

---

# Assignment 5

## CS498 Applied Machine Learning

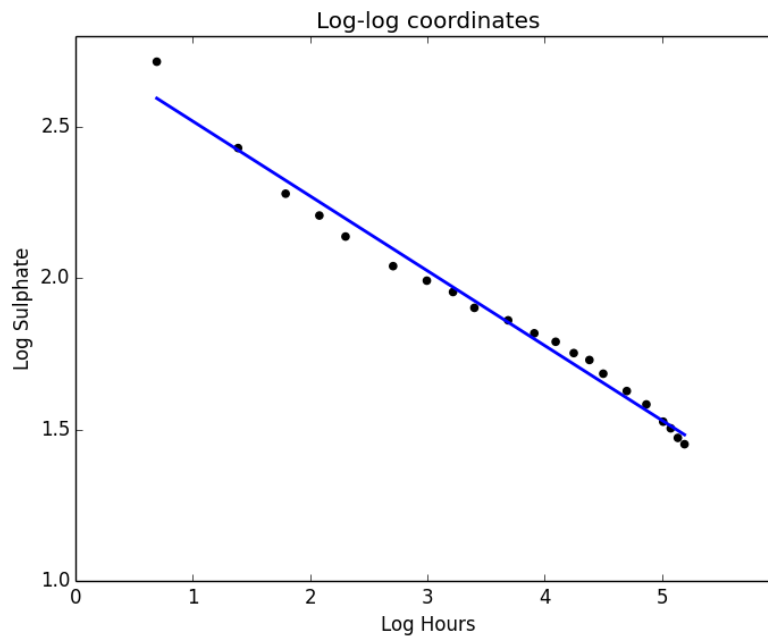
Jianshu Wang , Hari Manan, Jasdeep Duggal- March 12, 2018

---

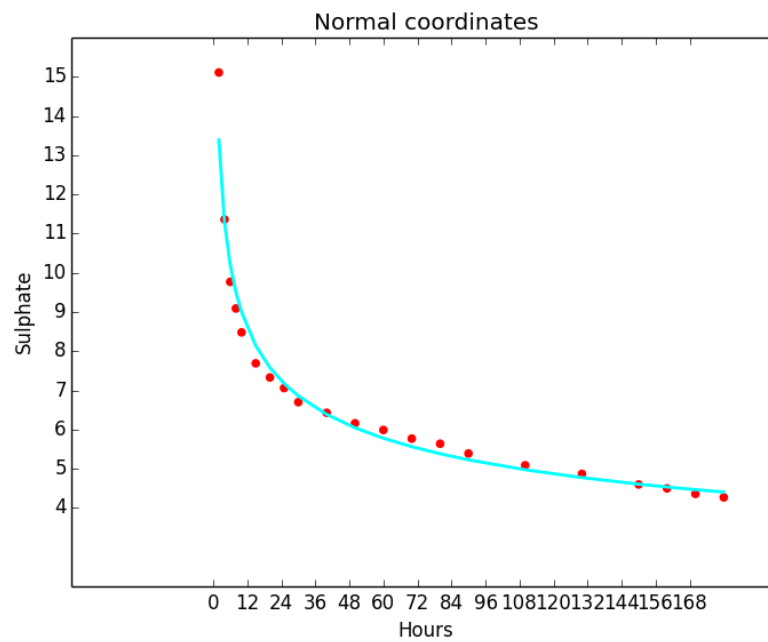
---

# Introduction

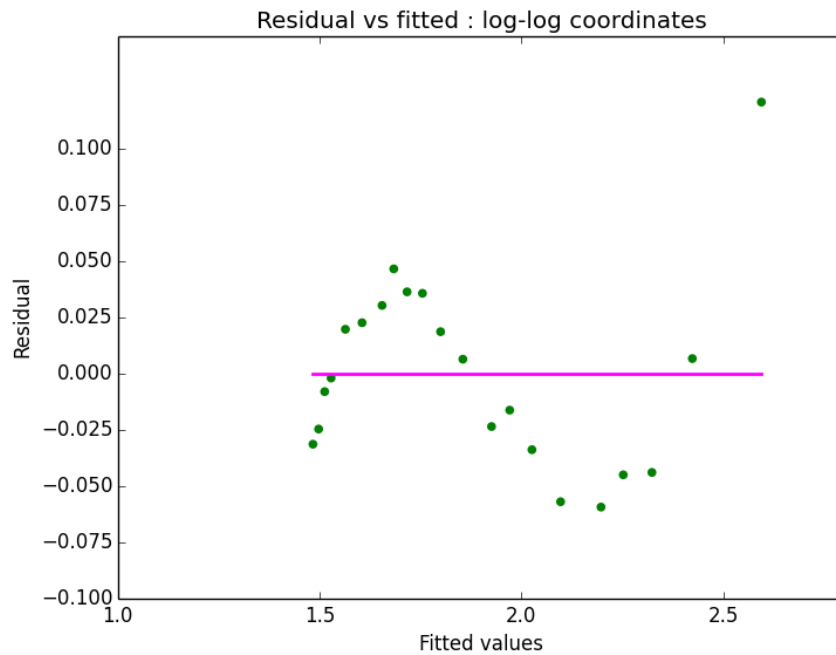
## Problem7.9



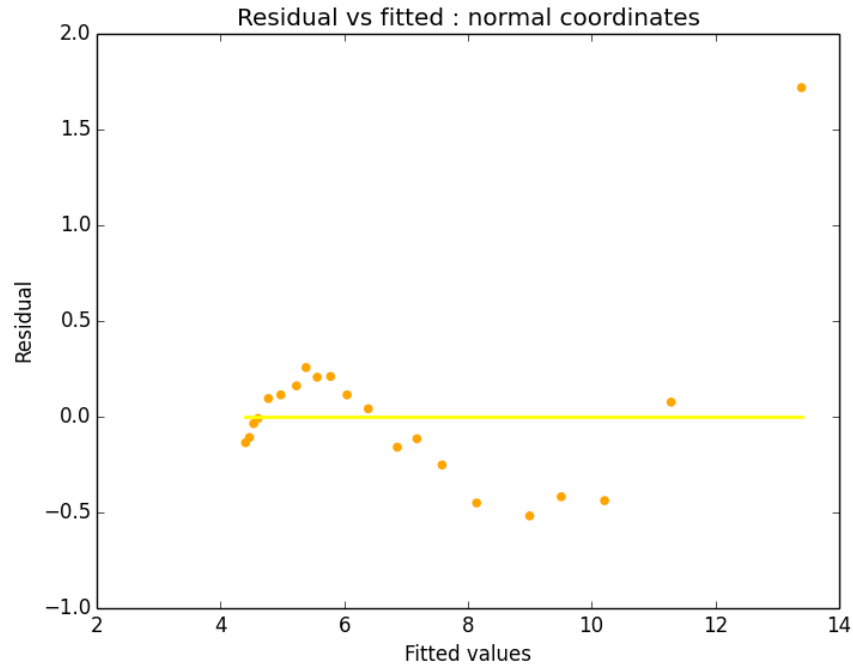
**Figure 1 (A) : Linear Regression in log-log Coordinates**



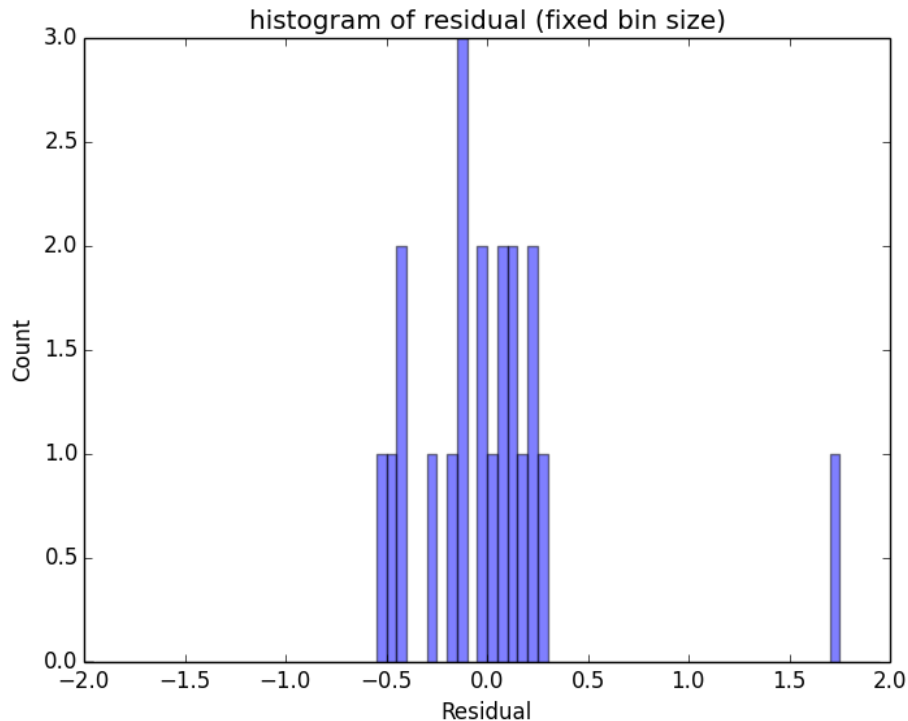
**Figure 2 (B) : Curve Line in Normal Coordinates**



**Figure 3 (C – A): Residual against Fitted Value in log-log Coordinates**



**Figure 4 ( C -B ) : Residual against Fitted Value in Normal Coordinates**



**Figure 5 (C Extra): Histogram of Residual Like a Normal Distribution**

Let's us calculate variance code of the model , the variance value for our model is 0.9839250931007382 .The best values is 1 , our model is 0.9839250931007382 which is very close to best And also, if we look at the figure 2 , the values of hours vs . Sulphate in normal coordinates , we can infer that the plots almost coincide with the scattered values, showing that it is a good regression.

Residual plots are considered to be good if they follow these 3 rules.

Figure 3 and 4 , the residual values in both the log and normal coordinates follow these rules.

- (1) they're pretty symmetrically distributed, tending to cluster towards the middle of the plot
- (2) they're clustered around the lower single digits of the y-axis (e.g., 0.5 or 1.5, not 30 or 150)
- (3) in general there aren't clear patterns

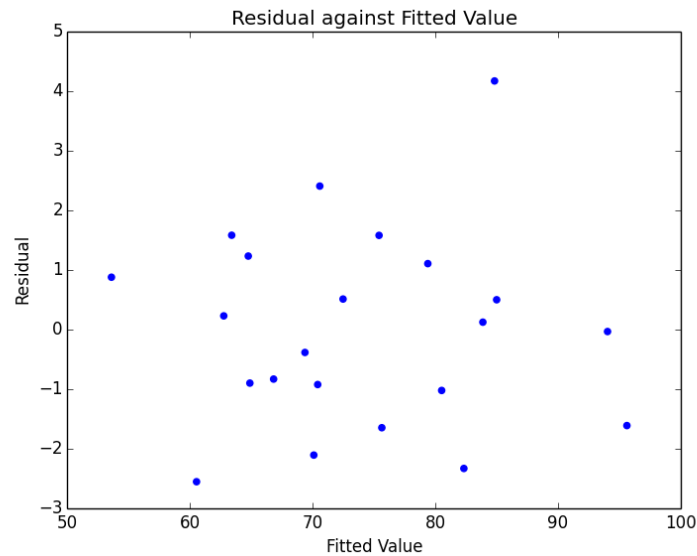
Source :

<http://docs.statwing.com/interpreting-residual-plots-to-improve-your-regression/>

---

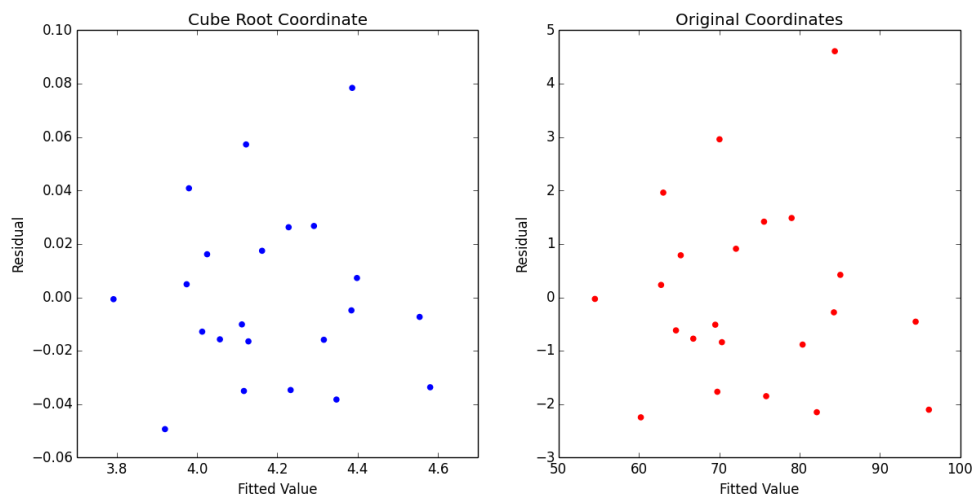
### Problem 7.10

Part a)



**Figure 6: Residual against Fitted Value**

Part b)



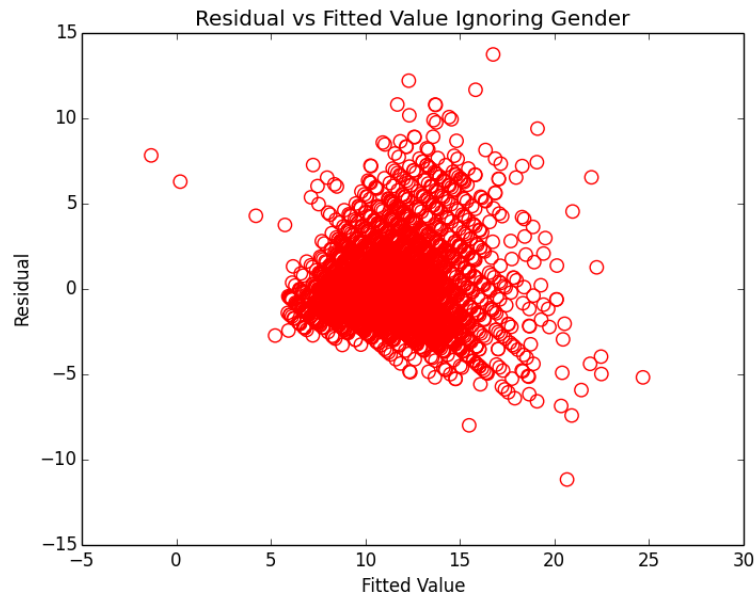
**Figure 7: Cube Root Residual in Cube Root Coordinates and Original Coordinates**

Part c) R squares are 0.977210661741 for normal vs 0.984234958257 for cube root, so I consider cube root to be a better one

---

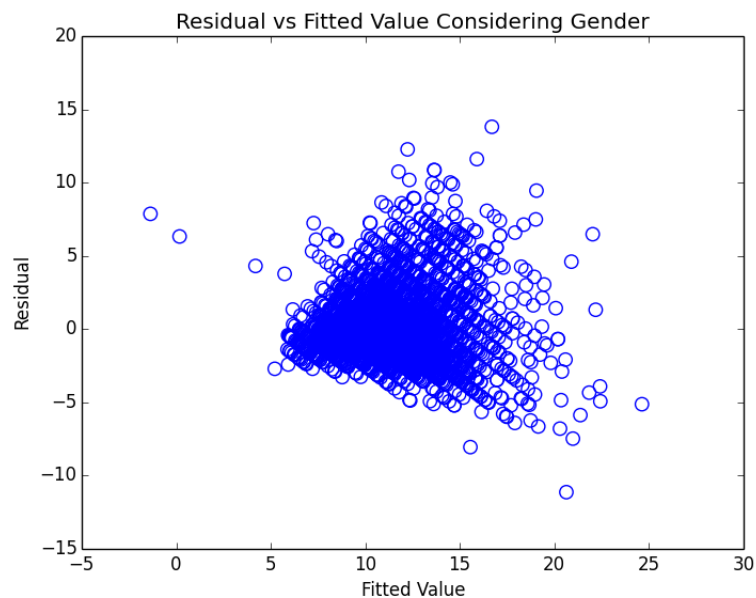
**Problem 7.11**

(a) Linear regression predicting the age from the measurements, ignoring Gender



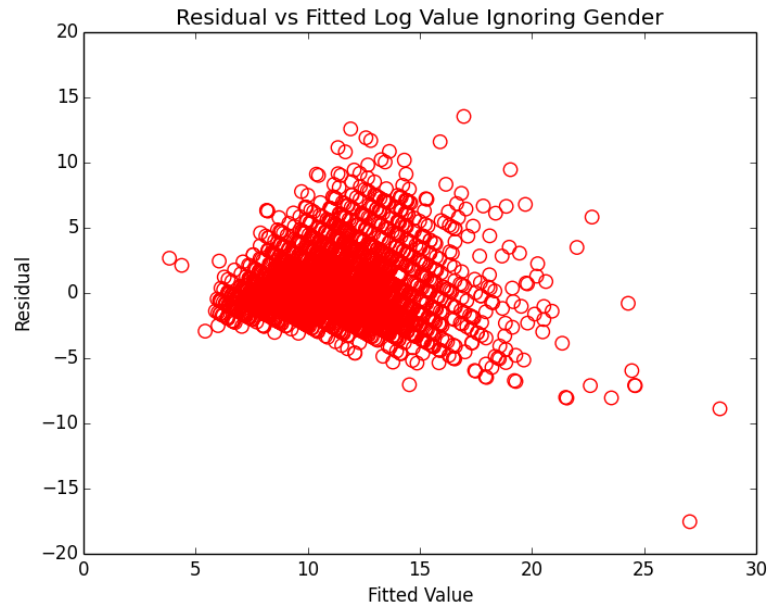
**Figure 8: Residual against Fitted Value with no Gender**

b) Linear regression predicting the age from the measurements, including gender.



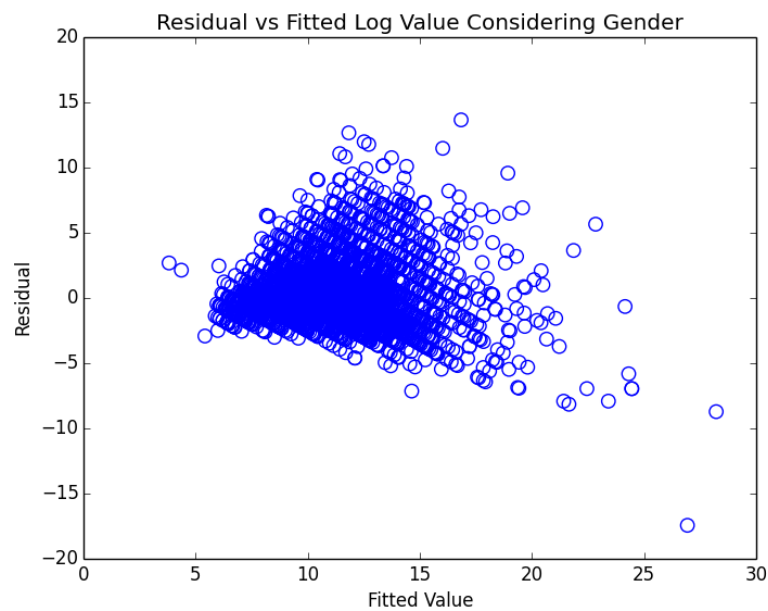
**Figure9: Residual vs Fitted Value with Gender**

c) Linear regression predicting the log of age from the measurements, ignoring gender.



**Figure 10: Log of age Residual against Fitted Value without Gender**

d) Linear regression predicting the log age from the measurements, including gender,



**Figure 11: Log of age Residual against Fitted Value with Gender**

---

e) Use your plots to explain which regression you would use to replace this procedure, and why.

### Calculating R Square:

The R square values for the above plots are as follows:

a. R square : 0. 527629939992

b. R square : 0. 527890935736

**c. R square : 0. 544422151851**

d. R square : 0. 544301293342

As the highest value of R square is for the case c, "Linear regression predicting the log age from the measurements, ignoring gender," I will choose this.

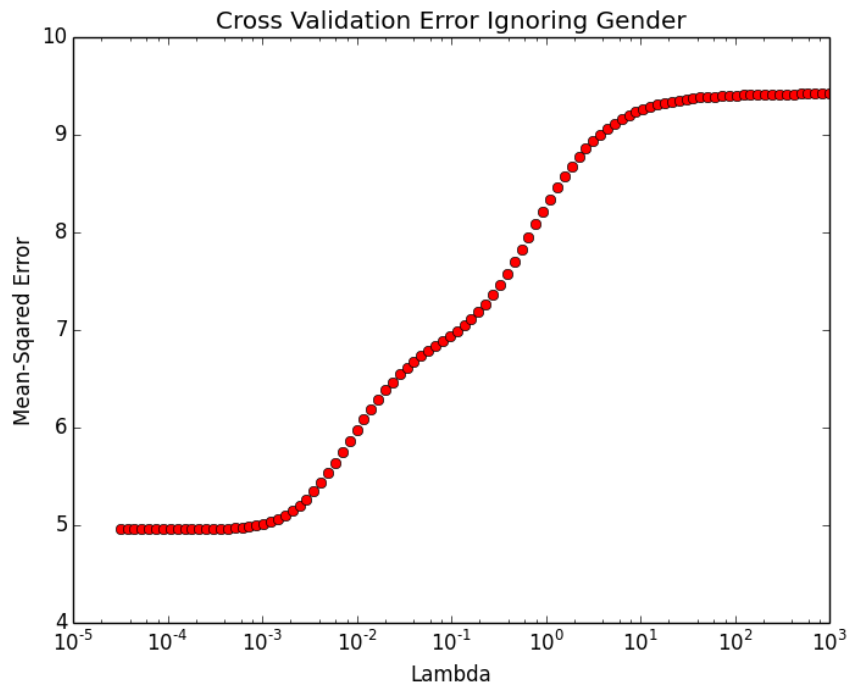
f) Can you improve these regressions by using a regularizer?

Here I used `sklearn.linear_model ElasticNet` library and `sklearn.linear_model regressionlibrary`

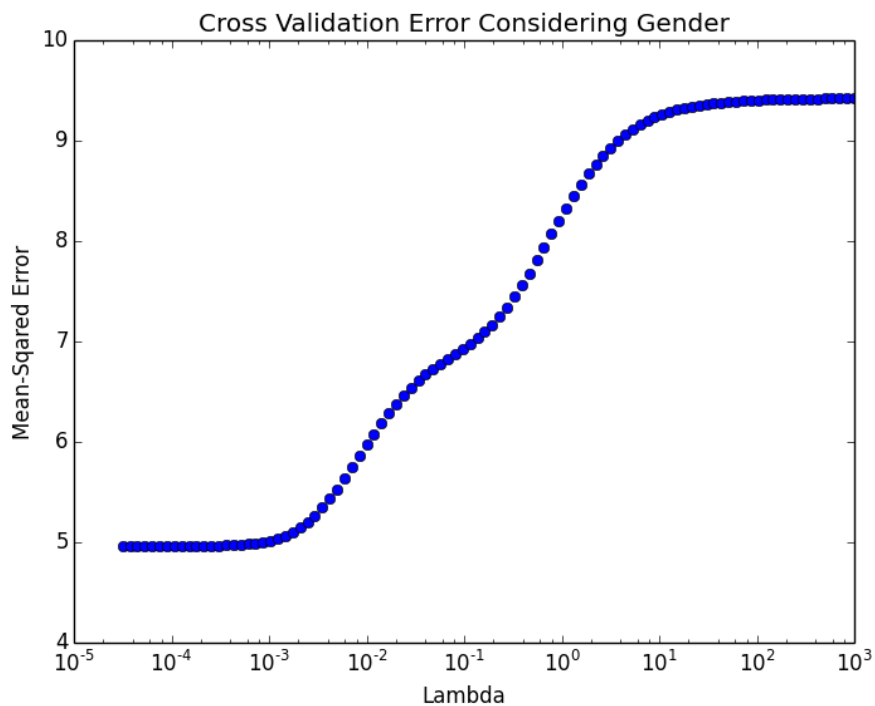
We tried to compare regular Regression vs Regularization results when  $\alpha = 0$  and following is our observation:

- Decreasing lambda value makes the Regularization result approach Regression results, but we could not get a better result. This does not necessarily mean that a better result is not possible. It can also mean that the good lambda range is too narrow that we cannot catch it.

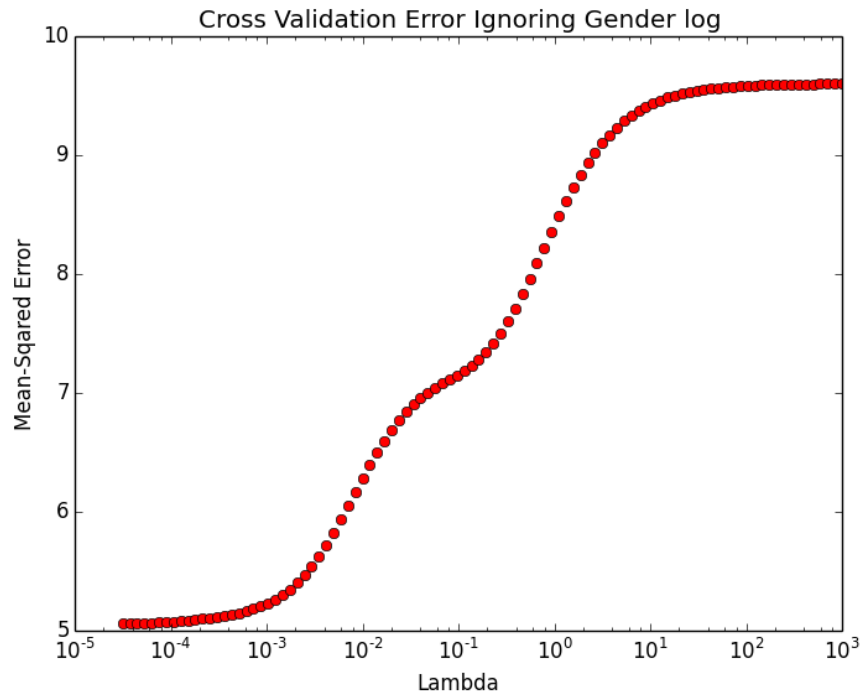




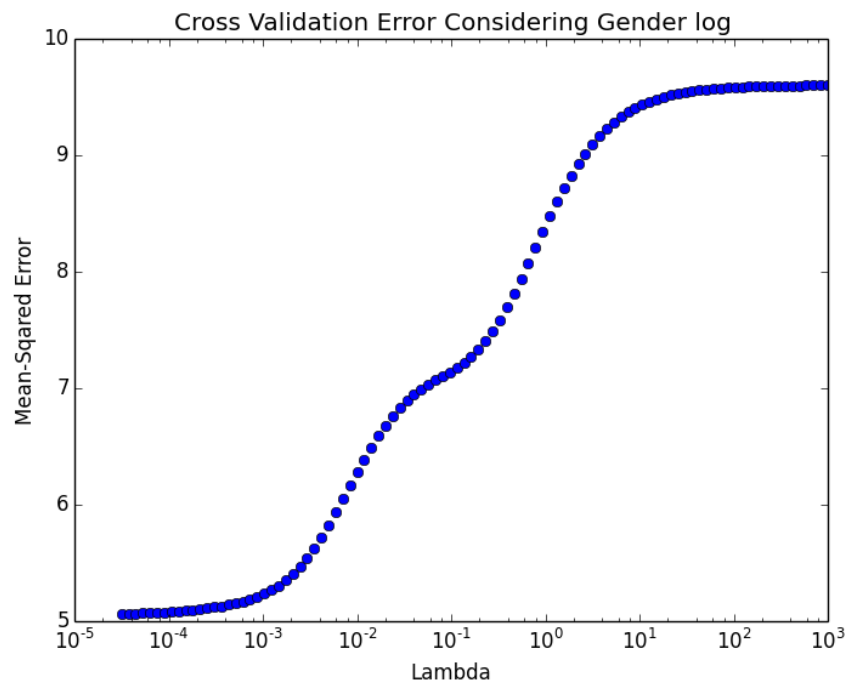
**Figure 12: Cross Validation of Regularization without Gender**



**Figure13: Cross Validation of Regularization with Gender**



**Figure 14: Cross Validation of Regularization without Gender and log of age**



**Figure 15: Cross Validation of Regularization with Gender and log of age**