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Homework 0
Github: https://github.com/gbass2/IntroToML

## Problem 1:

The first step in finding the linear regression model for X1, X2, and X3 was to first read the values from the csv file. This was done using pandas and then converted into a NumPy array. X1, X2, and X3 were setup as separate variable corresponding to it's column in the csv file. The ground truth (y) was also read from the csv in the same manner. Next the X1, X2, X3 was reshaped to be a 2-D array where the first column is filled with ones. This allows theta which is a 2x1 to be multiplied by X which is a mx2 matrix where m is the number of training samples. Next the cost is calculated. Theta was initialized as an array of 2 zeros. Which corresponds to theta0 and theta1. The initial cost came out to be 5.244 for X1, X2, and X3. This is the case because the starting theta values were 0. Once the cost is calculated the gradient descent is calculated. The gradient descent function returns theta for the regression model, the history of the cost for each iteration. The array holding the history of theta is used to plot the regression model over the number of iterations. The source code, graphs, and results can be found at the bottom of the report.

### Part 1:

The following is the linear regression models with their respective learning rates and iteration numbers.

For X1:
alpha = .02
iterations = 600
h(X1) = 5.52168752 - 1.88021764 * (X1)

For X2:
alpha = .01
iterations = 50
h(X1) = 0.32061638 + 0.68376091 * (X2)

For X3:
alpha = .01
iterations = 50
h(X1) = 2.69330966 - 0.45004043 * (X3)

### Part 2:

Figure 4, 5, and 6 shows the plot of the regression model over the number of iterations.

Figures 7, 8, and 9 shows the cost vs the iterations for X1, X2, X3

## Part 3:

The explanatory variable with the lowest cost that explains y is X1. The values in X1 best explained the output y and that is why it showed the lowest loss.

## Part 4:

Both the learning rate and the iterations play a role in reducing the final loss of a linear regression model. The higher the learning rate the faster the model can learn but a smaller learning rate can sometimes be better because the model will learn better. The number of iterations goes hand in hand with the learning rate. There is a point at which the model will not learn anymore on the same data. This can be seen in figures 7, 8, and 9 which shows a plot of their gradient descents. You want to have more iterations if you choose a small learning rate, and you want a smaller number of iterations if chose a higher learning rate. For X2 in problem 2 a smaller learning rate and number of iterations were used. This was since the loss converged quicker than X1 and X2 when calculating the gradient descent. The following learning rates and iterations is what I found best for X1, X2, and X3:

For X1:
alpha = .02
iterations = 600

For X2:
alpha = .01
iterations = 50

For X3:
alpha = .01
iterations = 600

# Problem 2:

Problem 2 was completed in a similar manner to problem 1 with a couple of changes. The first change was combining X1, X2, and X3 into one array. This allows a single model to learn on multiple variables which can lower the loss of the model. The array containing all 1's was also added to the first column of X. Once X was created, theta was initialized to an array of 4 zeros corresponding to theta0 through theta3. 2 more thetas were added compared to problem 1 because the 2 more input variables were added. The cost and gradient descent were calculated using the same functions as in problem 1.

## Part 1:

The following is the best linear regression model that I found with it's respective learning rate and number of iterations.

For X:
alpha = .02

iterations = 600

h(X) = 4.84189465 - 1.93700296 * (X1) + 0.61060345 * (X2) - 0.19637631 * (X3)

Part 2:

The plot of the loss can be seen in figure 10.

Part 3:

Both the learning rate and the iterations play a role in reducing the final loss of a linear regression model. The higher the learning rate the faster the model can learn but a smaller learning rate can sometimes be better because the model will learn better. The number of iterations goes hand in hand with the learning rate. There is a point at which the model will not learn anymore on the same data. This can be seen in figures 10 which shows a plot of the gradient descent for X. You want to have more iterations if you choose a small learning rate, and you want a smaller number of iterations if chose a higher learning rate. For X I chose a smaller learning rate and a larger number of iterations. This allowed me to get a lower cost function. I only ran the gradient descent over 600 iterations with an alpha of .02. Adding more iterations did not lower the cost enough to justify having more iterations. The cost only decreased by .2.

Part 4:

The predicted values were calculated using the following function:

h = theta[0] + theta[1]*X[0] + theta[2]*X[1] + theta[3]*X[2]

h is the predicted value and X is the explanatory variable to be predicted on. The following are the predicted values.

For X = (1, 1, 1)
Y = 3.525163184517707

For X = (2, 0, 4)
Y = 0.2317926141038631

For X = (3, 2, 1)
Y = 0.09306401330393993