

# exercise\_1

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## 1 CSCI 416 - HW1

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[ ]:

## 2 Problem 4

```
[ ]: #run first
    %matplotlib inline

    %load_ext autoreload
    %autoreload 2

    import numpy as np
    import matplotlib.pyplot as plt
    from IPython.display import display, clear_output

    '''
    Please run each block in sequence to get proper results.
    '''
```

```
[ ]: '\nPlease run each block in sequence to get proper results.\n'
```

```
[ ]: #####1#####
    A = np.matrix([[-2, -3], [1, 0]])
    B = np.matrix([[1, 1], [1, 0]])
    x = np.matrix([[-1], [1]])
```

```
[ ]: print("Part 1:\n", "A = \n", A, "\nB = \n", B, "\nx = \n", x)

    #####2#####
    C = np.linalg.inv(A)

    #####3#####
    AC = np.dot(A, C)
```

```

CA = np.dot(C, A)

#####4#####
Ax = np.dot(A, x)

#####5#####
ATranspose = np.transpose(A)
ATransposeA = np.dot(ATranspose, A)

#####6#####
Bx = np.dot(B, x)
AxMinusBx = Ax - Bx

#####7#####
xNorm = np.sqrt(np.dot(np.transpose(x), x))

#####8#####
AxBxNorm = np.linalg.norm(AxMinusBx)

#####9#####
#Array Slice of A: A[: 1]

#####10#####
B[0::, 0:1] = x[:,0]

#####11#####
temp1 = A[:, 0:1:1]
temp2 = A[:, 1:2:1]

res = np.multiply(temp1, temp2)
#####PRINTS#####

print("Part 2:\n", "C = \n", C)
print("Part 3:\n", "AC = \n", AC, "\nCA = \n", CA)
print("Part 4: \n", "Ax = \n", Ax)
print("Part 5:\n", "A^(T) A = \n", ATransposeA)
print("Part 6:\n", "Ax - Bx = \n", AxMinusBx)
print("Part 7:\n", "||x|| = \n", xNorm)
print("Part 8:\n", "||Ax - Bx|| = \n", AxBxNorm)
print("Part 9:\n", "The first column of A is: \n", A[0::, :1])
print("Part 10:\n", "New B matrix is: \n", B)
print("Part 11:\n", "The element-wise product between the first and second_
↵columns of A is: \n", res)

```

Part 1:

```

A =
[[-2 -3]
 [ 1  0]]

```

```

B =
[[1 1]
 [1 0]]
x =
[[-1]
 [ 1]]
Part 2:
C =
[[-0.          1.          ]
 [-0.33333333 -0.66666667]]
Part 3:
AC =
[[ 1.00000000e+00 -1.11022302e-16]
 [ 0.00000000e+00  1.00000000e+00]]
CA =
[[1. 0.]
 [0. 1.]]
Part 4:
Ax =
[[-1]
 [-1]]
Part 5:
A^(T) A =
[[5 6]
 [6 9]]
Part 6:
Ax - Bx =
[[-1]
 [ 0]]
Part 7:
||x|| =
[[1.41421356]]
Part 8:
||Ax - Bx|| =
1.0
Part 9:
The first column of A is:
[[-2]
 [ 1]]
Part 10:
New B matrix is:
[[-1 1]
 [ 1 0]]
Part 11:
The element-wise product between the first and second columns of A is:
[[6]
 [0]]

```

### 3 Problem 5

\*remember to complete part (1) to in hw1.pdf

### 4 Imports

Run this code to import necessary modules. Note that the functions `cost_function` and `gradient` imported from module `gd` are stubs. You will need to fill in the code in `gd.py`.

```
[ ]: %matplotlib inline

%load_ext autoreload
%autoreload 2

import numpy as np
import matplotlib.pyplot as plt
from IPython.display import display, clear_output

from gd import cost_function, gradient # stubs
```

The autoreload extension is already loaded. To reload it, use:

```
%reload_ext autoreload
```

### 5 Create a simple data set

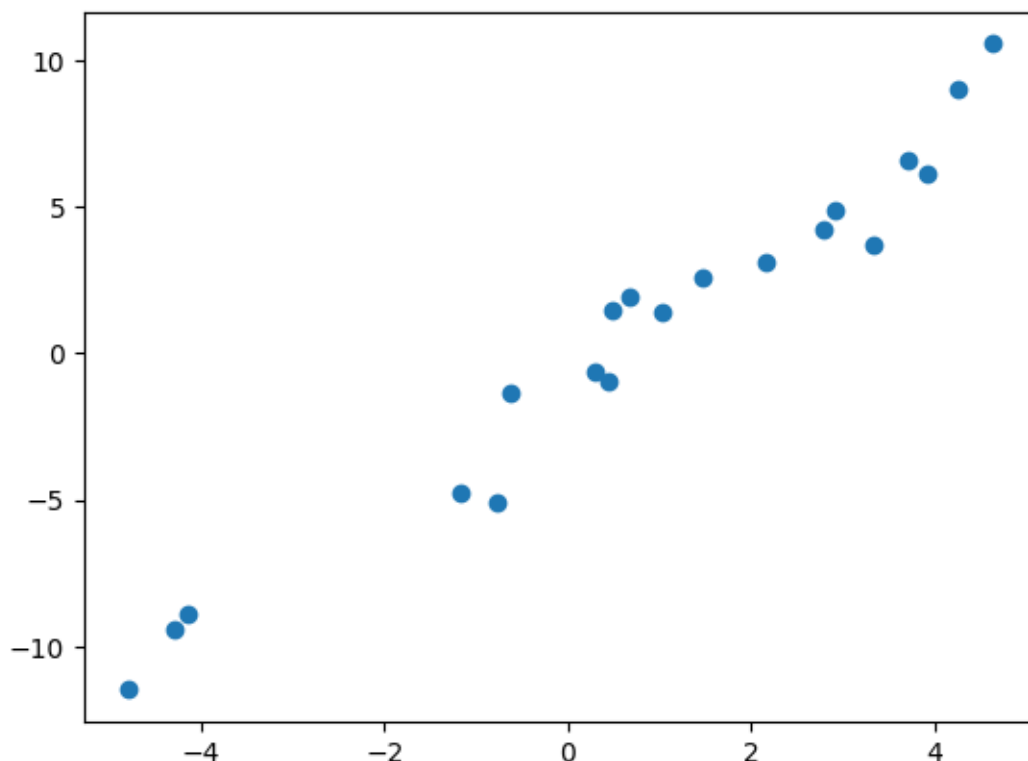
Run this cell to generate and plot some data from the linear model  $y \approx -1 + 2x$ , that is,  $\theta_0 = -1$  and  $\theta_1 = 2$ .

```
[ ]: # Set the random seed so the program will always generate the same data
np.random.seed(0)

# Generate n random x values between -5 and 5
n = 20
x = 10 * np.random.rand(n) - 5

# Generate y values from the model y ≈ 2x - 1
epsilon = np.random.randn(n)
y = -1 + 2*x + epsilon

plt.plot(x, y, marker='o', linestyle='none')
plt.show()
```



## 6 TODO: implement the cost function

The squared error cost function is

$$\frac{1}{2} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2.$$

Open the file `gd.py` and implement `cost_function`. Then run this cell to test it out.

```
[ ]: from gd import cost_function

print(cost_function(x, y, 0, 1))    # should print 104.772951994
print(cost_function(x, y, 2, -1))   # should print 744.953822077
print(cost_function(x, y, -1, 2))   # should print 14.090816198
```

```
104.77295199433607
744.9538220768487
14.090816198013721
```

## 7 Plotting setup

Run this cell. It sets up a routine `plot_model` that will be called later to illustrate the progress of gradient descent.

```
[ ]: # Construct a dense grid of (theta_0, theta_1) values
theta0_vals = np.linspace(-10, 10)
theta1_vals = np.linspace(-10, 10)
[THETA0, THETA1] = np.meshgrid(theta0_vals, theta1_vals)

# Define a cost function that has x and y "baked in"
def mycost(theta0, theta1):
    return cost_function(x, y, theta0, theta1)

# Now vectorize this cost function and apply it simultaneously to all
# pairs in dense grid of (theta_0, theta_1) values
mycost_vectorized = np.vectorize(mycost)
J_SURF = mycost_vectorized(THETA0, THETA1)

# Define the test inputs
x_test = np.linspace(-5, 5, 100)

fig = plt.figure(1, figsize=(10,4))

# Create the figure
def init_plot():
    fig.clf();

    # Build left subplot (cost function)
    ax1 = fig.add_subplot(1, 2, 1);
    ax1.contour(THETA0, THETA1, J_SURF, 20)
    ax1.set_xlabel('Intercept theta_0')
    ax1.set_ylabel('Slope theta_1')
    ax1.set_xlim([-10, 10])
    ax1.set_ylim([-10, 10])

    # The data will be added later for these plot elements:
    line, = ax1.plot([], []);
    dot, = ax1.plot([], [], marker='o');

    # Build right subplot (data + current hypothesis)
    ax2 = fig.add_subplot(1, 2, 2);
    ax2.plot(x, y, marker='o', linestyle='none')
    ax2.set_xlim([-6, 6])
    ax2.set_ylim([-10, 10])

    # The data will be added later for this:
    hyp, = ax2.plot( x_test, 0*x_test )

    return line, dot, hyp
```

```

# Define a function to update the plot
def update_plot(theta_0, theta_1, line, dot, hyp):
    line.set_xdata( np.append(line.get_xdata(), theta_0 ) )
    line.set_ydata( np.append(line.get_ydata(), theta_1 ) )
    dot.set_xdata([theta_0])
    dot.set_ydata([theta_1])
    hyp.set_ydata( theta_0 + theta_1 * x_test )

```

<Figure size 1000x400 with 0 Axes>

## 8 TODO: implement gradient descent

In this cell you will implement gradient descent. Follow these steps:

1. Review the mathematical expressions for  $\frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1)$  and  $\frac{\partial}{\partial \theta_1} J(\theta_0, \theta_1)$  for our model and cost function. (**Hint:** they are in the slides!)
2. Implement the function `gradient` in `gd.py` to return these two partial derivatives.
3. Complete the code below for gradient descent
  - Select a step size
  - Run for a fixed number of iterations (say, 20 or 200)
  - Update `theta_0` and `theta_1` using the partial derivatives
  - Record the value of the cost function attained in each iteration of gradient descent so you can examine its progress.

```

[ ]: line, dot, hyp = init_plot()

#comparing cost and iter
costArr = []

iters = 80 # change as needed

# TODO: initialize theta_0, theta_1, and step size

import gd

theta_0, theta_1 = 1, 2
step = 1e-2
cost = 0
#x, y = 1, 1

for i in range(0, iters):
    # Uncomment the code below to display progress of the algorithm so far
    # as it runs.
    #
    #clear_output(wait=True)
    update_plot(theta_0, theta_1, line, dot, hyp)
    #display(fig)

```

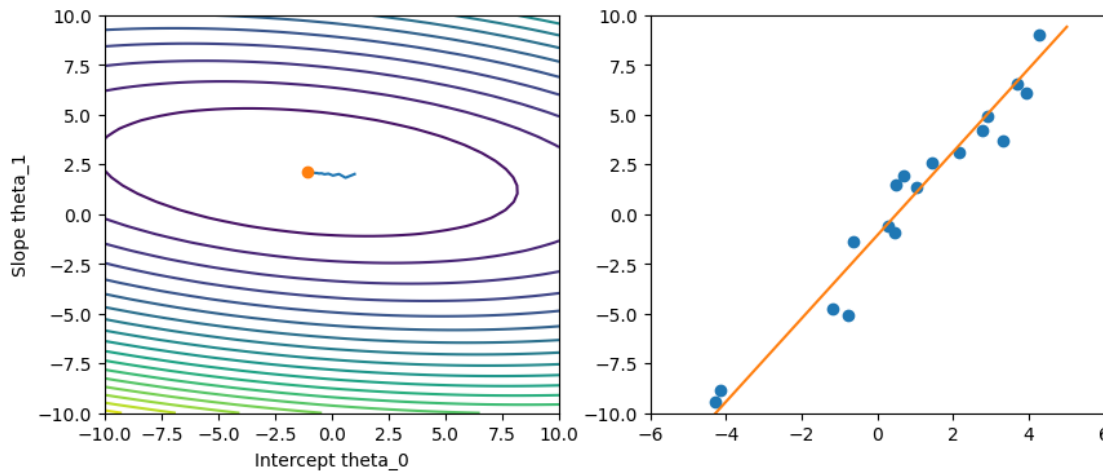
```

# TODO: write code to get partial derivatives (hint: call gradient in gd.
→py)
# and update theta_0 and theta_1
cost = mycost(theta_0, theta_1)
costArr.append(cost)
d_theta = gd.gradient(x, y, theta_0, theta_1)
#print(d_theta)

#theta <- theta - alpha * d/d_theta (cost function)
theta_0 -= step * d_theta[0]
theta_1 -= step * d_theta[1]

#moved so there's no flashing
display(fig)

```



## 9 TODO: assess convergence

Plot the cost function vs. iteration. Did the algorithm converge? (Converging means it found the actual setting of  $\theta$  that minimizes the cost. If the cost went up or did not go down as far as it could, it did not converge.)

```

[ ]: iterArr = [*range(1, iters + 1)]
      #print(iterArr, '\n', costArr)
      plt.plot(iterArr, costArr)
      newPlot = plt.figure(1, figsize=(10,10))
      #newPlot.xlabel('Iterations')
      #newPlot.ylabel('Cost')
      #newPlot.title("Cost function v.s. Iteration")
      newPlot.show()

```



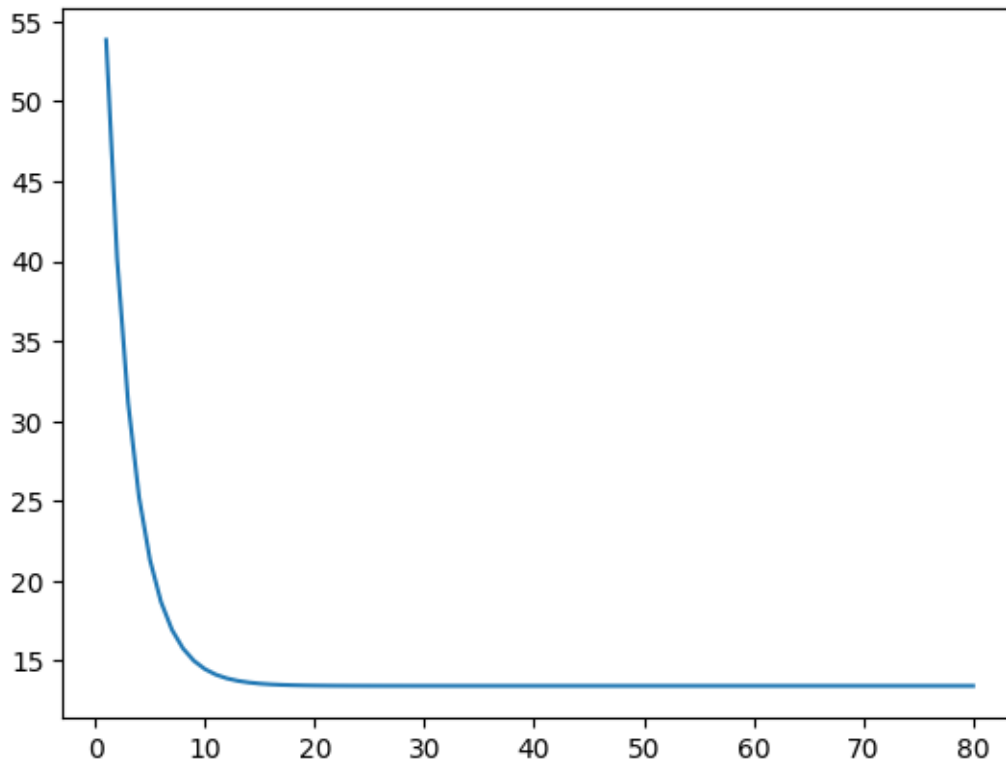
```
#algorithm converges on cost 13.4, likely local minimum
print(theta_0, theta_1, costArr[-1])
print("The algorithm does converge on a value.")
```

```
-1.0702533634351876 2.0934911022453084 13.425042793258282
```

The algorithm does converge on a value.

C:\Users\tankk\AppData\Local\Temp\ipykernel\_26396\2700473681.py:8: UserWarning:  
Matplotlib is currently using module://matplotlib\_inline.backend\_inline, which  
is a non-GUI backend, so cannot show the figure.

```
newPlot.show()
```



## 10 TODO: experiment with step size

After you have completed the implementation, do some experiments with different numbers of iterations and step sizes to assess convergence of the algorithm. Report the following: \* A step size for which the algorithm converges to the minimum in at most 200 iterations \* A step size for which the algorithm converges, but it takes more than 200 iterations \* A step size for which the algorithm does not converge, no matter how many iterations are run

**\*\* Write your answer here. \*\***

```
[ ]: print("0.01.")
```

0.01.

```
[ ]: print("0.001.")
```

0.001.

```
[ ]: print("20.")
```

20.

## 11 Problem 6

## 12 Problem Description

This notebook will guide you through implementation of **multivariate linear regression** to solve the **polynomial regression** problem:

$$h_{\theta}(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4 = \theta^T \mathbf{x}$$

$$\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} 1 \\ x \\ x^2 \\ x^3 \\ x^4 \end{bmatrix}$$

Below, you will

1. Implement the cost function for multivariate linear regression
2. Implement the normal equations method to solve a multivariate linear regression problem
3. Implement gradient descent for multivariate linear regression
4. Experiment with feature normalization to improve the convergence of gradient descent

### 12.1 Imports

Run this code.

```
[ ]: %matplotlib inline

import numpy as np
import matplotlib.pyplot as plt
```

### 12.2 Helper functions

Run this code to set up the helper functions. The function **feature\_expansion** accepts an vector of  $n$  scalar  $x$  values and returns an  $n \times 5$  data matrix by applying the feature expansion  $x \mapsto [1, x, x^2, x^3, x^4]$  to each scalar  $x$  value.

```
[ ]: def feature_expansion(x, deg):
    if x.ndim > 1:
        raise ValueError('x should be a 1-dimensional array')
    m = x.shape
    x_powers = [x**k for k in range(0,deg+1)]
    X = np.stack( x_powers, axis=1 )

    return X

def plot_model(X_test, theta):
    '''
    Note: uses globals x, y, x_test, which are assigned below
    when the dataset is created. Don't overwrite these variables.
    '''
    y_test = np.dot(X_test, theta)
    plt.scatter(x, y)
    plt.plot(x_test, y_test)
    plt.legend(['Test', 'Train'])
```

### 12.3 (2 points) List comprehensions

Read about list comprehensions. Explain what is happening in the line of code

```
x_powers = [x**k for k in range(0,deg+1)]
```

*\*\* Your answer here \*\**

The code is generating a list, `x_powers`, to powers of  $x$  from 0 to the value `deg`.

### 12.4 Create a data set for polynomial regression

Read and run the code below. This generates data from a fourth-degree polynomial and then uses feature expansion to set up the problem of learning the polynomial as multivariate linear regression

```
[ ]: # Set random seed
np.random.seed(0)

# Create random set of m training x values between -5 and 5
m = 100
x = np.random.rand(m)*10 - 5

# Create evenly spaced test x values (for plotting)
x_test = np.linspace(-5, 5, 100)
m_test = len(x_test);

# Feature expansion for training and test x values
deg = 4
X = feature_expansion(x, deg)
X_test = feature_expansion(x_test, deg)
```

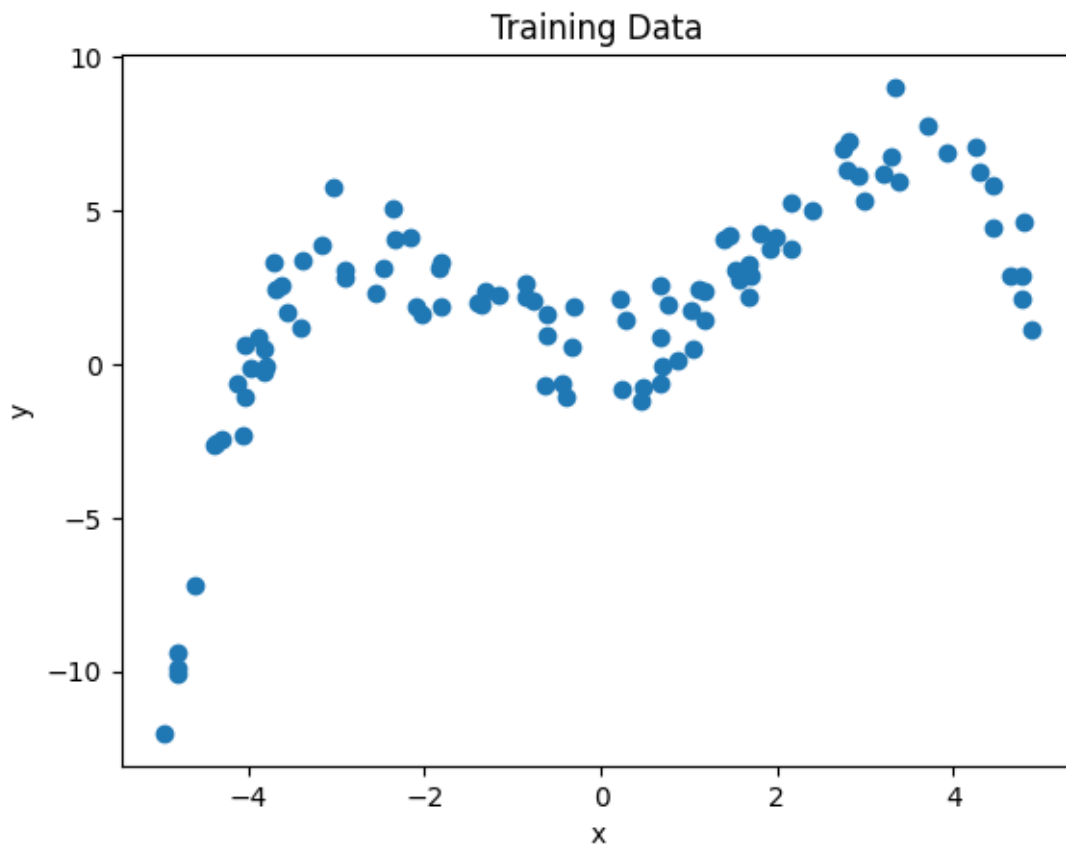
```

n = deg + 1  # total number of features including the '1' feature

# Define parameters (theta) and generate y values
theta = 0.1*np.array([1, 1, 10, 0.5, -0.5]);
y = np.dot(X, theta) + np.random.randn(m)  # polynomial plus noise

# Plot the training data
plt.scatter(x, y)
plt.title('Training Data')
plt.xlabel('x')
plt.ylabel('y')
plt.show()

```



## 12.5 (2 points) Implement the cost function

Complete the code below to implement the cost function for multivariate linear regression.

```

[ ]: def cost_function(X, y, theta):
      '''

```

*Compute the cost function for a particular data set and hypothesis (parameter vector)*

*Inputs:*

*X*            *m x n data matrix*  
*y*            *training output (length m vector)*  
*theta*        *parameters (length n vector)*

*Output:*

*cost*        *the value of the cost function (scalar)*  
*'''*

*# TODO: write correct code to compute the cost function*

`cost = 0`

`#print(theta.shape, '\n', X.shape)`

`#y ~= X dot theta`

`Xt = np.dot(X, theta)`

`XtY = np.subtract(Xt, y)`

`XtY_T = np.transpose(XtY)`

`#J(theta) = 1/2 (Xtheta - y)T dot (Xtheta - y)`

`cost = np.dot(XtY_T, XtY)`

`cost *= 0.5`

`return cost`

## 12.6 Test the cost function

Run this to test your cost function.

```
[ ]: np.random.seed(1)

theta_random = np.random.rand(n)
theta_zeros  = np.zeros(n)
theta_ones   = np.ones(n)

print( "Cost function (random): %.2f" % cost_function(X, y, theta_random)) #_
↪prints 54523.64
print( "Cost function (zeros): %.2f" % cost_function(X, y, theta_zeros))   #_
↪prints 845.65
print( "Cost function (ones): %.2f" % cost_function(X, y, theta_ones))     #_
↪prints 2524681.08
```

```
Cost function (random): 54523.64
Cost function (zeros): 845.65
Cost function (ones): 2524681.08
```

## 12.7 (6 points) Implement first training algorithm: normal equations

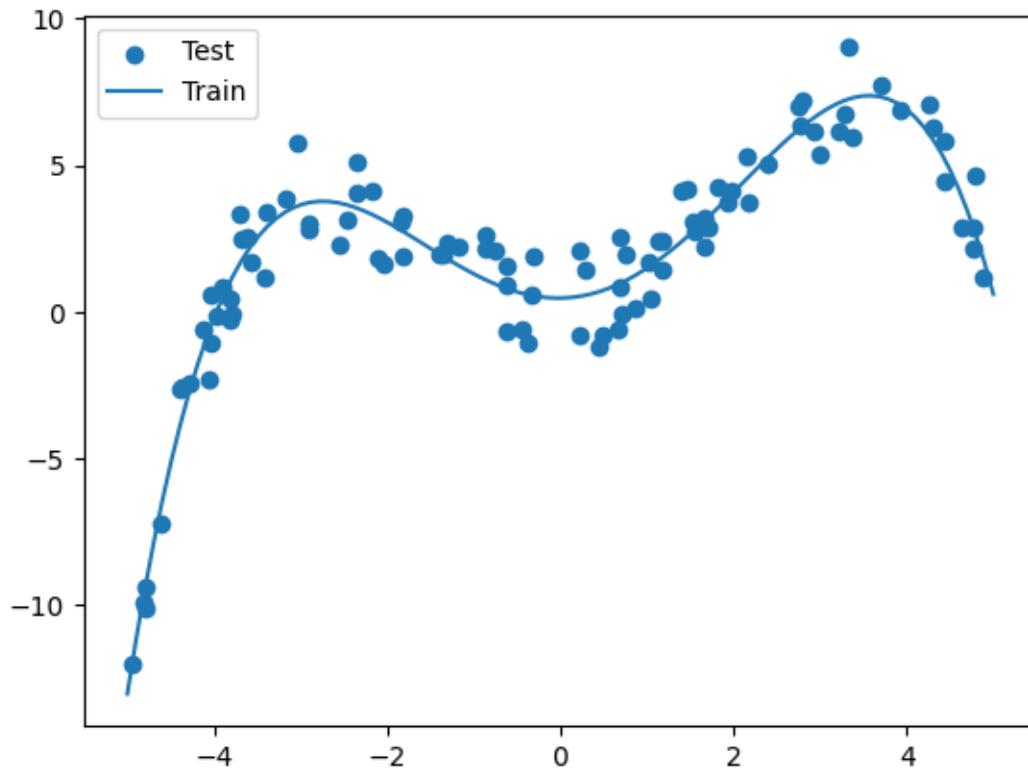
```
[ ]: def normal_equations(X, y):  
    '''  
    Train a linear regression model using the normal equations  
  
    Inputs:  
        X      m x n data matrix  
        y      training output (length m vector)  
    Output:  
        theta  parameters (length n vector)  
  
    '''  
    # TODO: write correct code to find theta using the normal equations  
    m, n = X.shape  
    XTX = np.dot(np.transpose(X), X)  
    theta = np.dot(np.linalg.inv(XTX), np.transpose(X))  
    theta = np.dot(theta, y)  
    return theta
```

## 12.8 Use normal equations to fit the model

Run this code to test your implementation of the normal equations. If it runs properly you will see a curve that fits the data well. Note the value of the cost function for `theta_normal_equations`.

```
[ ]: theta_normal_equations = normal_equations(X, y)  
plot_model(X_test, theta_normal_equations)  
print ("Cost function: %.2f" % cost_function(X, y, theta_normal_equations))
```

Cost function: 48.54



## 12.9 (6 points) Implement second training algorithm: (vectorized) gradient descent

Implement gradient descent for multivariate linear regression. Make sure your solution is vectorized.

```
[ ]: def gradient_descent( X, y, alpha, iters, theta=None ):
    '''
    Train a linear regression model by gradient descent

    Inputs:
        X        m x n data matrix
        y        training output (length m vector)
        alpha    step size
        iters    number of iterations
        theta    initial parameter values (length n vector; optional)

    Output:
        theta    learned parameters (length n vector)
        J_history trace of cost function value in each iteration

    '''
```

```

m,n = X.shape

if theta is None:
    theta = np.zeros(n)

# For recording cost function value during gradient descent
J_history = np.zeros(iters)

for i in range(0, iters):

    # TODO: compute gradient (vectorized) and update theta

    # Record cost function
    XT = np.transpose(X)
    Xtheta = np.dot(X, theta)
    #d/dtheta (J(theta)) = X^T dot (Xtheta - y)
    d_theta = np.dot(XT, Xtheta - y)

    theta = theta - alpha * d_theta

    J_history[i] = cost_function(X, y, theta)

return theta, J_history

```

## 12.10 (4 points) Use gradient descent to train the model

- Write code to call your `gradient_descent` method to learn parameter
- Plot the model fit (use `plot_model`)
- Plot the cost function vs. iteration to help assess convergence
- Print the final value of the cost function
- Experiment with different step sizes and numbers of iterations until you can find a good hypothesis. Try to match the cost function value from `normal_equations` to two decimal places. How many iterations does this take?

```

[ ]: # TODO: write code
alpha = 4e-7
iters = 217500

theta_vec, J_history = gradient_descent(X, y, alpha, iters)

iterArr = [*range(1, iters + 1)]

plot_model(X_test, theta_vec)

fig = plt.figure(2, figsize=(12,8))
newPlot = fig.add_subplot(1, 2, 2);
newPlot.plot(iterArr,J_history)

```



```

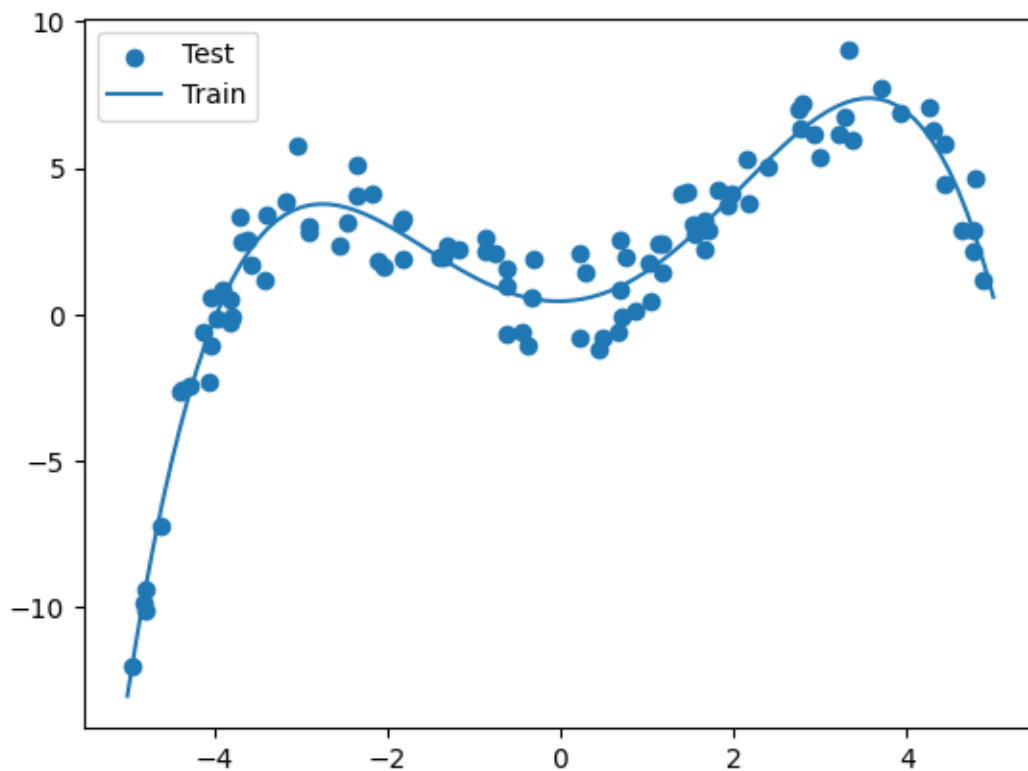
#algorithm converges on cost 13.4, likely local minimum
theta_normal_equations = normal_equations(X, y)
print ("Final cost from normal equations: %.2f" % cost_function(X, y,
↳theta_normal_equations))
print("Final cost from gradient descent is: %.2f" % J_history[-1],
↳'\nIterations needed to match the final cost from normal equations is,
↳approximately %d' %217500)

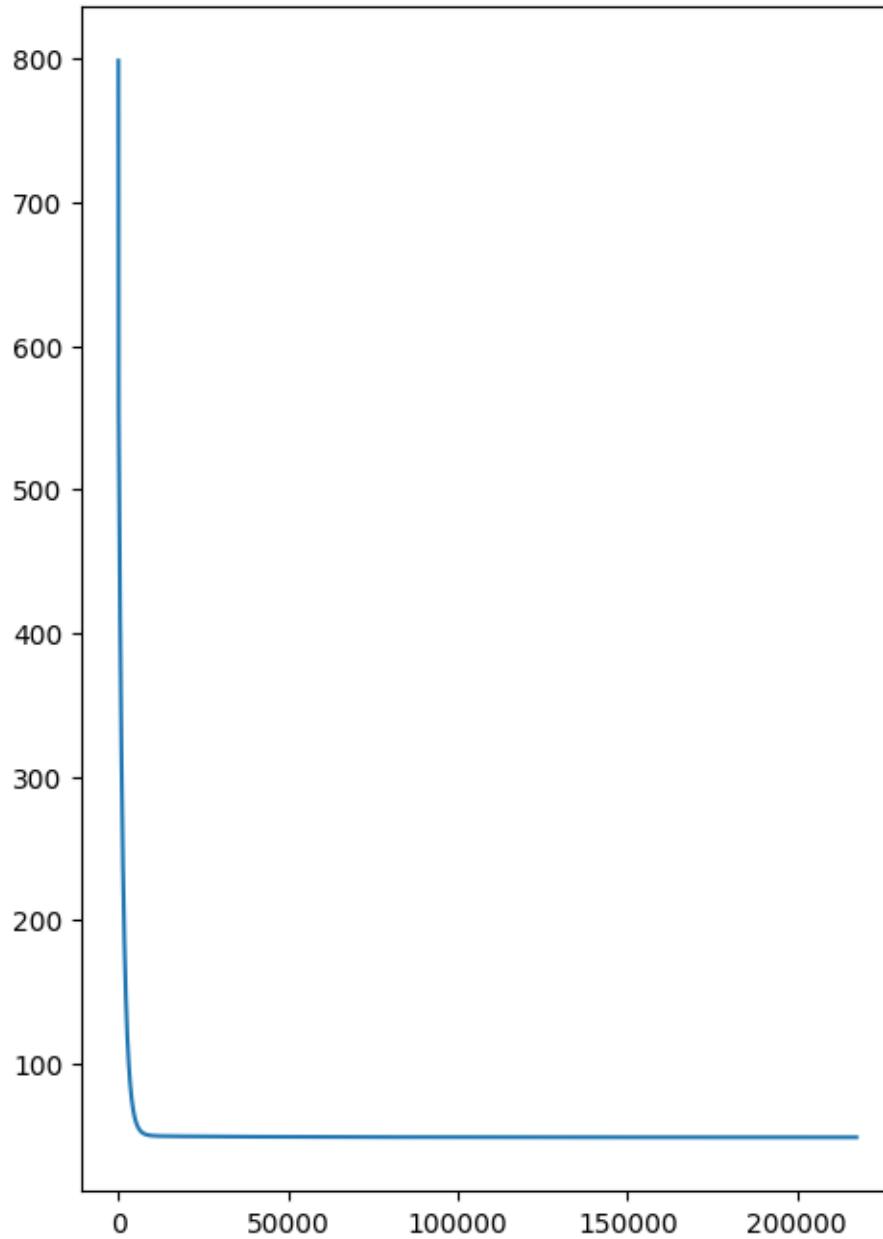
```

Final cost from normal equations: 48.54

Final cost from gradient descent is: 48.54

Iterations needed to match the final cost from normal equations is approximately 217500





### 12.11 (10 points) Gradient descent with feature normalization

You should have observed that it takes many iterations of gradient descent to match the cost function value achieved by the normal equations. Now you will implement feature normalization to improve the convergence of gradient descent. Remember that the formula for feature normalization is:

$$x_j^{(i)} \leftarrow \frac{x_j^{(i)} - \mu_j}{\sigma_j}$$

Here are some guidelines for the implementation:

- The same transformation should be applied to train and test data.
- The values  $\mu_j$  and  $\sigma_j$  are the mean and standard deviation of the  $j$ th column (i.e., feature) in the **training data**. (Hint: there are numpy functions to compute these.)
- Do not normalize the column of all ones. (Optional question: why?)
- Use broadcasting to do the normalization—don't write for loops

After normalizing both the training data and test data, follow the same steps as above to experiment with gradient descent using the *normalized* training and test data: print the value of the cost function, and create the same plots. Tune the step size and number of iterations again to make gradient descent converge as quickly as possible. How many iterations does it take to match the cost function value from `normal_equations` to two decimal places?

```
[ ]: # TODO: your code for gradient descent with feature normalization

#generate vectors and arrays for mu and sigma
mu1 = np.mean(X, axis = 0)
sigma1 = np.std(X, axis = 0)
mu2 = np.mean(X_test, axis = 0)
sigma2 = np.std(X_test, axis = 0)
'''muVector = np.mean(X, axis = 1)
muArray = np.array([muVector]).T
sigmaVector = np.std(X, axis = 1)
sigmaArray = np.array([sigmaVector]).T'''
mu1[0] = 0
mu2[0] = 0
sigma1[0] = 1
sigma2[0] = 1
#onesColumn = np.ones(X.shape[0])#np.matrix([np.ones(X.shape[0])]).T

#print(muVector, "\n", sigmaVector)
#print(X)
X_norm = X - mu1
X_norm /= sigma1

X_test_norm = X_test - mu2
X_test_norm /= sigma2
'''X_norm = X - muArray
X_norm = np.divide(X_norm, sigmaArray)

X_test_norm = X_test - muArray
X_test_norm /= sigmaArray
#print(onesColumn.shape)
#print(X_norm[0::, 0:1])'''

#force column 0 of X_norm and X_test_norm to all 1s
```

```

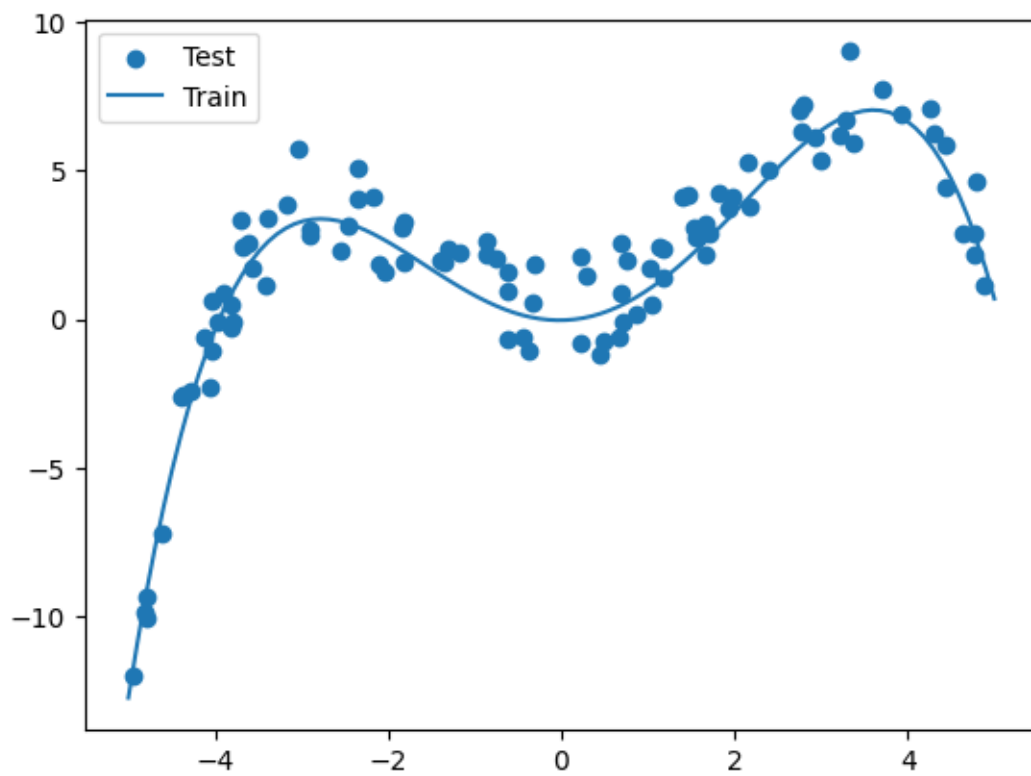
#X_norm[0::, 0:1:] = onesColumn[:,0]
#X_test_norm[0::, 0:1] = onesColumn[:,0]
#print(X_norm, '\n', X_norm.shape)
#print(X_test_norm, '\n', X_test_norm.shape)
#print(X_norm[0::, 0:1])
#print(X, "\n", X_norm)
#print(X_norm, "\n", X_test_norm)

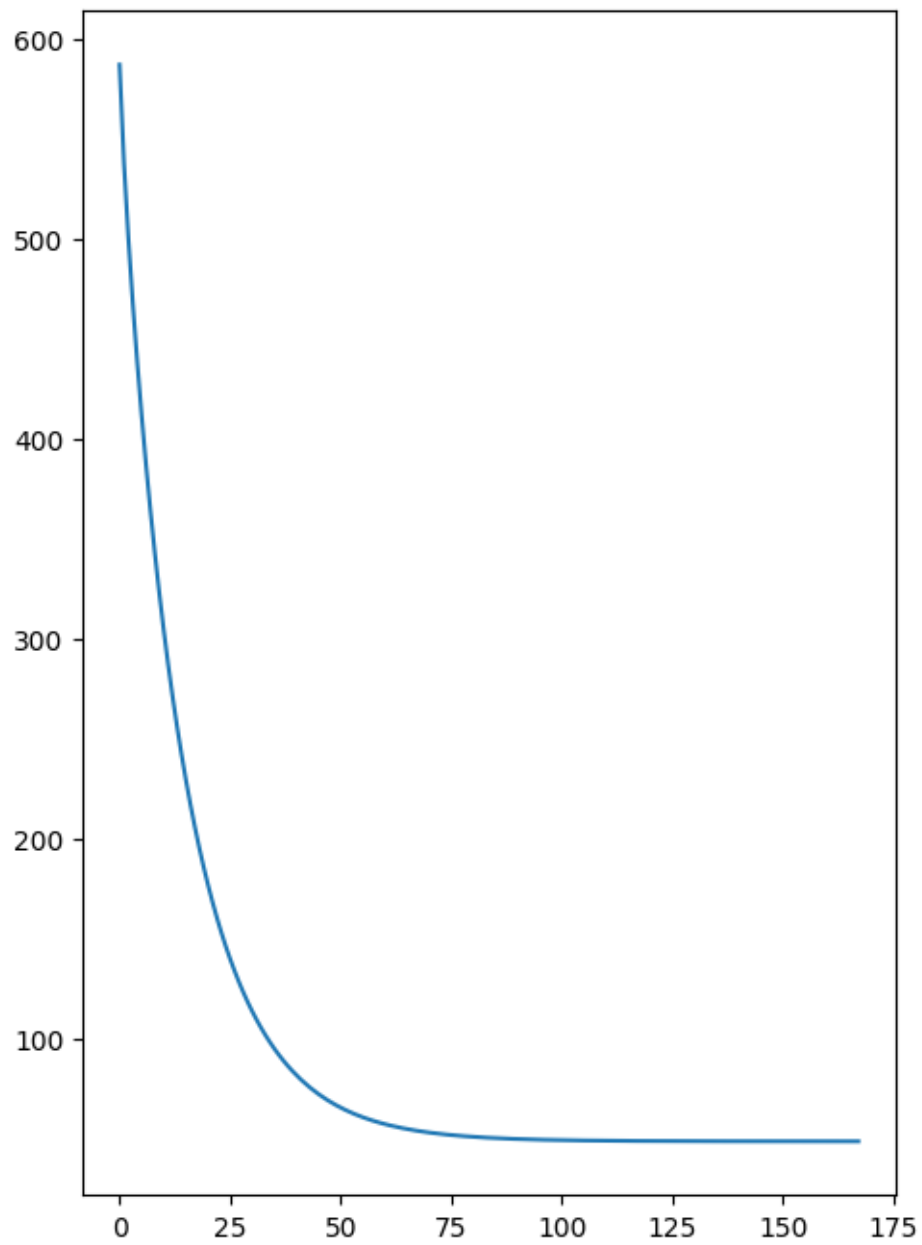
#theta_Xn, J_hist_Xn = gradient_descent(X_norm, y, 0.0092, 160)
iters = 168
theta_Xtn = None
J_hist_Xtn = None

theta_Xtn, J_hist_Xtn = gradient_descent(X_norm, y, 0.0092, iters, None)
#print(X_test_norm, theta_Xtn)
plot_model(X_test_norm, theta_Xtn)
iterations = [i for i in range(0, iters)]
fig = plt.figure(2, figsize=(12,8))
newPlot = fig.add_subplot(1, 2, 2);
newPlot.plot(iterations, J_hist_Xtn)
plt.show()
#print(theta_Xn)

#print(J_hist_Xn[-1])
print("Final Cost: %0.2f" % J_hist_Xtn[-1])

```





Final Cost: 48.54

*\*\* Write answer here: how many iterations? \*\**

168 iterations to get a final cost of 48.54, rounded down.