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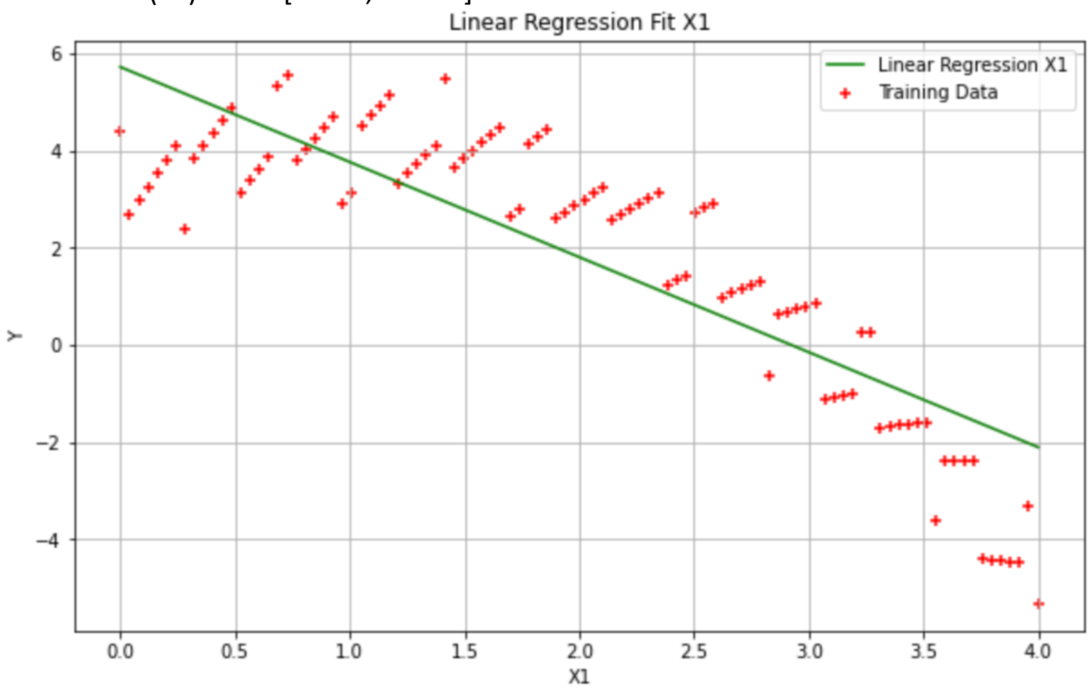
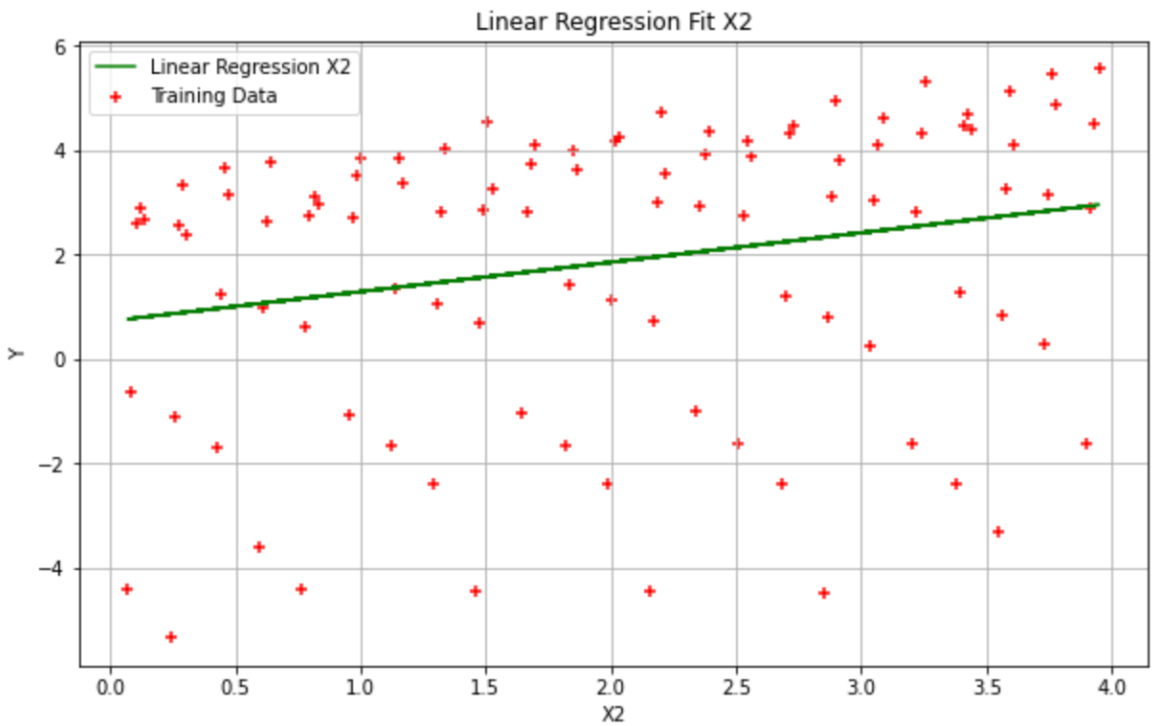
HW: 0
Github Link: https://github.com/fmcneill3/IntroML/blob/main/HW0.ipynb

Problem 1.

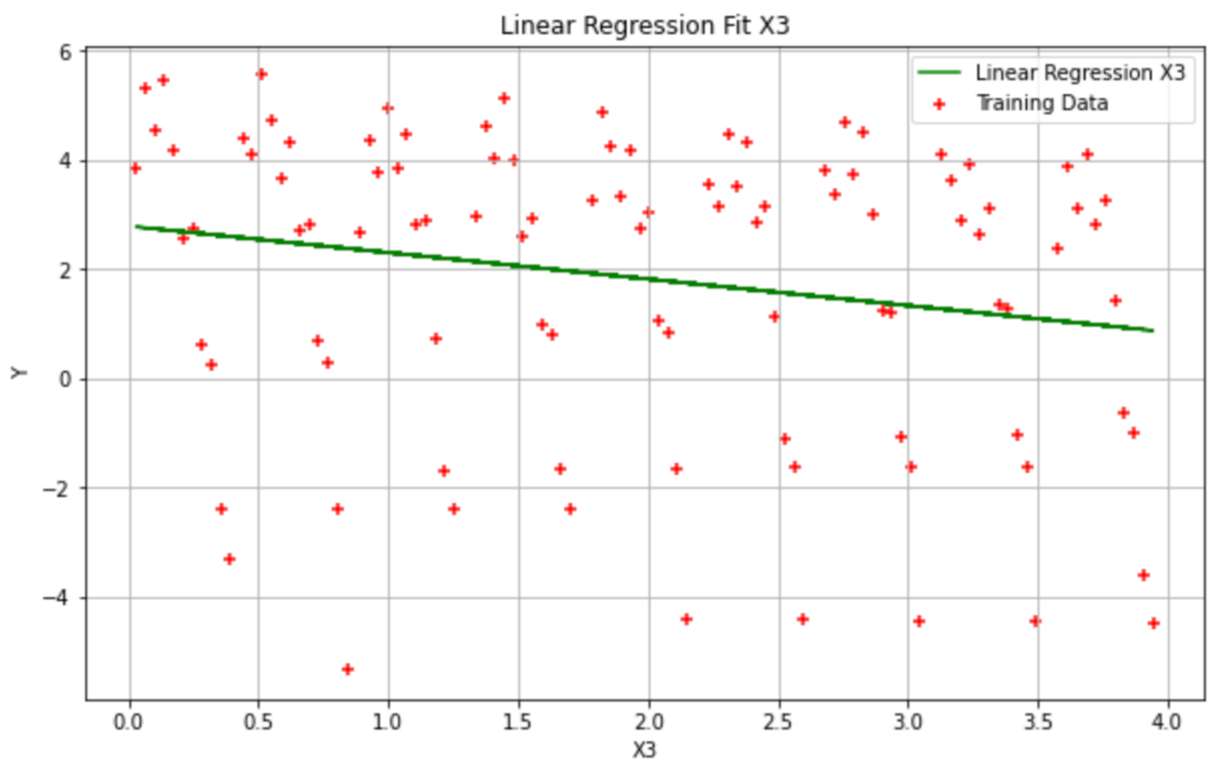
1. h(x1) = X1 •[5.718, -1.956]



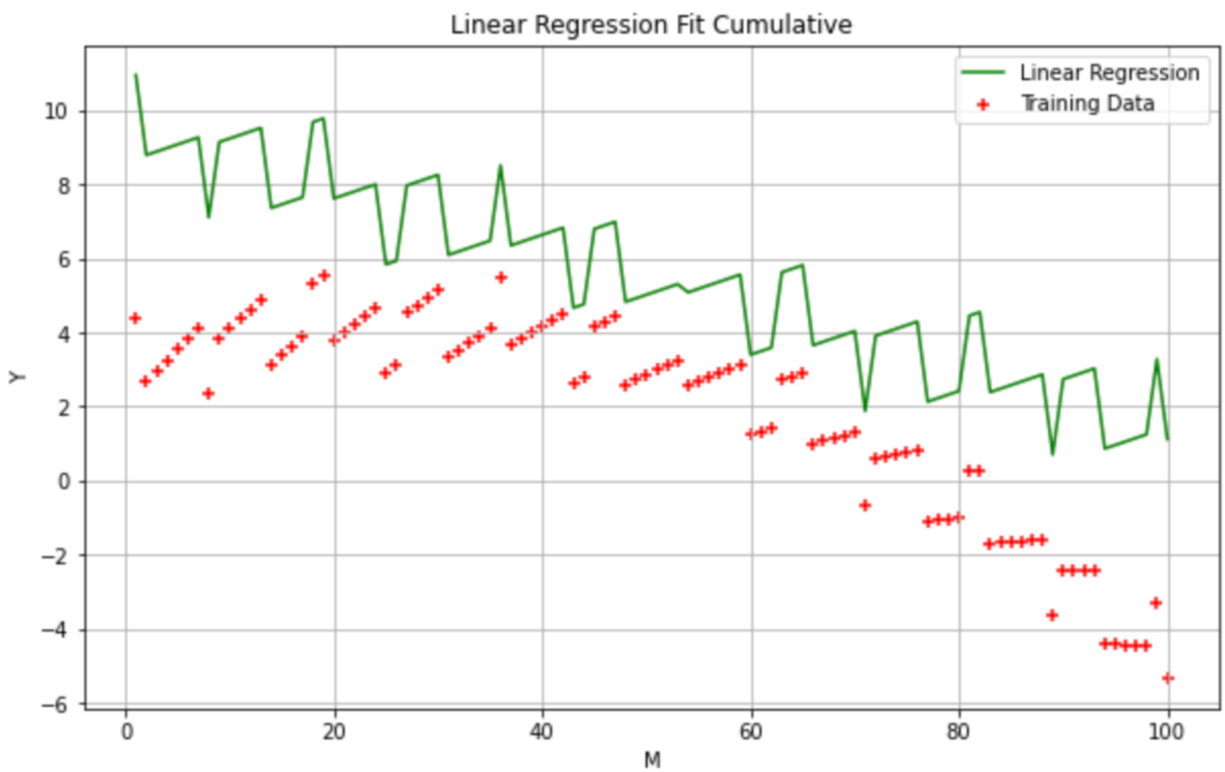
h(x2) = X2 •[0.719, 0.563]

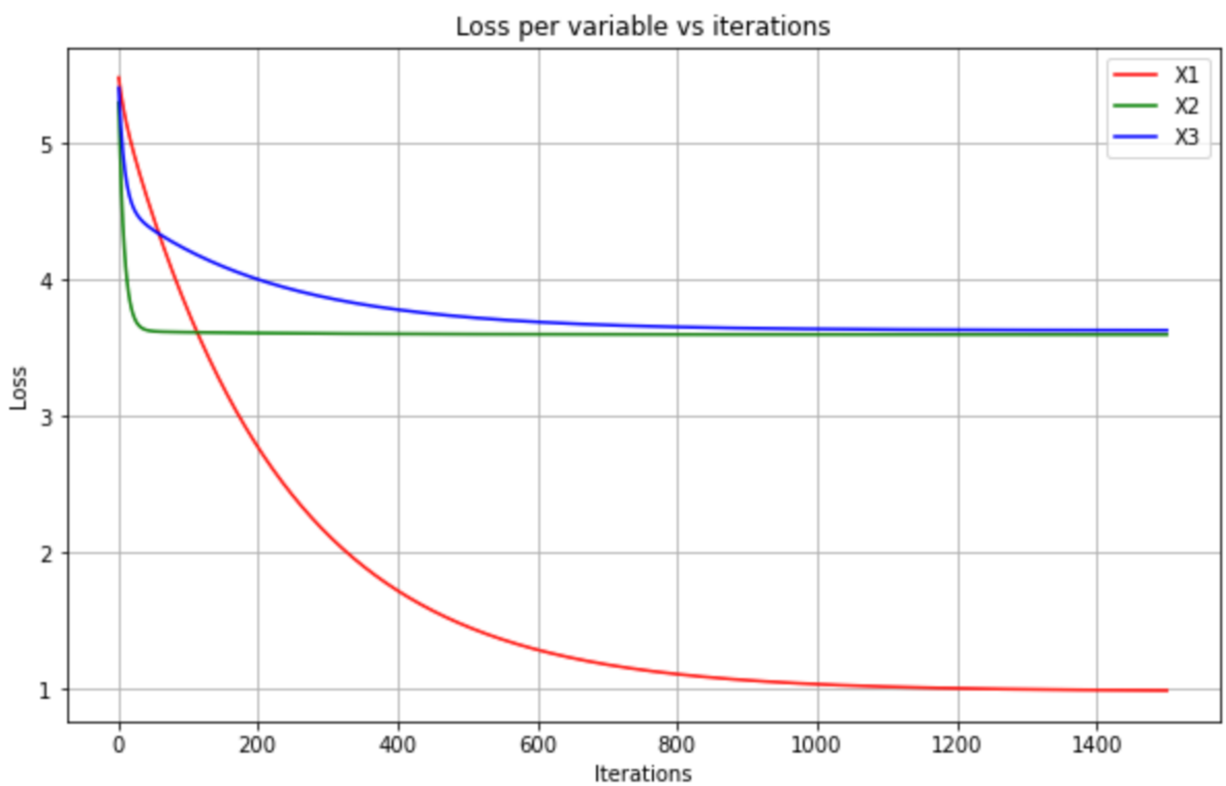


$h(x3) = X3 \bullet [2.780, -0.484]$



2.

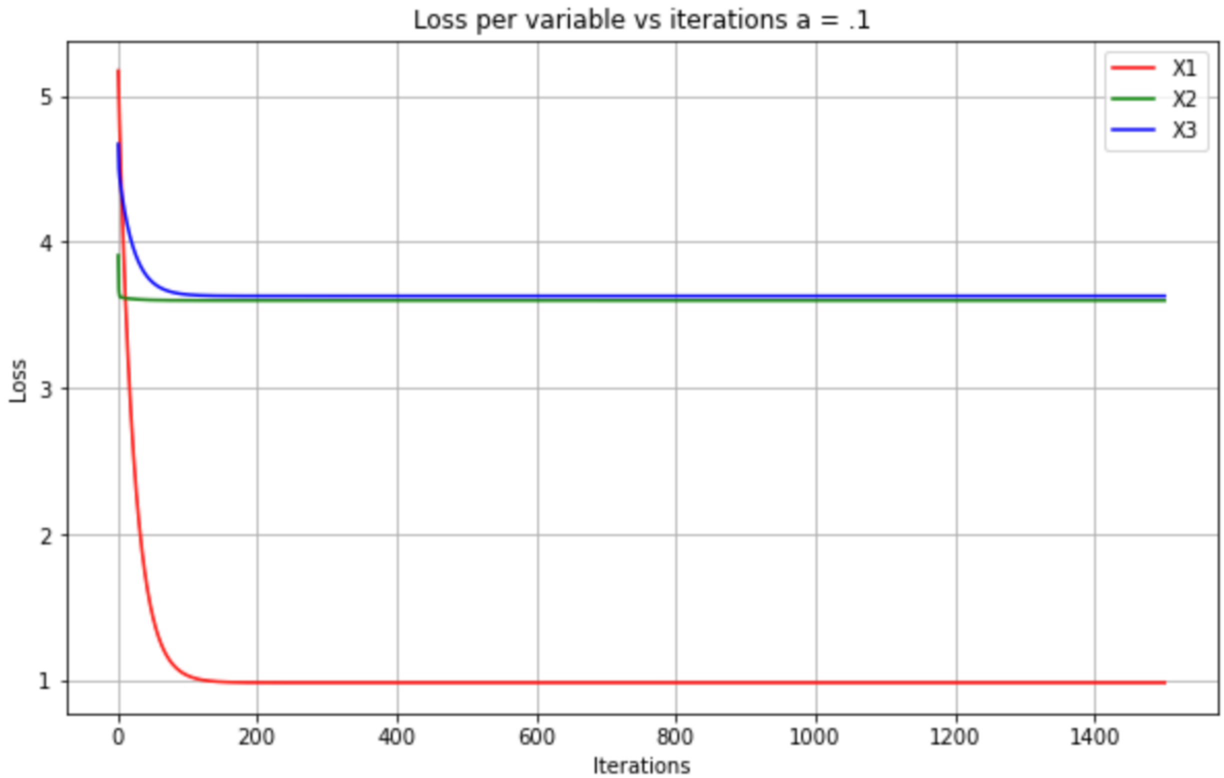


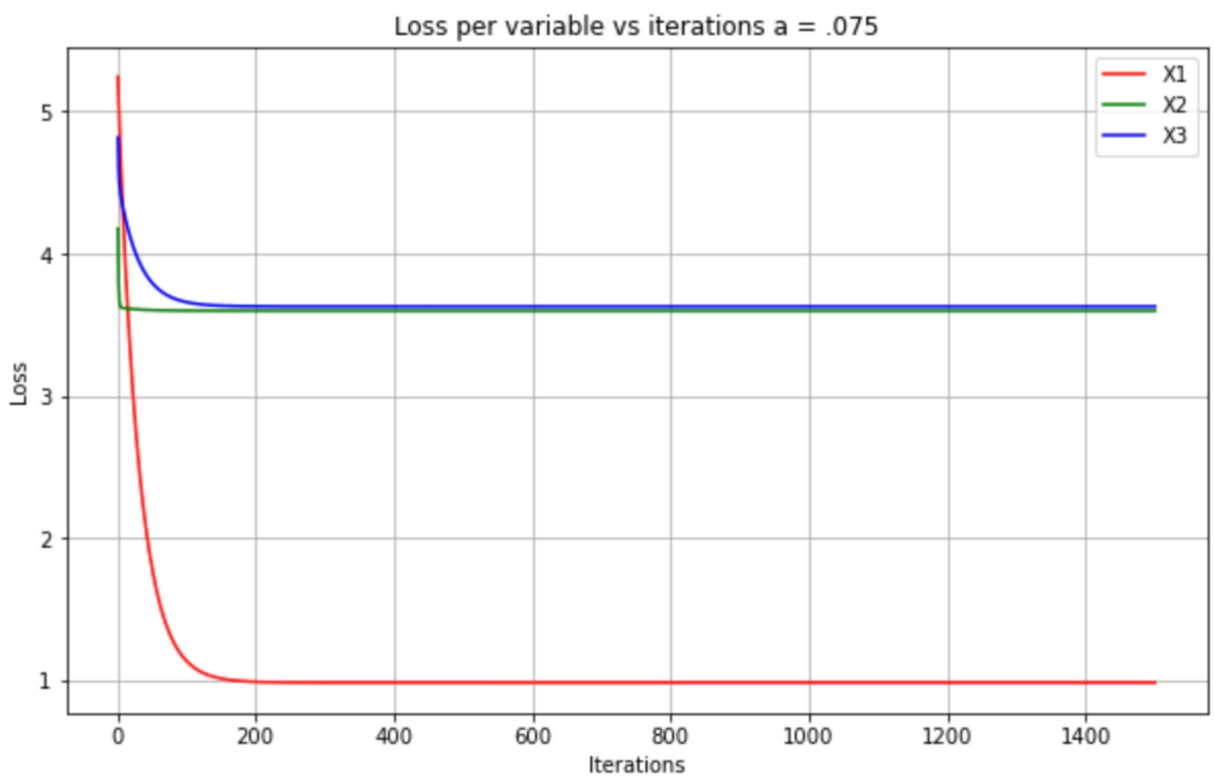


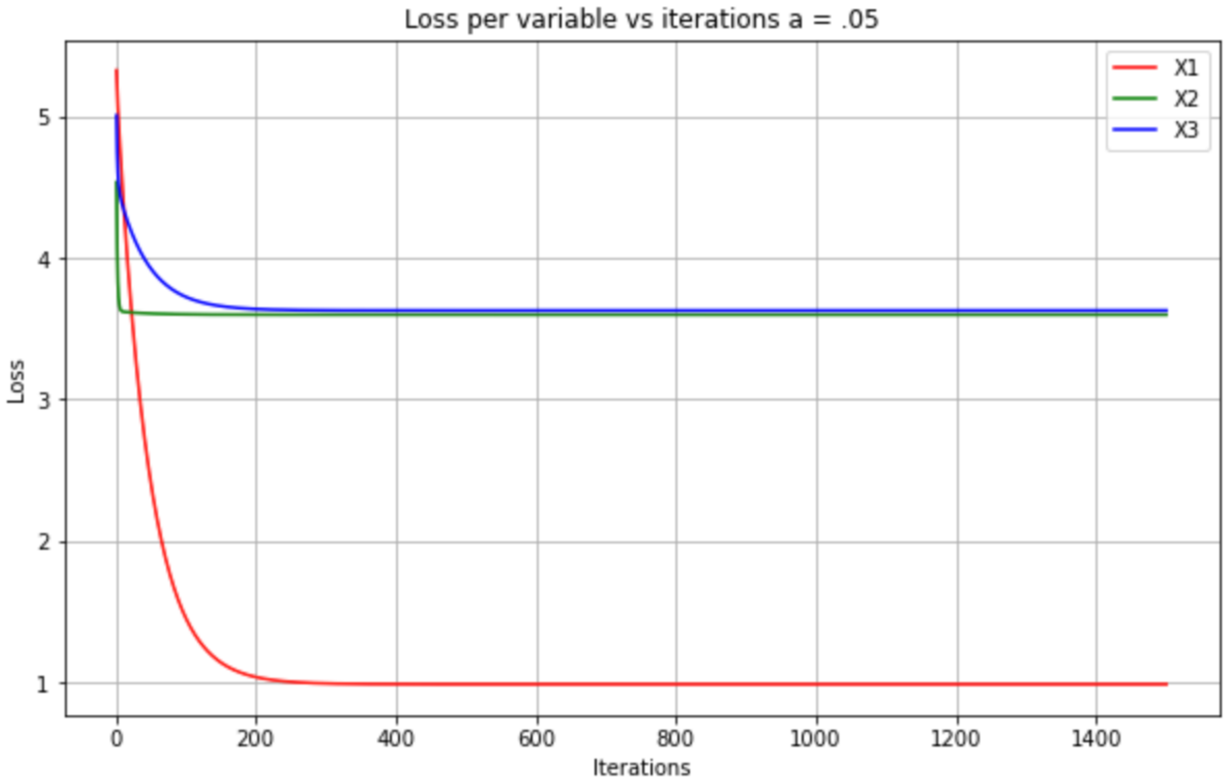
3.

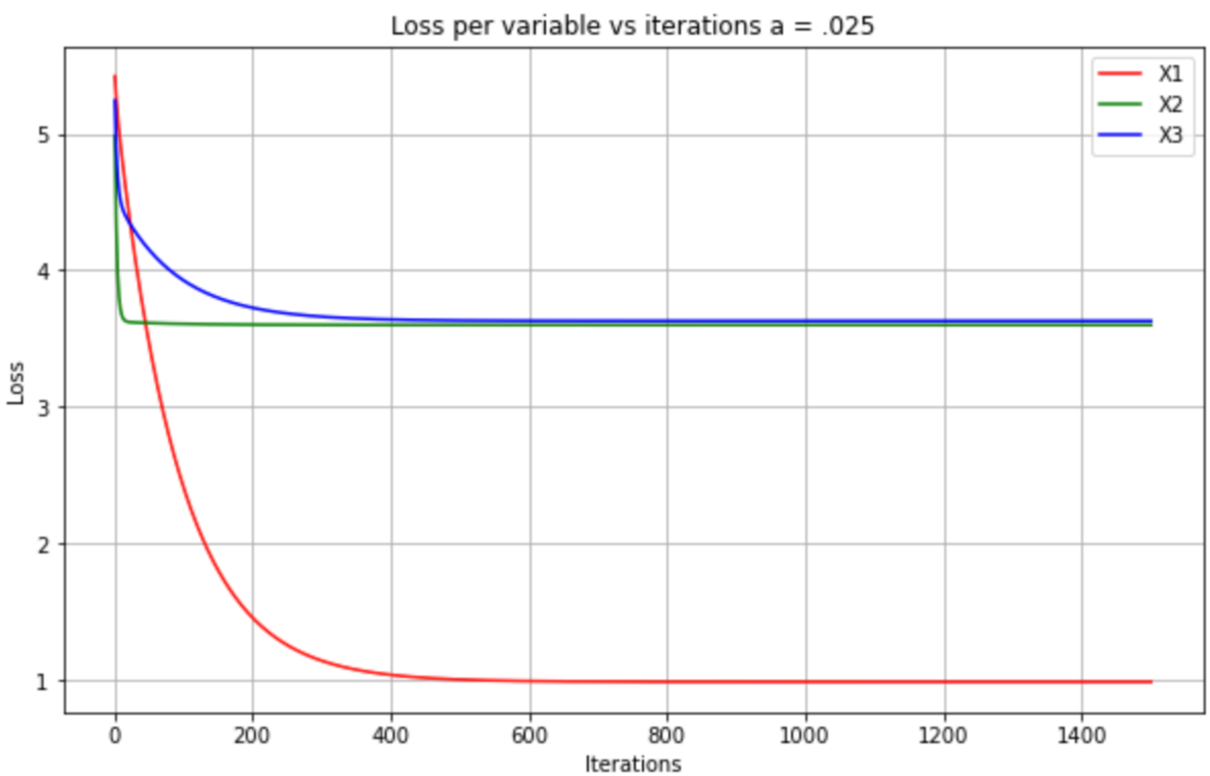
From the previous plot it is clear to see that X1 has the lowest cost with X2 and X3 having very close costs. From the plot it is also clear that the number of iterations is sufficient since the slope of the losses is flat.

4.


Loss per variable vs iterations a = .1
X1
X2
X3
Loss
Iterations
0
200
400
600
800
1000
1200
1400
1
2
3
4
5


Loss per variable vs iterations a = .075
X1
X2
X3
Loss
Iterations
0
200
400
600
800
1000
1200
1400
1
2
3
4
5



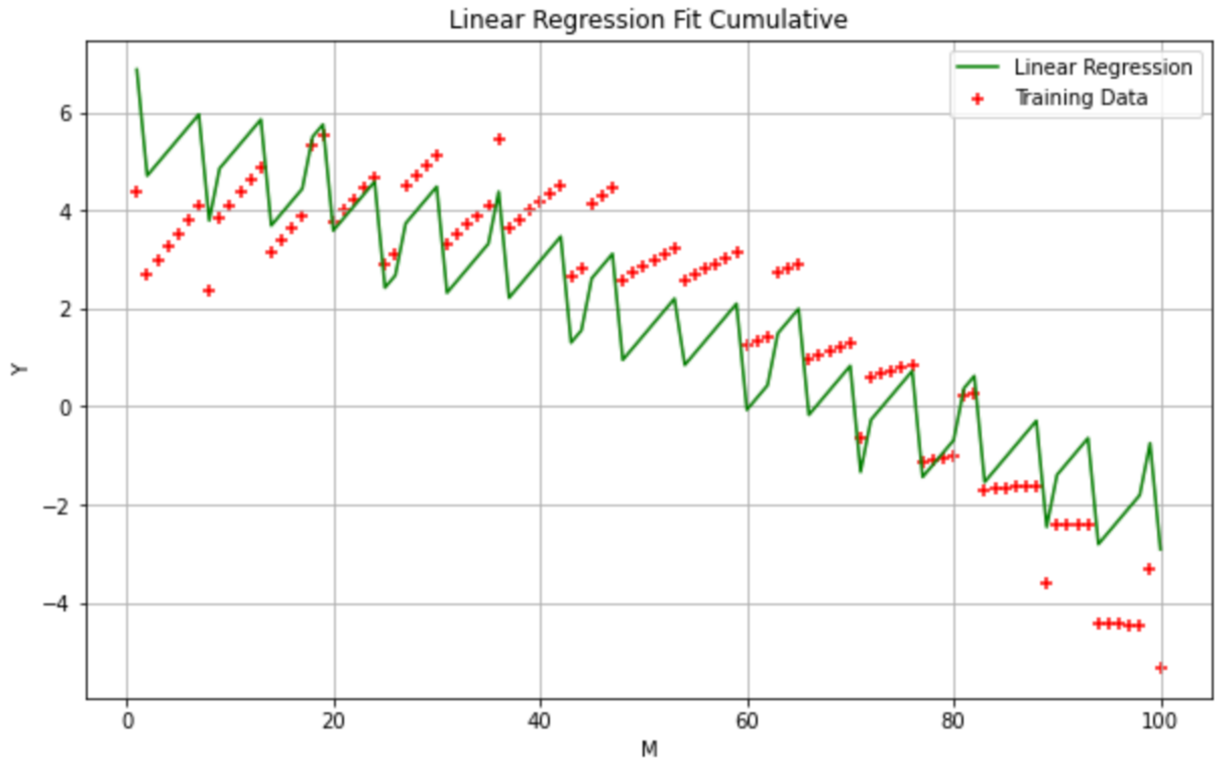


The plot in part 3 uses an a value of .01. From the plots with differing “a” values, it can be seen that a higher “a” value reduces the number if iterations required to reach a slope of zero and is most drastically seen in the losses of variables X1 and X3. With an “a” value of .1, X1’s loss reaches a slope of zero around iteration 150 vs iteration 1200 when “a” is .01. For X3, the slope reaches zero around 200 iterations when “a” is .1 vs 1400 when “a” is .01. This means that for a low “a” value, if there are not enough iterations, minimal loss will not be achieved.

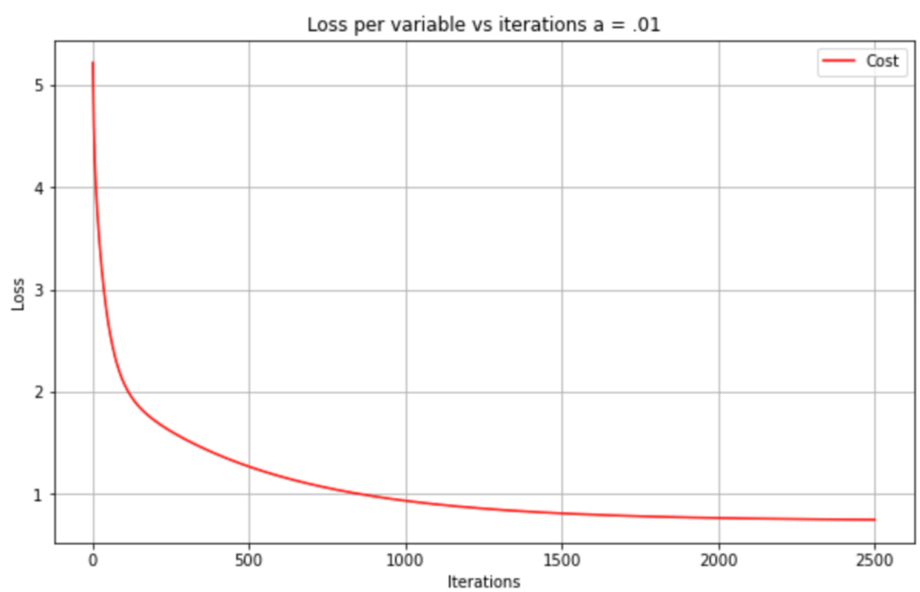
Problem 2.

1.

$h(X) = X \bullet [4.885, -1.943, 0.603, -0.202]$



2.



3. After testing different learning rates and number of iterations, it was found that a larger learning rate decreased loss and increasing iterations decreased loss. I decided to stick with a lower learning rate and a higher number of iterations to prevent possible error given the multiple variables. The final loss with “a” of .01 and 2500 iterations is 0.748.

4. h(1,1,1) = 3.342
h(2,0,4) = 0.188
h(3,2,1) = 0.060

These were calculated by creating a matrix with the input values and putting it into the linear model that was created.

In [257]:

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

In [258]:

```
Data = pd.read_csv('D3.csv',header= None)
print(Data)
M=len(Data)
```

```
           0         1         2         3
0   0.000000  3.440000  0.440000  4.387545
1   0.040404  0.134949  0.888485  2.679650
2   0.080808  0.829899  1.336970  2.968490
3   0.121212  1.524848  1.785455  3.254065
4   0.161616  2.219798  2.233939  3.536375
..       ...       ...       ...       ...
95  3.838384  1.460202  3.046061 -4.440595
96  3.878788  2.155152  3.494545 -4.458663
97  3.919192  2.850101  3.943030 -4.479995
98  3.959596  3.545051  0.391515 -3.304593
99  4.000000  0.240000  0.840000 -5.332455

[100 rows x 4 columns]
```

In [259]:

```
X1 = Data.values[:, 0] # First explanatory variable
X2 = Data.values[:, 1] # Second explanatory variable
X3 = Data.values[:, 2] # Third explanatroy variable
Y = Data.values[:, 3] # Results of explanatory variables
m = len(Y) # Number of training examples
num = list(range(1,m+1))

print('m = ', m)
```

```
m =  100
```

In [260]:

```
# Matrix used later for size compliance
X_0 = np.ones((m, 1))
X_0[:5]
```

Out[260]:

```
array([[1.],
       [1.],
       [1.],
       [1.],
       [1.]])
```

In [261]:

```
# Using reshape function convert X 1D array to 2D array of dimension 97x1
X_1 = X1.reshape(m, 1)
```

```
X_1[:5]
```

Out[261]:

```
array([[0.        ],
       [0.04040404],
       [0.08080808],
       [0.12121212],
       [0.16161616]])
```

In [262]:

```
X_2 = X2.reshape(m, 1)
X_2[:5]
```

Out[262]:

```
array([[3.44      ],
       [0.13494949],
       [0.82989899],
       [1.52484848],
       [2.21979798]])
```

In [263]:

```
X_3 = X3.reshape(m, 1)
X_3[:5]
```

Out[263]:

```
array([[0.44      ],
       [0.88848485],
       [1.3369697 ],
       [1.78545455],
       [2.23393939]])
```

In [264]:

```
# Cumulative X
X = np.hstack((X_0, X_1, X_2, X_3))
X[:5]
```

Out[264]:

```
array([[1.        , 0.        , 3.44      , 0.44      ],
       [1.        , 0.04040404, 0.13494949, 0.88848485],
       [1.        , 0.08080808, 0.82989899, 1.3369697 ],
       [1.        , 0.12121212, 1.52484848, 1.78545455],
       [1.        , 0.16161616, 2.21979798, 2.23393939]])
```

In [265]:

```
X1_1 = np.hstack((X_0, X_1))
X1_1[:5]
```

Out[265]:

```
array([[1.        , 0.        ],
       [1.        , 0.04040404],
       [1.        , 0.08080808],
       [1.        , 0.12121212],
       [1.        , 0.16161616]])
```

In [266]:

```
X2_2 = np.hstack((X_0, X_2))
X2_2[:5]
```

Out[266]:

```
array([[1.        , 3.44      ],
       [1.        , 0.13494949],
       [1.        , 0.82989899],
       [1.        , 1.52484848],
       [1.        , 2.21979798]])
```

In [267]:

```
X3_3 = np.hstack((X_0, X_3))
X3_3[:5]
```

Out[267]:

```
array([[1.        , 0.44      ],
       [1.        , 0.88848485],
       [1.        , 1.3369697 ],
       [1.        , 1.78545455],
       [1.        , 2.23393939]])
```

In [268]:

```
theta = np.zeros(2)
theta
```

Out[268]:

```
array([0., 0.])
```

In [269]:

```
def compute_cost(X, Y, theta):
 predictions = X.dot(theta)
 errors = np.subtract(predictions, Y)
 sqrErrors = np.square(errors)
 J = 1 / (2 * m) * np.sum(sqrErrors)
 return J
```

In [270]:

```
def gradient_descent(X, Y, theta, alpha, iterations):

 cost_history = np.zeros(iterations)
 for i in range(iterations):
    predictions = X.dot(theta)
    errors = np.subtract(predictions, Y)
    sum_delta = (alpha / m) * X.transpose().dot(errors);
    theta = theta - sum_delta;
    cost_history[i] = compute_cost(X, Y, theta)
 return theta, cost_history
```

In [271]:

```
theta = [0., 0.]
iterations = 2500;
alpha = 0.01;
itx = list(range(1,iterations+1))
```

In [272]:

```
# Theta for Explanatory variable 1
theta1, cost_history1 = gradient_descent(X1_1, Y, theta, alpha, iterations)
print('Final value of theta =', theta1)
```

```
print('cost_history =', cost_history1)
Final value of theta = [ 5.90516418 -2.0294687 ]
cost_history = [5.48226715 5.44290965 5.40604087 ... 0.9850599  0.98505961
0.98505931]
```

In [273]:

```
# Theta for Explanatory variable 2
theta2, cost_history2 = gradient_descent(X2_2, Y, theta, alpha, iterations)
print('Final value of theta =', theta2)
print('cost_history =', cost_history2)
Final value of theta = [0.73430056 0.55829257]
cost_history = [5.29831663 5.09909109 4.92356115 ... 3.59936642 3.59936642
3.59936641]
```

In [274]:

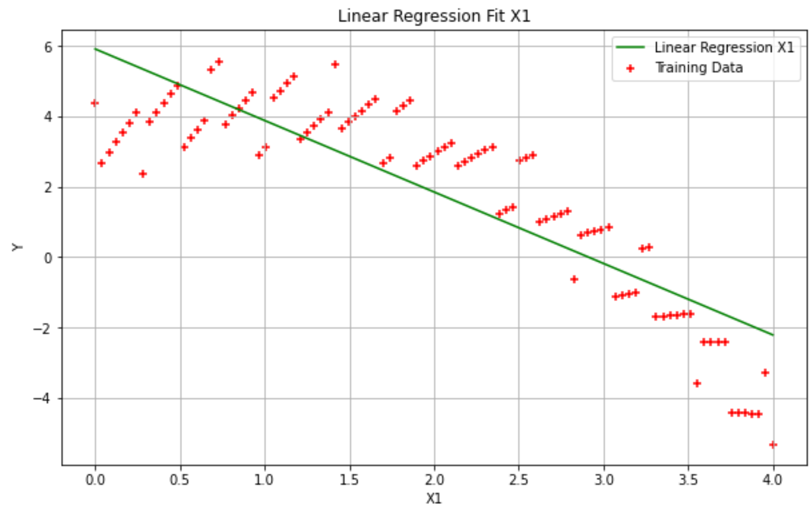
```
# Theta for Explanatory variable 3
theta3, cost_history3 = gradient_descent(X3_3, Y, theta, alpha, iterations)
print('Final value of theta =', theta3)
print('cost_history =', cost_history3)
Final value of theta = [ 2.86184509 -0.51669523]
cost_history = [5.40768785 5.30397076 5.21178297 ... 3.62946316 3.6294631
3.62946305]
```

In [275]:

```
# Varible X1
plt.scatter(X1_1[:, 1], Y, color='red', marker= '+', label= 'Training Data')
plt.plot(X1_1[:, 1],X1_1.dot(theta1), color='green', label='Linear Regression
X1')
plt.rcParams["figure.figsize"] = (10,6)
plt.grid()
plt.xlabel('X1')
plt.ylabel('Y')
plt.title('Linear Regression Fit X1')
plt.legend()
```

Out[275]:

```
<matplotlib.legend.Legend at 0x7f932939c490>
```

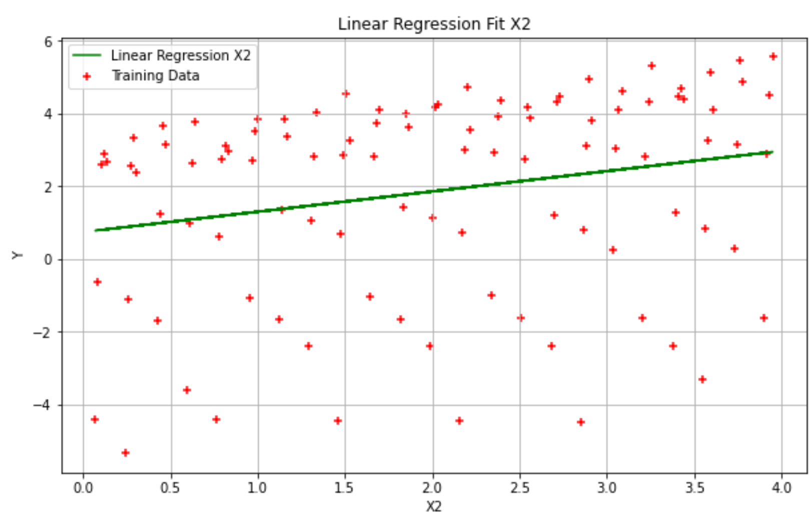


In [276]:

```
# Variable X2
plt.scatter(X2_2[:, 1], Y, color='red', marker= '+', label= 'Training Data')
plt.plot(X2_2[:, 1],X2_2.dot(theta2), color='green', label='Linear Regression
X2')
plt.rcParams["figure.figsize"] = (10,6)
plt.grid()
plt.xlabel('X2')
plt.ylabel('Y')
plt.title('Linear Regression Fit X2')
plt.legend()
```

Out[276]:

```
<matplotlib.legend.Legend at 0x7f9308a94940>
```



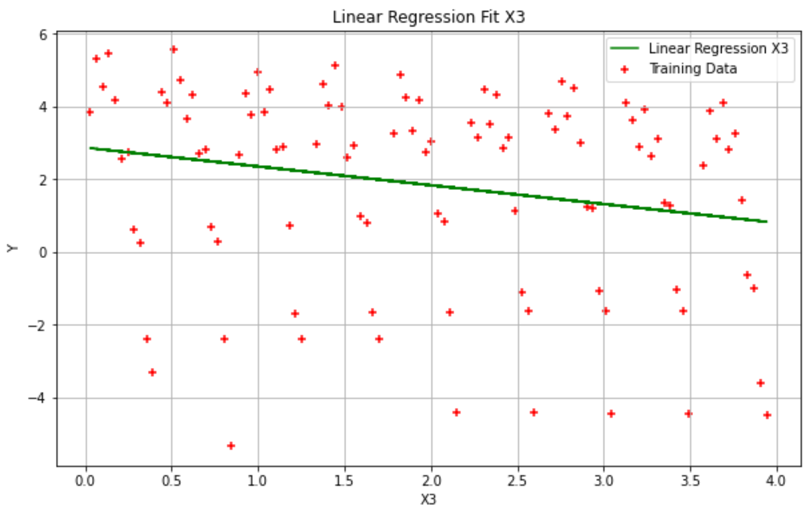
In [277]:

```
# Variable X3
plt.scatter(X3_3[:, 1], Y, color='red', marker= '+', label= 'Training Data')
plt.plot(X3_3[:, 1],X3_3.dot(theta3), color='green', label='Linear Regression
X3')
plt.rcParams["figure.figsize"] = (10,6)
```

```
plt.grid()
plt.xlabel('X3')
plt.ylabel('Y')
plt.title('Linear Regression Fit X3')
plt.legend()
```

Out[277]:

```
<matplotlib.legend.Legend at 0x7f93293d04f0>
```

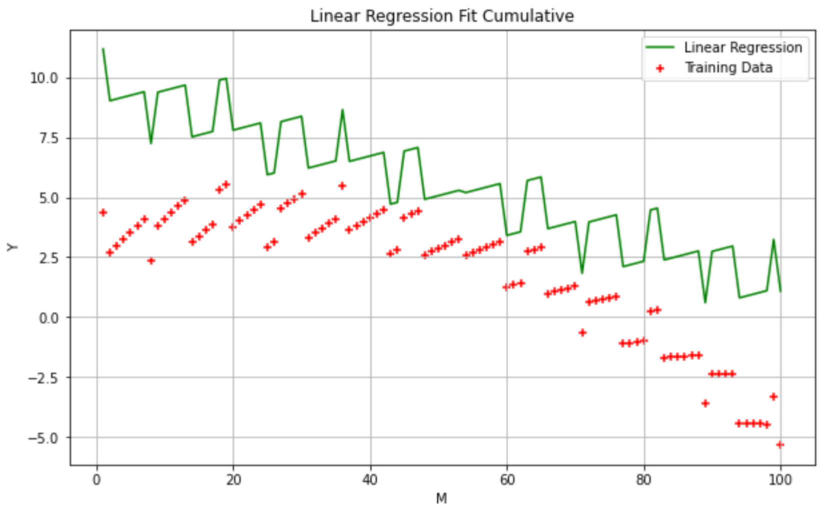


In [278]:

```
# All three variables
plt.scatter(num, Y, color='red', marker= '+', label= 'Training Data')
plt.plot(num,(X1_1.dot(theta1)+X2_2.dot(theta2)+X3_3.dot(theta3)),
color='green', label='Linear Regression')
plt.rcParams["figure.figsize"] = (10,6)
plt.grid()
plt.xlabel('M')
plt.ylabel('Y')
plt.title('Linear Regression Fit Cumulative')
plt.legend()
```

Out[278]:

```
<matplotlib.legend.Legend at 0x7f92fb4538b0>
```

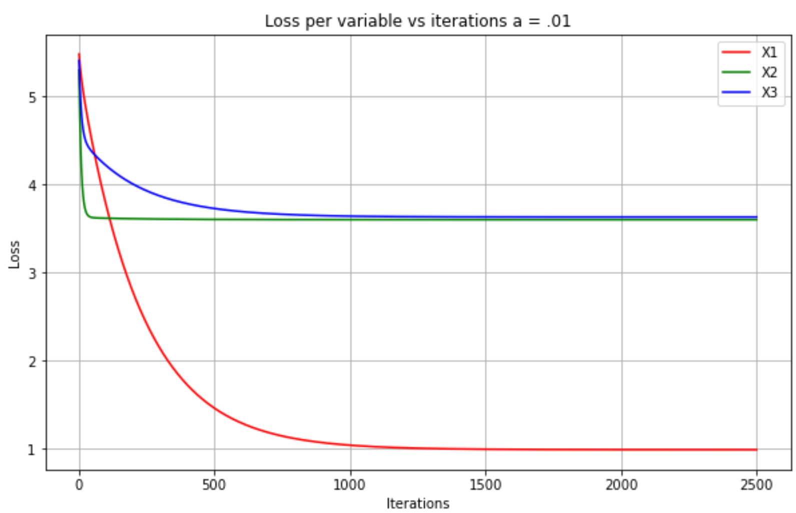


In [279]:

```
# Loss of three variables
plt.plot(itx, cost_history1, color='red',  label= 'X1')
plt.plot(itx, cost_history2, color='green', label='X2')
plt.plot(itx, cost_history3, color='blue', label='X3')
plt.rcParams["figure.figsize"] = (10,6)
plt.grid()
plt.xlabel('Iterations')
plt.ylabel('Loss')
plt.title('Loss per variable vs iterations a = .01')
plt.legend()
```

Out[279]:

```
<matplotlib.legend.Legend at 0x7f92c807af70>
```



In [280]:

```
# Problem 2. cumulative variable regression

P2theta = np.zeros(4)

# Theta and costs for cumulative explanatory variables
```

```
thetaP2, cost_historyP2 = gradient_descent(X, Y, P2theta, alpha, iterations)
print('Final value of theta =', thetaP2)
print('cost_history =', cost_historyP2)
```

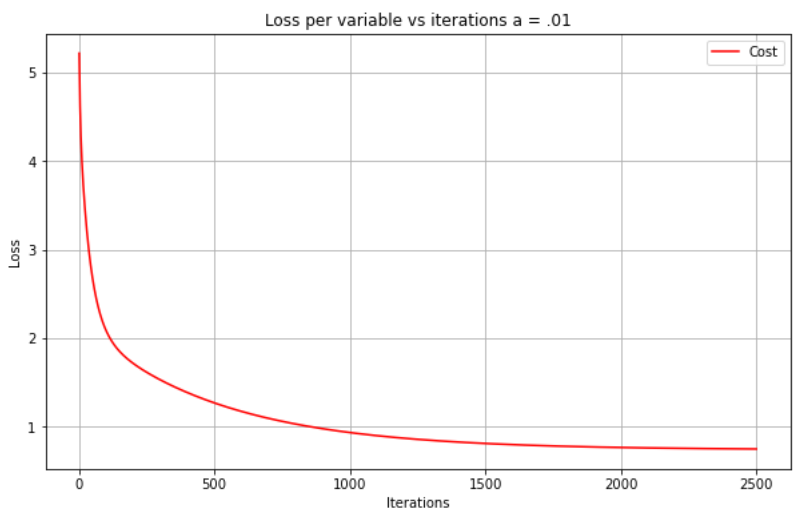
```
Final value of theta = [ 4.88518623 -1.94311861  0.60344978 -0.20272198]
cost_history = [5.21542243 4.97171977 4.7765543  ... 0.74830606 0.74828645
0.74826687]
```

In [281]:

```
# Loss of three variables
plt.plot(itx, cost_historyP2, color='red',  label= 'Cost')
plt.rcParams["figure.figsize"] = (10,6)
plt.grid()
plt.xlabel('Iterations')
plt.ylabel('Loss')
plt.title('Loss per variable vs iterations a = .01')
plt.legend()
```

Out[281]:

```
<matplotlib.legend.Legend at 0x7f93495a1d30>
```

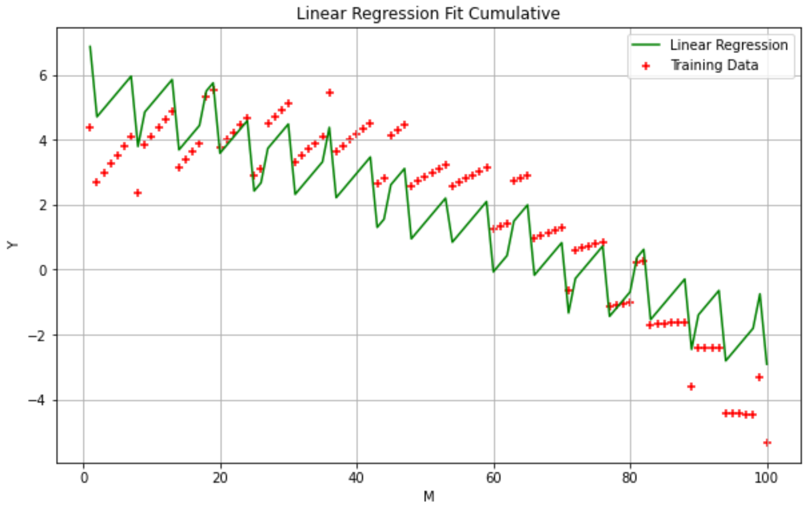


In [282]:

```
# All three variables
plt.scatter(num, Y, color='red', marker= '+', label= 'Training Data')
plt.plot(num,(X.dot(thetaP2)), color='green', label='Linear Regression')
plt.rcParams["figure.figsize"] = (10,6)
plt.grid()
plt.xlabel('M')
plt.ylabel('Y')
plt.title('Linear Regression Fit Cumulative')
plt.legend()
```

Out[282]:

```
<matplotlib.legend.Legend at 0x7f93495f01f0>
```



In [283]:

```
# Put test values into the linear model
Test = np.array([[1, 1, 1, 1], [1, 2, 0, 4], [1, 3, 2, 1]])
h = Test.dot(thetaP2)
print(h)
[3.34279542 0.1880611  0.06000798]
```

In [ ]:

In [ ]: