CT5133 - Deep Learning Assignment: 1

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Group Member 2: Manish Agarwal (19230064)

Work done by each member are mentioned on each code chuncks.

Part A - Feed Forward Neural Network with Back Propagation

In this section we are creating a fully connected feed forward neural network. (2 successive layers represents a bipartite graph)

Neural Network operates back and forth based on the below mentioned mechanism -

Feed Forward

Input signals are multiplied based on the connection weights and carried forward to the corresponding hidden nodes. The proces repeats until all the hidden layers are surpassed and finally we arrive at an output value.

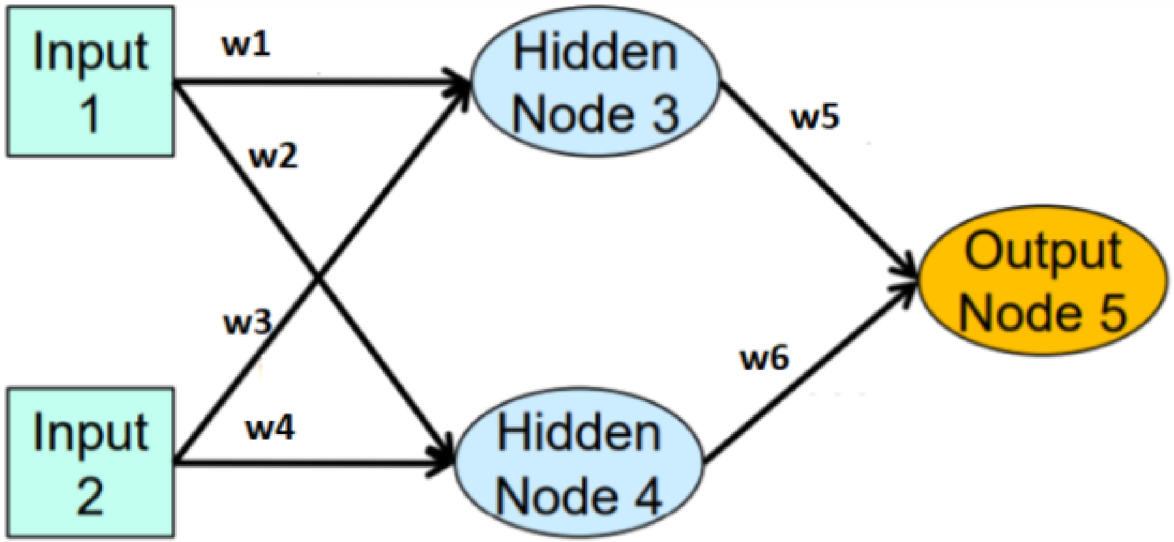
BackPropagation

Here we compute the error between our actual and predicted value based on cost function and initiate gradient descent to optimise each weights. Here weight gradients are propagated backwards to update each weights according to their contribution towards error.

Apart from the above mechanism explained activation function that takes sum of weighted inputs and passes it through a range function that produce values within a range. Ex: Sigmoid (range - (0 -1)) & RELU (range (0 - max)) functions.

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report

sns.set()
```

Backpropagation explained



Darivatives using chain rule.

$$\frac{\partial E}{\partial W5} = \frac{\partial E}{\partial O} * \frac{\partial O}{\partial So} * \frac{\partial So}{\partial W5}$$ (Similarly for w6)

$$\frac{\partial E}{\partial W1} = \frac{\partial E}{\partial O} * \frac{\partial O}{\partial So} * \frac{\partial So}{\partial h1} * \frac{\partial h1}{\partial Sh} * \frac{\partial Sh}{\partial W1}$$ (Similarly for w2,w3,w4)

Here

E = Error function
O = Output activation
So = Output Summation

W = Weights
h = Hidden layer activation
Sh = Hidden layer summation

Bias weight updation is also done similar to above illustration, derivative values are shown below

$$Error = 1/2 \sum_{i=1}^{m} (Predicted - Actual)^2$$

$$Weight_{summation} = \sum w_i x_i + bias$$

$$O = Activation = \frac{1}{(1 + e^{-Wsum})}$$

$$\frac{\partial O}{\partial So} = O * (1 - O)$$

[Here O represents value after activation)

$$\frac{\partial E}{\partial O} = Predicted - Actual$$

$$\frac{\partial So}{\partial W_i} = x_i$$

$$\frac{\partial So}{\partial h_i} = W_i$$

$$\frac{\partial So}{\partial b} = 1$$

Class FF_Neural_Net

Method Adopted:

```
- Stochastic Gradient Descent
- Cost function - Sum of squared errors
- 20 % of epoch data used for Cross Validation
- Input Nodes - Customisable
- 1 hidden layer - Fixed
- Hidden Layer Nodes Customisable
- 1 Output layer - Fixed
```

Parmeters Available:

```
-Epoch
-Learning rate
-Input nodes
-Hidden nodes
```

Methods Available:

```
- Train() --> Starts training Neural Network as per the parameters passed while object creation
- Test() --> Takes in test data and returns the ouput label
- Get_cost_epoch() ---> Return dictionary with cost @ each epoch
```

NOTE :

- Variable names assigned in backpropagation are as per the naming convention followed in the above image
- On each epoch holding out 20% data drawn at random from train set for cross validation, to inspect overfitting.

```
In [2]: class FF_Neural_Net():



            def __init__ (self,train_data,hidden_nodes,epoch,learning_rate):

                'Author: Seshadri Sundarrajan'

                np.random.seed(10)

                # Storing values between 0.25 and 0.75
                weight_values = [val/100 for val in range(25,75)]

                self.train_data = train_data
                self.input_nodes = train_data.shape[1] - 1
                self.hidden_nodes = hidden_nodes
                self.epoch = epoch
                self.alpha  = learning_rate
                self.error_epoch = {}

                #held out
                self.held_out = (int((len(self.train_data) * 80 ) / 100),len(self.train_data))

                # Input layer =  2 nodes & Hidden layer = 4 nodes
                self.input_layer = range(0,self.input_nodes)
                self.hidden_layer_1 = range(0,self.hidden_nodes)

                # Bias have constant value +1 and weights are initialised with 0.5
                self.b0 = np.random.choice(weight_values,size=len(self.hidden_layer_1),replace=True)
                self.b1 = 0.5

                # Generating random weights for where row = No of hidden layer & column = No of inputs
                self.hidden_layer1_weights = np.random.choice(weight_values,size=[len(self.hidden_layer_1),len(self.input_layer)],repla
        ce=True)


                # Updating Output layer weights randomly
                self.output_layer_weights = np.round(np.random.rand(len(self.hidden_layer_1)),2)


            'Author for below 3 functions: Manish Agarwal'

            def get_sigmoid_derivative(self,x):
                return x*(1-x)
```

```python
    def get_sigmoid (self,x):
        return 1 / (1+np.exp(-x))

    def get_cost_epoch(self):
        return self.error_epoch




    def train(self):

        'Author - Seshadri Sundarrajan'

        #Function to train the NN -  Initiates Feed forward and Back propagation iteratively

        for epoch in range(1,self.epoch+1):
            errors = []
            train = self.train_data.values
            np.random.shuffle(train)
            training_set = train[0:self.held_out[0]]
            cv_data = train[self.held_out[0]:self.held_out[1]]

            for row in training_set:

                ip_array = row[:len(self.input_layer)]

                #Feed forward --- Performing summation using matrix multiplication and adding bias to the result
                'Feed forward code Author: Manish Agarwal'

                # 1) Summation of Wi*xi  + c
                hl1_weights = self.hidden_layer1_weights.transpose()
                hl1_summation = ip_array.dot(hl1_weights) + np.array(self.b0)
                hl1_activation = self.get_sigmoid(hl1_summation)


                # 2) Summation and activation operations from hidden to output layer

                o_weights = self.output_layer_weights.transpose()
                o_summation = hl1_activation.dot(o_weights) + self.b1
                o_activation = self.get_sigmoid(o_summation)


                # Calculating Cost/error function
                error = 0.5 * ((o_activation - row[-1])**2)
                errors.append(error.item())
```

```
#Backpropagation - Variable names assigned as per the notation expained in the derivation above
'Backpropagation code Author: Seshadri Sundarrajan'

# Derivative of E/O
dE_dO = o_activation - row[-1]

# Derivative of Output activation fn
dO_dSo = self.get_sigmoid_derivative(o_activation)

#Output layer weights
dSo_dWo = hl1_activation

dE_dSo = dE_dO * dO_dSo

dE_dWo = dE_dSo * dSo_dWo

dE_dBo = dE_dSo # as bias value is 1

#Hidden layer weights

dSo_dH = self.output_layer_weights

dH_dSh = self.get_sigmoid_derivative(hl1_activation)

dSo_dSh = np.multiply(dSo_dH,dH_dSh)

dE_dSh = np.reshape( dE_dO * dO_dSo * dSo_dSh ,newshape = (len(self.hidden_layer_1),1))
dSh_dWh = ip_array.reshape(1,len(self.input_layer))


dE_dWh = dE_dSh.dot(dSh_dWh)

# dE_dBh = dE_dSh    as bias value is 1

#Updating output layer weights
self.output_layer_weights =  self.output_layer_weights- (self.alpha * dE_dWo)

self.b1 = self.b1 - (self.alpha* dE_dBo)


#Updating hidden layer weights
self.hidden_layer1_weights =  self.hidden_layer1_weights - (self.alpha*dE_dWh)

self.b0 = self.b0 - (self.alpha * dE_dSh.reshape(1,len(self.hidden_layer_1))[0])
```

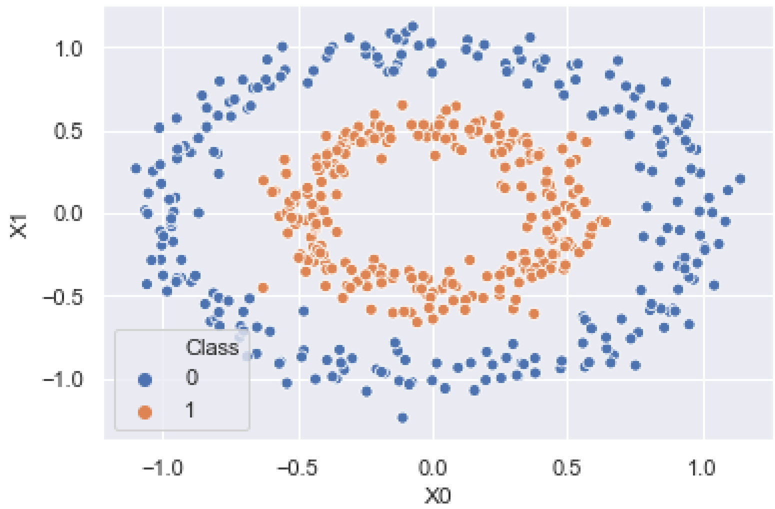
```
            self.error_epoch[epoch] = np.mean(errors)
            if (epoch % 10 == 0) or (epoch == 1) :
                op = self.test(cv_data)
                acc= accuracy_score(cv_data[:,-1], op)
                print('Epoch {} - Error = {} - CV accuracy - {}'.format(epoch,np.mean(errors),acc))




    def test(self,test):
        'Author: Manish Agarwal'

        op = []

        for i in test:

            ip_array = i[:len(self.input_layer)]

            'Feed forward --- Performing summation using matrix multiplication and adding bias to the result'

            # 1) Summation of Wi*xi  + c
            hl1_weights = self.hidden_layer1_weights.transpose()
            hl1_summation = ip_array.dot(hl1_weights) + np.array(self.b0)

            # 2) Sigmoid activation
            hl1_activation = 1 / ( 1 + np.exp(-hl1_summation))

            # 3) Summation and activation operations from hidden to output layer

            o_weights = self.output_layer_weights.transpose()
            o_summation = hl1_activation.dot(o_weights) + self.b1
            o_activation = 1 / ( 1 + np.exp(-o_summation))

            if o_activation > 0.5:
                o = 1
            else:
                o = 0
            op.append(o)

        return op
```

PART - B - Testing the NN on circles datset

Train to Test ratio - 3 : 1

In [3]:
```
'Author: Manish Agarwal'

df = pd.read_csv('circles500.csv')


train = df.iloc[:375]
test = df.iloc [375:]
sns.scatterplot(x='X0',y='X1',data=df,hue='Class')
```

Out[3]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x227c201ca90>
```



Model Parameters

- Epoch = 100 (Inspected with smaller epochs but model was underfit)
- Hidden Nodes = 3 (Since we have only 2 inputs increasing the number of nodes might just extrapolate the combinations)
- Learning Rates = 0.5 (Its chosen to be high as we are dealing with a small dataset and conversely if its decreased number of epochs needed for convergence also increases and inturns becomes computationally intensive).

In [4]:
```
'Author: Seshadri Sundarrajan'


nn = FF_Neural_Net(train,hidden_nodes = 3 ,epoch=100,learning_rate = 0.5)


nn.train()

er_epoch = nn.get_cost_epoch()

op = nn.test(test.values)

cm = confusion_matrix(test.iloc[:,2].values, op)
print('\nConfusion Matrix\n{}'.format(cm))


acc= accuracy_score(test.iloc[:,2], op)
print('\nAccuracy of the model - {}\n'.format(acc))


print('\nClassification Report\n\n{}\n'.format(classification_report(test.iloc[:,2], op, target_names=['pos', 'neg'])))
```

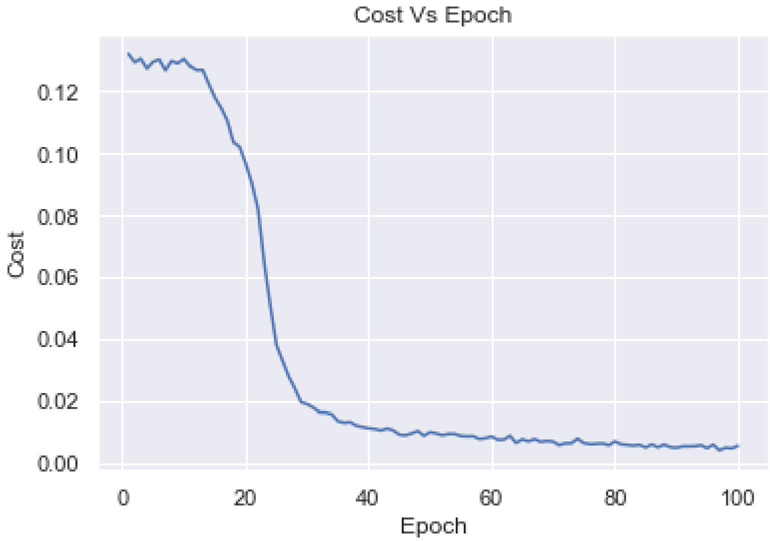
```
Epoch 1 - Error = 0.13197432475996246 - CV accuracy - 0.5333333333333333
Epoch 10 - Error = 0.13037305939899924 - CV accuracy - 0.5866666666666667
Epoch 20 - Error = 0.0966868819870413 - CV accuracy - 0.7466666666666667
Epoch 30 - Error = 0.018989329688035572 - CV accuracy - 0.9733333333333334
Epoch 40 - Error = 0.011277707019171182 - CV accuracy - 0.9866666666666667
Epoch 50 - Error = 0.010026882897554493 - CV accuracy - 1.0
Epoch 60 - Error = 0.00865304659072023 - CV accuracy - 1.0
Epoch 70 - Error = 0.006974883994799208 - CV accuracy - 0.9866666666666667
Epoch 80 - Error = 0.00704732384303246 - CV accuracy - 1.0
Epoch 90 - Error = 0.005007929119736312 - CV accuracy - 0.9866666666666667
Epoch 100 - Error = 0.005609652062655125 - CV accuracy - 1.0

Confusion Matrix
[[60  0]
 [ 1 64]]

Accuracy of the model - 0.992


Classification Report

              precision    recall  f1-score   support

         pos       0.98      1.00      0.99        60
         neg       1.00      0.98      0.99        65

    accuracy                           0.99       125
   macro avg       0.99      0.99      0.99       125
weighted avg       0.99      0.99      0.99       125
```

Error VS Epoch

We can see that after epoch 40 the model has converged and we have reached the minima and the corresponding graph is plotted below

In [5]:
```
'Author: Seshadri Sundarrajan'

plt.plot(list(er_epoch.keys()),list(er_epoch.values()))
plt.title('Cost Vs Epoch')
plt.xlabel('Epoch')
plt.ylabel('Cost')
```

Out[5]:
```
Text(0, 0.5, 'Cost')
```



Model Performance

Performace of the model is good as Accuracy and F1 score are 98 % . Model was able to perform well on the validation set as epoch increases and converges quickly. There is no trace of overfitting as we can't see any significant difference between validation set accuracy and test accuracy.

Inference :

Keeping in mind the dataset volume and set of variables involved, 1 layer Neural Network is performing better. As ANN are able to capture non-linearity the data on hand is perfectly non linear without much of noise. Hence we obtain precise classification.

Part 3 - CIFAR

Note - Code adopted to load CIFAR dataset into Jupyter notebook was taken from the Notebook shared as reference to this assignment.

In [6]:
```
# This function taken from the CIFAR website

def unpickle(file):
    import pickle
    with open(file, 'rb') as fo:
        dict = pickle.load(fo, encoding='bytes')
    return dict
```

Chose Batch1 as the subset for CIFAR NN implementation throughout this report

In [7]:
```
# Below functions was taken from the CIFAR Notebook shared for reference - Author Michael Madden

def loadbatch(batchname):
    folder = 'cifar-10-batches-py'
    batch = unpickle(folder+"/"+batchname)
    return batch

def loadlabelnames():
    folder = 'cifar-10-batches-py'
    meta = unpickle(folder+"/"+'batches.meta')
    return meta[b'label_names']

def visualise(data, index):

    picture = data[index]
    picture.shape = (3,32,32)
    picture = picture.transpose([1, 2, 0])
    plt.imshow(picture)
    plt.show()



batch1 = loadbatch('data_batch_1')
data = batch1[b'data']
labels = batch1[b'labels']
names = loadlabelnames()
```

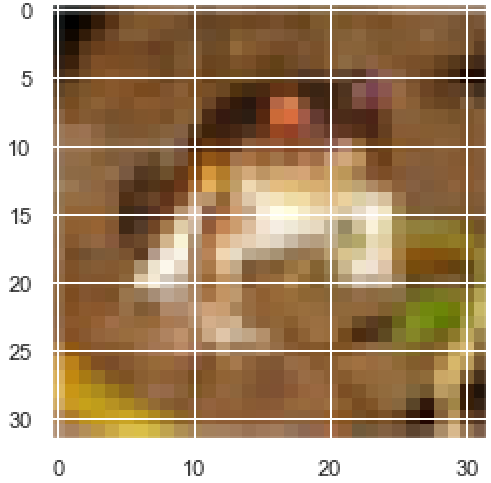
Classes given for classification -> Frog - 6 and Horse - 7

In [8]:
```
'Author : Seshadri Sundarrajan'

frog_horse_dict = {idx : 0 if lab == 6 else 1 for idx,lab in enumerate(labels) if lab in (6,7)}
data_fh = data[list(frog_horse_dict.keys())]
```

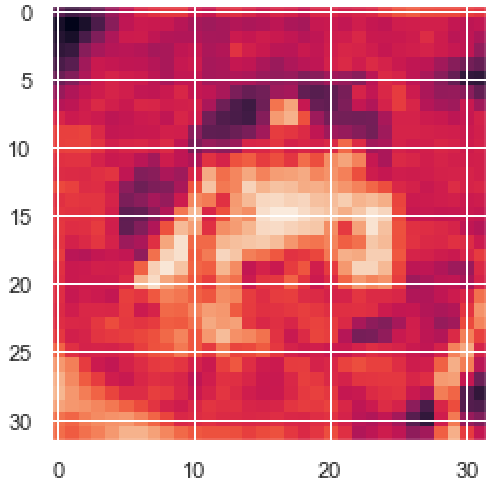
In [9]:

```
'Author: Manish Agarwal'

# Display  images from the batch
for i in range (0,2):
    print('Actual Image')
    visualise(data_fh, i)
    RGB =  data_fh[i].reshape(3,32,32)
    R,G,B = RGB[0],RGB[1],RGB[2]
    print('Actual image with only red channel')
    plt.imshow(R)
    plt.show()
```

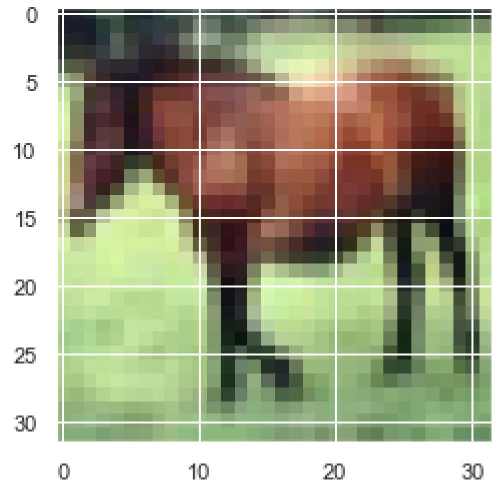
Actual Image



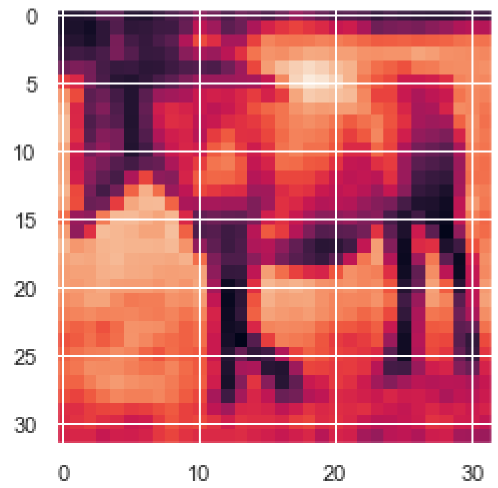
Actual image with only red channel



Actual Image



Actual image with only red channel



Filtering only Red channel values and normalised using max value

In [10]:
```
'Author : Seshadri Sundarrajan'

cifr_df = pd.DataFrame(data_fh)
cifr_df = cifr_df.iloc[:,:1024] # filtering only red channel values

# Max normalisation
cifr_df = cifr_df/255
cifr_df['labels'] = list(frog_horse_dict.values())
```

CIFR dataset for classes frog and horse

In [11]:
```
cifr_df
```

Out[11]:

	0	1	2	3	4	5	6	7	8	9	...	1015	1016	1017	1018	10
0	0.231373	0.168627	0.196078	0.266667	0.384314	0.466667	0.545098	0.568627	0.584314	0.584314	...	0.466667	0.509804	0.470588	0.360784	0.4039
1	0.109804	0.117647	0.129412	0.243137	0.247059	0.121569	0.113725	0.164706	0.215686	0.262745	...	0.384314	0.462745	0.474510	0.439216	0.5098
2	0.556863	0.674510	0.690196	0.725490	0.847059	0.882353	0.776471	0.509804	0.462745	0.513725	...	0.698039	0.592157	0.337255	0.298039	0.5647
3	0.643137	0.635294	0.635294	0.639216	0.635294	0.639216	0.643137	0.643137	0.647059	0.647059	...	0.521569	0.509804	0.509804	0.505882	0.5019
4	0.090196	0.184314	0.203922	0.352941	0.533333	0.745098	0.572549	0.200000	0.286275	0.415686	...	0.745098	0.737255	0.745098	0.760784	0.7568
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
2026	0.321569	0.407843	0.447059	0.392157	0.392157	0.427451	0.435294	0.388235	0.372549	0.392157	...	0.529412	0.682353	0.811765	0.658824	0.5176
2027	0.121569	0.184314	0.203922	0.160784	0.141176	0.160784	0.164706	0.160784	0.152941	0.141176	...	0.666667	0.831373	0.874510	0.674510	0.6117
2028	0.388235	0.368627	0.290196	0.262745	0.235294	0.286275	0.282353	0.294118	0.254902	0.372549	...	0.298039	0.203922	0.184314	0.184314	0.2627
2029	0.423529	0.431373	0.450980	0.470588	0.462745	0.450980	0.450980	0.478431	0.513725	0.498039	...	0.729412	0.796078	0.850980	0.882353	0.8745
2030	0.368627	0.360784	0.325490	0.400000	0.396078	0.364706	0.345098	0.423529	0.427451	0.403922	...	0.003922	0.000000	0.003922	0.007843	0.0078

2031 rows × 1025 columns

CIFAR Test - Train split is in the ratio 1: 3

In [12]:
```
'Author: Manish Agarwal'

train_cifr = cifr_df.iloc[:1550]
test_cifr = cifr_df.iloc [1550:]
```

Model Parameters

- Hidden nodes = 50 (1/20 of the input)
- Epoch = 200 (As the hidden nodes are limited using higher epoch)
- Learning rate = 0.1

In [13]:
```
'Author : Seshadri Sundarrajan'


# best params 10 hiden nodes and 0.1 & 80 % held out
nn = FF_Neural_Net(train_cifr,hidden_nodes = 50 ,epoch=200,learning_rate = 0.1)

nn.train()

op = nn.test(test_cifr.values)


cm = confusion_matrix(test_cifr.iloc[:,-1].values, op)
print('\nConfusion Matrix\n{}'.format(cm))

acc= accuracy_score(test_cifr.iloc[:,-1], op)
print('\nAccuracy of the model - {}\n'.format(acc))
```

```
Epoch 1 - Error = 0.2532258064242088 - CV accuracy - 0.4838709677419355
Epoch 10 - Error = 0.2568548386818804 - CV accuracy - 0.5129032258064516
Epoch 20 - Error = 0.2572580644882884 - CV accuracy - 0.5161290322580645
Epoch 30 - Error = 0.2572580644882883 - CV accuracy - 0.5161290322580645
Epoch 40 - Error = 0.25322580642420855 - CV accuracy - 0.4838709677419355
Epoch 50 - Error = 0.25040322577935276 - CV accuracy - 0.4612903225806452
Epoch 60 - Error = 0.25282258061780055 - CV accuracy - 0.4806451612903226
Epoch 70 - Error = 0.2560483870690643 - CV accuracy - 0.5064516129032258
Epoch 80 - Error = 0.25604838706906413 - CV accuracy - 0.5064516129032258
Epoch 90 - Error = 0.25806451610110404 - CV accuracy - 0.5225806451612903
Epoch 100 - Error = 0.2508064515857604 - CV accuracy - 0.4645161290322581
Epoch 110 - Error = 0.25040322577935237 - CV accuracy - 0.4612903225806452
Epoch 120 - Error = 0.2540322580370242 - CV accuracy - 0.49032258064516127
Epoch 130 - Error = 0.24758064513449643 - CV accuracy - 0.43870967741935485
Epoch 140 - Error = 0.2467741935216805 - CV accuracy - 0.432258064516129
Epoch 150 - Error = 0.2552419354562479 - CV accuracy - 0.5
Epoch 160 - Error = 0.25443548384343195 - CV accuracy - 0.4935483870967742
Epoch 170 - Error = 0.24999999997294423 - CV accuracy - 0.45806451612903226
Epoch 180 - Error = 0.25685483868187964 - CV accuracy - 0.5129032258064516
Epoch 190 - Error = 0.2504032257793521 - CV accuracy - 0.4612903225806452
Epoch 200 - Error = 0.2552419354562476 - CV accuracy - 0.5

Confusion Matrix
[[  0 242]
 [  0 239]]

Accuracy of the model - 0.4968814968814969
```

Model Performance

The 1 layer NN constructed in this part is doing badly for the CIFAR data . We can witness 'Accuracy Paradox' where the model just lables all instances as 0 or 1. Overall performance is poor and model is clearly underfit.

Reasons for the above mentioned behaviour -

- Since NN is fully connected, hidden layer nodes can extract specific features and gets confused by all signals from all input nodes.
- Image classification needs to be dealt as Convolutional neural network problem, where image data is processed using convolution & pooling layers to extract the spatial feature along with dimensionality reduction and later passed into a Fully connected network. But here image preprocessing part is not done and actual data is directly fed to network

Part 4 Enhancement

Group Member 1 : Seshadri Sundarrajan - "Two layer Fully Connected Neural Network"

Group Member 2 : Manish Agarwal - " Effect of RELU activation"

1) Two layered Network - (Author - Seshadri Sundarrajan)

Class FF_Neural_Net

Method Adopted:

```
- Stochastic Gradient Descent
- Cost function - Sum of squared errors
- 20 % of epoch data used for Cross Validation
- Input Nodes - Customisable
- 2 hidden layer - Fixed
- Hidden Layer Nodes Customisable
- 1 Output layer - Fixed
```

Parmeters Available:

```
-Epoch
-Learning rate
-Input nodes
-Hidden layer nodes
```

Methods Available:

```
- Train() --> Starts training Neural Network as per the parameters passed while object creation
- Test() --> Takes in test data and returns the ouput label
- Get_cost_epoch() ---> Return dictionary with cost @ each epoch
```

NOTE :

- Reusing the class defined earlier for 1 layer NN with some modifications.
- Variable names assigned in backpropagation are as per the naming convention followed in the above image
- On each epoch holding out 20% data drawn at random from train set for cross validation, to inspect overfitting.

In [14]:
```
class FF_Neural_Net2():

    'Author : Seshadri Sundarrajan'
    def __init__ (self,train_data,hidden_layer_1_nodes,epoch,learning_rate,hidden_layer_2_nodes):

        np.random.seed(10)

        # Storing values between 0.25 and 0.75
        weight_values = [val/100 for val in range(-75,75)]

        self.train_data = train_data
        self.input_nodes = train_data.shape[1] -1
        self.hidden_nodes = hidden_layer_1_nodes
        self.epoch = epoch
        self.alpha  = learning_rate
        self.error_epoch = {}
        self.hidden_layer_2_nodes = hidden_layer_2_nodes

        #held out
        self.held_out = (int((len(self.train_data) * 80 ) / 100),len(self.train_data))

        # Input layer =  2 nodes & Hidden layer = 4 nodes
        self.input_layer = range(0,self.input_nodes)
        self.hidden_layer_1 = range(0,self.hidden_nodes)
        self.hidden_layer_2 = range(0,self.hidden_layer_2_nodes)

        # Bias have constant value +1 and weights are initialised with 0.5
        self.b0 = np.random.choice(weight_values,size=len(self.hidden_layer_1),replace=True)
        self.b1 = np.random.choice(weight_values,size=len(self.hidden_layer_2),replace=True)
        self.b2 = 0.5

        # Generating random weights for where row = No of hidden layer & column = No of inputs
        self.hidden_layer1_weights = np.random.choice(weight_values,size=[len(self.hidden_layer_1),len(self.input_layer)],repla
ce=True)
        self.hidden_layer2_weights = np.random.choice(weight_values,size=[len(self.hidden_layer_2),len(self.hidden_layer_1)],re
place=True)

        # Updating Output layer weights randomly
        self.output_layer_weights = np.round(np.random.rand(len(self.hidden_layer_2)),2)


    def get_sigmoid_derivative(self,x):
        return x*(1-x)

    def get_sigmoid (self,x):
```

```
        return 1 / (1+np.exp(-x))


    def train(self):

        for epoch in range(1,self.epoch+1):
            errors = []
            train = self.train_data.values
            np.random.shuffle(train)
            training_set = train[0:self.held_out[0]]
            cv_data = train[self.held_out[0]:self.held_out[1]]

            for row in training_set:




                ip_array = row[:len(self.input_layer)]

                'Feed forward --- Performing summation using matrix multiplication and adding bias to the result'

                # 1) Summation of Wi*xi  + c
                hl1_weights = self.hidden_layer1_weights.transpose()
                hl1_summation = ip_array.dot(hl1_weights) + np.array(self.b0)
                hl1_activation = self.get_sigmoid(hl1_summation)


                hl2_weights = self.hidden_layer2_weights.transpose()
                hl2_summation = hl1_activation.dot(hl2_weights) + np.array(self.b1)
                hl2_activation = self.get_sigmoid(hl2_summation)

                # 2) Summation and activation operations from hidden to output layer

                o_weights = self.output_layer_weights.transpose()
                o_summation = hl2_activation.dot(o_weights) + self.b2
                o_activation = self.get_sigmoid(o_summation)


                # Calculating Cost/error function
                error = 0.5 * ((o_activation - row[-1])**2)
                errors.append(error.item())



                'Backpropagation - Variable names assigned as per the notation followed in the derivatives explained in the abo
ve picture'
```

```
# Derivative of E/O
dE_dO = o_activation - row[-1]

# Derivative of Output activation fn
dO_dSo = self.get_sigmoid_derivative(o_activation)

#Output layer weights
dSo_dWo = hl2_activation

dE_dSo = dE_dO * dO_dSo

dE_dWo = dE_dSo * dSo_dWo

dE_dBo = dE_dSo # as bias value is 1


#Hidden layer 2 weights

dSo_dH = self.output_layer_weights

dH_dSh = self.get_sigmoid_derivative(hl2_activation)

dSo_dSh = np.multiply(dSo_dH,dH_dSh)

dE_dSh = np.reshape( dE_dSo * dSo_dSh ,newshape = (len(self.hidden_layer_2),1))

dSh_dWh = hl1_activation.reshape(1,len(self.hidden_layer_1))

dE_dWh = dE_dSh.dot(dSh_dWh)



# dE_dBh = dE_dSh    as bias value is 1

#Hidden layer 1 weights

prev_derv = dE_dSh

dSh_dH1 = self.hidden_layer2_weights

dE_dH1 = np.sum(prev_derv * dSh_dH1,axis =0).T.reshape(len(self.hidden_layer_1),1)

dH1_dSh1 = np.reshape( self.get_sigmoid_derivative(hl1_activation) ,newshape = (len(self.hidden_layer_1),1))
```

```
                dSh1_dWh1 = ip_array.reshape(1,len(self.input_layer))

                dH1_dWh1 = dH1_dSh1.dot(dSh1_dWh1)

                dE_dWh1 = dH1_dWh1 * dE_dH1


                dE_db0 =   (dH1_dSh1 * self.b0.reshape(1,len(self.hidden_layer_1)).transpose()) * dE_dH1

                #Updating output layer weights
                self.output_layer_weights =  self.output_layer_weights- (self.alpha * dE_dWo)

                self.b2= self.b2 - (self.alpha* dE_dBo)


                #Updating hidden layer 2 weights
                self.hidden_layer2_weights =  self.hidden_layer2_weights - (self.alpha*dE_dWh)

                self.b1 = self.b1 - (self.alpha * dE_dSh.reshape(1,len(self.hidden_layer_2))[0])

                 #Updating hidden layer 1 weights
                self.hidden_layer1_weights =  self.hidden_layer1_weights - (self.alpha*dE_dWh1)

                self.b0 = self.b0  - (self.alpha * dE_db0.reshape(1,len(self.hidden_layer_1))[0])



            if (epoch % 10 == 0) or (epoch == 1) :
                op = self.test(cv_data)
                self.error_epoch[epoch] = np.mean(errors)
                acc= accuracy_score(cv_data[:,-1], op)
                print('Epoch {} - Error = {} - CV accuracy - {}'.format(epoch,np.mean(errors),acc))


    def test(self,test):

        op = []

        for i in test:

            ip_array = i[:len(self.input_layer)]

            'Feed forward --- Performing summation using matrix multiplication and adding bias to the result'
            hl1_weights = self.hidden_layer1_weights.transpose()
            hl1_summation = ip_array.dot(hl1_weights) + np.array(self.b0)
            hl1_activation = self.get_sigmoid(hl1_summation)
```

```
            hl2_weights = self.hidden_layer2_weights.transpose()
            hl2_summation = hl1_activation.dot(hl2_weights) + np.array(self.b1)
            hl2_activation = self.get_sigmoid(hl2_summation)

            # 2) Summation and activation operations from hidden to output layer

            o_weights = self.output_layer_weights.transpose()
            o_summation = hl2_activation.dot(o_weights) + self.b2
            o_activation = self.get_sigmoid(o_summation)

            if o_activation > 0.5:
                o = 1
            else:
                o = 0
            op.append(o)

        return op


    def get_cost_epoch(self):
        return self.error_epoch
```

Model Parameters

```
-Epoch = 100 ( Inspected with smaller epochs but model performed poorly, chosen based on CV accuracy and error rate)

-Hidden layer 1 Nodes = 50 ( Chose 1/20 of the input nodes as hidden nodes)

-Hodden layer 2 nodes = 30 ( Precious layer has 50 nodes so tried to reduce the dimensionality)

-Learning Rates = 0.1 ( Its chosen high because after inspecting smaller learning rate where convergence was too slow and needed to i
ncrease the epoch, which again was computationally intensive).
```

In [15]:

```
'Author : Seshadri Sundarrajan'

nn = FF_Neural_Net2(train_cifr,hidden_layer_1_nodes = 50 ,epoch=100,learning_rate = 0.1,hidden_layer_2_nodes = 30)

nn.train()

op = nn.test(test_cifr.values)


cm = confusion_matrix(test_cifr.iloc[:,-1].values, op)
print('\nConfusion Matrix\n{}'.format(cm))


acc= accuracy_score(test_cifr.iloc[:,-1].values, op)
print('\nAccuracy of the model - {}\n'.format(acc))


print('\nClassification Report\n\n{}\n'.format(classification_report(test_cifr.iloc[:,-1].values, op, target_names=['frog', 'ho
rse'])))
```

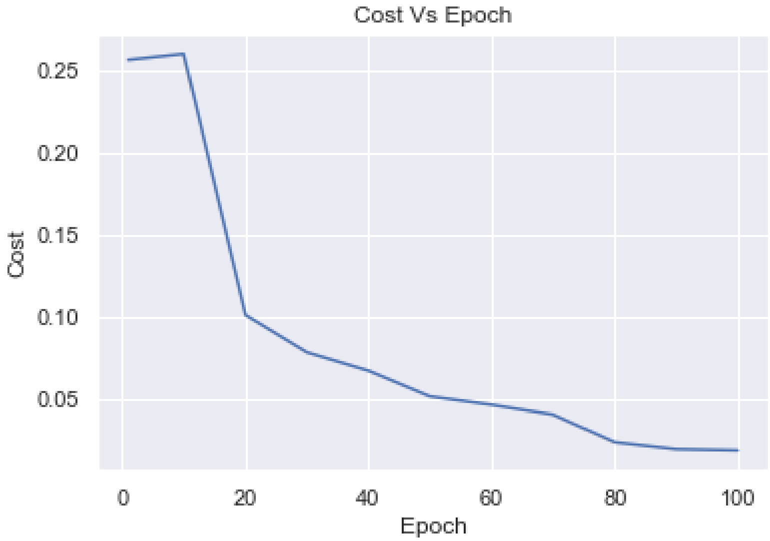
```
Epoch 1 - Error = 0.25601653157094223 - CV accuracy - 0.5064516129032258
Epoch 10 - Error = 0.2595922177679693 - CV accuracy - 0.535483870967742
Epoch 20 - Error = 0.1009789679275237 - CV accuracy - 0.7193548387096774
Epoch 30 - Error = 0.0782675886531301 - CV accuracy - 0.7774193548387097
Epoch 40 - Error = 0.0671127654106343 - CV accuracy - 0.8161290322580645
Epoch 50 - Error = 0.05152094606547574 - CV accuracy - 0.8483870967741935
Epoch 60 - Error = 0.046476510609585596 - CV accuracy - 0.864516129032258
Epoch 70 - Error = 0.04050839183048056 - CV accuracy - 0.9032258064516129
Epoch 80 - Error = 0.02380769857813752 - CV accuracy - 0.9580645161290322
Epoch 90 - Error = 0.019599760558195123 - CV accuracy - 0.964516129032258
Epoch 100 - Error = 0.018885782884254822 - CV accuracy - 0.9580645161290322

Confusion Matrix
[[174  68]
 [ 55 184]]

Accuracy of the model - 0.7442827442827443


Classification Report

              precision    recall  f1-score   support

        frog       0.76      0.72      0.74       242
       horse       0.73      0.77      0.75       239

    accuracy                           0.74       481
   macro avg       0.74      0.74      0.74       481
weighted avg       0.75      0.74      0.74       481
```

Error VS Epoch

We can see that after epoch 80 the model starts to converge and corrsponding graph is plotted below

In [16]:
```
'Author : Seshadri Sundarrajan'
er_epoch = nn.get_cost_epoch()
plt.plot(list(er_epoch.keys()),list(er_epoch.values()))
plt.title('Cost Vs Epoch')
plt.xlabel('Epoch')
plt.ylabel('Cost')
```

Out[16]:
```
Text(0, 0.5, 'Cost')
```



Model Performance

Two layer Neural Network performs better than the single layer NN implemented for the same CIFAR dataset. The presence of additional layer is able to capture some spatial features of the image. Also eliminated Accuracy Paradox and Performace of the model is good comparitively as Accuracy and F1 score are 75 % . Model was able to perform well on the validation set as epoch increases and converges slowly. There is a trace of overfitting as we can see difference between final validation set accuracy and test accuracy is 20%.

Further Extensions to this enhancement:

- Hidden nodes can be increased and RELU activation function can be used to aid quick convergence.
- Here some configurations of the network are limited due to the computational resource available on the local machine, so various parameter settings can be experimented.
- Sparse Network can be incorporated as model tends to focus on certain spacial characteristics of the image.

Conclusion

- Conventinal ANN implementation with 2 hidden layers is performing better than 1 layer network for low pixel binary image classification without incoropprating any of the CNN image processing techniques.

Enhancement 2 - Effect of ReLU activation - (Author - Manish Agarwal)

Class FF_Neural_Net_Relu

Method Adopted:

```
- Stochastic Gradient Descent
- ReLu Activation function
- Cost function - Sum of squared errors
- 20 % of epoch data used for Cross Validation
- Input Nodes - Customisable
- 1 hidden layer - Fixed
- Hidden Layer Nodes Customisable
- 1 Output layer - Fixed
```

Parmeters Available:

```
-Epoch
-Learning rate
-Input nodes
-Hidden layer nodes
```

Methods Available:

```
- Train() --> Starts training Neural Network as per the parameters passed while object creation
- Test() --> Takes in test data and returns the ouput label
- Get_cost_epoch() ---> Return dictionary with cost @ each epoch
```

NOTE :

- Reusing the class defined earlier for 1 layer NN with some modifications in the activation function.
- Variable names assigned in backpropagation are as per the naming convention followed in the above image
- On each epoch holding out 20% data drawn at random from train set for cross validation, to inspect overfitting.

In [17]:
```
class FF_Neural_Net_Relu():



    def __init__ (self,train_data,hidden_nodes,epoch,learning_rate):


        np.random.seed(10)

        # Storing values between 0.25 and 0.75
        weight_values = [val/100 for val in range(25,75)]

        self.train_data = train_data
        self.input_nodes = train_data.shape[1] - 1
        self.hidden_nodes = hidden_nodes
        self.epoch = epoch
        self.alpha  = learning_rate
        self.error_epoch = {}

        #held out
        self.held_out = (int((len(self.train_data) * 80 ) / 100),len(self.train_data))

        # Input layer =  2 nodes & Hidden layer = 4 nodes
        self.input_layer = range(0,self.input_nodes)
        self.hidden_layer_1 = range(0,self.hidden_nodes)

        # Bias have constant value +1 and weights are initialised with 0.5
        self.b0 = np.random.choice(weight_values,size=len(self.hidden_layer_1),replace=True)
        self.b1 = 0.5

        # Generating random weights for where row = No of hidden layer & column = No of inputs
        self.hidden_layer1_weights = np.random.choice(weight_values,size=[len(self.hidden_layer_1),len(self.input_layer)],repla
ce=True)


        # Updating Output layer weights randomly
        self.output_layer_weights = np.round(np.random.rand(len(self.hidden_layer_1)),2)

    def get_relu_derivative(self,x):
        return 1.0*(x>0)

    def get_relu (self,x):
        return x*(x>0)

    def get_sigmoid_derivative(self,x):
```

```
        return x*(1-x)

    def get_sigmoid (self,x):
        return 1 / (1+np.exp(-x))

    def get_cost_epoch(self):
        return self.error_epoch




    def train(self):


        #Function to train the NN -  Initiates Feed forward and Back propagation iteratively

        for epoch in range(1,self.epoch+1):
            errors = []
            train = self.train_data.values
            np.random.shuffle(train)
            training_set = train[0:self.held_out[0]]
            cv_data = train[self.held_out[0]:self.held_out[1]]

            for row in training_set:

                ip_array = row[:len(self.input_layer)]

                #Feed forward --- Performing summation using matrix multiplication and adding bias to the result

                # 1) Summation of Wi*xi  + c
                hl1_weights = self.hidden_layer1_weights.transpose()
                hl1_summation = ip_array.dot(hl1_weights) + np.array(self.b0)
                hl1_activation = self.get_relu(hl1_summation)


                # 2) Summation and activation operations from hidden to output layer

                o_weights = self.output_layer_weights.transpose()
                o_summation = hl1_activation.dot(o_weights) + self.b1
                o_activation = self.get_relu(o_summation)


                # Calculating Cost/error function
                error = 0.5 * ((o_activation - row[-1])**2)
                errors.append(error.item())
```

```
#Backpropagation - Variable names assigned as per the notation expained in the derivation above

# Derivative of E/O
dE_dO = o_activation - row[-1]

# Derivative of Output activation fn
dO_dSo = self.get_relu_derivative(o_activation)

#Output layer weights
dSo_dWo = hl1_activation

dE_dSo = dE_dO * dO_dSo

dE_dWo = dE_dSo * dSo_dWo

dE_dBo = dE_dSo # as bias value is 1

#Hidden layer weights

dSo_dH = self.output_layer_weights

dH_dSh = self.get_relu_derivative(hl1_activation)

dSo_dSh = np.multiply(dSo_dH,dH_dSh)

dE_dSh = np.reshape( dE_dO * dO_dSo * dSo_dSh ,newshape = (len(self.hidden_layer_1),1))
dSh_dWh = ip_array.reshape(1,len(self.input_layer))


dE_dWh = dE_dSh.dot(dSh_dWh)

# dE_dBh = dE_dSh    as bias value is 1

#Updating output layer weights
self.output_layer_weights =  self.output_layer_weights- (self.alpha * dE_dWo)

self.b1 = self.b1 - (self.alpha* dE_dBo)


#Updating hidden layer weights
self.hidden_layer1_weights =  self.hidden_layer1_weights - (self.alpha*dE_dWh)

self.b0 = self.b0 - (self.alpha * dE_dSh.reshape(1,len(self.hidden_layer_1))[0])
```

```python
            self.error_epoch[epoch] = np.mean(errors)
            if (epoch % 10 == 0) or (epoch == 1) :
                op = self.test(cv_data)
                acc= accuracy_score(cv_data[:,-1], op)
                print('Epoch {} - Error = {} - CV accuracy - {}'.format(epoch,np.mean(errors),acc))




    def test(self,test):

        op = []

        for i in test:

            ip_array = i[:len(self.input_layer)]

            'Feed forward --- Performing summation using matrix multiplication and adding bias to the result'

            # 1) Summation of Wi*xi  + c
            hl1_weights = self.hidden_layer1_weights.transpose()
            hl1_summation = ip_array.dot(hl1_weights) + np.array(self.b0)

            # 2) Sigmoid activation
            hl1_activation = 1 / ( 1 + np.exp(-hl1_summation))

            # 3) Summation and activation operations from hidden to output layer

            o_weights = self.output_layer_weights.transpose()
            o_summation = hl1_activation.dot(o_weights) + self.b1
            o_activation = 1 / ( 1 + np.exp(-o_summation))

            if o_activation > 0.5:
                o = 1
            else:
                o = 0
            op.append(o)

        return op
```

Model Parameters

-Epoch = 200 -Hidden layer Nodes = 50 -Learning Rates = 0.1

The value of the parameters are taken same as it is in base neural network model on which the ennhancement has been done, so that the comparision of performance can be done more accurately.

In [18]:

```
nn = FF_Neural_Net_Relu(train_cifr,hidden_nodes = 50 ,epoch=200,learning_rate = 0.1)

nn.train()

op = nn.test(test_cifr.values)


cm = confusion_matrix(test_cifr.iloc[:,-1].values, op)
print('\nConfusion Matrix\n{}'.format(cm))

acc= accuracy_score(test_cifr.iloc[:,-1], op)
print('\nAccuracy of the model - {}\n'.format(acc))
```

```
Epoch 1 - Error = 13065.616539232435 - CV accuracy - 0.5161290322580645
Epoch 10 - Error = 0.24314516129032257 - CV accuracy - 0.4870967741935484
Epoch 20 - Error = 0.24274193548387096 - CV accuracy - 0.4838709677419355
Epoch 30 - Error = 0.24274193548387096 - CV accuracy - 0.4838709677419355
Epoch 40 - Error = 0.2467741935483871 - CV accuracy - 0.5161290322580645
Epoch 50 - Error = 0.2495967741935484 - CV accuracy - 0.5387096774193548
Epoch 60 - Error = 0.24717741935483872 - CV accuracy - 0.5193548387096775
Epoch 70 - Error = 0.2439516129032258 - CV accuracy - 0.4935483870967742
Epoch 80 - Error = 0.2439516129032258 - CV accuracy - 0.4935483870967742
Epoch 90 - Error = 0.24193548387096775 - CV accuracy - 0.4774193548387097
Epoch 100 - Error = 0.24919354838709679 - CV accuracy - 0.535483870967742
Epoch 110 - Error = 0.2495967741935484 - CV accuracy - 0.5387096774193548
Epoch 120 - Error = 0.24596774193548387 - CV accuracy - 0.5096774193548387
Epoch 130 - Error = 0.2524193548387097 - CV accuracy - 0.5612903225806452
Epoch 140 - Error = 0.2532258064516129 - CV accuracy - 0.567741935483871
Epoch 150 - Error = 0.24475806451612903 - CV accuracy - 0.5
Epoch 160 - Error = 0.24556451612903227 - CV accuracy - 0.5064516129032258
Epoch 170 - Error = 0.25 - CV accuracy - 0.5419354838709678
Epoch 180 - Error = 0.24314516129032257 - CV accuracy - 0.4870967741935484
Epoch 190 - Error = 0.2495967741935484 - CV accuracy - 0.5387096774193548
Epoch 200 - Error = 0.24475806451612903 - CV accuracy - 0.5

Confusion Matrix
[[242   0]
 [239   0]]

Accuracy of the model - 0.5031185031185031
```

Model Performance

ReLU activation function performed slightly better than the sigmoid function in the single layer NN implemented for the same CIFAR dataset. The additional advantage of using ReLU function instead of sigmoid, it aid to quick convergence since gradient of ReLU is 0 or 1 and thus it also saves the computational cost.

Further Extensions to this enhancement: With additional hidden layer along with ReLU activation function , can increase the performance of the model significantly.

Conclusion : Neural Network with ReLU activation function performs slightly better than the sigmoid function.

References

- http://cs229.stanford.edu/notes/cs229-notes-deep_learning.pdf (http://cs229.stanford.edu/notes/cs229-notes-deep_learning.pdf)
- https://www.cs.toronto.edu/~kriz/cifar.html (https://www.cs.toronto.edu/~kriz/cifar.html)
- https://mattmazur.com/2015/03/17/a-step-by-step-backpropagation-example/ (https://mattmazur.com/2015/03/17/a-step-by-step-backpropagation-example/)
- https://www.anotsorandomwalk.com/backpropagation-example-with-numbers-step-by-step/ (https://www.anotsorandomwalk.com/backpropagation-example-with-numbers-step-by-step/)