Practice lab: Logistic Regression

In this exercise, we will implement logistic regression and apply it to two different datasets.

In [13]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import copy
import math
```

In [14]:
```
# Load dataset
"""
X_train contains exam scores on two exams for a student
y_train is the admission decision
y_train = 1 if the student was admitted
y_train = 0 if the student was not admitted
Both X_train and y_train are numpy arrays.
"""
df = pd.read_csv(r'...')
X_train, y_train = df.to_numpy()
```

In [15]:
```
print("First five elements in X_train are:\n", X_train[:5])
print("Type of X_train:",type(X_train))
```

```
First five elements in X_train are:
 [[34.62365962 78.02469282]
 [30.28671077 43.89499752]
 [35.84740877 72.90219803]
 [60.18259939 86.3085521 ]
 [79.03273605 75.34437644]]
Type of X_train: <class 'numpy.ndarray'>
```

In [16]:
```
print("First five elements in y_train are:\n", y_train[:5])
print("Type of y_train:",type(y_train))
```

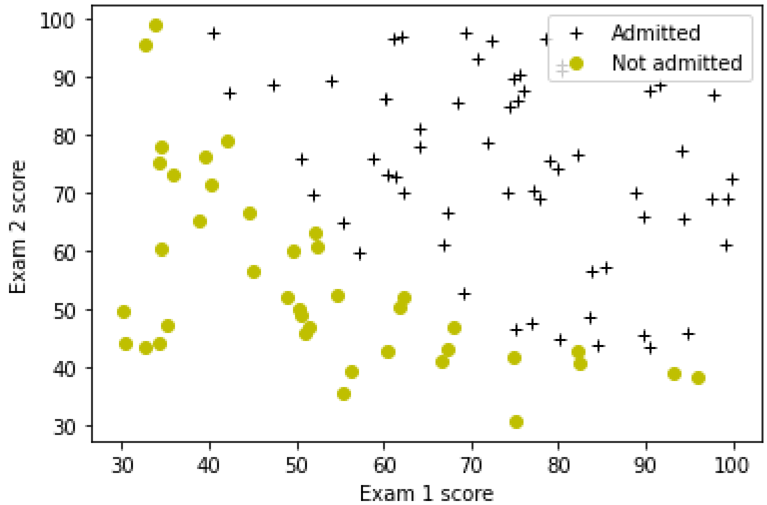
```
First five elements in y_train are:
 [0. 0. 0. 1. 1.]
Type of y_train: <class 'numpy.ndarray'>
```

In [17]:
```
print ('The shape of X_train is: ' + str(X_train.shape))
print ('The shape of y_train is: ' + str(y_train.shape))
print ('We have m = %d training examples' % (len(y_train)))
```

```
The shape of X_train is: (100, 2)
The shape of y_train is: (100,)
We have m = 100 training examples
```

In [18]:
```
# Plot examples
plot_data(X_train, y_train[:], pos_label="Admitted", neg_label="Not admitted")

# Set the y-axis label
plt.ylabel('Exam 2 score')
# Set the x-axis label
plt.xlabel('Exam 1 score')
```

```
plt.legend(loc="upper right")
plt.show()
```



In [22]:

```
# implement sigmoid function

def sigmoid(z):
    """
    Compute the sigmoid of z

    Args:
        z (ndarray): A scalar, numpy array of any size.

    Returns:
        g (ndarray): sigmoid(z), with the same shape as z

    """
    g = 1/(1+np.exp(-z))
    return g
```

In [33]:

```
# implement compute_cost
def compute_cost(X, y, w, b, lambda_= 1):
    """
    Computes the cost over all examples
    Args:
      X : (ndarray Shape (m,n)) data, m examples by n features
      y : (array_like Shape (m,)) target value
      w : (array_like Shape (n,)) Values of parameters of the model
      b : scalar Values of bias parameter of the model
      lambda_: unused placeholder
    Returns:
      total_cost: (scalar)         cost
    """
    m, n = X.shape

    loss_sum = 0
    for i in range(m):
        z_i = 0
        for j in range(n):
            # Add the corresponding term to z_wb
            z_ij = np.dot(X[i,j],w[j])
            z_i +=z_ij
        # Add the bias term to z_wb
```

```
        z_i = z_i +b
        # Add the sigmoid function to z_wb
        f_wb_i = sigmoid(z_i)
        loss =  -y[i]*np.log(f_wb_i) - (1-y[i])*np.log(1-f_wb_i)
        loss_sum += loss
    total_cost =  loss_sum/m

    return total_cost
```

In [34]:
```
m, n = X_train.shape

# Compute and display cost with w initialized to zeroes
initial_w = np.zeros(n)
initial_b = 0.
cost = compute_cost(X_train, y_train, initial_w, initial_b)
print('Cost at initial w (zeros): {:.3f}'.format(cost))
```

```
Cost at initial w (zeros): 0.693
```

In [48]:
```
# implement gradient descent function
def compute_gradient(X, y, w, b, lambda_=None):
    """
    Computes the gradient for logistic regression

    Args:
      X : (ndarray Shape (m,n)) variable such as house size
      y : (array_like Shape (m,1)) actual value
      w : (array_like Shape (n,1)) values of parameters of the model
      b : (scalar)                 value of parameter of the model
      lambda_: unused placeholder.
    Returns
      dj_dw: (array_like Shape (n,1)) The gradient of the cost w.r.t. the parameters w
      dj_db: (scalar)                The gradient of the cost w.r.t. the parameter b.
    """
    m, n = X.shape
    dj_dw = np.zeros(w.shape)
    dj_db = 0.

    for i in range(m):
        z_wb = 0
        for j in range(n):
            z_wb += np.dot(X[i,j],w[j])
        z_wb += b
        f_wb = sigmoid(z_wb)

        dj_db_i = f_wb - y[i]
        dj_db += dj_db_i

        for j in range(n):
            dj_dw[j] += (f_wb - y[i])*X[i,j]


    dj_dw = (1/m)*dj_dw
    dj_db = (1/m)*dj_db


    return dj_db, dj_dw
```

In [49]:
```
# Compute and display gradient with w initialized to zeroes
initial_w = np.zeros(n)
initial_b = 0.

dj_db, dj_dw = compute_gradient(X_train, y_train, initial_w, initial_b)
print(f'dj_db at initial w (zeros):{dj_db}' )
print(f'dj_dw at initial w (zeros):{dj_dw.tolist()}' )
```

```
dj_db at initial w (zeros):-0.1
dj_dw at initial w (zeros):[-12.00921658929115, -11.262842205513591]
```

Learning parameters using gradient descent

In [51]:
```
def gradient_descent(X, y, w_in, b_in, cost_function, gradient_function, alpha, num_it
    """
    Performs batch gradient descent to learn theta. Updates theta by taking
    num_iters gradient steps with learning rate alpha

    Args:
      X :    (array_like Shape (m, n)
      y :    (array_like Shape (m,))
      w_in : (array_like Shape (n,))  Initial values of parameters of the model
      b_in : (scalar)                 Initial value of parameter of the model
      cost_function:                  function to compute cost
      alpha : (float)                 Learning rate
      num_iters : (int)               number of iterations to run gradient descent
      lambda_ (scalar, float)         regularization constant

    Returns:
      w : (array_like Shape (n,)) Updated values of parameters of the model after
          running gradient descent
      b : (scalar)                Updated value of parameter of the model after
          running gradient descent
    """

    # number of training examples
    m = len(X)

    # An array to store cost J and w's at each iteration for graphing
    J_history = []
    w_history = []

    for i in range(num_iters):

        # Calculate the gradient and update the parameters
        dj_db, dj_dw = gradient_function(X, y, w_in, b_in, lambda_)

        # Update Parameters using w, b, alpha and gradient
        w_in = w_in - alpha * dj_dw
        b_in = b_in - alpha * dj_db

        # Save cost J at each iteration
        if i<100000:      # prevent resource exhaustion
            cost =  cost_function(X, y, w_in, b_in, lambda_)
            J_history.append(cost)

        # Print cost every at intervals 10 times or as many iterations if < 10
        if i% math.ceil(num_iters/10) == 0 or i == (num_iters-1):
```

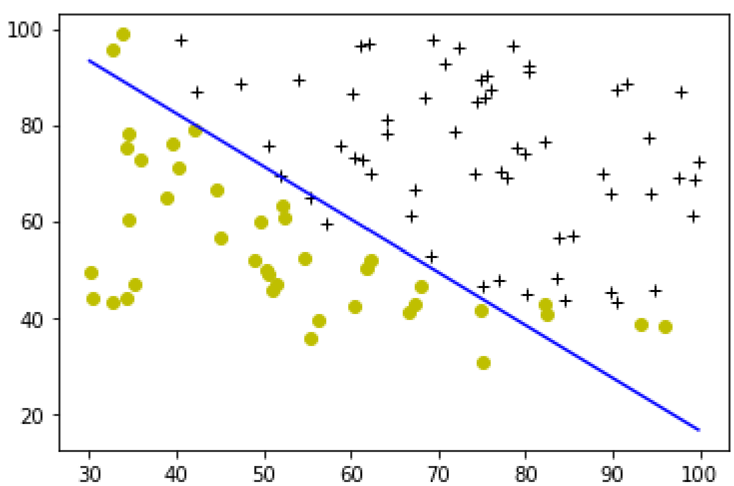
```
            w_history.append(w_in)
            print(f"Iteration {i:4}: Cost {float(J_history[-1]):8.2f}   ")

    return w_in, b_in, J_history, w_history #return w and J,w history for graphing
```

In [52]:
```
# run gradient descent to learn the parameters
np.random.seed(1)
intial_w = 0.01 * (np.random.rand(2).reshape(-1,1) - 0.5)
initial_b = -8


# Some gradient descent settings
iterations = 10000
alpha = 0.001

w,b, J_history,_ = gradient_descent(X_train ,y_train, initial_w, initial_b,
                                   compute_cost, compute_gradient, alpha, iterations,
```

```
Iteration    0: Cost     1.01
Iteration 1000: Cost     0.31
Iteration 2000: Cost     0.30
Iteration 3000: Cost     0.30
Iteration 4000: Cost     0.30
Iteration 5000: Cost     0.30
Iteration 6000: Cost     0.30
Iteration 7000: Cost     0.30
Iteration 8000: Cost     0.30
Iteration 9000: Cost     0.30
Iteration 9999: Cost     0.30
```

Plotting the decision boundary

In [53]:
```
plot_decision_boundary(w, b, X_train, y_train)
```



Evaluating logistic regression

In [56]:
```
# implement predict function to produce 1 or 0 predictions given a dataset and w,b

def predict(X, w, b):
    """
    Predict whether the label is 0 or 1 using learned logistic
```

```
    regression parameters w

    Args:
    X : (ndarray Shape (m, n))
    w : (array_like Shape (n,))      Parameters of the model
    b : (scalar, float)              Parameter of the model

    Returns:
    p: (ndarray (m,1))
        The predictions for X using a threshold at 0.5
    """
    # number of training examples
    m, n = X.shape
    p = np.zeros(m)

    # Loop over each example
    for i in range(m):
        z_wb = 0
        # Loop over each feature
        for j in range(n):
            # Add the corresponding term to z_wb
            z_wb += np.dot(X[i,j],w[j])

        # Add bias term
        z_wb += b

        # Calculate the prediction for this example
        f_wb = sigmoid(z_wb)

        # Apply the threshold (here it is 0.5)
        p[i] = 1 if f_wb>=0.5 else 0

    return p
```

In [58]:

```
#Compute accuracy on training set
p = predict(X_train, w,b)
print('Train Accuracy: %f'%(np.mean(p == y_train) * 100))
```

```
Train Accuracy: 92.000000
```

Regularized Logistic Regression

In this part of the exercise, we 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.

In [59]:

```
# load dataset
df = pd.read_csv(r'...')
X_train, y_train = df.to_numpy()
```

In [60]:

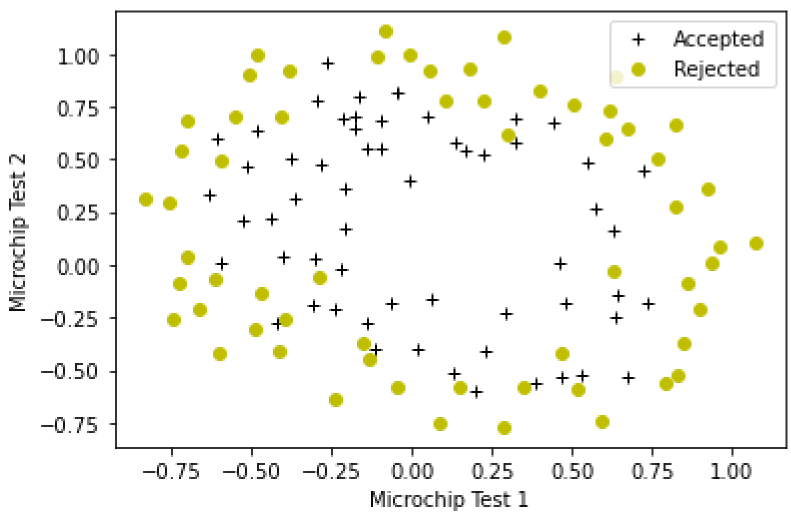
```
# print X_train
print("X_train:", X_train[:5])
print("Type of X_train:",type(X_train))

# print y_train
print("y_train:", y_train[:5])
print("Type of y_train:",type(y_train))
```

```
X_train: [[ 0.051267  0.69956 ]
 [-0.092742  0.68494 ]
 [-0.21371   0.69225 ]
 [-0.375     0.50219 ]
 [-0.51325   0.46564 ]]
Type of X_train: <class 'numpy.ndarray'>
y_train: [1. 1. 1. 1. 1.]
Type of y_train: <class 'numpy.ndarray'>
```

In [61]:
```
print ('The shape of X_train is: ' + str(X_train.shape))
print ('The shape of y_train is: ' + str(y_train.shape))
print ('We have m = %d training examples' % (len(y_train)))
```

```
The shape of X_train is: (118, 2)
The shape of y_train is: (118,)
We have m = 118 training examples
```

In [62]:
```
# Plot examples
plot_data(X_train, y_train[:], pos_label="Accepted", neg_label="Rejected")

# Set the y-axis label
plt.ylabel('Microchip Test 2')
# Set the x-axis label
plt.xlabel('Microchip Test 1')
plt.legend(loc="upper right")
plt.show()
```



Feature mapping

feature mapping allows us to build a more expressive classifier

In [63]:
```
print("Original shape of data:", X_train.shape)

mapped_X =  map_feature(X_train[:, 0], X_train[:, 1])
print("Shape after feature mapping:", mapped_X.shape)
```

```
Original shape of data: (118, 2)
Shape after feature mapping: (118, 27)
```

In [64]:
```
print("X_train[0]:", X_train[0])
print("mapped X_train[0]:", mapped_X[0])
```

```
X_train[0]: [0.051267 0.69956 ]
mapped X_train[0]: [5.12670000e-02 6.99560000e-01 2.62830529e-03 3.58643425e-02
 4.89384194e-01 1.34745327e-04 1.83865725e-03 2.50892595e-02
 3.42353606e-01 6.90798869e-06 9.42624411e-05 1.28625106e-03
 1.75514423e-02 2.39496889e-01 3.54151856e-07 4.83255257e-06
 6.59422333e-05 8.99809795e-04 1.22782870e-02 1.67542444e-01
 1.81563032e-08 2.47750473e-07 3.38066048e-06 4.61305487e-05
 6.29470940e-04 8.58939846e-03 1.17205992e-01]
```

3.4 Cost function for regularized logistic regression

feature mapping is more susceptible to overfitting, we will implement regularized logistic regression to fit the data and regularize them to prevent overfitting.

In [65]:

```python
# implement cost function for regularized logistic regression
def compute_cost_reg(X, y, w, b, lambda_ = 1):
    """
    Computes the cost over all examples
    Args:
      X : (array_like Shape (m,n)) data, m examples by n features
      y : (array_like Shape (m,)) target value
      w : (array_like Shape (n,)) Values of parameters of the model
      b : (array_like Shape (n,)) Values of bias parameter of the model
      lambda_ : (scalar, float)    Controls amount of regularization
    Returns:
      total_cost: (scalar)         cost
    """

    m, n = X.shape

    # Calls the compute_cost function that you implemented above
    cost_without_reg = compute_cost(X, y, w, b)

    reg_cost = 0.

    for j in range(n):
        reg_cost += w[j]**2

    # Add the regularization cost to get the total cost
    total_cost = cost_without_reg + (lambda_/(2 * m)) * reg_cost

    return total_cost
```

Gradient for regularized logistic regression

In [ ]:

```python
# implement gradient descent for regularized logistic regression
def compute_gradient_reg(X, y, w, b, lambda_ = 1):
    """
    Computes the gradient for linear regression

    Args:
      X : (ndarray Shape (m,n))   variable such as house size
      y : (ndarray Shape (m,))    actual value
      w : (ndarray Shape (n,))    values of parameters of the model
      b : (scalar)                value of parameter of the model
      lambda_ : (scalar,float)    regularization constant
    Returns
```

```
      dj_db: (scalar)             The gradient of the cost w.r.t. the parameter b.
      dj_dw: (ndarray Shape (n,)) The gradient of the cost w.r.t. the parameters w.

    """
    m, n = X.shape

    dj_db, dj_dw = compute_gradient(X, y, w, b)

    for j in range(n):
        dj_dw_j_reg = w[j] * lambda_ / m
        dj_dw[j] = dj_dw[j]+dj_dw_j_reg
    return dj_db, dj_dw
```

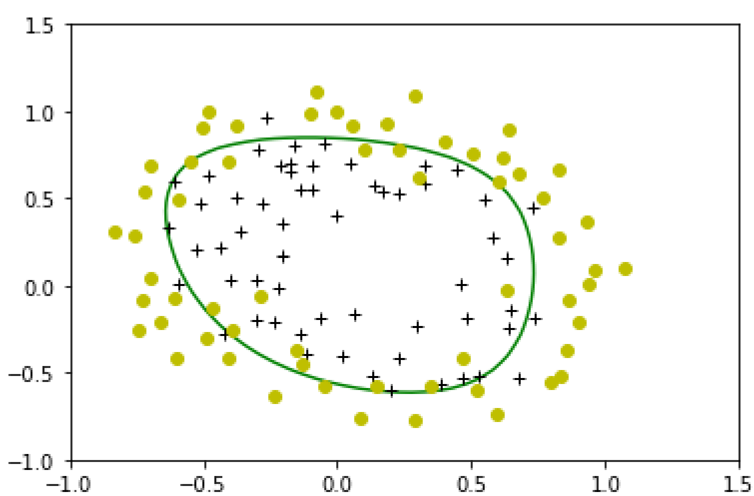
In [83]:

```
## learning parameters using gradient descent
# Initialize fitting parameters
np.random.seed(1)
initial_w = np.random.rand(X_mapped.shape[1])-0.5
initial_b = 1.

# Set regularization parameter lambda_ (you can try varying this)
lambda_ = 0.01

# Some gradient descent settings
iterations = 10000
alpha = 0.01

w,b, J_history,_ = gradient_descent(X_mapped, y_train, initial_w, initial_b,
                                    compute_cost_reg, compute_gradient_reg,
                                    alpha, iterations, lambda_)
```

```
Iteration    0: Cost     0.72
Iteration 1000: Cost     0.59
Iteration 2000: Cost     0.56
Iteration 3000: Cost     0.53
Iteration 4000: Cost     0.51
Iteration 5000: Cost     0.50
Iteration 6000: Cost     0.48
Iteration 7000: Cost     0.47
Iteration 8000: Cost     0.46
Iteration 9000: Cost     0.45
Iteration 9999: Cost     0.45
```

In [84]:

```
plot_decision_boundary(w, b, X_mapped, y_train)
```



In [85]:
```
#Compute accuracy on the training set
p = predict(X_mapped, w, b)

print('Train Accuracy: %f'%(np.mean(p == y_train) * 100))
```

```
Train Accuracy: 82.203390
```