Practice Lab: Linear Regression

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import copy
import math
```

In [2]:
```
#x_train is the population of a city
#y_train is the profit of a restaurant in that city. A negative value for profit indic
# Both X_train and y_train are numpy arrays.

x_train, y_train = load_data(...)
```

In [3]:
```
# print x_train
print("Type of x_train:",type(x_train))
print("First five elements of x_train are:\n", x_train[:5])
```

```
Type of x_train: <class 'numpy.ndarray'>
First five elements of x_train are:
 [6.1101 5.5277 8.5186 7.0032 5.8598]
```

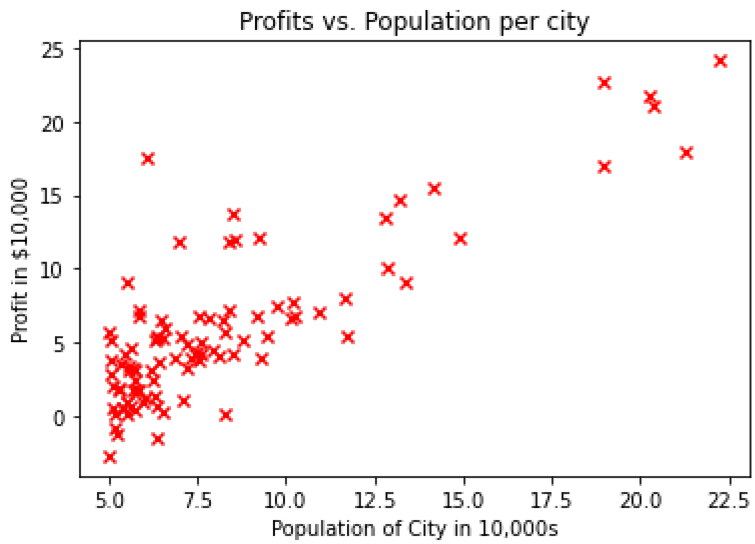
In [4]:
```
# print y_train
print("Type of y_train:",type(y_train))
print("First five elements of y_train are:\n", y_train[:5])
```

```
Type of y_train: <class 'numpy.ndarray'>
First five elements of y_train are:
 [17.592   9.1302 13.662  11.854   6.8233]
```

In [5]:
```
print ('The shape of x_train is:', x_train.shape)
print ('The shape of y_train is: ', y_train.shape)
print ('Number of training examples (m):', len(x_train))
```

```
The shape of x_train is: (97,)
The shape of y_train is:  (97,)
Number of training examples (m): 97
```

In [6]:
```
# Create a scatter plot of the data. To change the markers to red "x",
# we used the 'marker' and 'c' parameters
plt.scatter(x_train, y_train, marker='x', c='r')

# Set the title
plt.title("Profits vs. Population per city")
# Set the y-axis label
plt.ylabel('Profit in $10,000')
# Set the x-axis label
plt.xlabel('Population of City in 10,000s')
plt.show()
```



Compute Cost function

In [7]:
```
# compute cost function fwb(x) = wx +b

def compute_cost(x, y, w, b):
    """
    Computes the cost function for linear regression.

    Args:
        x (ndarray): Shape (m,) Input to the model (Population of cities)
        y (ndarray): Shape (m,) Label (Actual profits for the cities)
        w, b (scalar): Parameters of the model

    Returns
        total_cost (float): The cost of using w,b as the parameters for linear regress
               to fit the data points in x and y
    """
    # number of training examples
    m = x.shape[0]
    total_cost = 0

    cum_cost =0
    for i in range(m):
        f_wb = np.dot(x[i],w)+b
        cost = (f_wb - y[i])**2
        cum_cost = cum_cost + cost
    total_cost = cum_cost/(2*m)

    return total_cost
```

Gradient descent

In [9]:
```
# compute_gradient
def compute_gradient(x, y, w, b):
    """
    Computes the gradient for linear regression
    Args:
      x (ndarray): Shape (m,) Input to the model (Population of cities)
      y (ndarray): Shape (m,) Label (Actual profits for the cities)
```

```
      w, b (scalar): Parameters of the model
    Returns
      dj_dw (scalar): 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
     """

    # Number of training examples
    m = x.shape[0]

    # returning dj_dw, dj_db
    dj_dw = 0
    dj_db = 0
    for i in range(m):
        f_wb=w*x[i]+b
        dj_dw_i= (f_wb-y[i])*x[i]
        dj_db_i= f_wb-y[i]
        dj_dw = dj_dw + dj_dw_i
        dj_db = dj_db + dj_db_i
    dj_dw = dj_dw/m
    dj_db = dj_db/m
    return dj_dw, dj_db
```

In [11]:

```
# Compute and display cost and gradient with random w
test_w = 0.2
test_b = 0.2
tmp_dj_dw, tmp_dj_db = compute_gradient(x_train, y_train, test_w, test_b)

print('Gradient at test w, b:', tmp_dj_dw, tmp_dj_db)
```

```
Gradient at test w, b: -47.41610118114435 -4.007175051546391
```

Learning parameters using batch gradient descent

In [12]:

```
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 :    (ndarray): Shape (m,)
      y :    (ndarray): Shape (m,)
      w_in, b_in : (scalar) Initial values of parameters of the model
      cost_function: function to compute cost
      gradient_function: function to compute the gradient
      alpha : (float) Learning rate
      num_iters : (int) number of iterations to run gradient descent
    Returns
      w : (ndarray): Shape (1,) 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 — primarily for graphing late
    J_history = []
    w_history = []
```

```
    w = copy.deepcopy(w_in)  #avoid modifying global w within function
    b = b_in

    for i in range(num_iters):

        # Calculate the gradient and update the parameters
        dj_dw, dj_db = gradient_function(x, y, w, b )

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

        # Save cost J at each iteration
        if i<100000:      # prevent resource exhaustion
            cost =  cost_function(x, y, w, b)
            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:
            w_history.append(w)
            print(f"Iteration {i:4}: Cost {float(J_history[-1]):8.2f}   ")

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

In [13]:
```
# initialize fitting parameters
initial_w = 0.
initial_b = 0.

# some gradient descent settings
iterations = 1500
alpha = 0.01

w,b,_,_ = gradient_descent(x_train ,y_train, initial_w, initial_b,
                     compute_cost, compute_gradient, alpha, iterations)
print("w,b found by gradient descent:", w, b)
```

```
Iteration    0: Cost     6.74
Iteration  150: Cost     5.31
Iteration  300: Cost     4.96
Iteration  450: Cost     4.76
Iteration  600: Cost     4.64
Iteration  750: Cost     4.57
Iteration  900: Cost     4.53
Iteration 1050: Cost     4.51
Iteration 1200: Cost     4.50
Iteration 1350: Cost     4.49
w,b found by gradient descent: 1.166362350335582 -3.63029143940436
```

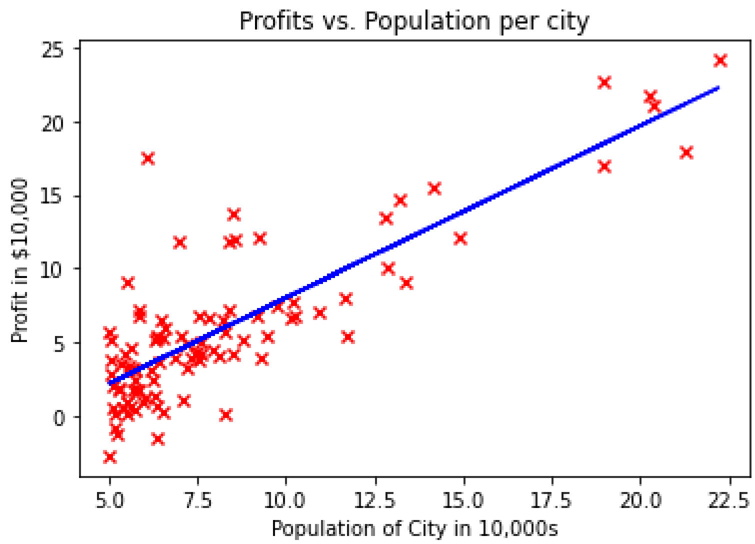
In [14]:
```
# use the generated w,b to calculate the predictions
m = x_train.shape[0]
predicted = np.zeros(m)

for i in range(m):
    predicted[i] = w * x_train[i] + b
```

In [15]:
```
# Plot the linear fit
plt.plot(x_train, predicted, c = "b")

# Create a scatter plot of the data.
```

```python
plt.scatter(x_train, y_train, marker='x', c='r')

# Set the title
plt.title("Profits vs. Population per city")
# Set the y-axis label
plt.ylabel('Profit in $10,000')
# Set the x-axis label
plt.xlabel('Population of City in 10,000s')
```

Out[15]:

```
Text(0.5, 0, 'Population of City in 10,000s')
```



In [16]:

```python
# predict the profit in the areas of 35,000 and 70,000 people
predict1 = 3.5 * w + b
print('For population = 35,000, we predict a profit of $%.2f' % (predict1*10000))

predict2 = 7.0 * w + b
print('For population = 70,000, we predict a profit of $%.2f' % (predict2*10000))
```

```
For population = 35,000, we predict a profit of $4519.77
For population = 70,000, we predict a profit of $45342.45
```