PROJECT 2

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Subject: `Machine Learning`

Problem Statement

Write a complete code to train a 2-layer(hidden) Neural Network for predicting corona cases in USA and world with regularization.

- In this model, neural network model composed 2 hidden layer is implemented with regularization for predicting corona cases in World different countries.

Neural Network Model for Predicting Corona Cases in World

Step 1: Importing necesaary libraries for the model.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Useful links from where data was taken and cleaned for this specific model.

For corona cases data:

- 1) https://github.com/owid/covid-19-data/blob/master/public/data/owid-covid-data.csv (https://github.com/owid/covid-19-data/blob/master/public/data/owid-covid-data.csv)

For weather temperarure data:

- 2) https://www.timeanddate.com/weather/ (https://www.timeanddate.com/weather/)

Population density:

- 3) https://github.com/owid/covid-19-data/blob/master/public/data/owid-covid-data.csv (https://github.com/owid/covid-19-data/blob/master/public/data/owid-covid-data.csv)

Human Development Index:

- 4)https://github.com/owid/covid-19-data/blob/master/public/data/owid-covid-data.csv (https://github.com/owid/covid-19-data/blob/master/public/data/owid-covid-data.csv)

Step 2: Importing csv file of World Data using pandas

In [2]:
```
df=pd.read_csv('Worldwide final.csv')
```

Imported Data named `df`

In [3]:
```
df.head()
```

Out[3]:

	CONTINENT	LOCATION	DATE	COUNTRY_SERIES	DATE_CODE	COUNTRY_CODE	POPULATION DENSITY	HU
0	Asia	Afghanistan	1/23/2020	0	0	0	54.42	
1	Asia	Afghanistan	1/24/2020	1	1	0	54.42	
2	Asia	Afghanistan	1/25/2020	2	2	0	54.42	
3	Asia	Afghanistan	1/26/2020	3	3	0	54.42	
4	Asia	Afghanistan	1/27/2020	4	4	0	54.42	

Step 3: Cleaning Data frame

Checking Nan values in data

In [4]:
```
df.isna().sum()
```

Out[4]:
```
CONTINENT                  0
LOCATION                   0
DATE                       0
COUNTRY_SERIES             0
DATE_CODE                  0
COUNTRY_CODE               0
POPULATION DENSITY      1280
HUMAN_DEVELOPMENT_INDEX 1920
TEMPERATURES               0
CASES                      0
dtype: int64
```

In [5]:
```
df["POPULATION DENSITY"]=df["POPULATION DENSITY"].fillna(df["POPULATION DENSITY"].mean()
```

In [6]:
```
df["HUMAN_DEVELOPMENT_INDEX"]=df["HUMAN_DEVELOPMENT_INDEX"].fillna(df["HUMAN_DEVELOPMENT
```

In [7]:
```
df.isna().sum()
```

Out[7]:
```
CONTINENT               0
LOCATION                0
DATE                    0
COUNTRY_SERIES          0
DATE_CODE               0
COUNTRY_CODE            0
POPULATION DENSITY      0
HUMAN_DEVELOPMENT_INDEX 0
TEMPERATURES            0
CASES                   0
dtype: int64
```

Step 4: Creating features `x` and prediction label `y`

In [8]:
```
x=df.drop(["CONTINENT","LOCATION","DATE","COUNTRY_SERIES","CASES"],axis=1)
```

`x` is our features.

In [9]:
```python
x.head()
```

Out[9]:

	DATE_CODE	COUNTRY_CODE	POPULATION DENSITY	HUMAN_DEVELOPMENT_INDEX	TEMPERATURES
0	0	0	54.42	0.498	7.0
1	1	0	54.42	0.498	7.0
2	2	0	54.42	0.498	13.0
3	3	0	54.42	0.498	2.0
4	4	0	54.42	0.498	6.0

Features information:

Here, We have 5 features:

```
*1) DATE_CODE = In this model "date" is numerically coded. For example:
    Model date starts from 23 January 2020 and ends at 7th December 2020.
    *Here: 23/01/2020 is 0 and 7th December is 319.
*2) COUNTRY_CODE: Country codes are also numerically coded. For example:
     *Here: 1 = Afghanistan, 2= Albania and 170=Zimbabwe.
*3) HUMAN_DEVELOPMENT_INDEX: Average Human development index of particular stat
e
*4) POPULATION_DENSITY: Population Density of particular country.
*5) TEMPERATURES: Tempearures in C of particular country at particular date.
```

In [10]:
```python
y=df["CASES"]
```

y is our prediction label.

In [11]:
```python
y.head()
```

Out[11]:
```
0    0
1    0
2    0
3    0
4    0
Name: CASES, dtype: int64
```

Step 5: Normalization/ Scaling of features

In [12]:
```python
for j in range(0, len(x.columns)):
    x=(x-x.min())/(x.max()-x.min())
```

In [13]:
```
x.head()
```
Out[13]:

	DATE_CODE	COUNTRY_CODE	POPULATION DENSITY	HUMAN_DEVELOPMENT_INDEX	TEMPERATURES
0	0.000000	0.0	0.002711	0.240401	0.338235
1	0.003135	0.0	0.002711	0.240401	0.338235
2	0.006270	0.0	0.002711	0.240401	0.426471
3	0.009404	0.0	0.002711	0.240401	0.264706
4	0.012539	0.0	0.002711	0.240401	0.323529

Step 6: Splitting dataframe into training(60%) validation(20%) and testing data (20%)

In [14]:
```
train_split=round(0.6*len(df))
valid_split=round(train_split + 0.2*len(df))

x_train,y_train= x[:train_split],y[:train_split]
x_valid,y_valid=x[train_split:valid_split], y[train_split:valid_split]
x_test,y_test=x[valid_split:],y[valid_split:]
```

In [15]:
```
x_train.shape, x_valid.shape,x_test.shape,y_train.shape,y_valid.shape,y_test.shape
```
Out[15]:
```
((32832, 5), (10944, 5), (10944, 5), (32832,), (10944,), (10944,))
```

Step 7: Changing the shape of data sets for the model as per the code requirement.

In [16]:
```
x_train=x_train.T
y_train=y_train.values.reshape(1,x_train.shape[1])
x_valid=x_valid.T
y_valid=y_valid.values.reshape(1,x_valid.shape[1])
x_test=x_test.T
y_test=y_test.values.reshape(1,x_test.shape[1])
```

In [17]:
```
x_train.shape, x_valid.shape,x_test.shape,y_train.shape,y_valid.shape,y_test.shape
```
Out[17]:
```
((5, 32832), (5, 10944), (5, 10944), (1, 32832), (1, 10944), (1, 10944))
```

Step 8: Defining the architecture of Neural Network

```
x -- input dataset of shape (input size, number of examples)
ny -- labels of shape (output size, number of examples)
n_x -- the size of the input layer
n_h1 -- the size of the first hidden layer
n_h2 -- the size of the second hidden layer
n_y -- the size of the output layer
```

Our model architecture will be:

```
- 1) Input Layer (5 Neurons)

- 2) Hidden layer 1 (10 Neurons)

- 3) Hidden Layer 2 (10 Neurons)

- 4) Output Layer (1 Neuron)
```

In [18]:
```
def layer_sizes(x, y):
    ### START CODE HERE ### (≈ 4 lines of code)
    n_x = x.shape[0] # size of input layer
    n_h1 = 10
    n_h2 = 10
    n_y = y.shape[0] # size of output layer
    ### END CODE HERE ###
    return (n_x, n_h1, n_h2, n_y)
```

Step 8.1: Checking size of differnt layers of model

In [19]:
```
(n_x, n_h1,n_h2, n_y) = layer_sizes(x_train, y_train)
print("The size of the input layer is: n_x = " + str(n_x))
print("The size of the hidden layer is: n_h1 = " + str(n_h1))
print("The size of the hidden layer is: n_h2 = " + str(n_h2))
print("The size of the output layer is: n_y = " + str(n_y))
```

```
The size of the input layer is: n_x = 5
The size of the hidden layer is: n_h1 = 10
The size of the hidden layer is: n_h2 = 10
The size of the output layer is: n_y = 1
```

Step 9: Initializing the parameters of Neural Network model

```
n_x -- size of the input layer
n_h1 -- size of the hidden layer 1
n_h2 -- size of the hidden layer 2
n_y -- size of the output layer
params -- python dictionary containing your parameters:
                W1 -- weight matrix of shape (n_h1, n_x)
                b1 -- bias vector of shape (n_h1, 1)
                W2 -- weight matrix of shape (n_h2, n_h1)
                b2 -- bias vector of shape (n_h2, 1)
                W3 -- weight matrix of shape (n_y, n_h2)
                b3 -- bias vector of shape (n_y, 1)
```

In [20]:
```
def initialize_parameters(n_x, n_h1,n_h2, n_y):

    np.random.seed(2) # we set up a seed so that your output matches ours although the i
    W1 = np.random.randn(n_h1,n_x)*0.01
    b1 = np.zeros((n_h1,1))
    W2 = np.random.randn(n_h2,n_h1)*0.01
    b2 = np.zeros((n_h2,1))
    W3 = np.random.randn(n_y,n_h2)*0.01
    b3 = np.zeros((n_y,1))
    assert (W1.shape == (n_h1, n_x))
    assert (b1.shape == (n_h1, 1))
    assert (W2.shape == (n_h2, n_h1))
    assert (b2.shape == (n_h2, 1))
    assert (W3.shape == (n_y, n_h2))
    assert (b3.shape == (n_y, 1))
    parameters = {"W1": W1,
                  "b1": b1,
                  "W2": W2,
                  "b2": b2,
                  "W3": W3,
                  "b3": b3}
    return parameters
```

Step 9.1: Checking the initialization of model parameters as per the layer size

In [21]:
```
parameters = initialize_parameters(n_x, n_h1,n_h2, n_y)
print("W1 = " + str(parameters["W1"]))
print("b1 = " + str(parameters["b1"]))
print("W2 = " + str(parameters["W2"]))
print("b2 = " + str(parameters["b2"]))
print("W3 = " + str(parameters["W3"]))
print("b3 = " + str(parameters["b3"]))
```

```
W1 = [[-4.16757847e-03 -5.62668272e-04 -2.13619610e-02  1.64027081e-02
  -1.79343559e-02]
 [-8.41747366e-03  5.02881417e-03 -1.24528809e-02 -1.05795222e-02
  -9.09007615e-03]
 [ 5.51454045e-03  2.29220801e-02  4.15393930e-04 -1.11792545e-02
   5.39058321e-03]
 [-5.96159700e-03 -1.91304965e-04  1.17500122e-02 -7.47870949e-03
   9.02525097e-05]
 [-8.78107893e-03 -1.56434170e-03  2.56570452e-03 -9.88779049e-03
  -3.38821966e-03]
 [-2.36184031e-03 -6.37655012e-03 -1.18761229e-02 -1.42121723e-02
  -1.53495196e-03]
 [-2.69056960e-03  2.23136679e-02 -2.43476758e-02  1.12726505e-03
   3.70444537e-03]
 [ 1.35963386e-02  5.01857207e-03 -8.44213704e-03  9.76147160e-08
   5.42352572e-03]
 [-3.13508197e-03  7.71011738e-03 -1.86809065e-02  1.73118467e-02
   1.46767801e-02]
 [-3.35677339e-03  6.11340780e-03  4.79705919e-04 -8.29135289e-03
   8.77102184e-04]]
b1 = [[0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]]
W2 = [[ 0.01000366 -0.00381093 -0.00375669 -0.00074471  0.00433496  0.01278379
  -0.00634679  0.00508396  0.00216116 -0.01858612]
 [-0.00419316 -0.00132329 -0.0003957   0.00326003 -0.02040323  0.00046256
  -0.00677676 -0.01439439  0.00524296  0.0073528 ]
 [-0.0065325   0.00842456 -0.00381516  0.00066489 -0.01098739  0.01584487
  -0.02659449 -0.00091453  0.0069512  -0.02033467]
 [-0.00189469 -0.00077219  0.00824703  0.01248213 -0.00403892 -0.01384519
   0.01367235  0.01217886 -0.00462005  0.00350888]
 [ 0.00381866  0.00566275  0.00204208  0.01406696 -0.0173796   0.01040824
   0.00380472 -0.00217135  0.01173531 -0.02343603]
 [ 0.01161521  0.00386078 -0.01133133  0.00433093 -0.00304086  0.02585295
   0.01835333  0.0044069  -0.00719254 -0.00583415]
 [-0.0032505  -0.00560235 -0.00902246 -0.00590972 -0.00276179 -0.00516884
  -0.0069859  -0.00928892  0.02550438 -0.01473173]
 [-0.01021415  0.00432396 -0.0032358   0.00423825  0.0079918   0.01262614
   0.00751965 -0.00993761  0.01109143 -0.01764918]
 [-0.00114421 -0.00498174 -0.01060799  0.00591667 -0.00183257  0.01019855
  -0.01482465  0.00846312  0.0049794   0.00126504]
 [-0.01418811 -0.00251774 -0.01546675 -0.02082652  0.03279745  0.00970861
   0.01792593 -0.00429013  0.00696198  0.00697416]]
b2 = [[0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
```

```
 [0.]]
W3 = [[ 6.01515814e-03  3.65949071e-05 -2.28247558e-03 -2.06961226e-02
   6.10144086e-03  4.23496900e-03  1.11788673e-02 -2.74242089e-03
   1.74181219e-02 -4.47500876e-03]]
b3 = [[0.]]
```

Step 10: Defining the sigmoid function

In [22]:
```
def sigmoid(z):
        return 1.0/(1.0+np.exp(-z))
```

Step 11: Defining the forward propagation function

```
x -- input data of size (n_x, m) # m is the no of training examples
parameters -- python dictionary containing your parameters (output of initializ
ation function)
A3 -- The  output
cache -- a dictionary containing "Z1", "A1", "Z2", "A2" , "Z3" and "A3"
```

In [23]:
```
def forward_propagation(x, parameters):

    # Retrieve each parameter from the dictionary "parameters"

    W1 = parameters["W1"]
    b1 = parameters["b1"]
    W2 = parameters["W2"]
    b2 = parameters["b2"]
    W3 = parameters["W3"]
    b3 = parameters["b3"]

    Z1 = np.dot(W1,x) + b1
    A1 = sigmoid(Z1)
    Z2 = np.dot(W2,A1) + b2
    A2 = sigmoid(Z2)
    Z3 = np.dot(W3,A2) + b3
    A3 = Z3

    assert(A3.shape == (1, x.shape[1]))

    cache = {"Z1": Z1,
             "A1": A1,
             "Z2": Z2,
             "A2": A2,
             "Z3": Z3,
             "A3": A3
            }

    return A3, cache
```

Step 11.1: Checking the forward propagation function

In [24]:
```
A3, cache = forward_propagation(x_train, parameters)
print(np.mean(cache['Z1']) ,np.mean(cache['A1']),np.mean(cache['Z2']),np.mean(cache['A2'
```

```
-0.0009693024074162636 0.4997576688535688 -0.0004336513870412932 0.49989159836950375 0.
0073001544017051246 0.0073001544017051246
```

Step 12: Defining the cost function

```
Computes the cost:

`A3` -- The  output of shape (1, number of examples)
`y` -- "true" labels vector of shape (1, number of examples)
`parameters` -- python dictionary containing your parameters W1, b1, W2 and b2
`lambda_` -- Regularization parameter
```

In [25]:
```python
def compute_cost(A3, y, parameters,lambda_):

    W1 = parameters["W1"]
    b1 = parameters["b1"]
    W2 = parameters["W2"]
    b2 = parameters["b2"]
    W3 = parameters["W3"]
    b3 = parameters["b3"]

    m = y.shape[1] # number of training examples

    cost=(np.sum(np.power((A3-y),2))+lambda_*(np.sum(np.power(W1,2))+np.sum(np.power(W2,

    cost = np.squeeze(cost)
    assert(isinstance(cost, float))

    return cost
```

Step 13: Defining the backward propagation function

```
Implements the backward propagation:

parameters -- python dictionary containing our parameters
cache -- a dictionary containing "Z1", "A1", "Z2" "A2", "Z3" ANd "A3"
x -- input data of shape (7, number of examples)
y -- "true" labels vector of shape (1, number of examples)
lambda_ -- Regularization parameter

Returns:
grads -- python dictionary containing your gradients with respect to parameters
of model
```

In [26]:
```python
def backward_propagation(parameters, cache, x, y,lambda_):

    m = x.shape[1]

    W1 = parameters["W1"]
    W2 = parameters["W2"]
    W3 = parameters["W3"]

    A1 = cache["A1"]
    A2 = cache["A2"]
    A3 = cache["A3"]

    dZ3 = A3-y
    dW3 = 1/m*(np.dot(dZ3,A2.T)) + (lambda_/m)*W3
    db3 = 1/m*(np.sum(dZ3,axis=1, keepdims=True))
    dZ2 = np.multiply(np.dot(W3.T,dZ3),(A2*(1-A2)))
    dW2 = 1/m*(np.dot(dZ2,A1.T)) + (lambda_/m)*W2
    db2 = 1/m*(np.sum(dZ2,axis=1, keepdims=True))
    dZ1 = np.multiply(np.dot(W2.T,dZ2),(A1*(1-A1)))
    dW1 = 1/m*(np.dot(dZ1,x.T)) + (lambda_/m)*W1
    db1 = 1/m*(np.sum(dZ1,axis=1, keepdims=True))

    grads = {"dW1": dW1,
             "db1": db1,
             "dW2": dW2,
             "db2": db2,
             "dW3": dW3,
             "db3": db3}

    return grads
```

Step 13.1:Checking the gradients obtained from backward propagation function

```
In [27]: grads = backward_propagation(parameters, cache, x_train, y_train,lambda_=0.7)
print ("dW1 = "+ str(grads["dW1"]))
print ("db1 = "+ str(grads["db1"]))
print ("dW2 = "+ str(grads["dW2"]))
print ("db2 = "+ str(grads["db2"]))
print ("dW3 = "+ str(grads["dW3"]))
print ("db3 = "+ str(grads["db3"]))
```

```
dW1 = [[-1.07469352e-02 -4.45961753e-03 -1.64594098e-04 -9.88435943e-03
  -8.70468697e-03]
 [ 6.06907279e-03  2.51867677e-03  9.24326418e-05  5.58213047e-03
   4.91556956e-03]
 [ 2.07143992e-02  8.59623740e-03  3.16380980e-04  1.90523349e-02
   1.67774385e-02]
 [ 2.00805509e-03  8.33332188e-04  3.09221764e-05  1.84691875e-03
   1.62651694e-03]
 [ 1.04813860e-02  4.34951596e-03  1.60143999e-04  9.64049433e-03
   8.48943759e-03]
 [-2.62554094e-02 -1.08953125e-02 -4.01260783e-04 -2.41492990e-02
  -2.12654186e-02]
 [ 2.89127877e-02  1.19983614e-02  4.41072603e-04  2.65933859e-02
   2.34177515e-02]
 [ 6.02867258e-03  2.50170266e-03  9.18932585e-05  5.54479073e-03
   4.88277160e-03]
 [-2.15210717e-02 -8.93033977e-03 -3.29095510e-04 -1.97940435e-02
  -1.74304051e-02]
 [ 2.08712680e-02  8.66112548e-03  3.18785053e-04  1.91967688e-02
   1.69046122e-02]]
db1 = [[-0.01468053]
 [ 0.00829082]
 [ 0.02829637]
 [ 0.00274324]
 [ 0.01431821]
 [-0.0358657 ]
 [ 0.03949584]
 [ 0.008235  ]
 [-0.02939833]
 [ 0.02851092]]
dW2 = [[-0.7948308  -0.78916473 -0.79870129 -0.79235414 -0.78985921 -0.79036171
  -0.79902703 -0.80185548 -0.80408338 -0.79379353]
 [-0.00483538 -0.00480084 -0.00485884 -0.00482015 -0.00480548 -0.00480809
  -0.00486096 -0.00487833 -0.00489146 -0.00482882]
 [ 0.30157532  0.29942571  0.30304381  0.3006357   0.29968886  0.29988016
   0.3031669   0.30424071  0.30508617  0.30118124]
 [ 2.7346368   2.71514156  2.74795252  2.72611531  2.71753145  2.71926073
   2.74907318  2.75880533  2.76646992  2.73106606]
 [-0.80622842 -0.80048077 -0.81015415 -0.8037158  -0.80118587 -0.80169517
  -0.81048447 -0.81335385 -0.81561334 -0.80517624]
 [-0.55954196 -0.55555314 -0.56226697 -0.55779844 -0.5560423  -0.55639556
  -0.56249562 -0.56448724 -0.56605584 -0.55881168]
 [-1.47702771 -1.46649802 -1.48421978 -1.47242499 -1.46778882 -1.46872299
  -1.48482497 -1.49008155 -1.49422079 -1.47509927]
 [ 0.36237684  0.35979375  0.36414147  0.36124789  0.36011054  0.36033981
   0.36429019  0.36557946  0.36659562  0.36190349]
 [-2.30159515 -2.28518714 -2.31280229 -2.29442267 -2.28719857 -2.28865393
  -2.31374549 -2.32193604 -2.32838728 -2.29858971]
 [ 0.59130789  0.5870927   0.59418706  0.58946509  0.58761023  0.5879837
   0.59443007  0.59653398  0.5981916   0.59053622]]
db2 = [[-1.59208989]
 [-0.00968534]
 [ 0.60407211]
 [ 5.47762681]
 [-1.61491968]
 [-1.12079356]
 [-2.95856697]
 [ 0.72586101]
 [-4.61022063]
```

```
 [ 1.18442258]]
dW3 = [[-529.50405618 -525.24232872 -524.4128369  -532.68248537 -530.50836081
  -534.75808034 -524.4756477  -530.24170217 -529.01628869 -531.59975134]]
db3 = [[-1058.71863795]]
```

Step 14: Defining the updating parameters function to update the parameters with optimized parameters obtained from gradient descent.

```
Updates parameters using the gradient descent update rule:

Arguments:
parameters -- python dictionary containing your parameters
alpha -- learning rate for the gradient descent model
grads -- python dictionary containing your gradients

Returns:
parameters -- python dictionary containing your updated parameters
```

In [28]:

```python
def update_parameters(parameters, grads, alpha = 0.001):


    W1 = parameters["W1"]
    b1 = parameters["b1"]
    W2 = parameters["W2"]
    b2 = parameters["b2"]
    W3 = parameters["W3"]
    b3 = parameters["b3"]

    dW1 = grads["dW1"]
    db1 = grads["db1"]
    dW2 = grads["dW2"]
    db2 = grads["db2"]
    dW3 = grads["dW3"]
    db3 = grads["db3"]

    W1 = W1 - alpha*dW1
    b1 = b1 - alpha*db1
    W2 = W2 - alpha*dW2
    b2 = b2 - alpha*db2
    W3 = W3 - alpha*dW3
    b3 = b3 - alpha*db3

    parameters = {"W1": W1,
                  "b1": b1,
                  "W2": W2,
                  "b2": b2,
                  "W3": W3,
                  "b3": b3}

    return parameters
```

Step 14.1:Updating the parameters

In [29]:
```python
parameters = update_parameters(parameters, grads)

print("W1 = " + str(parameters["W1"]))
print("b1 = " + str(parameters["b1"]))
print("W2 = " + str(parameters["W2"]))
print("b2 = " + str(parameters["b2"]))
print("W3 = " + str(parameters["W3"]))
print("b3 = " + str(parameters["b3"]))
```

```
W1 = [[-4.15683154e-03 -5.58208655e-04 -2.13617964e-02  1.64125924e-02
  -1.79256512e-02]
 [-8.42354273e-03  5.02629549e-03 -1.24529733e-02 -1.05851043e-02
  -9.09499172e-03]
 [ 5.49382605e-03  2.29134839e-02  4.15077549e-04 -1.11983068e-02
   5.37380577e-03]
 [-5.96360505e-03 -1.92138297e-04  1.17499813e-02 -7.48055641e-03
   8.86259928e-05]
 [-8.79156032e-03 -1.56869122e-03  2.56554438e-03 -9.89743098e-03
  -3.39670910e-03]
 [-2.33558490e-03 -6.36565481e-03 -1.18757216e-02 -1.41880230e-02
  -1.51368654e-03]
 [-2.71948239e-03  2.23016695e-02 -2.43481168e-02  1.10067166e-03
   3.68102762e-03]
 [ 1.35903100e-02  5.01607037e-03 -8.44222893e-03 -5.44717602e-06
   5.41864295e-03]
 [-3.11356090e-03  7.71904772e-03 -1.86805775e-02  1.73316407e-02
   1.46942105e-02]
 [-3.37764465e-03  6.10474667e-03  4.79387134e-04 -8.31054966e-03
   8.60197572e-04]]
b1 = [[ 1.46805252e-05]
 [-8.29081612e-06]
 [-2.82963733e-05]
 [-2.74324430e-06]
 [-1.43182091e-05]
 [ 3.58656985e-05]
 [-3.94958363e-05]
 [-8.23499585e-06]
 [ 2.93983254e-05]
 [-2.85109163e-05]]
W2 = [[ 1.07984897e-02 -3.02176044e-03 -2.95799294e-03  4.76465118e-05
   5.12482251e-03  1.35741540e-02 -5.54776602e-03  5.88581791e-03
   2.96524344e-03 -1.77923303e-02]
 [-4.18832945e-03 -1.31848814e-03 -3.90843559e-04  3.26485448e-03
  -2.03984250e-02  4.67363321e-04 -6.77189482e-03 -1.43895119e-02
   5.24785576e-03  7.35762458e-03]
 [-6.83407800e-03  8.12513711e-03 -4.11820863e-03  3.64254396e-04
  -1.12870783e-02  1.55449904e-02 -2.68976615e-02 -1.21876694e-03
   6.64610988e-03 -2.06358467e-02]
 [-4.62932945e-03 -3.48732822e-03  5.49907754e-03  9.75601390e-03
  -6.75645415e-03 -1.65644474e-02  1.09232811e-02  9.42005100e-03
  -7.38652340e-03  7.77818884e-04]
 [ 4.62489076e-03  6.46323518e-03  2.85223394e-03  1.48706782e-02
  -1.65784092e-02  1.12099347e-02  4.61520417e-03 -1.35799884e-03
   1.25509283e-02 -2.26308557e-02]
 [ 1.21747569e-02  4.41633361e-03 -1.07690658e-02  4.88872399e-03
  -2.48482209e-03  2.64093442e-02  1.89158228e-02  4.97138597e-03
  -6.62648258e-03 -5.27533426e-03]
 [-1.77346857e-03 -4.13584705e-03 -7.53824090e-03 -4.43729776e-03
  -1.29400611e-03 -3.70011594e-03 -5.50107453e-03 -7.79883769e-03
   2.69986031e-02 -1.32566332e-02]
 [-1.05765241e-02  3.96416326e-03 -3.59994217e-03  3.87699919e-03
   7.63168941e-03  1.22657968e-02  7.15535830e-03 -1.03031893e-02
   1.07248372e-02 -1.80110808e-02]
 [ 1.15738218e-03 -2.69655480e-03 -8.29518807e-03  8.21108788e-03
   4.54632831e-04  1.24872012e-02 -1.25109093e-02  1.07850550e-02
   7.30778876e-03  3.56363146e-03]
 [-1.47794134e-02 -3.10483388e-03 -1.60609332e-02 -2.14159844e-02
```

```
   3.22098438e-02  9.12062950e-03  1.73314985e-02 -4.88666716e-03
   6.36378819e-03  6.38362650e-03]]
b2 = [[ 1.59208989e-03]
 [ 9.68534169e-06]
 [-6.04072110e-04]
 [-5.47762681e-03]
 [ 1.61491968e-03]
 [ 1.12079356e-03]
 [ 2.95856697e-03]
 [-7.25861010e-04]
 [ 4.61022063e-03]
 [-1.18442258e-03]]
W3 = [[0.53551921 0.52527892 0.52213036 0.51198636 0.5366098  0.53899305
  0.53565452 0.52749928 0.54643441 0.52712474]]
b3 = [[1.05871864]]
```

Step 15: Defining the function which combines all the steps mentioned above for number of iterations

```
    x -- dataset of shape (5, number of examples)
    y -- labels of shape (1, number of examples)
    n_h1 -- size of the hidden layer 1
    n_h2 -- size of the hidden layer 2
    num_iterations -- Number of iterations in gradient descent loop
    print_cost -- if True, print the cost every 1000 iterations
    lambda_ = Regularization Parameter

    Returns:
    parameters -- parameters learnt by the model. They can then be used to predict.
    cost_history_train -- Cost for training data set after iterations.
    cost_history_valid -- Cost for validation data set after iterations.
    cost_history_test --  Cost for test data set after iterations.
```

In [30]:
```python
def nn_model(x, y, n_h1,n_h2,num_iterations=500 ,print_cost=False, lambda_= 0.7):

    np.random.seed(3)
    n_x = layer_sizes(x, y)[0]
    n_y = layer_sizes(x, y)[3]
    cost_history_train=[]
    cost_history_valid=[]
    cost_history_test= []

    parameters = initialize_parameters(n_x,n_h1,n_h2, n_y)
    W1 = parameters["W1"]
    b1 = parameters["b1"]
    W2 = parameters["W2"]
    b2 = parameters["b2"]
    W3 = parameters["W3"]
    b3 = parameters["b3"]

    # Looping for no of iterations (gradient descent)

    for i in range(0, num_iterations):

        A3, cache = forward_propagation(x_train, parameters)
        A3_valid,cache1 = forward_propagation(x_valid, parameters)
        A3_test, cache2 = forward_propagation(x_test, parameters)

        cost_train = compute_cost(A3,y_train,parameters,lambda_)
        cost_history_train.append(cost_train)
        cost_valid = compute_cost(A3_valid,y_valid,parameters,lambda_)
        cost_history_valid.append(cost_valid)
        cost_test = compute_cost(A3_test,y_test,parameters,lambda_)
        cost_history_test.append(cost_test)

        # Backpropagation. Inputs: "parameters, cache, X, Y". Outputs: "grads".
        grads = backward_propagation(parameters,cache,x,y,lambda_)

        # Gradient descent parameter update. Inputs: "parameters, grads". Outputs: "para
        parameters = update_parameters(parameters,grads)

        ### END CODE HERE ###

        # Print the cost every 100 iterations
        if print_cost and i % 1== 0:
            print ("Cost after iteration %i: %f" %(i, cost_train))

    return parameters, cost_history_train,cost_history_valid,cost_history_test
```

Step 15.1: Calculating paramters and cost of each data set

- alpha is learning rate =0.001
- Iterations=1000
- lambda_ is regularization parameter= 0.7

Here, when we put

```
* lambda_ = 0, there will no regularizarion
```

In [31]:
```
parameters,J_train,J_valid,J_test = nn_model(x_train, y_train, 10,10, num_iterations=100
print("W1 = " + str(parameters["W1"]))
print("b1 = " + str(parameters["b1"]))
print("W2 = " + str(parameters["W2"]))
print("b2 = " + str(parameters["b2"]))
print("W3 = " + str(parameters["W3"]))
print("b3 = " + str(parameters["b3"]))
```

```
Cost after iteration 932: 15392386.479991
Cost after iteration 933: 15392386.479980
Cost after iteration 934: 15392386.479969
Cost after iteration 935: 15392386.479958
Cost after iteration 936: 15392386.479948
Cost after iteration 937: 15392386.479937
Cost after iteration 938: 15392386.479927
Cost after iteration 939: 15392386.479917
Cost after iteration 940: 15392386.479908
Cost after iteration 941: 15392386.479898
Cost after iteration 942: 15392386.479889
Cost after iteration 943: 15392386.479880
Cost after iteration 944: 15392386.479871
Cost after iteration 945: 15392386.479862
Cost after iteration 946: 15392386.479854
Cost after iteration 947: 15392386.479845
Cost after iteration 948: 15392386.479837
Cost after iteration 949: 15392386.479829
Cost after iteration 950: 15392386.479822
Cost after iteration 951: 15392386.479814
```

In [32]:
```
J_train[:10], J_valid[:10], J_test[:10]
```

Out[32]:
```
([15952828.075152187,
  15948910.819044728,
  15943685.099985596,
  15934937.083458932,
  15923322.763482,
  15911617.875039106,
  15900233.307561986,
  15889112.895125555,
  15878240.413670197,
  15867607.649806704],
 [3469958.938162652,
  3466889.1785047892,
  3462797.8456258047,
  3455953.7280502305,
  3446885.6988470852,
  3437791.9739733473,
  3428979.1592095713,
  3420398.6446227506,
  3412036.561896,
  3403885.721241993],
 [68387441.45441163,
  68379876.71042694,
  68369762.09303981,
  68352740.77850384,
  68330008.77536017,
  68307062.28669694,
  68284639.67093971,
  68262615.92604165,
  68240961.75771847,
  68219665.37197411])
```

Step 16: Defining the prediction function for calculating predictions using forward propagation and updated model paramters

```
    Using the learned parameters, predicts a class for each example in differnt dat
    a sets

    Arguments:
    parameters -- python dictionary containing your parameters
    x -- input data of size (n_x, m)

    Returns
    predictions -- vector of predictions of our model
    """
```

In [33]:
```
def predict(parameters, x):

    A3, cache = forward_propagation(x,parameters)
    predictions = A3

    return predictions
```

Step 16.1: Calculating Predictions for training set

In [34]:
```
predictions_train = predict(parameters, x_train)
```

In [35]:
```
predictions_train
```

Out[35]:
```
array([[1058.70894492, 1058.70894498, 1058.70894307, ..., 1058.70894149,
        1058.70894132, 1058.70894255]])
```

Step 16.2: Calculating Predictions for validation data set

In [36]:
```
predictions_valid = predict(parameters, x_valid)
```

In [37]:
```
predictions_valid
```

Out[37]:
```
array([[1058.70894161, 1058.70894213, 1058.70894218, ..., 1058.70893967,
        1058.70893955, 1058.70893972]])
```

Step 16.3: Calculating Predictions for test data set

In [38]:
```
predictions_test = predict(parameters, x_test)
```

In [39]:
```
predictions_test
```

Out[39]:
```
array([[1058.70893974, 1058.70893963, 1058.70893979, ..., 1058.70894858,
        1058.70894815, 1058.70894824]])
```

Step 17: Calculating the mean absolute error on all data sets.

Step 17.1: Calculating the mean absolute error on training data set.

In [40]:
```
MAE_train=np.sum(np.absolute(y_train.T-predictions_train.T))/len(x_train.T)
MAE_train
```

Out[40]:
```
1667.030415925165
```

Mean absolute Error is `1667` for training set. It means that model is predicting `1667` values wrong from actual cases.

Step 17.2: Calculating the mean absolute error on validation data set.

In [42]:
```
MAE_valid=np.sum(np.absolute(y_valid.T-predictions_valid.T))/len(x_valid.T)
MAE_valid
```

Out[42]:
```
1345.8220110094935
```

Mean absolute Error is `1375` for validation set. It means that model is predicting `1375` values wrong from actual cases.

Step 17.3: Calculating the mean absolute error on test data set.

In [43]:
```
MAE_test=np.sum(np.absolute(y_test.T-predictions_test.T))/len(x_test.T)
MAE_test
```

Out[43]:
```
2670.35200802638
```

Mean absolute Error is `2670` for test set. It means that model is predicting `2670` values wrong from actual cases.

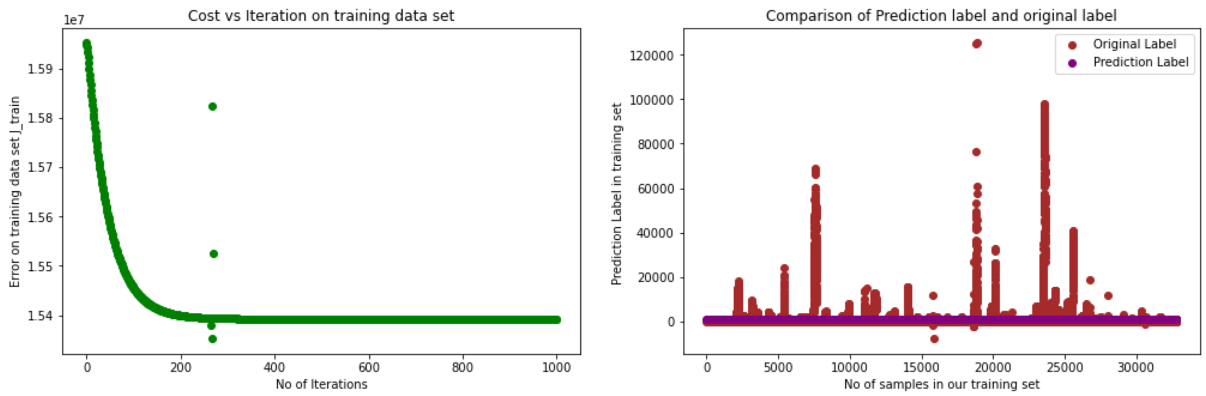
Step 18: Results and Data Visualization

Step 18.1: Results and Data Visualization of training data set

A) Graph of Cost vs Iterations to check the working of our model.

B) Scattter plot for our predictions in training set and y_train.

In [44]:
```
fig,(ax1,ax2)=plt.subplots(figsize=(17,5),
                           nrows=1,
                           ncols=2)
ax1.scatter(x=list(range(0,1000)),y=J_train,color="green")
ax1.set(xlabel="No of Iterations", ylabel = "Error on training data set J_train", title
ax2.scatter(x=list(range(0,len(x_train.T))),y=y_train.T,color='brown',label='Original La
ax2.scatter(x=list(range(0,len(x_train.T))),y=predictions_train.T,color='purple',label='
ax2.set(xlabel='No of samples in our training set',
       ylabel='Prediction Label in training set ',
       title='Comparison of Prediction label and original label')
ax2.legend();
```

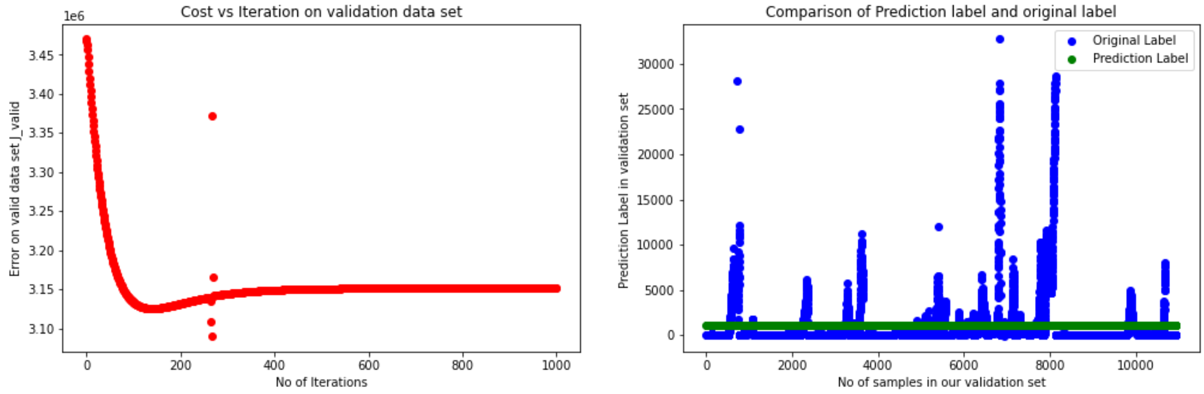


Step 18.2: Results and Data Visualization of validation data set

A) Graph of Cost vs Iterations to check the working of our model.

B) Scattter plot for our predictions in validation data set and y_valid.

In [45]:
```
fig,(ax1,ax2)=plt.subplots(figsize=(17,5),
                           nrows=1,
                           ncols=2)
ax1.scatter(x=list(range(0,1000)),y=J_valid,color="red")
ax1.set(xlabel="No of Iterations", ylabel = "Error on valid data set J_valid", title ="C
ax2.scatter(x=list(range(0,len(x_valid.T))),y=y_valid.T,color='blue',label='Original Lab
ax2.scatter(x=list(range(0,len(x_valid.T))),y=predictions_valid.T,color='green',label='P
ax2.set(xlabel='No of samples in our validation set',
       ylabel='Prediction Label in validation set ',
       title='Comparison of Prediction label and original label')
ax2.legend();
```

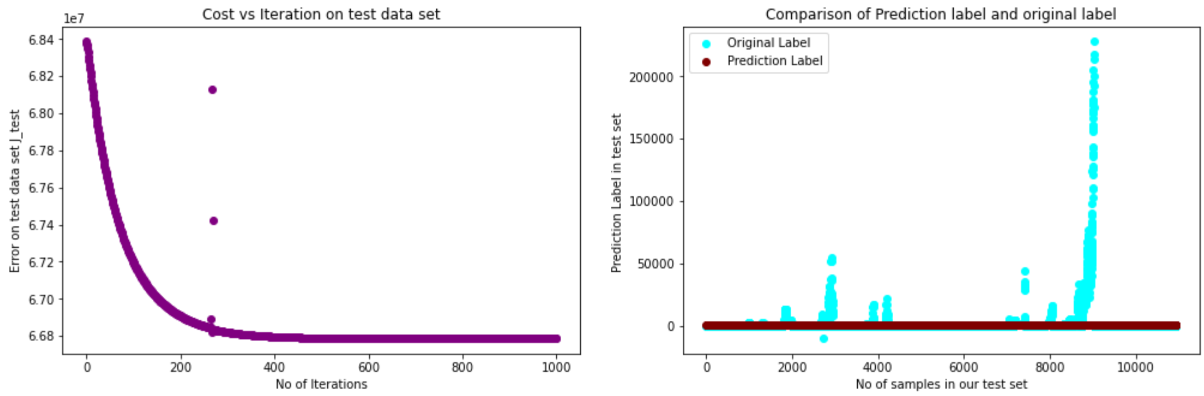


Step 18.3: Results and Data Visualization of test data set

A) Graph of Cost vs Iterations to check the working of our model.

B) Scattter plot for our predictions in test data set and y_test.

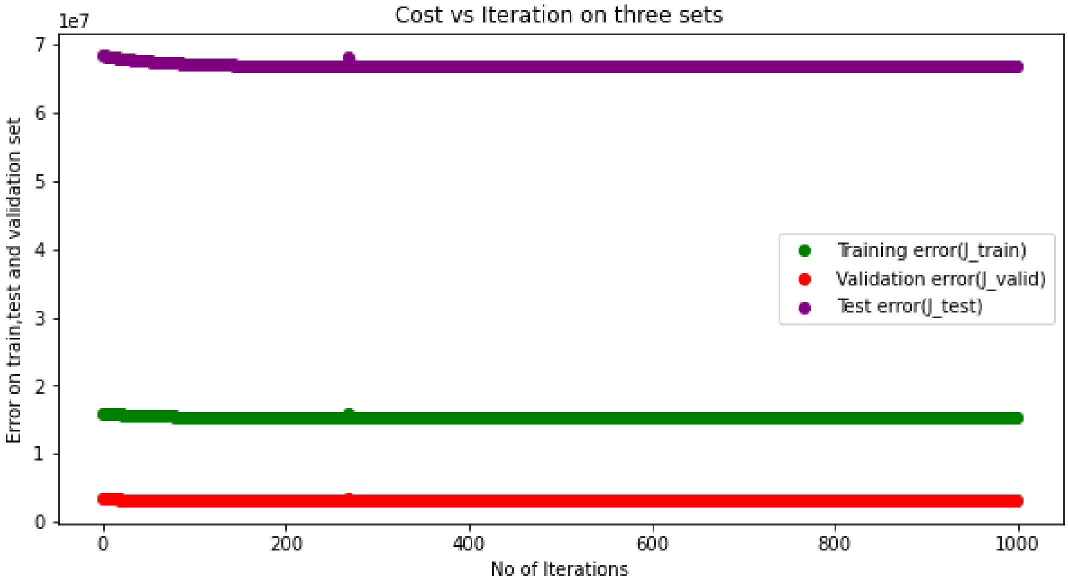
In [46]:
```
fig,(ax1,ax2)=plt.subplots(figsize=(17,5),
                           nrows=1,
                           ncols=2)
ax1.scatter(x=list(range(0,1000)),y=J_test,color="purple")
ax1.set(xlabel="No of Iterations", ylabel = "Error on test data set J_test", title ="Cos
ax2.scatter(x=list(range(0,len(x_test.T))),y=y_test.T,color='cyan',label='Original Label
ax2.scatter(x=list(range(0,len(x_test.T))),y=predictions_test.T,color='maroon',label='Pr
ax2.set(xlabel='No of samples in our test set',
       ylabel='Prediction Label in test set ',
       title='Comparison of Prediction label and original label')
ax2.legend();
```



Step 18.4: Error of all data sets

In [47]:

```
fig,(ax1)=plt.subplots(figsize=(10,5),
                          nrows=1,
                          ncols=1)
ax1.scatter(x=list(range(0,1000)),y=J_train,color='green',label='Training error(J_train)
ax1.scatter(x=list(range(0,1000)),y=J_valid,color='red',label='Validation error(J_valid)
ax1.scatter(x=list(range(0,1000)),y=J_test,color="purple",label='Test error(J_test)')
ax1.set(xlabel="No of Iterations", ylabel = "Error on train,test and validation set", ti
ax1.legend();
```



In [ ]: