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BS in Computer Science IV

Questions:

Note that the weights are generated randomly, and the results may vary across executions. While you have a function for generating random weights, assume that the initial weights are all 0s.

init_w = np.array([0.0, 0.0, 0.0, 0.0])

1. **What are the optimal weights found by your implemented gradient descent? Plug it into the linear model:**

   $$h_\theta(x) = \theta_0 + \theta_1 TV + \theta_2 Radio + \theta_3 Newspaper$$

   What are your interpretations regarding the formed linear model?

   The linear model is: $h\theta(x)$ = 4.35589486e-04 + 7.37383146e-01 * TV + 5.36307180e-01 * $Radio$ + 3.14254020e-03 * $Newspaper$

   Looking at the linear model, we can observe that *TV* is the greatest predictor compared to *Radio* and *Newspaper*. Next to *TV* is *Radio,* followed by *Newspaper*.

2. **Provide a scatter plot of the $(\widehat{y^{(i)}})$ and $y^{(i)}$ for both the train and test set. Is there a trend? Provide an r2 score (also available in sklearn).**

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The R2 score using train set is: 0.8936793584593189
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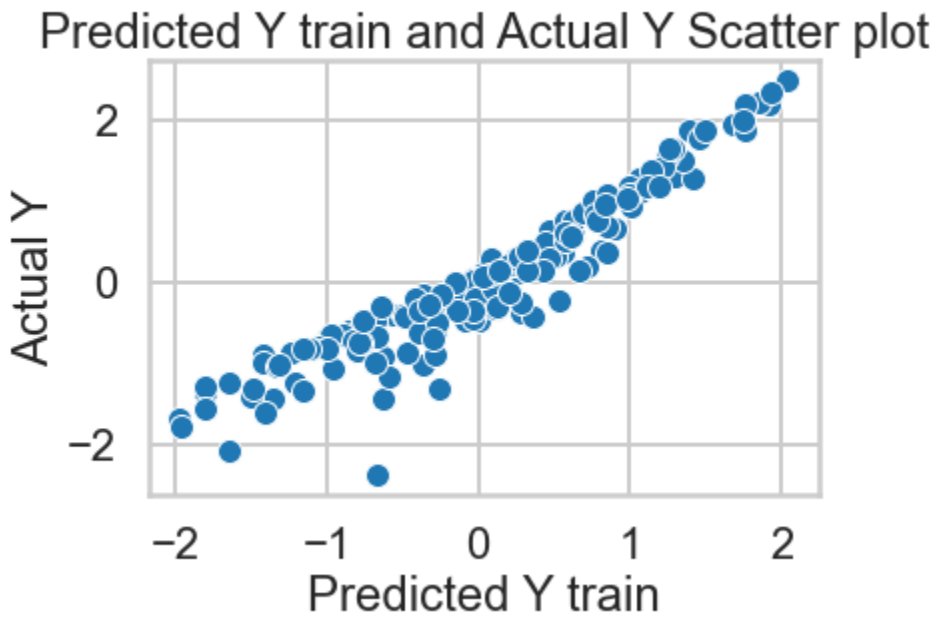

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The R2 score using test set is: 0.911027570209169
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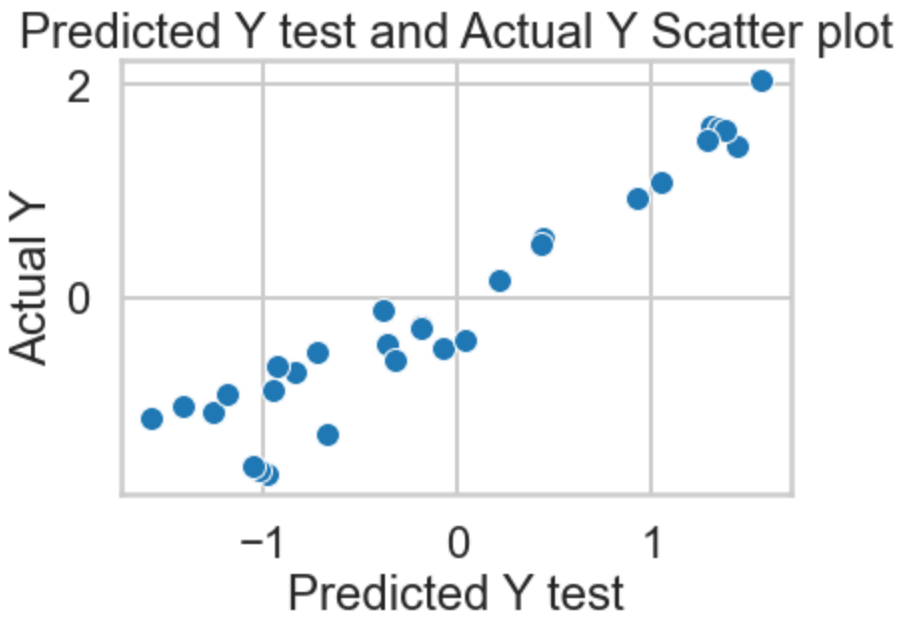


3. **What happens to the error, r2, and cost as the number of iterations increases? Show your data and proof. You can alternatively plot your result data for visualization and check until 50000 iterations or more (actually).**
   The Cost for 500 iteration is: 0.051185390643040306
   The r2 score for 500 iteration is: 0.896415695070808
   The MAE for 500 iteration is: 0.24134539353189827

   The Cost for 1000 iteration is: 0.051079831065374885
   The r2 score 1000 500 iteration is: 0.8969142691949464
   The MAE for 1000 iteration is: 0.2399596550148806

   The Cost for 10000 iteration is: 0.051079554729786925
   The r2 score for 10000 iteration is: 0.8969225203073516
   The MAE for 10000 iteration is: 0.2398886365772415

   It can be observed base on the results of cost, r2 score and MAE that the higher the number of iteration, the r2 score increases while the cost and MAE decreases. However, these differences are really small.

4. **Once you determine the optimal number of iterations, check the effect on the cost and error as you change the learning rate. The common learning rates in machine learning include 0.1, 0.01, 0.001, 0.0001, 0.2 but you have the option to include others. Visualize the cost function (vs the optimal number of iterations) of each learning rate in ONLY ONE PLOT. Provide your analysis.**
   The optimal iteration is at: 395

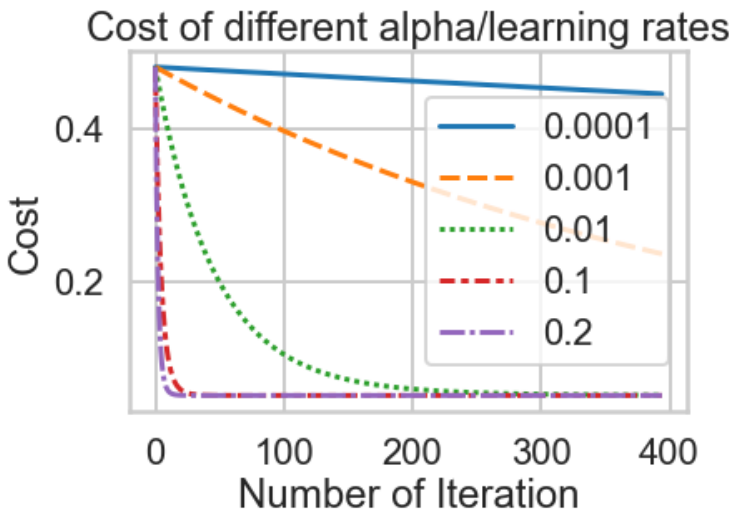
When alpha rate is: 0.1
Cost: 0.05107955472978691
R2: 0.8969225203072294
MAE: 0.2398886365786446

When alpha rate is: 0.01
Cost: 0.051500250039664096
R2: 0.8953717254069102
MAE: 0.24272053055351145

When alpha rate is: 0.001
Cost: 0.23622673852442644
R2: 0.5060374784393623
MAE: 0.563782776791368

When alpha rate is: 0.0001
Cost: 0.44536428998765176
R2: 0.07286799176886316
MAE: 0.7890090157139464

When alpha rate is: 0.2
Cost: 0.051079554729786925
R2: 0.8969225203073514
MAE: 0.239888636577241



It can be observed from the graph that the 0.2 reached the lowest cost the fastest and it was followed by 0.1 then followed by 0.01. While, 0.001 is linear and lastly, 0.0001 did not achieve the lowest cost at 395 iteration. Both 0.001 and 0.0001 did not reach lowest cost within the optimal iteration.

5. **Is there a relationship between the learning rate and the number of iterations?**
   Based on the previous graph, if the learning rate is higher, then the number of iterations needed to get the optimal cost will decrease. Hence, the learning rate and the number of iterations have an inversely proportional relationship.

6. **Compare the results with the results of the ordinary least squares function.**
   R2 score of the Linear Regression:
   0.9110275702091712
   R2 scores of the weight of the optimal iteration of the gradient descent:
   0.906288920753653

   The difference between the two is not that big but the R2 score that used linear regression is much closer to 1 than the R2 score that used optimal iteration of the gradient descent.