Problem no. 1 Suppose you are the CEO of a restaurant. Now you want to open some new outlets in different cities. Your restaurant already has trucks in various cities, and you have data for profits and populations from those cities. The file “dataset_1_one_variable.txt” contains the dataset. The first column is the population of a city and the second column is the profit in that city. A negative value for profit indicates a loss.
Use linear regression with this data to select which city to expand to next. When solving the problem, you must comply with the following conditions.

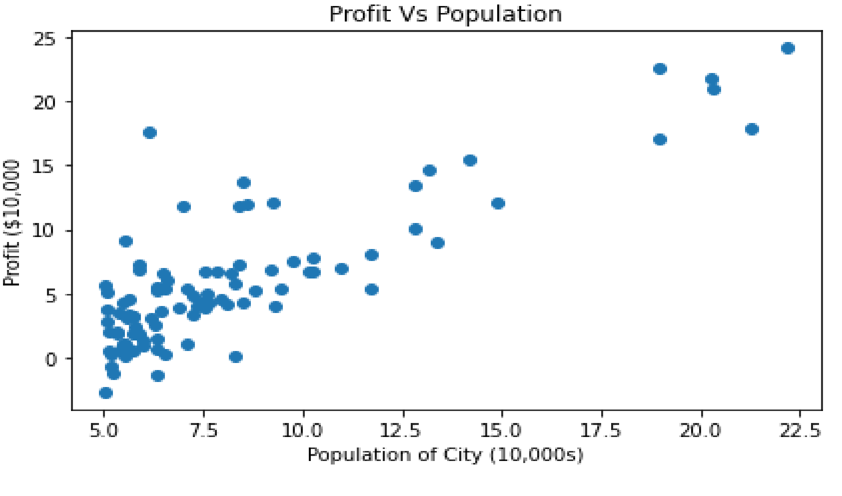
- Use Gradient Descent method to optimize the regression line.
- Use Mean Squared Error (MSE) in the Cost function.
- Implement different functions to measure Cost and Gradient Descent.
- Show the Scatter plot of the training data and the regression line of the final model.
- Show the loss curve of the whole training.
- Predict values for population sizes of 20,000 and 26,000 on the final model.
- Use python (and Jupyter notebook) to solve the problem.
- Implement the linear regression from the scratch and do not use any build in function for linear regression.

```
#Connect to Google COlab and upload file/s
from google.colab import files
files.upload()
```

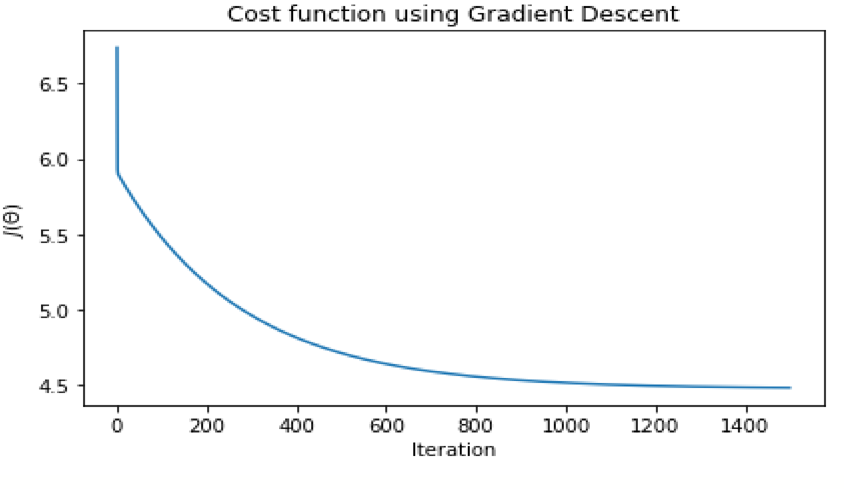
```
#Import Necessary Libraries
import numpy as np
from numpy import genfromtxt
import pandas as pd
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
```

```
#Load data
data=pd.read_csv("p1.txt", header=None)
data.head()
```

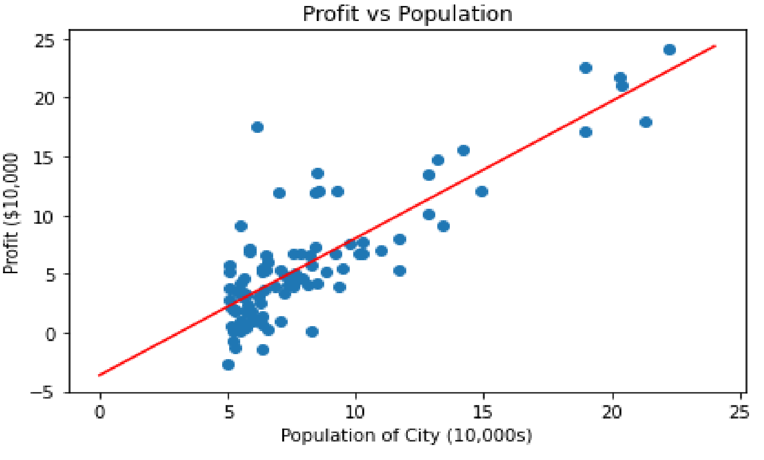
```
#Visualiza the original data
plt.scatter(data[0],data[1])
plt.xlabel("Population of City (10,000s)")
plt.ylabel("Profit ($10,000")
plt.title("Profit Vs Population")
plt.tight_layout()
```



```
#Split the dataset
X= data.iloc[:, :-1].values
y= data.iloc[:, -1].values

#Compute Cost function
def computeCost(X,y,theta):
    m=len(y)
    predictions=X.dot(theta)
    square_err=(predictions - y)**2
    return 1/(2*m) * np.sum(square_err)

data_n=data.values
m=len(data_n[:,-1])
X=np.append(np.ones((m,1)),data_n[:,0].reshape(m,1),axis=1)
y=data_n[:,1].reshape(m,1)
theta=np.zeros((2,1))
computeCost(X,y,theta)

#Gradient Descent function
def gradientDescent(X,y,theta,alpha,num_iters):
    m=len(y)
    J_history=[]
    for i in range(num_iters):
        predictions = X.dot(theta)
        error = np.dot(X.transpose(),(predictions -y))
        descent=alpha * 1/m * error
        theta-=descent
        J_history.append(computeCost(X,y,theta))
    return theta, J_history
theta,J_history = gradientDescent(X,y,theta,0.01,1500)
print("h(x) ="+str(round(theta[0,0],2))+" + "+str(round(theta[1,0],2))+"x1")

#Loss curve Visualization
plt.plot(J_history)
plt.xlabel("Iteration")
plt.ylabel("$J(\Theta)$")
plt.title("Cost function using Gradient Descent")
plt.tight_layout()
```



```python
#Regression line
plt.scatter(data[0],data[1])
x_value=[x for x in range(25)]
y_value=[y*theta[1]+theta[0] for y in x_value]
plt.plot(x_value,y_value,color="r")
plt.xlabel("Population of City (10,000s)")
plt.ylabel("Profit ($10,000")
plt.title("Profit vs Population")
plt.tight_layout()
```



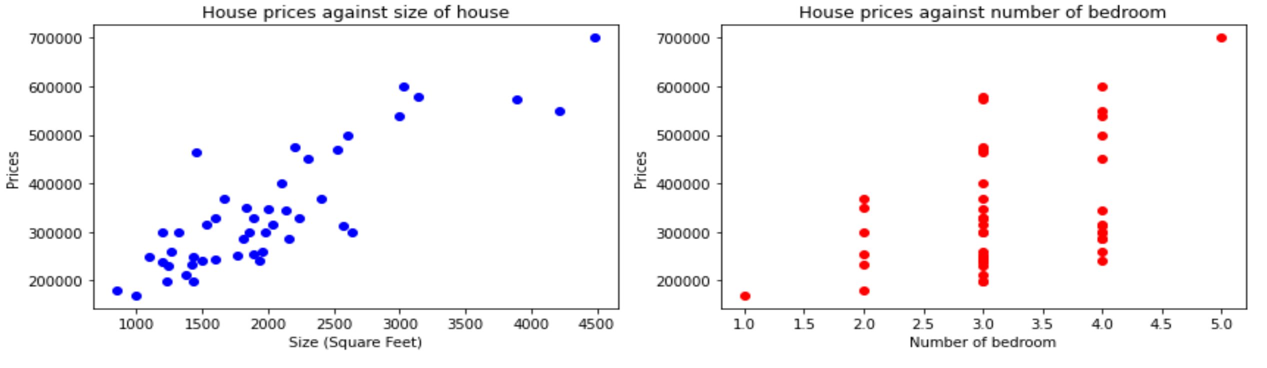

```python
#Predict function
def predict(x,theta):
    predictions= np.dot(theta.transpose(),x)
    return predictions[0]


#Predicting
predict1=predict(np.array([1,3.5]),theta)*10000
print("For population = 35,000, we predict a profit of $"+str(round(predict1,0)))


predict2=predict(np.array([1,70]),theta)*10000
print("For population = 70,000, we predict a profit of $"+str(round(predict2,0)))
```

Problem no. 2 The file “dataset_2_multiple_variable.txt” contains house prices based on size and number of bedrooms. The first column is the sizes of the house, the second column is the number of bed rooms, and the third column is the price of the house. Use linear regression using this data to build a model to predict the price of the house for new values. When solving the problem, you must comply with the following conditions.

- Use Gradient Descent method to optimize the regression line.
- Use Mean Squared Error (MSE) in the Cost function.
- Implement different functions to measure Cost and Gradient Descent.
- Show the Scatter plot of the training data and the regression line of the final model.
- Show the loss curve of the whole training.
- Estimate the price of a 1360 sq-ft, 3 bed rooms house.
- Use python (and Jupyter notebook) to solve the problem.
- Implement the linear regression from the scratch and do not use any build in function for linear regression.

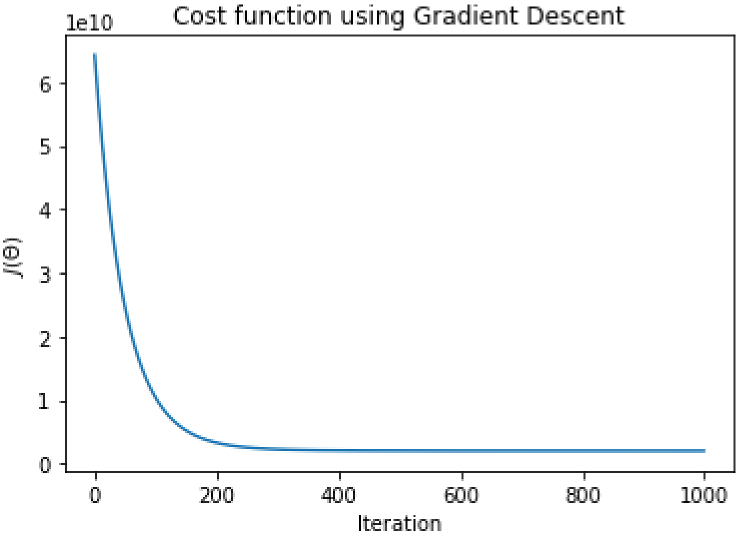
```python
#Connect to Google COlab and upload file/s
from google.colab import files
files.upload()
```

```python
#Import Necessary Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D


#Load the data
data=pd.read_csv("p2.txt", header=None)
data.head()


# Create 2 subplot, 1 for each variable
fig, axes = plt.subplots(figsize=(12,4),nrows=1,ncols=2)
axes[0].scatter(data[0],data[2],color="b")
axes[0].set_xlabel("Size (Square Feet)")
axes[0].set_ylabel("Prices")
axes[0].set_title("House prices against size of house")
axes[1].scatter(data[1],data[2],color="r")
axes[1].set_xlabel("Number of bedroom")
axes[1].set_ylabel("Prices")
axes[1].set_title("House prices against number of bedroom")
# Enhance layout
plt.tight_layout()
```




```python
#Cost Function
def computeCost(X,y,theta):
    m=len(y)
    predictions=X.dot(theta)
    square_err=(predictions - y)**2
    return 1/(2*m) * np.sum(square_err)


#Gradient Descent Function
def gradientDescent(X,y,theta,alpha,num_iters):
    m=len(y)
    J_history=[]
    for i in range(num_iters):
        predictions = X.dot(theta)
        error = np.dot(X.transpose(),(predictions -y))
        descent=alpha * 1/m * error
        theta-=descent
        J_history.append(computeCost(X,y,theta))
    return theta, J_history
```

```
#Feature Normalization
def featureNormalization(X):
    mean=np.mean(X,axis=0)
    std=np.std(X,axis=0)
    X_norm = (X - mean)/std
    return X_norm , mean , std
data_new=data.values
m2=len(data_new[:,-1])
X2=data_new[:,0:2].reshape(m2,2)
X2, mean_X2, std_X2 = featureNormalization(X2)
X2 = np.append(np.ones((m2,1)),X2,axis=1)
y2=data_new[:,-1].reshape(m2,1)
theta2=np.zeros((3,1))


#Function Calling
theta2, J_history2 = gradientDescent(X2,y2,theta2,0.01,1000)
print("h(x)= "+str(round(theta2[0,0],2))+" + "+str(round(theta2[1,0],2))+"x1 + "+
str(round(theta2[2,0],2))+"x2")


#Loss curve visualization
plt.plot(J_history2)
plt.xlabel("Iteration")
plt.ylabel("$J(\Theta)$")
plt.title("Cost function using Gradient Descent")
```



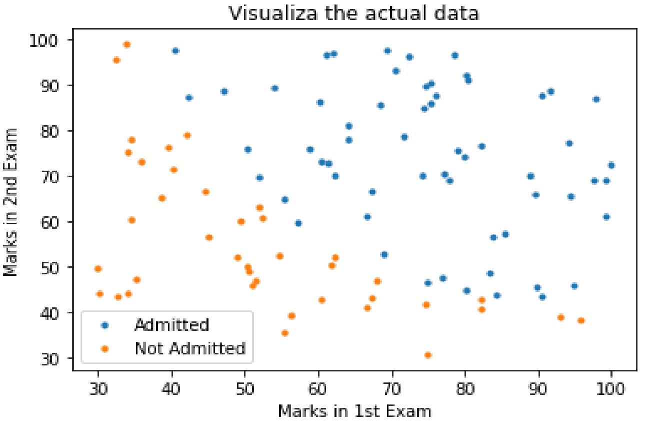

```
#Predict function
def predict(x,theta):
    predictions= np.dot(theta.transpose(),x)
    return predictions[0]


#Predicting
x_sample = featureNormalization(np.array([1650,3]))[0]
x_sample=np.append(np.ones(1),x_sample)
predict3= predict(x_sample,theta2)
print("For size of house = 1650, Number of bedroom = 3, we predict a house value
of $"+str(round(predict3,0)))
```

Problem no. 3 In this part of the exercise, you will build a logistic regression model to predict whether a student gets admitted into a university. Suppose that you are the administrator of a university department and you want to determine each applicant's chance of admission based on their results on two exams. You have historical data from previous applicants that you can use as a training set ("dataset_prob_3") for logistic regression. For each training example, you have the applicant's scores on two exams and the admissions decision. Your task is to build a classification model that estimates an applicant's probability of admission based the scores from those two exams.

When solving the problem, you must comply with the following conditions.

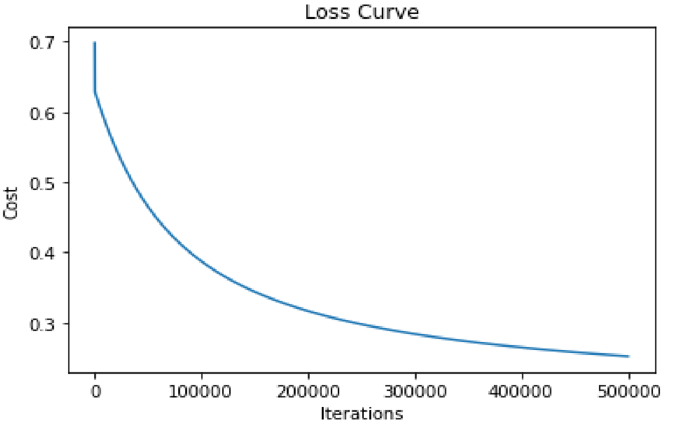
- Use Gradient Descent method to optimize the regression line.
- Implement different functions to measure Cost and Gradient Descent.
- Show the Scatter plot of the training data and the decision boundary of the final model.
- Show the loss curve of the whole training.
- Use python (and Jupyter notebook) to solve the problem.
- Implement the logistic regression from the scratch and do not use any build in function for logistic
- regression.

```python
#Conncet to Google colab
from google.colab import files
files.upload()

#Import Necessary Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

#Load data
data= pd.read_csv("p3.txt", header=None)
data.head()

#Split the dataset
x= data.iloc[:,:-1].values
y= data.iloc[:,-1].values
m,n= x.shape

#Filter out the data between admitted and non admitted
ad = data.loc[y == 1]
non_ad= data.loc[y==0]

#Visualization of the original data
plt.scatter(ad.iloc[:, 0], ad.iloc[:, 1], s=10, label="Admitted")
plt.scatter(non_ad.iloc[:, 0], non_ad.iloc[:, 1], s=10, label="Not Admitted")
plt.xlabel("Marks in 1st Exam")
plt.ylabel("Marks in 2nd Exam")
plt.legend()
plt.title('Visualiza the actual data')
plt.show()
```

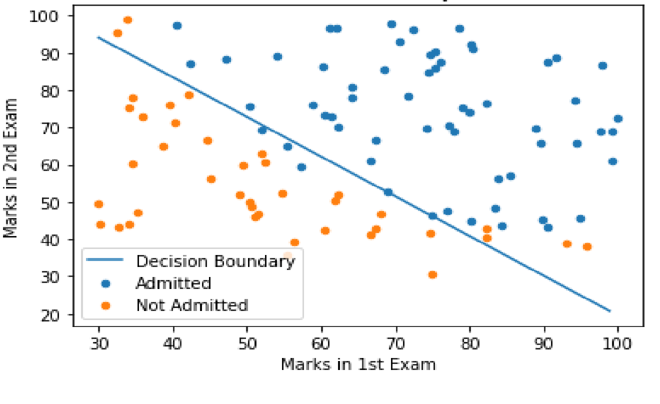



```
#Add a column of ones in X
z=np.ones(m)
z=z.reshape(m,1)
x=np.append(z,x,axis=1)
x.shape

#Add a column of zeros for theta
m,n= x.shape
theta= np.zeros(n)
theta= theta.reshape(n,1)
y= y.reshape(-1,1)

#Sigmoid function
def sigmoid(z):
  return 1/(1+np.exp(-z))

#Hypothesis function
def hypothesis(x, theta):
  return np.dot(x, theta)

#Cost function
def compute_cost(theta, x, y):
  res= -y*(np.log(sigmoid(hypothesis(x, theta))))- (1-y)*(np.log(1-
sigmoid(hypothesis(x, theta))))
  j= np.sum(res)/m
  return j
compute_cost(theta, x, y)

#Define learning rate and iterations
iteration= 500000
alpha=0.1

#Gradient Descent function
cost_history = []
def gradient_descent(x, y, theta, alpha, iteration):
  for i in range(iteration):
    res= sigmoid(hypothesis(x, theta))-y
    grad= np.dot(x.transpose(), res)/m
    theta= theta- (alpha/m)*grad
    cost= compute_cost(theta, x, y)
```

```
    cost_history.append(cost)
  return theta
theta= gradient_descent(x, y, theta, alpha, iteration)
theta

compute_cost(theta, x, y)

#Loss curve visualization
plt.plot(cost_history)
plt.title('Loss Curve')
plt.xlabel('Iterations')
plt.ylabel('Cost')
plt.show()
```



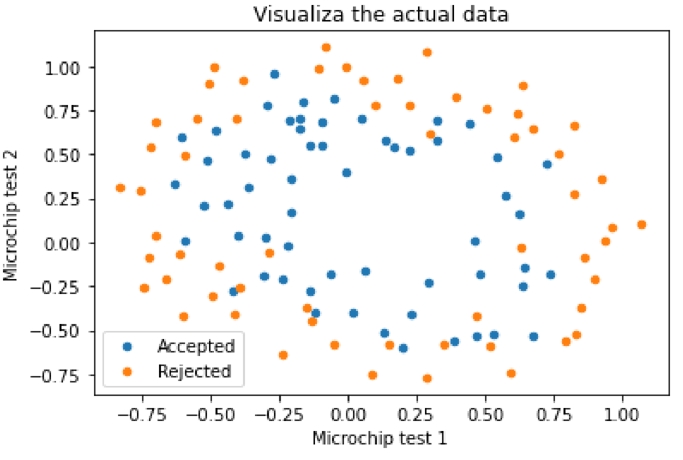

```
#Regression line visualization
x_values = [np.min(x[:, 1] ), np.max(x[:, 2] )]
a,b =x_values
y_min = - (theta[0] + np.dot(theta[1], a)) / theta[2]
y_max = - (theta[0] + np.dot(theta[1], b)) / theta[2]
y_values= y_min, y_max
plt.scatter(ad.iloc[:, 0], ad.iloc[:, 1], s=20, label="Admitted")
plt.scatter(non_ad.iloc[:, 0], non_ad.iloc[:, 1], s=20, label="Not Admitted")
plt.plot(x_values, y_values, label='Decision Boundary')
plt.xlabel('Marks in 1st Exam')
plt.ylabel('Marks in 2nd Exam')
plt.legend()
plt.title('Decision Boundary')
plt.show()
```



Problem no. 4 In this part of the exercise, you will implement regularized logistic regression to predict whether microchips from a fabrication plant passes quality assurance (QA). During QA, each microchip goes through various tests to ensure it is functioning correctly. Suppose you are the product manager of the factory and you have the test results for some microchips on two different tests. From these two tests, you would like to determine whether the microchips should be accepted or rejected. To help you make the decision, you have a dataset ("dataset_prob_4") of test results on past microchips, from which you can build a logistic regression model. When solving the problem, you must comply with the following conditions.

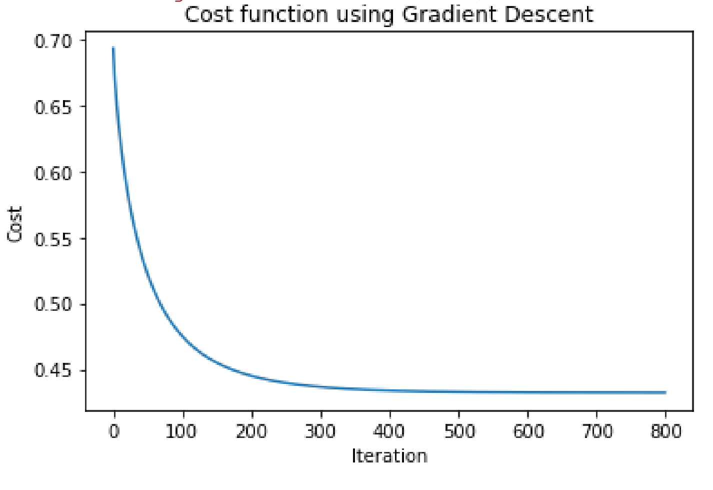
- Use Gradient Descent method to optimize the regression line.
- Implement different functions to measure Cost and Gradient Descent.
- Show the Scatter plot of the training data and the decision boundary of the final model.
- Show the loss curve of the whole training.
- Use python (and Jupyter notebook) to solve the problem.
- Implement the logistic regression from the scratch and do not use any build in function for logistic regression.

```python
#Connect to the google colab
from google.colab import files
files.upload()


#Import the necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt


#Load Data
data= pd.read_csv('p4.txt', header=None)
data.head()


#Split the dataset
x= data.iloc[:, :-1].values
y= data.iloc[:, -1].values
m,n= x.shape


#Filter out whether the chip is accepted or rejected
accepted = data.loc[y == 1]
rejected= data.loc[y==0]


#Original data visualization
plt.scatter(accepted.iloc[:, 0], accepted.iloc[:, 1], c='r', s=20, label="Accepte
d")
plt.scatter(rejected.iloc[:, 0], rejected.iloc[:, 1], c='b', s=20, label="Rejecte
d")
plt.xlabel("Microchip test 1")
plt.ylabel("Microchip test 2")
plt.title('Visualiza the actual data')
plt.legend()
plt.show()
```



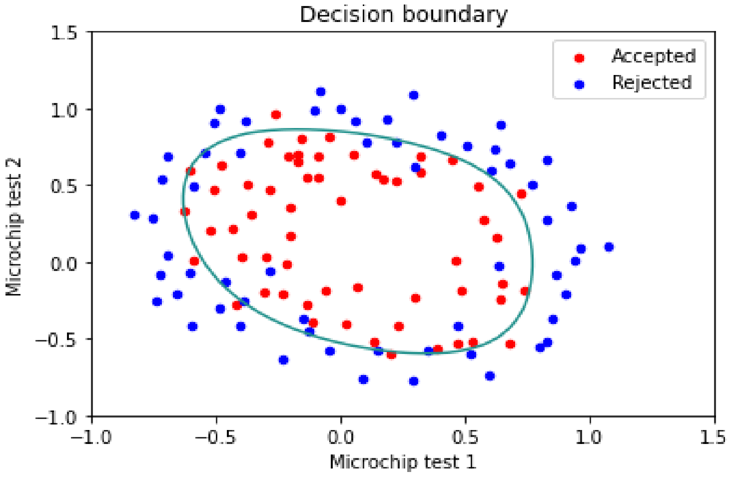

```
#Polynomial function
def mapping(x1,x2,degree):
    res = np.ones(len(x1)).reshape(len(x1),1)
    for i in range(1,degree+1):
        for j in range(i+1):
            terms= (x1**(i-j) * x2**j).reshape(len(x1),1)
            res= np.hstack((res,terms))
    return res
x = mapping(x[:,0], x[:,1],6)
x.shape

#Sigmoid function
def sigmoid(z):
  return 1/(1+np.exp(-z))

#Cost function
def compute_cost(theta, x, y ,Lambda):
    m=len(y)
    y=y[:,np.newaxis]
    h = sigmoid(x @ theta)
    error = (-y * np.log(h)) - ((1-y)*np.log(1-h))
    cost = 1/m * sum(error)
    regCost= cost + Lambda/(2*m) * sum(theta**2)
    # compute gradient
    j_0= 1/m * (x.transpose() @ (h - y))[0]
    j_1 = 1/m * (x.transpose() @ (h - y))[1:] + (Lambda/m)* theta[1:]
    grad= np.vstack((j_0[:,np.newaxis],j_1))
    return regCost[0], grad

#Initialization of the parameter
initial_theta = np.zeros((x.shape[1], 1))
Lambda = 1
alpha= 1
iteration= 800
cost, grad= compute_cost(initial_theta, x, y, Lambda)
cost
```

```
#Gradient Descent function
def gradientDescent(x,y,theta,alpha,num_iters,Lambda):
    m=len(y)
    cost_history= []
    for i in range(num_iters):
        cost, grad = compute_cost(theta,x,y,Lambda)
        theta = theta - (alpha * grad)
        cost_history.append(cost)
    return theta , cost_history
theta, cost_history = gradientDescent(x, y, initial_theta, alpha, iteration, 0.2)


theta


#Loss curve visualization
plt.plot(cost_history)
plt.xlabel("Iteration")
plt.ylabel("Cost")
plt.title("Cost function using Gradient Descent")
```




```
#Plotting function
def mapFeaturePlot(x1, x2, degree):
    res = np.ones(1)
    for i in range(1, degree+1):
        for j in range(i+1):
            terms= (x1**(i-j) * x2**j)
            res= np.hstack((res,terms))
    return res


#Decesion boundary visualization
a= np.linspace(-1,1.5,50)
b= np.linspace(-1,1.5,50)
c= np.zeros((len(a),len(b)))
for i in range(len(a)):
    for j in range(len(b)):
        c[i,j] =mapFeaturePlot(a[i], b[j],6) @ theta
plt.contour(a, b, c.T, 0)
plt.scatter(accepted.iloc[:, 0], accepted.iloc[:, 1], c='r', s=20, label="Accepte
d")
```

```
plt.scatter(rejected.iloc[:, 0], rejected.iloc[:, 1], c='b', s=20, label="Rejecte
d")
plt.xlabel("Microchip test 1")
plt.ylabel("Microchip test 2")
plt.title('Decision boundary')
plt.legend()
plt.show()
```

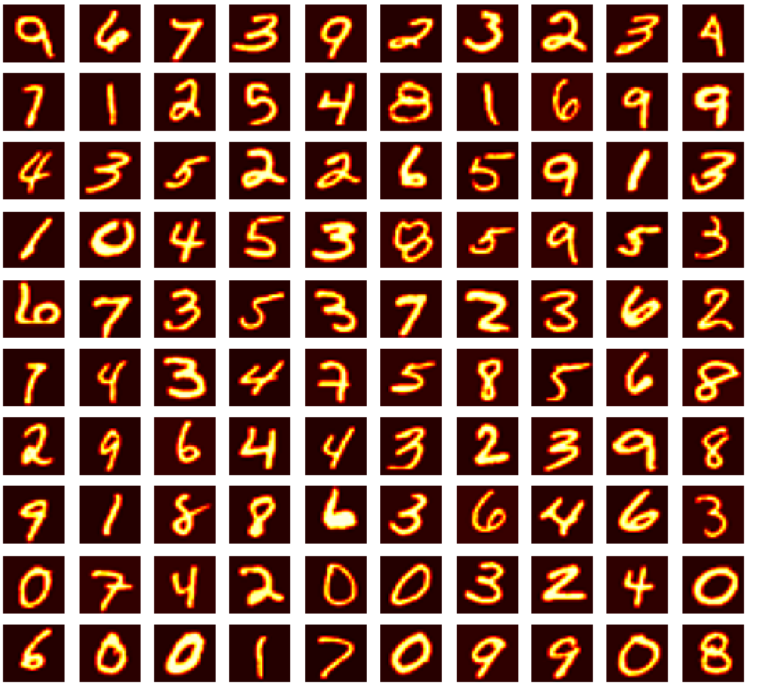


Problem no. 5 In the first part of the exercise, you will extend your previous implementation of logistic regression using the above dataset and apply it to one-vs-all classification.

- When solving the problem, you must comply with the following conditions.
- Use Gradient Descent method to optimize the regression line.
- Implement different functions for Vectorized Logistic Regression, vectorized cost function and
- vectorized gradient.
- Show the loss curve of the whole training.
- Use python (and Jupyter notebook) to solve the problem.

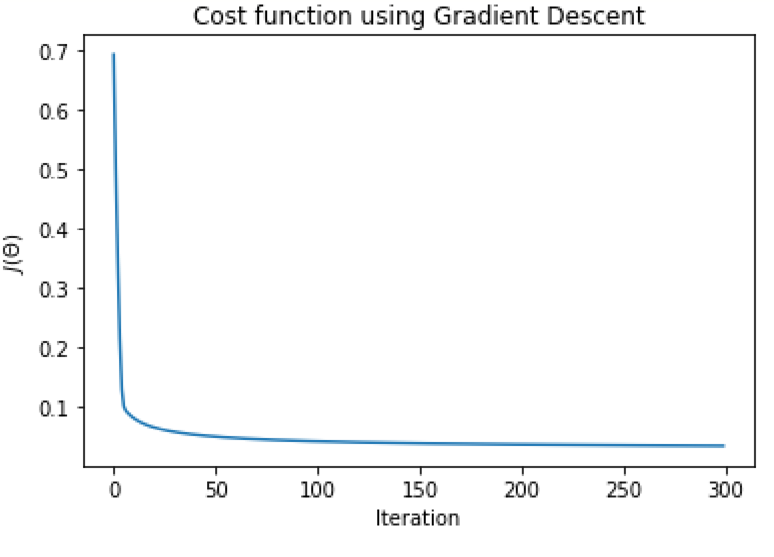
```
#Connect to Google Colab and upload the necessary file/s
from google.colab import files
files.upload()


#Import Necessary Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.io import loadmat


# Use loadmat to load matlab files
mat=loadmat("p5.mat")
X=mat["X"]
y=mat["y"]


#Original data visualization
import matplotlib.image as mpimg
fig, axis = plt.subplots(10,10,figsize=(8,8))
for i in range(10):
    for j in range(10):
```

```
        axis[i,j].imshow(X[np.random.randint(0,5001),:].reshape(20,20,order="F"),
cmap="hot") #reshape back to 20 pixel by 20 pixel
        axis[i,j].axis("off")
```



```
#Sigmoid Function
def sigmoid(z):
    return 1/ (1 + np.exp(-z))

#Cost Function
def lrCostFunction(theta, X, y, Lambda):
    m=len(y)
    predictions = sigmoid(X @ theta)
    error = (-y * np.log(predictions)) - ((1-y)*np.log(1-predictions))
    cost = 1/m * sum(error)
    regCost= cost + Lambda/(2*m) * sum(theta[1:]**2)
    # compute gradient
    j_0= 1/m * (X.transpose() @ (predictions - y))[0]
    j_1 = 1/m * (X.transpose() @ (predictions - y))[1:] + (Lambda/m)* theta[1:]
    grad= np.vstack((j_0[:,np.newaxis],j_1))
    return regCost[0], grad

#Parameters modification Function Calling
theta_t = np.array([-2,-1,1,2]).reshape(4,1)
X_t =np.array([np.linspace(0.1,1.5,15)]).reshape(3,5).T
X_t = np.hstack((np.ones((5,1)), X_t))
y_t = np.array([1,0,1,0,1]).reshape(5,1)
J, grad = lrCostFunction(theta_t, X_t, y_t, 3)
print("Cost:",J,"Expected cost: 2.534819")
print("Gradients:\n",grad,"\nExpected gradients:\n 0.146561\n -
0.548558\n 0.724722\n 1.398003")
```

```
#Gradient Descent Function
def gradientDescent(X,y,theta,alpha,num_iters,Lambda):
    m=len(y)
    J_history =[]
    for i in range(num_iters):
        cost, grad = lrCostFunction(theta,X,y,Lambda)
        theta = theta - (alpha * grad)
        J_history.append(cost)
    return theta , J_history


#One Vs All Function
def oneVsAll(X, y, num_labels, Lambda):
    m, n = X.shape[0], X.shape[1]
    initial_theta = np.zeros((n+1,1))
    all_theta = []
    all_J=[]
    # add intercept terms
    X = np.hstack((np.ones((m,1)),X))
    for i in range(1,num_labels+1):
        theta , J_history = gradientDescent(X,np.where(y==i,1,0),initial_theta,1,
300,Lambda)
        all_theta.extend(theta)
        all_J.extend(J_history)
    return np.array(all_theta).reshape(num_labels,n+1), all_J
all_theta, all_J= oneVsAll(X, y, 10, 1)


#Loss curve visualization
plt.plot(all_J[0:300])
plt.xlabel("Iteration")
plt.ylabel("$J(\Theta)$")
plt.title("Cost function using Gradient Descent")
```




```
#Predicting the Accuracy
def predictOneVsAll(all_theta, X):
    m= X.shape[0]
    X = np.hstack((np.ones((m,1)),X))
```

```
    predictions = X @ all_theta.T
    return np.argmax(predictions,axis=1)+1
pred = predictOneVsAll(all_theta, X)
print("Training Set Accuracy:",sum(pred[:,np.newaxis]==y)[0]/5000*100,"%"
```

Problem no. 6 In the previous part of this exercise, you implemented multi-class logistic regression to recognize handwritten digits. However, logistic regression cannot form more complex hypotheses as it is only a linear classifier (You could add more features - such as polynomial features - to logistic regression, but that can be very expensive to train). In this part of the exercise, you will implement a neural network to recognize handwritten digits using the same training set as before. The neural network will be able to represent complex models that form nonlinear hypotheses. For this experiment, you will be using parameters from a neural network that are already trained. Your goal is to implement the feedforward propagation algorithm to use the weights for prediction. In the next exercise, you will write the backpropagation algorithm for learning the neural network parameters.

When solving the problem, you must comply with the following conditions.

- Implement the feedforward propagation algorithm to use the weights ($\Theta(1)$, $\Theta(2)$) for prediction.
- Use python (and Jupyter notebook) to solve the problem.

```
#Connect the Google Colab and upload File/s
from google.colab import files
files.upload()

#Import Necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.io import loadmat

# Use loadmat to load matlab files
mat=loadmat("p5.mat")
X=mat["X"]
y=mat["y"]
mat2=loadmat("p6.mat")
Theta1=mat2["Theta1"] # Theta1 has size 25 x 401
Theta2=mat2["Theta2"] # Theta2 has size 10 x 26

#Sigmoid function
def sigmoid(z):
    return 1/ (1 + np.exp(-z))

#Using feedforward propagation for prediction
def predict(Theta1, Theta2, X):
    m= X.shape[0]
    X = np.hstack((np.ones((m,1)),X))
    a1 = sigmoid(X @ Theta1.T)
    a1 = np.hstack((np.ones((m,1)), a1)) # hidden layer
    a2 = sigmoid(a1 @ Theta2.T) # output layer
    return np.argmax(a2,axis=1)+1
pred2 = predict(Theta1, Theta2, X)
print("Training Set Accuracy:",sum(pred2[:,np.newaxis]==y)[0]/5000*100,"%")
```

```python
#Sigmoid Gradient
def sigmoidGradient(z):
    sigmoid = 1/(1 + np.exp(-z))
    return sigmoid *(1-sigmoid)

#Cost Function and Gradient
def nnCostFunction(nn_params,input_layer_size, hidden_layer_size, num_labels,X, y,Lambda):
    # Reshape nn_params back into the parameters Theta1 and Theta2
    Theta1 = nn_params[:((input_layer_size+1) * hidden_layer_size)].reshape(hidden_layer_size,input_layer_size+1)
    Theta2 = nn_params[((input_layer_size +1)* hidden_layer_size ):].reshape(num_labels,hidden_layer_size+1)
    m = X.shape[0]
    J=0
    X = np.hstack((np.ones((m,1)),X))
    y10 = np.zeros((m,num_labels))
    a1 = sigmoid(X @ Theta1.T)
    a1 = np.hstack((np.ones((m,1)), a1)) # hidden layer
    a2 = sigmoid(a1 @ Theta2.T) # output layer
    for i in range(1,num_labels+1):
        y10[:,i-1][:,np.newaxis] = np.where(y==i,1,0)
    for j in range(num_labels):
        J = J + sum(-y10[:,j] * np.log(a2[:,j]) - (1-y10[:,j])*np.log(1-a2[:,j]))
    cost = 1/m* J
    reg_J = cost + Lambda/(2*m) * (np.sum(Theta1[:,1:]**2) + np.sum(Theta2[:,1:]**2))
    # Implement the backpropagation algorithm to compute the gradients
    grad1 = np.zeros((Theta1.shape))
    grad2 = np.zeros((Theta2.shape))
    for i in range(m):
        xi= X[i,:] # 1 X 401
        a1i = a1[i,:] # 1 X 26
        a2i =a2[i,:] # 1 X 10
        d2 = a2i - y10[i,:]
        d1 = Theta2.T @ d2.T * sigmoidGradient(np.hstack((1,xi @ Theta1.T)))
        grad1= grad1 + d1[1:][:,np.newaxis] @ xi[:,np.newaxis].T
        grad2 = grad2 + d2.T[:,np.newaxis] @ a1i[:,np.newaxis].T
    grad1 = 1/m * grad1
    grad2 = 1/m*grad2
    grad1_reg = grad1 + (Lambda/m) * np.hstack((np.zeros((Theta1.shape[0],1)),Theta1[:,1:]))
    grad2_reg = grad2 + (Lambda/m) * np.hstack((np.zeros((Theta2.shape[0],1)),Theta2[:,1:]))
    return cost, grad1, grad2,reg_J, grad1_reg,grad2_reg
```

```
#Parameter Initialization
input_layer_size  = 400
hidden_layer_size = 25
num_labels = 10
nn_params = np.append(Theta1.flatten(),Theta2.flatten())
J,reg_J = nnCostFunction(nn_params, input_layer_size, hidden_layer_size, num_labe
ls, X, y, 1)[0:4:3]
print("Cost at parameters (non-
regularized):",J,"\nCost at parameters (Regularized):",reg_J)


#Weight Initialization
def randInitializeWeights(L_in, L_out):
    epi = (6**1/2) / (L_in + L_out)**1/2
    W = np.random.rand(L_out,L_in +1) *(2*epi) -epi
    return W
initial_Theta1 = randInitializeWeights(input_layer_size, hidden_layer_size)
initial_Theta2 = randInitializeWeights(hidden_layer_size, num_labels)
initial_nn_params = np.append(initial_Theta1.flatten(),initial_Theta2.flatten())


#Gradient Descent Function
def gradientDescentnn(X,y,initial_nn_params,alpha,num_iters,Lambda,input_layer_si
ze, hidden_layer_size, num_labels):
    Theta1 = initial_nn_params[:((input_layer_size+1) * hidden_layer_size)].resha
pe(hidden_layer_size,input_layer_size+1)
    Theta2 = initial_nn_params[((input_layer_size +1)* hidden_layer_size ):].resh
ape(num_labels,hidden_layer_size+1)
    m=len(y)
    J_history =[]
    for i in range(num_iters):
        nn_params = np.append(Theta1.flatten(),Theta2.flatten())
        cost, grad1, grad2 = nnCostFunction(nn_params,input_layer_size, hidden_la
yer_size, num_labels,X, y,Lambda)[3:]
        Theta1 = Theta1 - (alpha * grad1)
        Theta2 = Theta2 - (alpha * grad2)
        J_history.append(cost)
    nn_paramsFinal = np.append(Theta1.flatten(),Theta2.flatten())
    return nn_paramsFinal , J_history
nnTheta, nnJ_history = gradientDescentnn(X,y,initial_nn_params,0.8,800,1,input_la
yer_size, hidden_layer_size, num_labels)
Theta1 = nnTheta[:((input_layer_size+1) * hidden_layer_size)].reshape(hidden_laye
r_size,input_layer_size+1)
Theta2 = nnTheta[((input_layer_size +1)* hidden_layer_size ):].reshape(num_labels
,hidden_layer_size+1)


#Predict the Accuracy
pred3 = predict(Theta1, Theta2, X)
print("Training Set Accuracy:",sum(pred3[:,np.newaxis]==y)[0]/5000*100,"%")
```