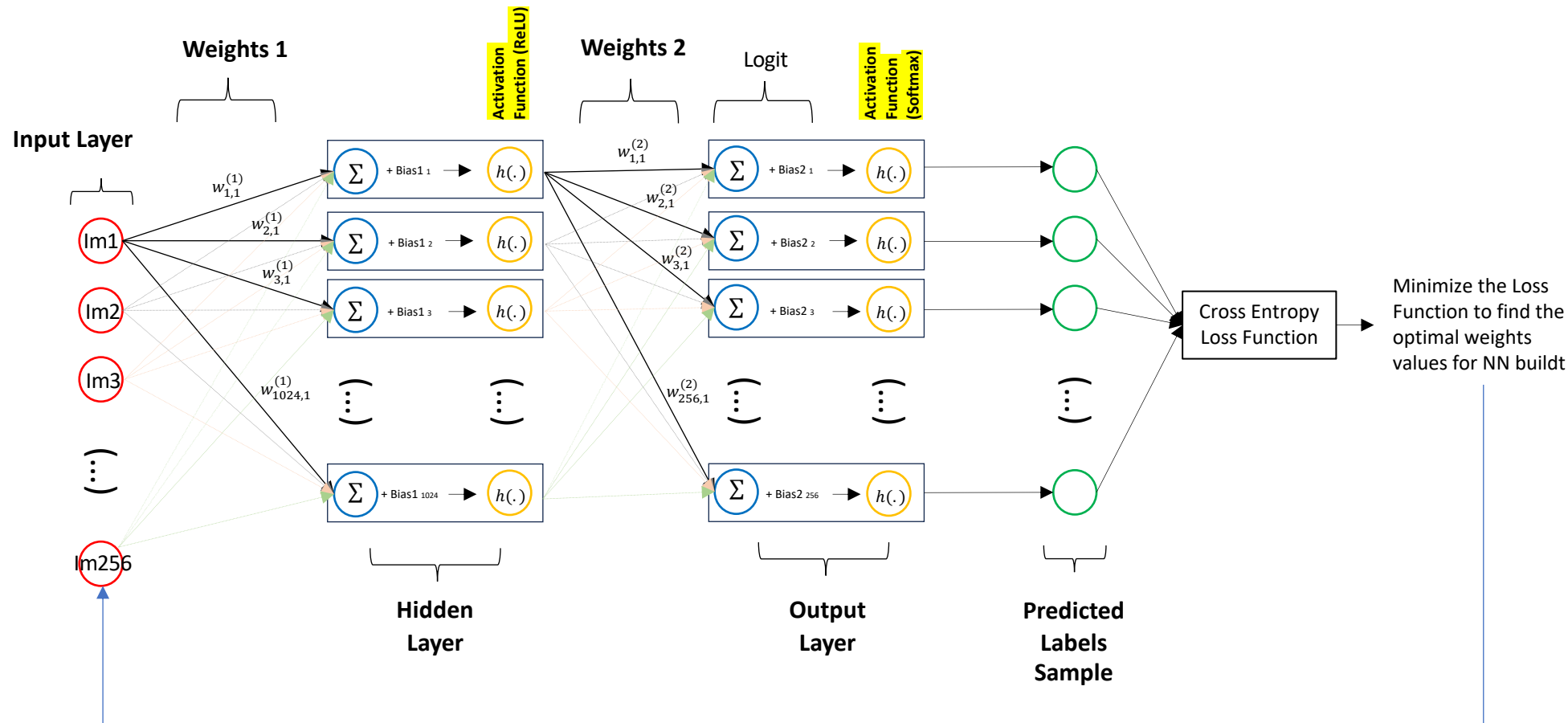
    # Predictions for the training, validation, and test data.
    train_prediction = softmax_logits
    valid_hidden_layer_output = tf.nn.relu(tf.matmul(tf_valid_dataset, weights1) + biases1)
    valid_prediction = tf.nn.softmax(tf.matmul(valid_hidden_layer_output, weights2) + biases2)
    test_hidden_layer_output = tf.nn.relu(tf.matmul(tf_test_dataset, weights1) + biases1)
    test_prediction = tf.nn.softmax(tf.matmul(test_hidden_layer_output, weights2) + biases2)

```

The code represents the following Neural Network structure:



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```

with graph.as_default():
    # Input data placeholders
    tf_train_dataset = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, image_size * image_size))
    tf_train_labels = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, num_labels))
    tf_valid_dataset = tf.constant(X_valid)
    tf_test_dataset = tf.constant(X_test)

    # Variables
    weights1 = tf.Variable(tf.random.truncated_normal([image_size * image_size, num_hidden_units]))
    biases1 = tf.Variable(tf.zeros([num_hidden_units]))
    weights2 = tf.Variable(tf.random.truncated_normal([num_hidden_units, num_labels]))
    biases2 = tf.Variable(tf.zeros([num_labels]))

    # Hidden layer computation with ReLU activation
    hidden_layer_output = tf.nn.relu(tf.matmul(tf_train_dataset, weights1) + biases1)

    # Logits computation
    logits = tf.matmul(hidden_layer_output, weights2) + biases2

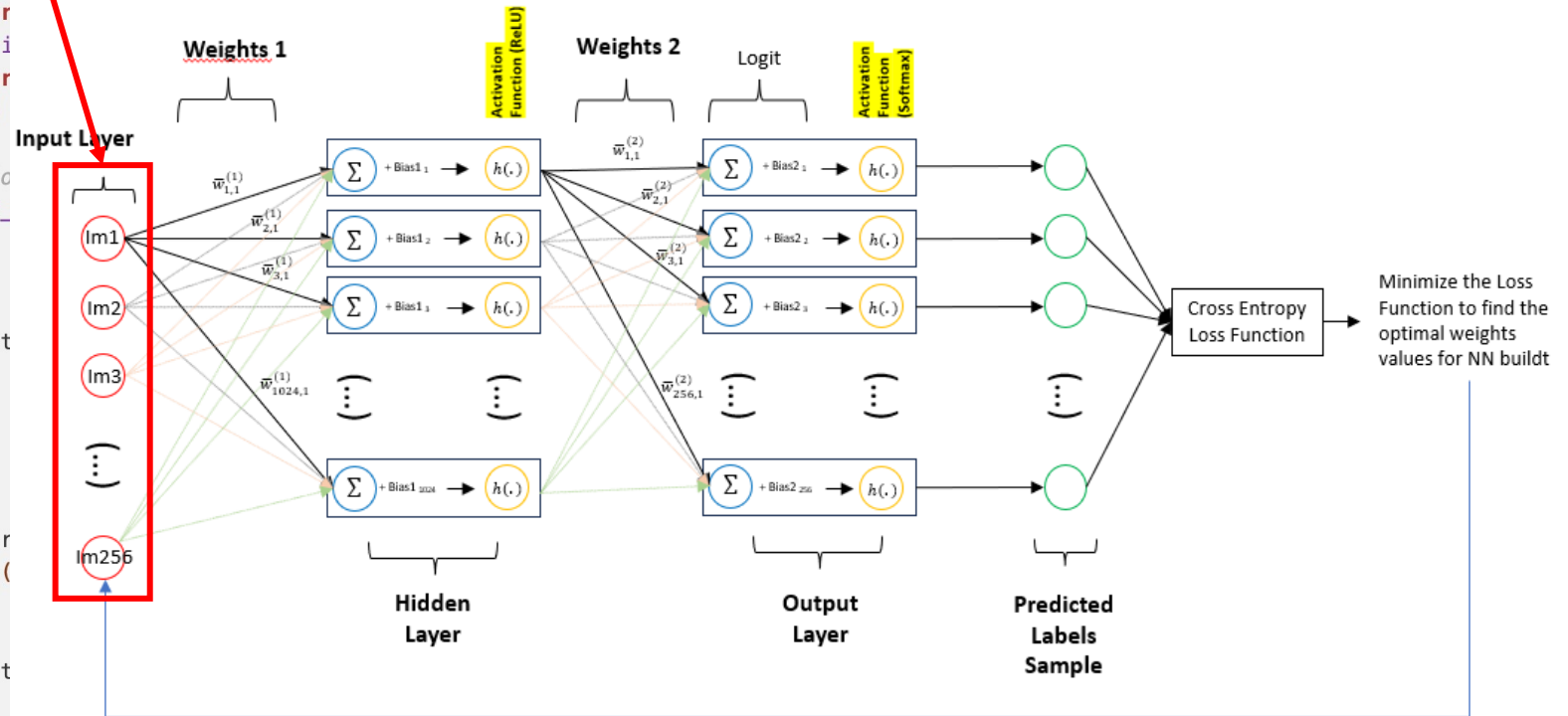
    # Softmax activation for logits
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    # Loss computation
    loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits, tf_train_labels) +
                           lambda1 * tf.nn.l2_loss(weights1) + lambda2 * tf.nn.l2_loss(weights2))

    # Optimizer
    optimizer = tf.compat.v1.train.GradientDescentOptimizer(loss)

    # Predictions for the training, validation, and test data.
    train_prediction = softmax_logits
    valid_hidden_layer_output = tf.nn.relu(tf.matmul(tf_valid_dataset, weights1) + biases1)
    valid_prediction = tf.nn.softmax(tf.matmul(valid_hidden_layer_output, weights2) + biases2)
    test_hidden_layer_output = tf.nn.relu(tf.matmul(tf_test_dataset, weights1) + biases1)
    test_prediction = tf.nn.softmax(tf.matmul(test_hidden_layer_output, weights2) + biases2)

```



```
with graph.as_default():
    # Input data placeholders
    tf_train_dataset = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, image_size * image_size))
    tf_train_labels = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, num_labels))
    tf_valid_dataset = tf.constant(X_valid)
    tf_test_dataset = tf.constant(X_test)
```

# Variables

```
weights1 = tf.Variable(tf.random.truncated_normal([image_size * image_size, num_hidden_units]))
biases1 = tf.Variable(tf.zeros([num_hidden_units]))
weights2 = tf.Variable(tf.random.truncated_normal([num_hidden_units, num_labels]))
biases2 = tf.Variable(tf.zeros([num_labels]))
```

# Hidden layer computation with ReLU activation

```
hidden_layer_output = tf.nn.relu(tf.matmul(tf_train_data
```

# Logits computation

```
logits = tf.matmul(hidden_layer_output, weights2) + bias
```

# Softmax activation for logits

```
softmax_logits = tf.nn.softmax(logits)
```

# Loss computation

```
loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_
| | | | |
| | | | | lambda1 * tf.nn.l2_loss(weights1)
```

# Optimizer

```
optimizer = tf.compat.v1.train.GradientDescentOptimizer
```

# Predictions for the training, validation, and test da

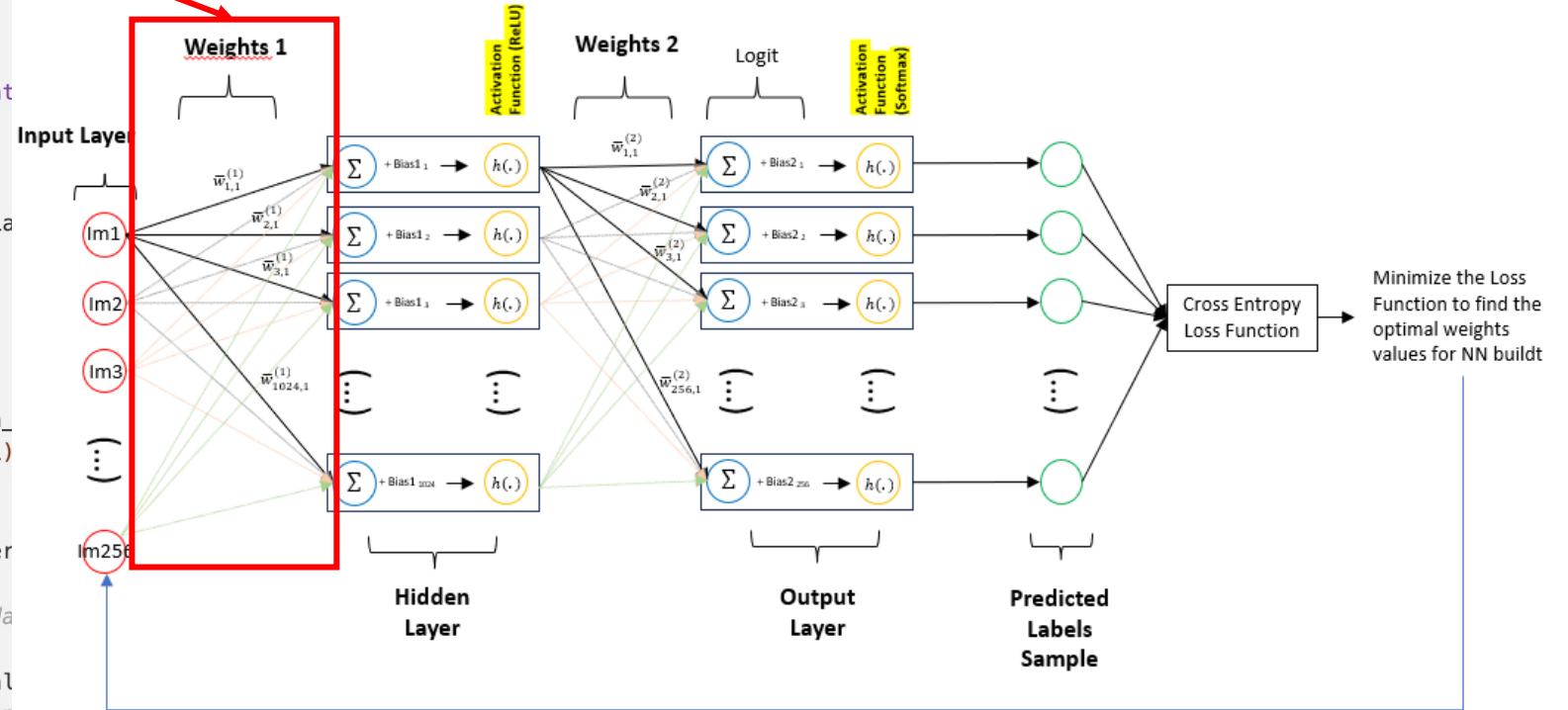
```
train_prediction = softmax_logits
```

```
valid_hidden_layer_output = tf.nn.relu(tf.matmul(tf_val
```

```
valid_prediction = tf.nn.softmax(tf.matmul(valid_hidden
```

```
test_hidden_layer_output = tf.nn.relu(tf.matmul(tf_test_dataset, weights1) + biases1)
```

```
test_prediction = tf.nn.softmax(tf.matmul(test_hidden_layer_output, weights2) + biases2)
```



```

with graph.as_default():
    # Input data placeholders
    tf_train_dataset = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, image_size * image_size))
    tf_train_labels = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, num_labels))
    tf_valid_dataset = tf.constant(X_valid)
    tf_test_dataset = tf.constant(X_test)

    # Variables
    weights1 = tf.Variable(tf.random.truncated_normal([image_size * image_size, num_hidden_units]))
    biases1 = tf.Variable(tf.zeros([num_hidden_units]))
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    # Hidden layer computation with ReLU activation
    hidden_layer_output = tf.nn.relu(tf.matmul(tf_train_dataset, weights1) + biases1)

    # Logits computation
    logits = tf.matmul(hidden_layer_output, weights2) + biases2

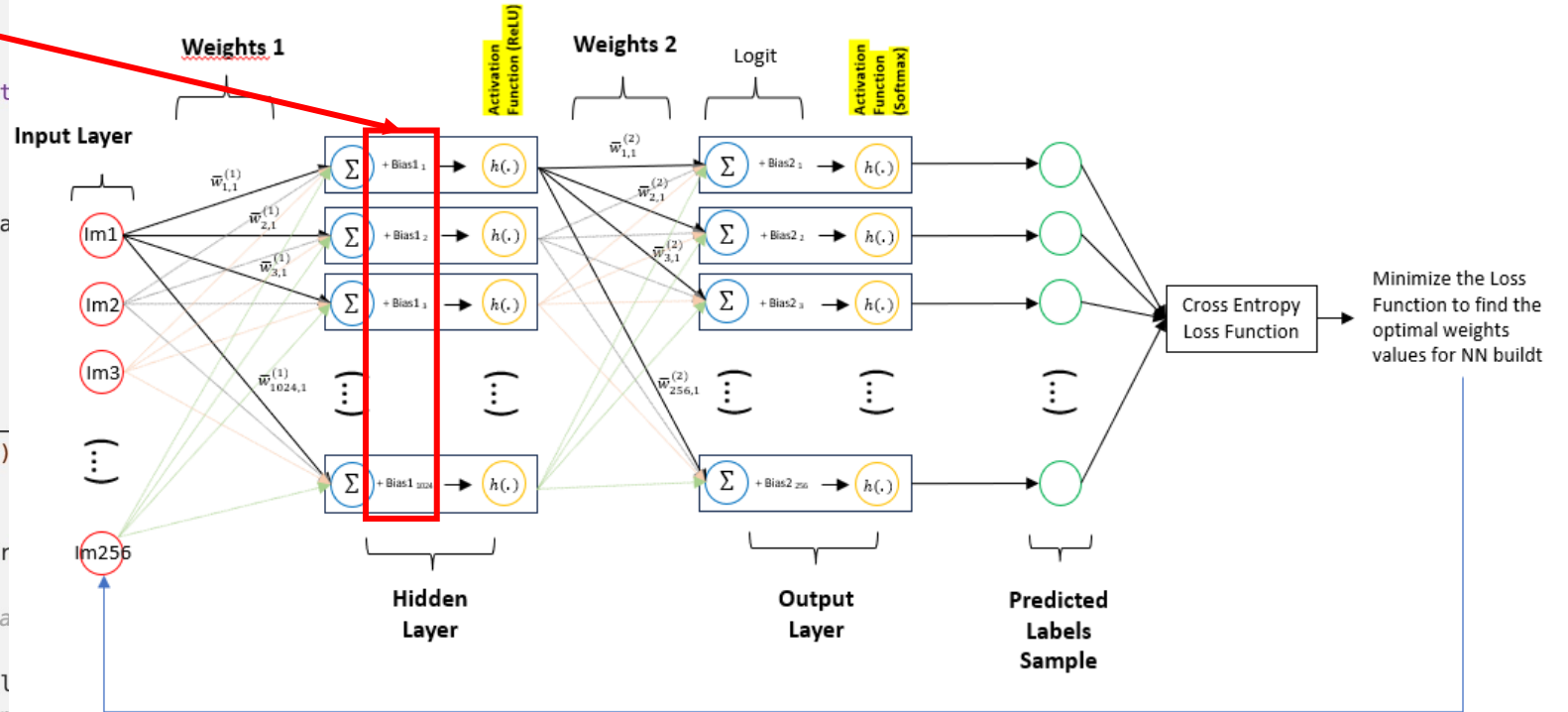
    # Softmax activation for logits
    softmax_logits = tf.nn.softmax(logits)

    # Loss computation
    loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits, tf_train_labels) +
                          lambda1 * tf.nn.l2_loss(weights1))

    # Optimizer
    optimizer = tf.compat.v1.train.GradientDescentOptimizer(loss)

    # Predictions for the training, validation, and test data
    train_prediction = softmax_logits
    valid_hidden_layer_output = tf.nn.relu(tf.matmul(tf_valid_dataset, weights1) + biases1)
    valid_prediction = tf.nn.softmax(tf.matmul(valid_hidden_layer_output, weights2) + biases2)
    test_hidden_layer_output = tf.nn.relu(tf.matmul(tf_test_dataset, weights1) + biases1)
    test_prediction = tf.nn.softmax(tf.matmul(test_hidden_layer_output, weights2) + biases2)

```





```

with graph.as_default():
    # Input data placeholders
    tf_train_dataset = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, image_size * image_size))
    tf_train_labels = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, num_labels))
    tf_valid_dataset = tf.constant(X_valid)
    tf_test_dataset = tf.constant(X_test)

    # Variables
    weights1 = tf.Variable(tf.random.truncated_normal([image_size * image_size, num_hidden_units]))
    biases1 = tf.Variable(tf.zeros([num_hidden_units]))
    weights2 = tf.Variable(tf.random.truncated_normal([num_hidden_units, num_labels]))
    biases2 = tf.Variable(tf.zeros([num_labels]))

    # Hidden layer computation with ReLU activation
    hidden_layer_output = tf.nn.relu(tf.matmul(tf_train_data

    # Logits computation
    logits = tf.matmul(hidden_layer_output, weights2) + biases2

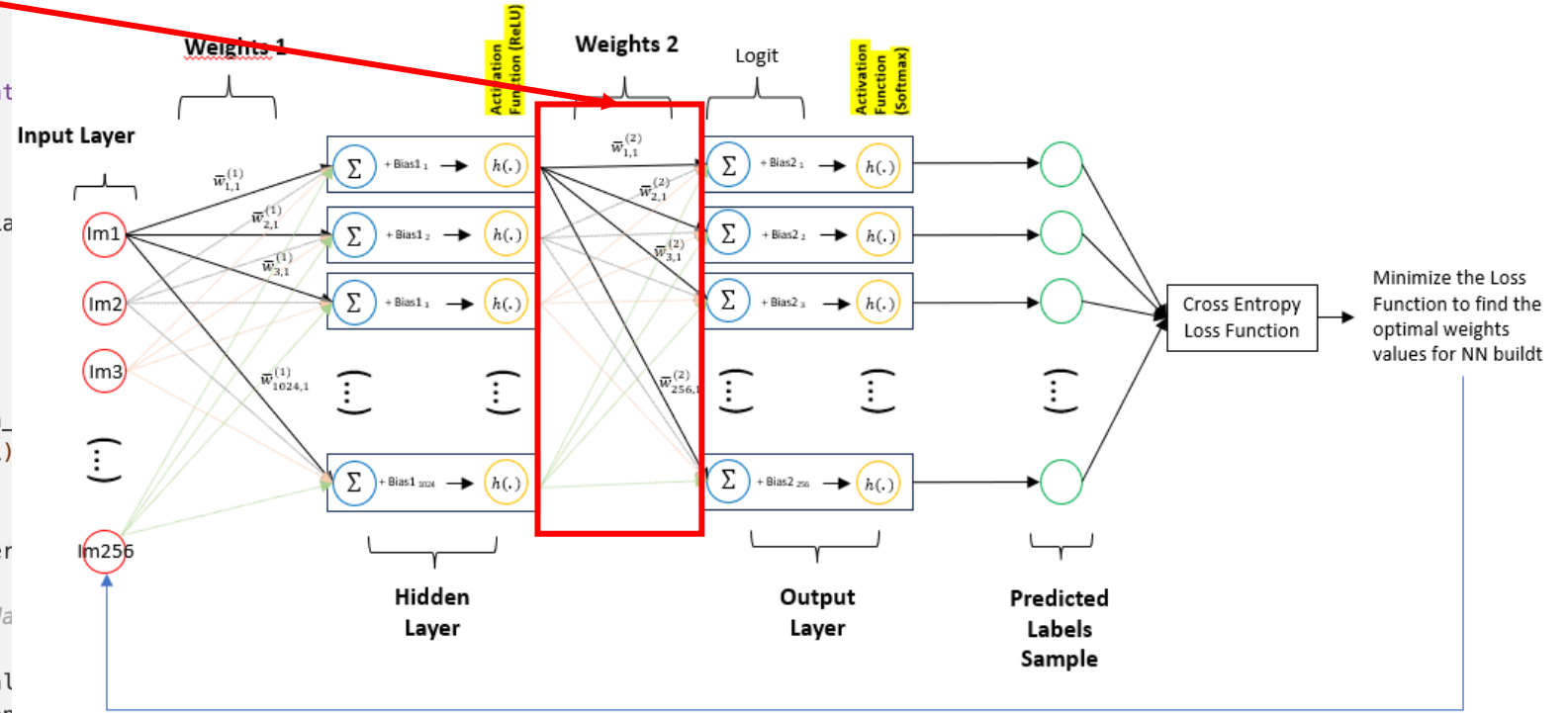
    # Softmax activation for logits
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    # Loss computation
    loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits, tf_train_labels) +
                          lambda1 * tf.nn.l2_loss(weights1) +
                          lambda1 * tf.nn.l2_loss(weights2) +
                          lambda1 * tf.nn.l2_loss(biases1) +
                          lambda1 * tf.nn.l2_loss(biases2))

    # Optimizer
    optimizer = tf.compat.v1.train.GradientDescentOptimizer(loss)

    # Predictions for the training, validation, and test data
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    valid_prediction = tf.nn.softmax(tf.matmul(valid_hidden_layer_output, weights2) + biases2)
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```



```

with graph.as_default():
    # Input data placeholders
    tf_train_dataset = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, image_size * image_size))
    tf_train_labels = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, num_labels))
    tf_valid_dataset = tf.constant(X_valid)
    tf_test_dataset = tf.constant(X_test)

    # Variables
    weights1 = tf.Variable(tf.random.truncated_normal([image_size * image_size, num_hidden_units]))
    biases1 = tf.Variable(tf.zeros([num_hidden_units]))
    weights2 = tf.Variable(tf.random.truncated_normal([num_hidden_units, num_labels]))
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    # Hidden layer computation with ReLU activation
    hidden_layer_output = tf.nn.relu(tf.matmul(tf_train_data

    # Logits computation
    logits = tf.matmul(hidden_layer_output, weights2) + biases2

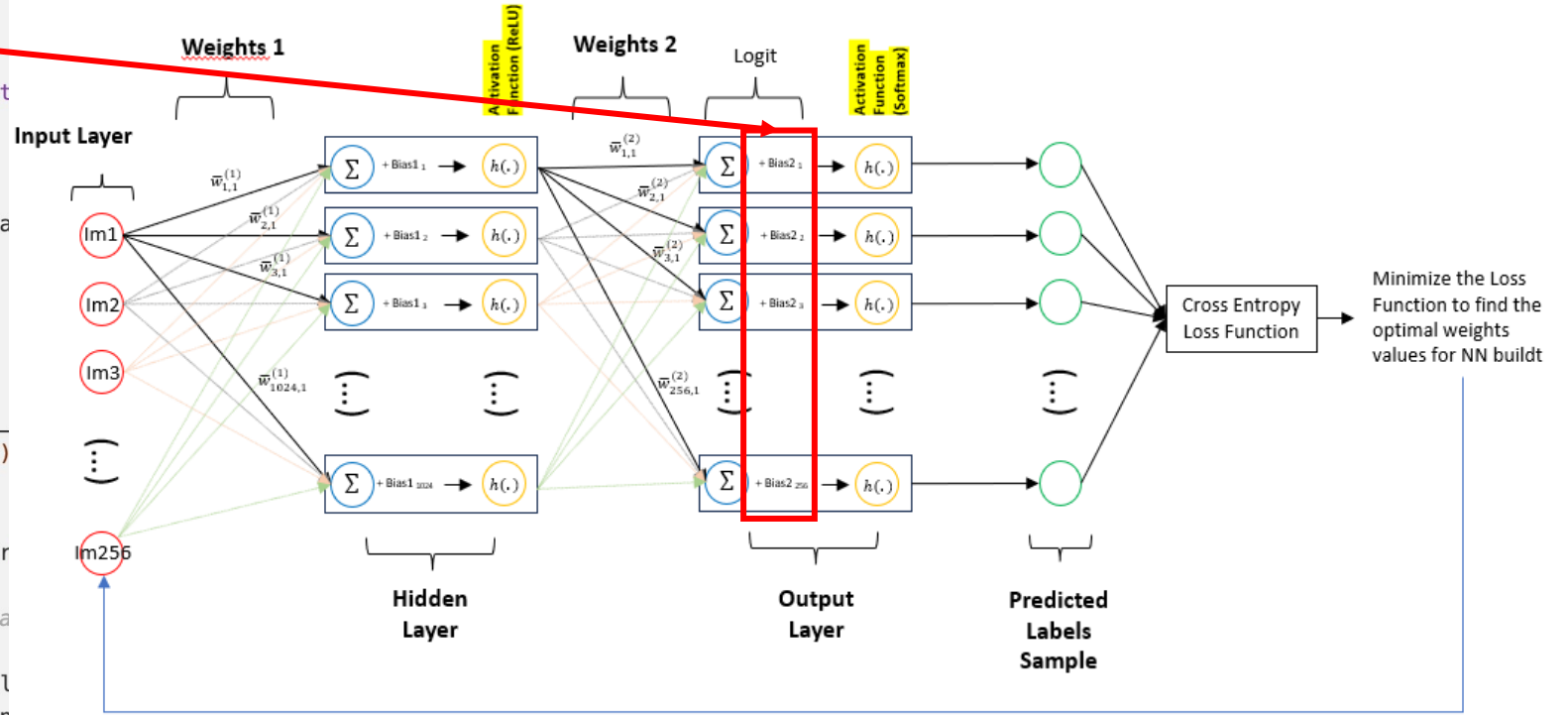
    # Softmax activation for logits
    softmax_logits = tf.nn.softmax(logits)

    # Loss computation
    loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits, tf_train_labels) +
                          lambda1 * tf.nn.l2_loss(weights1))

    # Optimizer
    optimizer = tf.compat.v1.train.GradientDescentOptimizer(loss)

    # Predictions for the training, validation, and test data
    train_prediction = softmax_logits
    valid_hidden_layer_output = tf.nn.relu(tf.matmul(tf_valid_dataset, weights1) + biases1)
    valid_prediction = tf.nn.softmax(tf.matmul(valid_hidden_layer_output, weights2) + biases2)
    test_hidden_layer_output = tf.nn.relu(tf.matmul(tf_test_dataset, weights1) + biases1)
    test_prediction = tf.nn.softmax(tf.matmul(test_hidden_layer_output, weights2) + biases2)

```



```
with graph.as_default():
    # Input data placeholders
    tf_train_dataset = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, image_size * image_size))
    tf_train_labels = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, num_labels))
    tf_valid_dataset = tf.constant(X_valid)
    tf_test_dataset = tf.constant(X_test)
```

# Variables

```
weights1 = tf.Variable(tf.random.truncated_normal([image_size * image_size, num_hidden_units]))
biases1 = tf.Variable(tf.zeros([num_hidden_units]))
weights2 = tf.Variable(tf.random.truncated_normal([num_hidden_units, num_labels]))
biases2 = tf.Variable(tf.zeros([num_labels]))
```

# Hidden layer computation with ReLU activation

```
hidden_layer_output = tf.nn.relu(tf.matmul(tf_train_dataset, weights1) + biases1)
```

# Logits computation

```
logits = tf.matmul(hidden_layer_output, weights2) + biases2
```

# Softmax activation for logits

```
softmax_logits = tf.nn.softmax(logits)
```

# Loss computation

```
loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(
    logits=logits, labels=tf_train_labels) +
    lambda1 * tf.nn.l2_loss(weights1))
```

# Optimizer

```
optimizer = tf.compat.v1.train.GradientDescentOptimizer(loss)
```

# Predictions for the training, validation, and test data

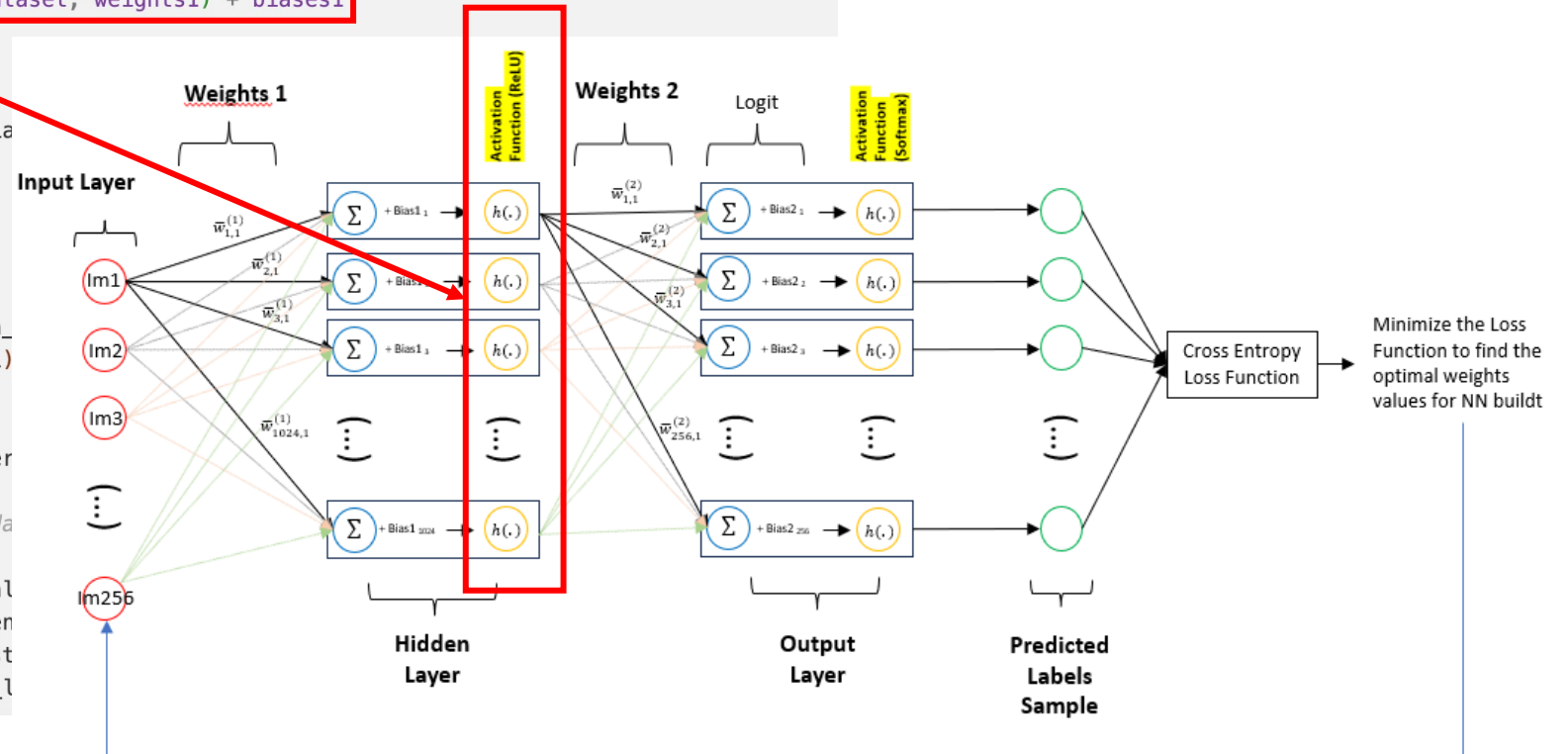
```
train_prediction = softmax_logits
```

```
valid_hidden_layer_output = tf.nn.relu(tf.matmul(tf_valid_dataset, weights1) + biases1)
```

```
valid_prediction = tf.nn.softmax(tf.matmul(valid_hidden_layer_output, weights2) + biases2)
```

```
test_hidden_layer_output = tf.nn.relu(tf.matmul(tf_test_dataset, weights1) + biases1)
```

```
test_prediction = tf.nn.softmax(tf.matmul(test_hidden_layer_output, weights2) + biases2)
```





```
with graph.as_default():
    # Input data placeholders
    tf_train_dataset = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, image_size * image_size))
    tf_train_labels = tf.compat.v1.placeholder(tf.float32, shape=(batch_size, num_labels))
    tf_valid_dataset = tf.constant(X_valid)
    tf_test_dataset = tf.constant(X_test)
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# Variables

```
weights1 = tf.Variable(tf.random.truncated_normal([image_size * image_size, num_hidden_units]))
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weights2 = tf.Variable(tf.random.truncated_normal([num_hidden_units, num_labels]))
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# Hidden layer computation with ReLU activation

```
hidden_layer_output = tf.nn.relu(tf.matmul(tf_train_dataset, weights1) + biases1)
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logits = tf.matmul(hidden_layer_output, weights2) + biases2
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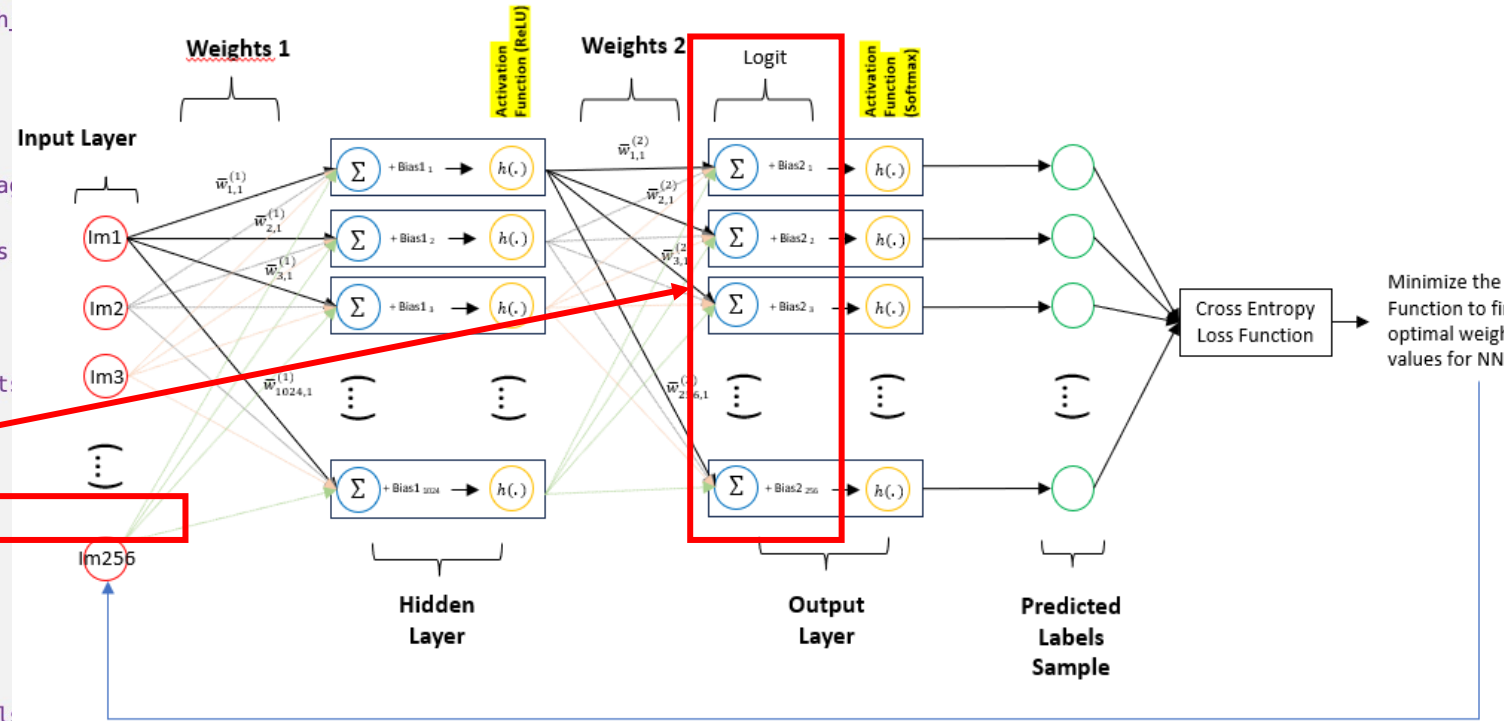
```
loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(labels=tf_train_labels, logits=logits) +
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```
optimizer = tf.compat.v1.train.GradientDescentOptimizer(0.008).minimize(loss)
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# Predictions for the training, validation, and test data.

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train_prediction = softmax_logits
valid_hidden_layer_output = tf.nn.relu(tf.matmul(tf_valid_dataset, weights1) + biases1)
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test_hidden_layer_output = tf.nn.relu(tf.matmul(tf_test_dataset, weights1) + biases1)
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```



```

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    # Input data placeholders
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    # Variables
    weights1 = tf.Variable(tf.random.truncated_normal([image_size * image_size, num_hidden_units]))
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    # Hidden layer computation with ReLU activation
    hidden_layer_output = tf.nn.relu(tf.matmul(tf_train_dataset, weights1) + biases1

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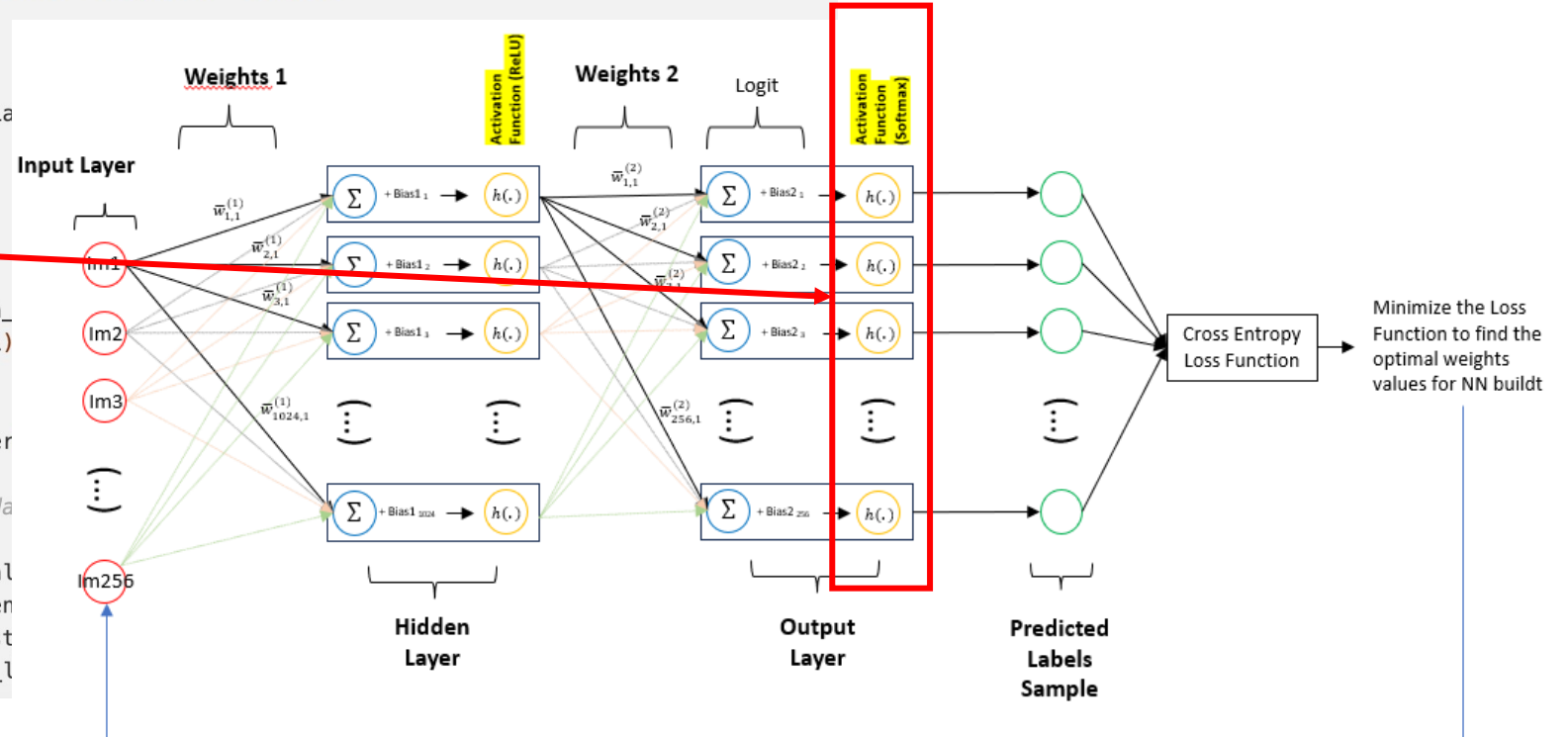
    # Softmax activation for logits
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    loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits, tf_train_labels) +
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    test_prediction = tf.nn.softmax(tf.matmul(test_hidden_layer_output, weights2) + biases2)

```





```

with graph.as_default():
    # Input data placeholders
    tf_train_dataset = tf.compat.v1.placeholder(tf.float32,
    tf_train_labels = tf.compat.v1.placeholder(tf.float32,
    tf_valid_dataset = tf.constant(X_valid)
    tf_test_dataset = tf.constant(X_test)

    # Variables
    weights1 = tf.Variable(tf.random.truncated_normal([img
    biases1 = tf.Variable(tf.zeros([num_hidden_units]))
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    # Hidden layer computation with ReLU activation
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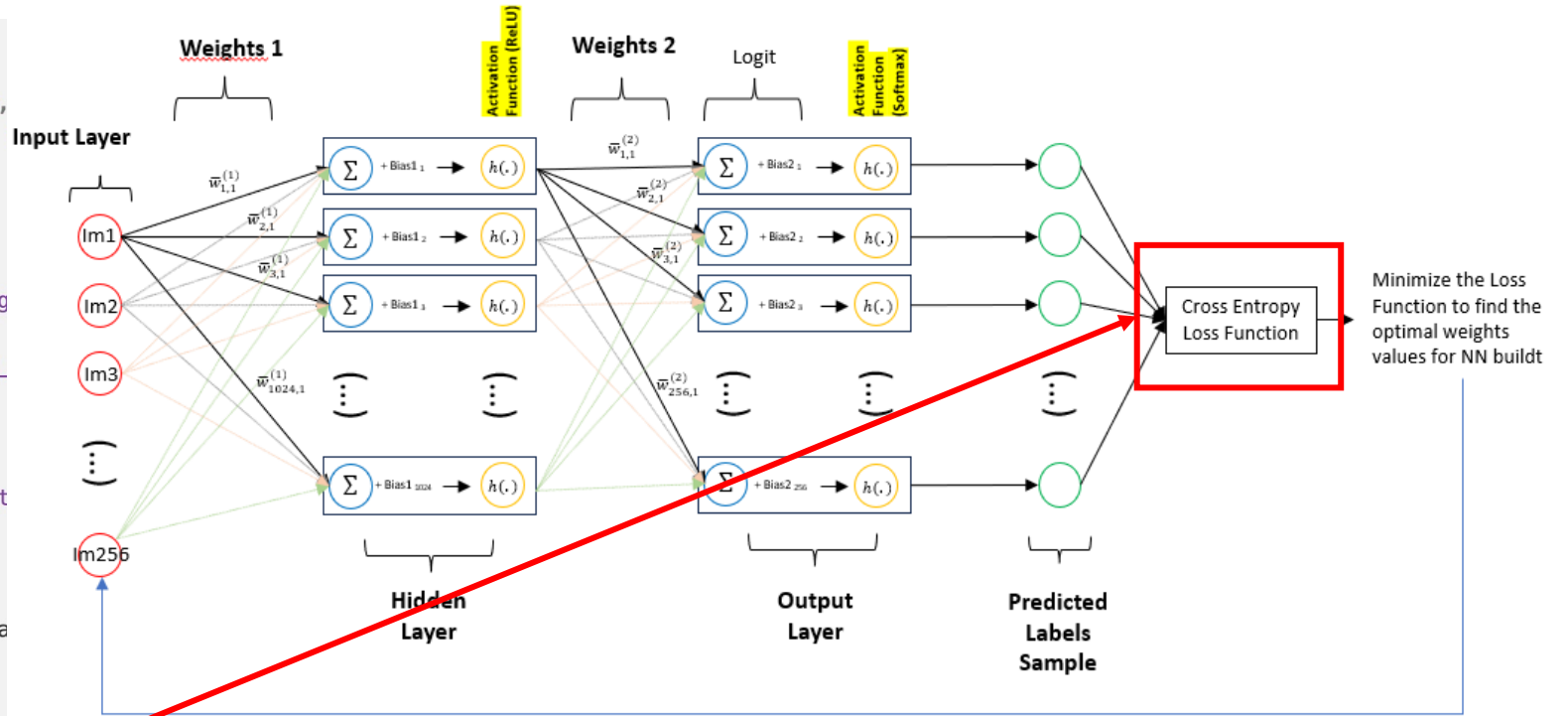
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    loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(labels=tf_train_labels, logits=softmax_logits) + \
    | | | | | lambda1 * tf.nn.l2_loss(weights1) + lambda2 * tf.nn.l2_loss(weights2))

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```



```

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    # Input data placeholders
    tf_train_dataset = tf.compat.v1.placeholder(tf.float32,
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    # Variables
    weights1 = tf.Variable(tf.random.truncated_normal([img
    biases1 = tf.Variable(tf.zeros([num_hidden_units]))
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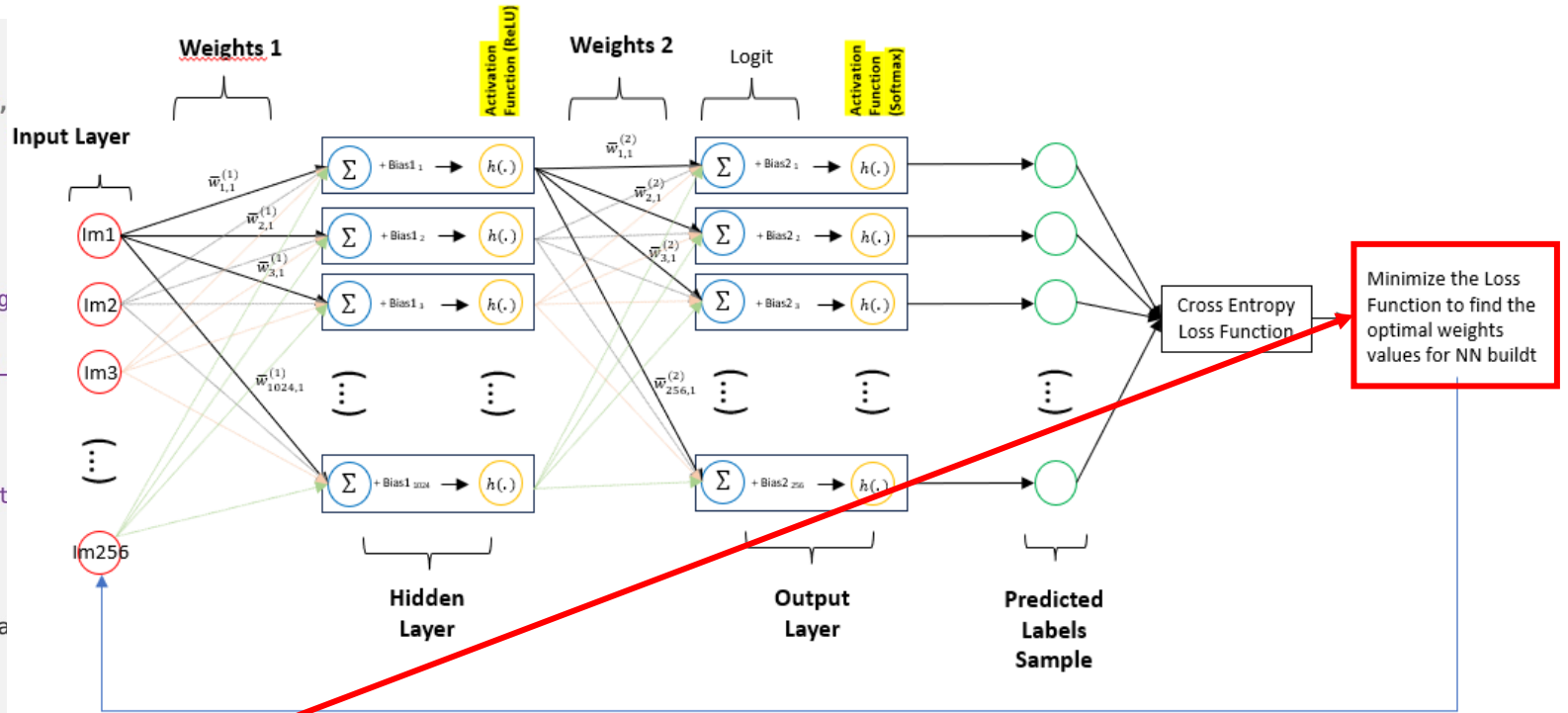
    # Softmax activation for logits
    softmax_logits = tf.nn.softmax(logits)

    # Loss computation
    loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(labels=tf_train_labels, logits=softmax_logits) + \
    | | | | | lambda1 * tf.nn.l2_loss(weights1) + lambda2 * tf.nn.l2_loss(weights2))

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    optimizer = tf.compat.v1.train.GradientDescentOptimizer(0.008).minimize(loss)

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    train_prediction = softmax_logits
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    valid_prediction = tf.nn.softmax(tf.matmul(valid_hidden_layer_output, weights2) + biases2)
    test_hidden_layer_output = tf.nn.relu(tf.matmul(tf_test_dataset, weights1) + biases1)
    test_prediction = tf.nn.softmax(tf.matmul(test_hidden_layer_output, weights2) + biases2)

```



“n” refers to the sample indice

Since is a 2-layer neural network, we have:  $y^n = h^{(2)}(\sum_{j=0}^M w_{kj}^{(2)} h^{(1)}(\sum_{i=0}^D w_{ji}^{(1)} x_i + bias1) + bias2)$

- Each sample will have  $y^n$  equation, for this case, we will have 256 for each iteration

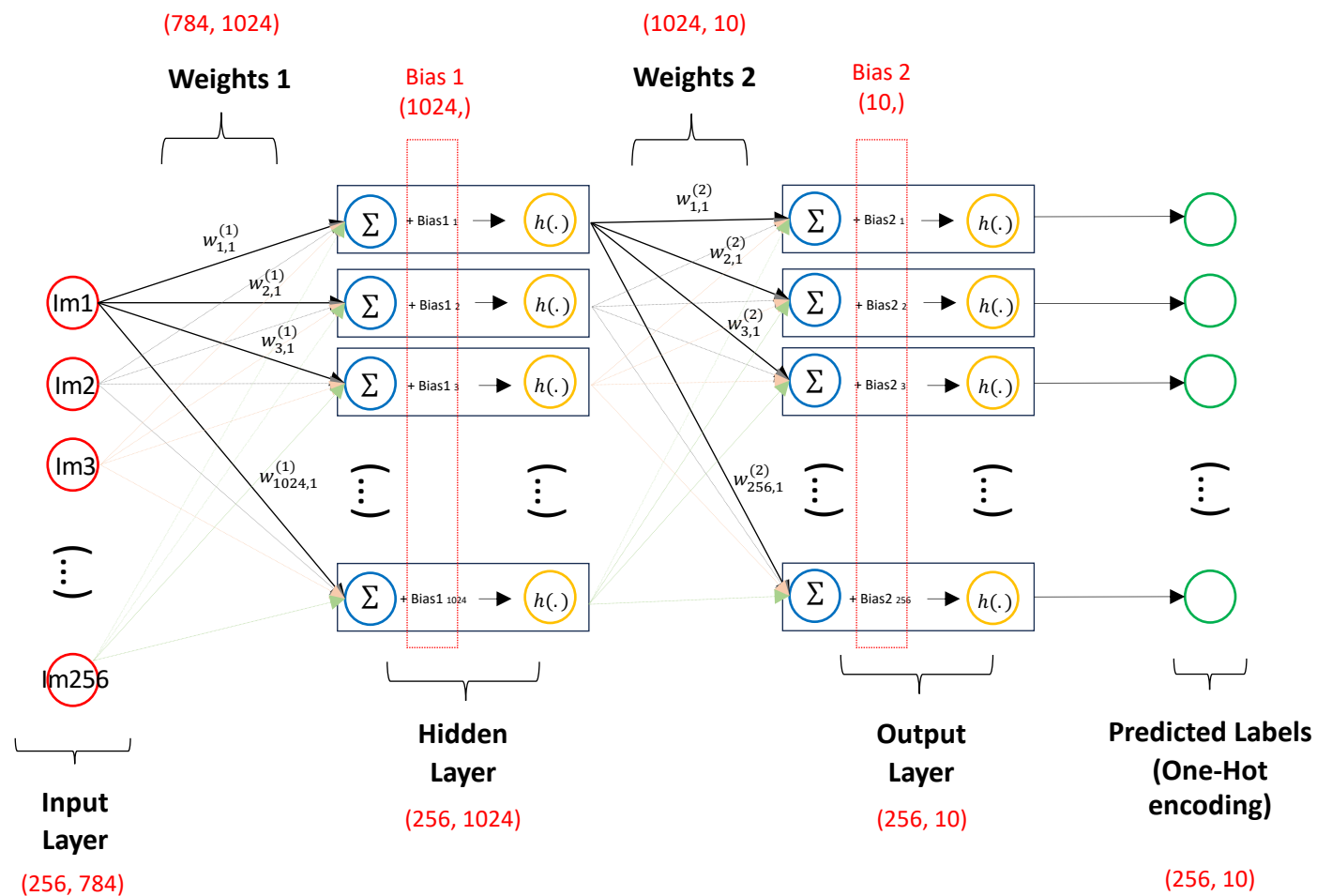
Cross Entropy Loss Function( $E$ ):  $min_{\underline{w}} - \sum_{n=1}^N t^n \log(y^n) + (1 - t^n) \log(1 - y^n)$

- We will have a sum of  $256 t^n \log(y^n) + (1 - t^n) \log(1 - y^n)$  for this example

Gradient Descent algorithm:  $\underline{w}^{i+1} = \underline{w}^i - \alpha \nabla_{\underline{w}} E$

- Will be done 6001 iterations

# Dimension Analysis:



Here is when the optimization part starts:

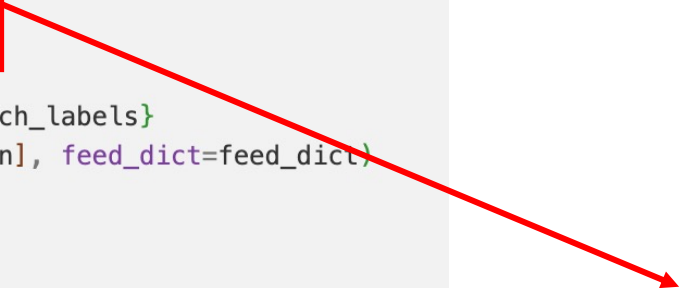
```
with tf.compat.v1.Session(graph=graph) as session:
    session.run(tf.compat.v1.global_variables_initializer())

    num_steps = 6001
    ll = []
    atr = []
    av = []

    for step in range(num_steps):
        offset = (step * batch_size) % (y_train.shape[0] - batch_size)
        batch_data = X_train[offset:(offset + batch_size), :]
        batch_labels = y_train[offset:(offset + batch_size), :]

        feed_dict = {tf_train_dataset : batch_data, tf_train_labels : batch_labels}
        _, l, predictions = session.run([optimizer, loss, train_prediction], feed_dict=feed_dict)

        if (step % 500 == 0):
            ll.append(l)
            a = accuracy(predictions, batch_labels)
            atr.append(a)
            print("Minibatch loss at step %d: %f" % (step, l))
            print("Minibatch accuracy: %.1f%%" % a)
            a = accuracy(valid_prediction.eval(), y_valid)
            av.append(a)
            print("Validation accuracy: %.1f%%" % a)
            print("Test accuracy: %.1f%%" % accuracy(test_prediction.eval(), y_test))
```



Since our Neural Network has only 256 input spot, we will divide our train dataset into mini batches

Here is when the optimization part starts:

```
with tf.compat.v1.Session(graph=graph) as session:
    session.run(tf.compat.v1.global_variables_initializer())

    num_steps = 6001
    ll = []
    atr = []
    av = []

    for step in range(num_steps):
        offset = (step * batch_size) % (y_train.shape[0] - batch_size)
        batch_data = X_train[offset:(offset + batch_size), :]
        batch_labels = y_train[offset:(offset + batch_size), :]

        feed_dict = {tf_train_dataset : batch_data, tf_train_labels : batch_labels}
        _, l, predictions = session.run([optimizer, loss, train_prediction], feed_dict)

        if (step % 500 == 0):
            ll.append(l)
            a = accuracy(predictions, batch_labels)
            atr.append(a)
            print("Minibatch loss at step %d: %f" % (step, l))
            print("Minibatch accuracy: %.1f%%" % a)
            a = accuracy(valid_prediction.eval(), y_valid)
            av.append(a)
            print("Validation accuracy: %.1f%%" % a)
            print("Test accuracy: %.1f%%" % accuracy(test_prediction.eval(), y_test))
```

This represents the total number of samples processed so far in the training loop



Here is when the optimization part starts:

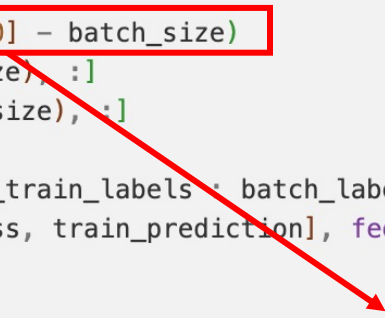
```
with tf.compat.v1.Session(graph=graph) as session:
    session.run(tf.compat.v1.global_variables_initializer())

    num_steps = 6001
    ll = []
    atr = []
    av = []

    for step in range(num_steps):
        offset = (step * batch_size) % (y_train.shape[0] - batch_size)
        batch_data = X_train[offset:(offset + batch_size), :]
        batch_labels = y_train[offset:(offset + batch_size), :]

        feed_dict = {tf_train_dataset : batch_data, tf_train_labels : batch_labels}
        _, l, predictions = session.run([optimizer, loss, train_prediction], feed_dict)

        if (step % 500 == 0):
            ll.append(l)
            a = accuracy(predictions, batch_labels)
            atr.append(a)
            print("Minibatch loss at step %d: %f" % (step, l))
            print("Minibatch accuracy: %.1f%%" % a)
            a = accuracy(valid_prediction.eval(), y_valid)
            av.append(a)
            print("Validation accuracy: %.1f%%" % a)
            print("Test accuracy: %.1f%%" % accuracy(test_prediction.eval(), y_test))
```



Represents the maximum valid indice value that will not exceed the bounds of the dataset.

Here is when the optimization part starts:

```
with tf.compat.v1.Session(graph=graph) as session:
    session.run(tf.compat.v1.global_variables_initializer())

    num_steps = 6001
    ll = []
    atr = []
    av = []

    for step in range(num_steps):
        offset = (step * batch_size) % (y_train.shape[0] - batch_size)
        batch_data = X_train[offset:(offset + batch_size), :]
        batch_labels = y_train[offset:(offset + batch_size), :]

        feed_dict = {tf_train_dataset : batch_data, tf_train_labels : batch_labels}
        _, l, predictions = session.run([optimizer, loss, train_prediction], feed_dict=feed_dict)

        if (step % 500 == 0):
            ll.append(l)
            a = accuracy(predictions, batch_labels)
            atr.append(a)
            print("Minibatch loss at step %d: %f" % (step, l))
            print("Minibatch accuracy: %.1f%%" % a)
            a = accuracy(valid_prediction.eval(), y_valid)
            av.append(a)
            print("Validation accuracy: %.1f%%" % a)
            print("Test accuracy: %.1f%%" % accuracy(test_prediction.eval(), y_test))
```

By doing the modulo operation at each step, we will find the indices for each mini batch.

This assures that we are getting different minibatches from training and also will wrap around once get to the end of the training dataset.



## An example:

```
X_train:
[[ 1.76405235  0.40015721  0.97873798]
 [ 2.2408932  1.86755799 -0.97727788]
 [ 0.95008842 -0.15135721 -0.10321885]
 [ 0.4105985  0.14404357  1.45427351]
 [ 0.76103773  0.12167502  0.44386323]
 [ 0.33367433  1.49407907 -0.20515826]
 [ 0.3130677  -0.85409574 -2.55298982]
 [ 0.6536186  0.8644362  -0.74216502]
 [ 2.26975462 -1.45436567  0.04575852]
 [-0.18718385  1.53277921  1.46935877]]
```

When the code wraps  
around once get to almost  
the end of the training  
dataset

```
batch_size = 3

y_train.shape[0] = 10
```

```
Step 0
Offset: 0
Batch Data:
[[ 1.76405235  0.40015721  0.97873798]
 [ 2.2408932  1.86755799 -0.97727788]
 [ 0.95008842 -0.15135721 -0.10321885]]
```

```
Step 1
Offset: 3
Batch Data:
[[ 0.4105985  0.14404357  1.45427351]
 [ 0.76103773  0.12167502  0.44386323]
 [ 0.33367433  1.49407907 -0.20515826]]
```

```
Step 2
Offset: 6
Batch Data:
[[ 0.3130677  -0.85409574 -2.55298982]
 [ 0.6536186  0.8644362  -0.74216502]
 [ 2.26975462 -1.45436567  0.04575852]]
```

```
Step 3
Offset: 2
Batch Data:
[[ 0.95008842 -0.15135721 -0.10321885]
 [ 0.4105985  0.14404357  1.45427351]
 [ 0.76103773  0.12167502  0.44386323]]
```

```
Step 4
Offset: 5
Batch Data:
[[ 0.33367433  1.49407907 -0.20515826]
 [ 0.3130677  -0.85409574 -2.55298982]
 [ 0.6536186  0.8644362  -0.74216502]]
```

$$\text{Offset} = (0 * 3) \% (10 - 3) = 0$$

$$\text{Offset} = (1 * 3) \% (10 - 3) = 3$$

- Since 3 cant be divided by 7, then offset will be 3

$$\text{Offset} = (2 * 3) \% (10 - 3) = 6$$

- Since 6 cant be divided by 7, then offset will be 6

$$\text{Offset} = (3 * 3) \% (10 - 3) = 2$$

- Since 9 can be divided by 7 once, then offset will be 2

$$\text{Offset} = (4 * 3) \% (10 - 3) = 5$$

- Since 12 can be divided by 7 once, then offset will be 5

Here is when the optimization part starts:

```
with tf.compat.v1.Session(graph=graph) as session:
    session.run(tf.compat.v1.global_variables_initializer())

    num_steps = 6001
    ll = []
    atr = []
    av = []

    for step in range(num_steps):
        offset = (step * batch_size) % (y_train.shape[0] - batch_size)
        batch_data = X_train[offset:(offset + batch_size), :]
        batch_labels = y_train[offset:(offset + batch_size), :]

        feed_dict = {tf_train_dataset : batch_data, tf_train_labels : batch_labels}
        _, l, predictions = session.run([optimizer, loss, train_prediction], feed_dict=feed_dict)

        if (step % 500 == 0):
            ll.append(l)
            a = accuracy(predictions, batch_labels)
            atr.append(a)
            print("Minibatch loss at step %d: %f" % (step, l))
            print("Minibatch accuracy: %.1f%%" % a)
            a = accuracy(valid_prediction.eval(), y_valid)
            av.append(a)
            print("Validation accuracy: %.1f%%" % a)
            print("Test accuracy: %.1f%%" % accuracy(test_prediction.eval(), y_test))
```

Creating a dictionary to be fed in to the placeholder that we have defined as input layers

Here is when the optimization part starts:

```
with tf.compat.v1.Session(graph=graph) as session:
    session.run(tf.compat.v1.global_variables_initializer())

    num_steps = 6001
    ll = []
    atr = []
    av = []

    for step in range(num_steps):
        offset = (step * batch_size) % (y_train.shape[0] - batch_size)
        batch_data = X_train[offset:(offset + batch_size), :]
        batch_labels = y_train[offset:(offset + batch_size), :]

        feed_dict = {tf.train.dataset : batch_data, tf.train.labels : batch_labels}
        _, l, predictions = session.run([optimizer, loss, train_prediction], feed_dict=feed_dict)

        if (step % 500 == 0):
            ll.append(l)
            a = accuracy(predictions, batch_labels)
            atr.append(a)
            print("Minibatch loss at step %d: %f" % (step, l))
            print("Minibatch accuracy: %.1f%%" % a)
            a = accuracy(valid_prediction.eval(), y_valid)
            av.append(a)
            print("Validation accuracy: %.1f%%" % a)
            print("Test accuracy: %.1f%%" % accuracy(test_prediction.eval(), y_test))
```

Creating a dictionary to be fed in to the placeholder that we have defined as input layers

## Logic behind session run() :

session run() receives 2 inputs, session.run(fetches, feed\_dict)

- fetches: This is where you specify what you want to compute or evaluate. It can be a single TensorFlow tensor or operation, or a list of tensors/operations.
- feed\_dict (optional): If you have placeholders in your computation graph that need to be provided with actual data, you use a feed\_dict dictionary to feed data into those placeholders during the session execution. It's used to map placeholders to the actual data you want to use for that particular run.

### Example

```
# Create a session
with tf.compat.v1.Session() as session:
    # Define tensors
    a = tf.constant(3)
    b = tf.constant(5)

    # Add tensors and evaluate
    sum_result = session.run(a + b)
    print("Sum result:", sum_result) # Output: 8

    # Using a feed_dict
    x = tf.compat.v1.placeholder(tf.float32)
    y = x * 2
    feed_dict = {x: 5.0}
    product_result = session.run(y, feed_dict=feed_dict)
    print("Product result:", product_result) # Output: 10.0
```

## In case of Neural Networks:

session.run() receives:

- fetches: [optimizer, loss, train\_prediction]
- feed\_dict (optional): `feed_dict = {tf_train_dataset : batch_data, tf_train_labels : batch_labels}`

“optimizer” do the following calculations:

- Optimizer will do the forward pass starting with random weights and bias values

$$y^n = h^{(2)}\left(\sum_{j=0}^M w_{kj}^{(2)} h^{(1)}\left(\sum_{i=0}^D w_{ji}^{(1)} x_i + bias1\right) + bias2\right)$$

- Then runs the gradient descent algorithm

Computing  $\nabla_{\underline{w}} E$  from Cross Entropy Loss Function( $E$ ):  $\min_{\underline{w}} - \sum_{n=1}^N t^n \log(y^n) + (1 - t^n) \log(1 - y^n)$

Gradient Descent algorithm:  $\underline{w}^{i+1} = \underline{w}^i - \alpha \nabla_{\underline{w}} E$

In case of Neural Networks:

session run() receives:

- fetches: [optimizer, loss, train\_prediction]
- feed\_dict (optional): `feed_dict = {tf_train_dataset : batch_data, tf_train_labels : batch_labels}`

“loss” and “train” are given to fetches to calculate the loss over each iteration and get the predicted labels from the training process

Here is when the optimization part starts:

```
with tf.compat.v1.Session(graph=graph) as session:
    session.run(tf.compat.v1.global_variables_initializer())


    num_steps = 6001
    ll = []
    atr = []
    av = []

    for step in range(num_steps):
        offset = (step * batch_size) % (y_train.shape[0] - batch_size)
        batch_data = X_train[offset:(offset + batch_size), :]
        batch_labels = y_train[offset:(offset + batch_size), :]

        feed_dict = {tf_train_dataset : batch_data, tf_train_labels : batch_labels}
        _, l, predictions = session.run([optimizer, loss, train_prediction], feed_dict=feed_dict)

        if (step % 500 == 0):
            ll.append(l)
            a = accuracy(predictions, batch_labels)
            atr.append(a)
            print("Minibatch loss at step %d: %f" % (step, l))
            print("Minibatch accuracy: %.1f%%" % a)
            a = accuracy(valid_prediction.eval(), y_valid)
            av.append(a)
            print("Validation accuracy: %.1f%%" % a)
            print("Test accuracy: %.1f%%" % accuracy(test_prediction.eval(), y_test))
```

Finally we compute some graphs to analyze the loss decay and accuracy



# Keras CNN











