Linear Regression using Gradient Descent

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link to code:https://github.com/Santiagomrn/Linear_regresion

I. Introduction

Implement Linear Regression using Gradient Descent to predict weights of males and females based on their heights. We will use height as the input variable and weight as the output variable Heights (”height.dat”) and weights (”weight.dat”) are in inches and pounds, respectively. Use the Mean-Square-Error (MSE) function.

A. Theoretical framework

Hypothesis:

$$h(x) = b_0 + b_1 x \tag{1}$$

Loss Function:

$$L(b_0, b_1) = \frac{1}{2n}\sum_{i=1}^{n}(h(x_i) - y_i)^2 \tag{2}$$

Update Rule:
for b0:

$$\begin{gathered} b_0 = b_0 - \alpha\frac{dL(b_0, b_1)}{db_0} \\ b_0 = b_0 - \alpha\frac{1}{n}\sum_{i=1}^{n}(h(x_i) - y_i) \end{gathered} \tag{3}$$

for b1:

$$\begin{gathered} b_1 = b_1 - \alpha\frac{dL(b_0, b_1)}{db_1} \\ b_1 = b_1 - \alpha\frac{1}{n}\sum_{i=1}^{n}(h(x_i) - y_i)x_i \end{gathered} \tag{4}$$

II. Development of practice

A. Plot your data set and label the axes (“Heights”, “Weights”).

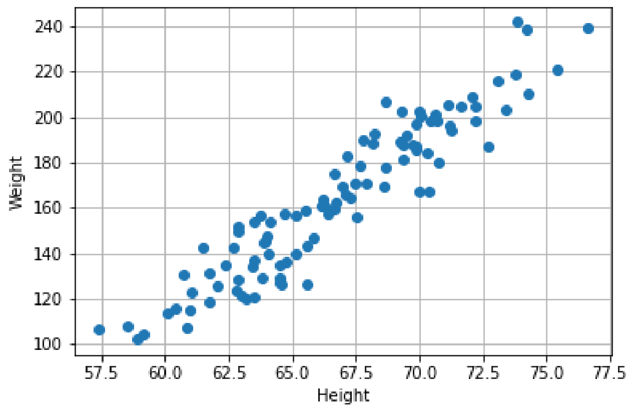


Fig. 1. Weight versus height graph.

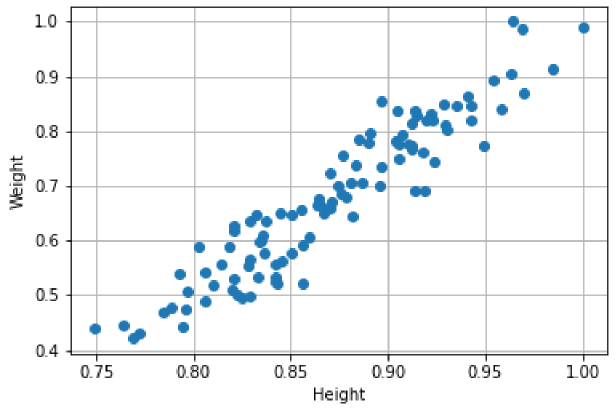
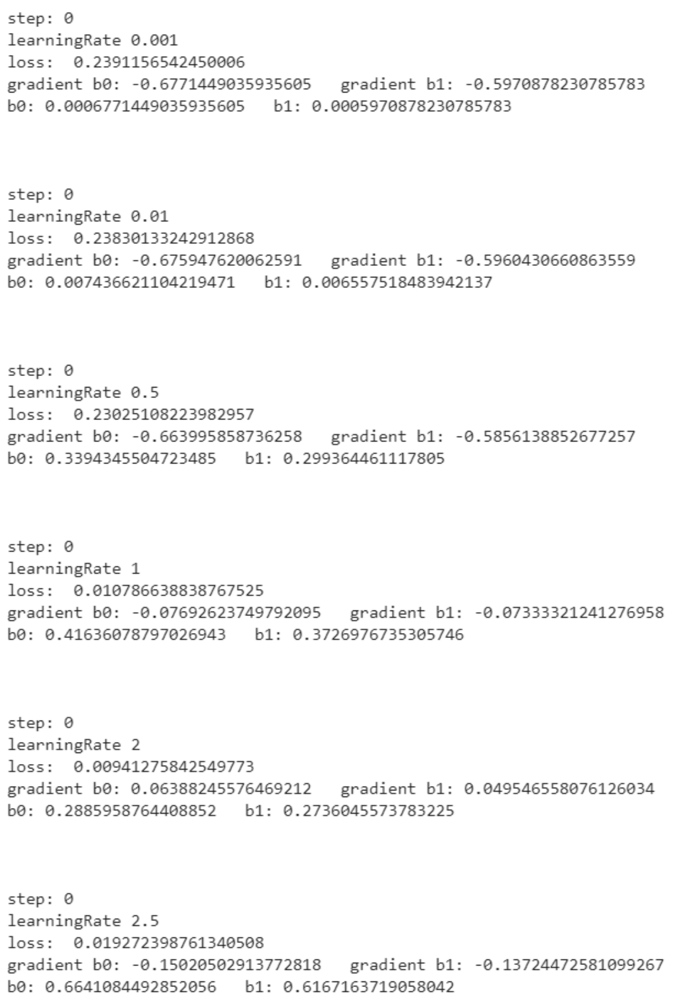


Fig. 2. Normalized weight versus height graph.

B. Try= 0.001, 0.01, 0.5, 1, 2, 2.5 to perform the following:

1) Initialize the parameters and of your linear model to zero. Run one iteration of gradient descent from this initial starting point. Record the value of your parameters after this first iteration.
Normalized data are used for training because if they are not normalized the training with the proposed learning rates fails.



```
step: 0
learningRate 0.001
loss:  0.2391156542450006
gradient b0: -0.6771449035935605   gradient b1: -0.5970878230785783
b0: 0.0006771449035935605   b1: 0.0005970878230785783



step: 0
learningRate 0.01
loss:  0.23830133242912868
gradient b0: -0.675947620062591   gradient b1: -0.5960430660863559
b0: 0.007436621104219471   b1: 0.006557518483942137



step: 0
learningRate 0.5
loss:  0.23025108223982957
gradient b0: -0.663995858736258   gradient b1: -0.5856138852677257
b0: 0.3394345504723485   b1: 0.299364461117805



step: 0
learningRate 1
loss:  0.010786638838767525
gradient b0: -0.07692623749792095   gradient b1: -0.07333321241276958
b0: 0.41636078797026943   b1: 0.3726976735305746



step: 0
learningRate 2
loss:  0.00941275842549773
gradient b0: 0.06388245576469212   gradient b1: 0.049546558076126034
b0: 0.2885958764408852   b1: 0.2736045573783225

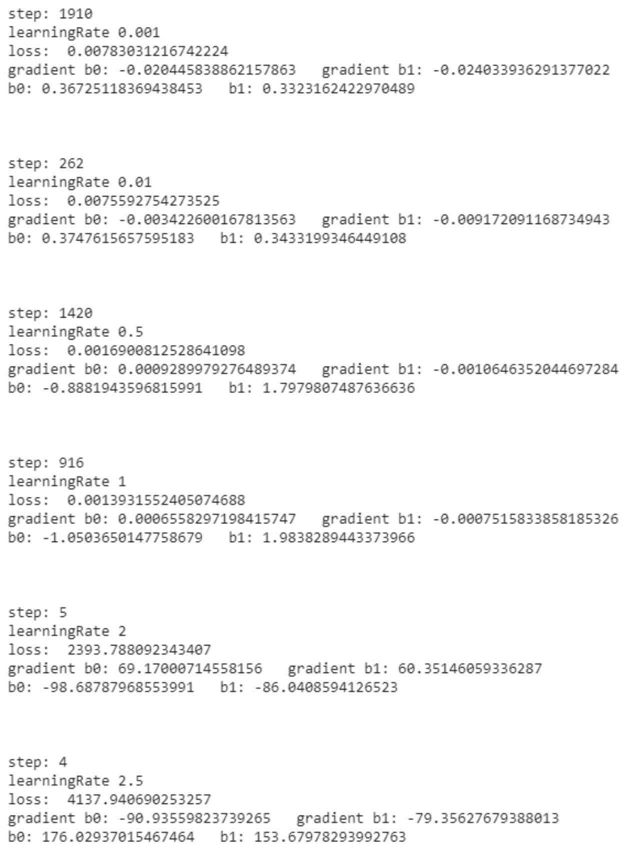


step: 0
learningRate 2.5
loss:  0.019272398761340508
gradient b0: -0.15020502913772818   gradient b1: -0.13724472581099267
b0: 0.6641084492852056   b1: 0.6167163719058042
```

Fig. 3. Results of the first iterations with various learning rates

2) Continue running gradient descent for more iterations until your parameters converge. Plot your loss values after each iteration and record your parameters final values.
The absolute value difference between the current loss and the last loss is used to verify convergence.

$$|loss - lastLoss| < 0.000001 \tag{5}$$



```
step: 1910
learningRate 0.001
loss:  0.00783031216742224
gradient b0: -0.020445838862157863   gradient b1: -0.024033936291377022
b0: 0.36725118369438453   b1: 0.3323162422970489



step: 262
learningRate 0.01
loss:  0.0075592754273525
gradient b0: -0.003422600167813563   gradient b1: -0.009172091168734943
b0: 0.3747615657595183   b1: 0.3433199346449108



step: 1420
learningRate 0.5
loss:  0.0016900812528641098
gradient b0: 0.0009289979276489374   gradient b1: -0.0010646352044697284
b0: -0.8881943596815991   b1: 1.7979807487636636



step: 916
learningRate 1
loss:  0.0013931552405074688
gradient b0: 0.0006558297198415747   gradient b1: -0.0007515833858185326
b0: -1.0503650147758679   b1: 1.9838289443373966



step: 5
learningRate 2
loss:  2393.788092343407
gradient b0: 69.17000714558156   gradient b1: 60.35146059336287
b0: -98.68787968553991   b1: -86.0408594126523



step: 4
learningRate 2.5
loss:  4137.940690253257
gradient b0: -90.93559823739265   gradient b1: -79.35627679388013
b0: 176.02937015467464   b1: 153.67978293992763
```

Fig. 4. Parameters final values with various learning rates

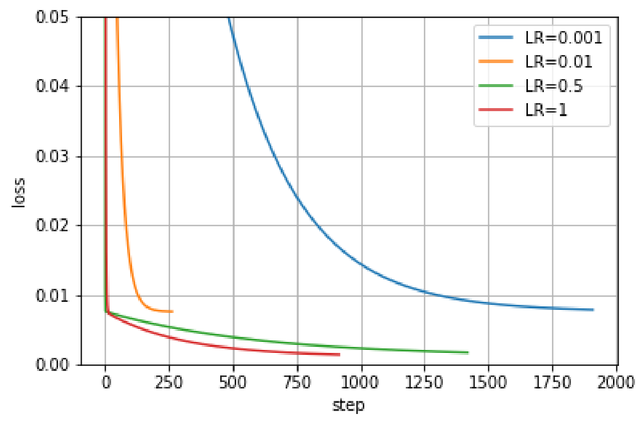


Fig. 5. Loss with various learning rates

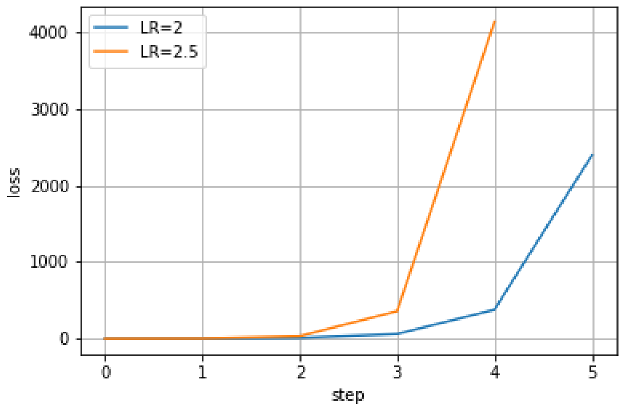


Fig. 6. Loss with various learning rates

3) What step size value performs best?.

   Based on the loss function the model trained with 1 of learning rate is the best model.

C. After convergence, plot the straight line fit from your algorithm on the same graph as your data.

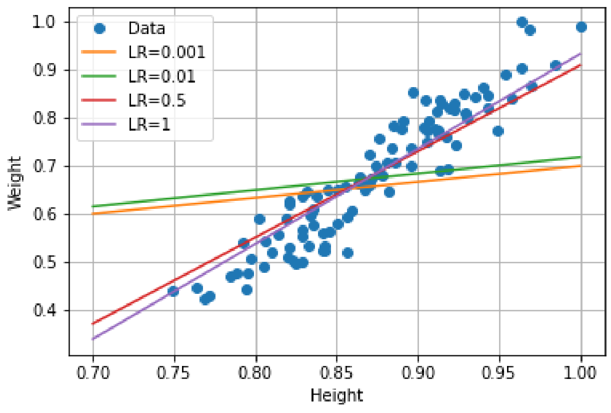


Fig. 7. Models with various learning rates.

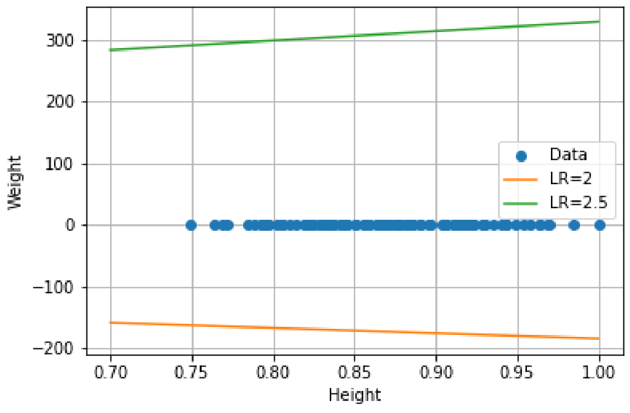


Fig. 8. Models with various learning rates.

D. use your trained model to predict the weight for a person of height 71.731 inches. Show your results.

```
195.2950545233966
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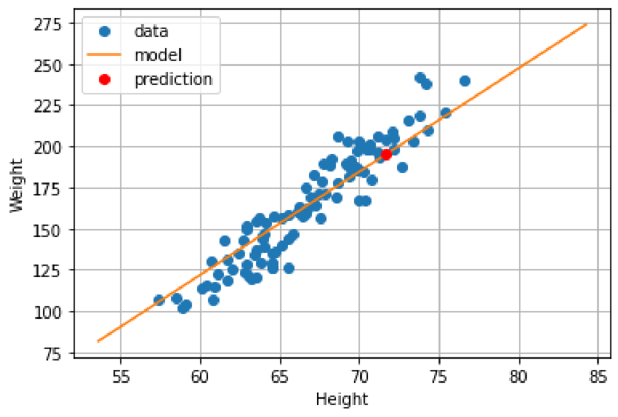

Fig. 9. Prediction with data and model.

References

[1] Andrew Ng. *CS229 Lecture Notes*, http://cs229.stanford.edu/notes2020spring/cs229-notes1.pdf.