# CS5691: Assignment 2

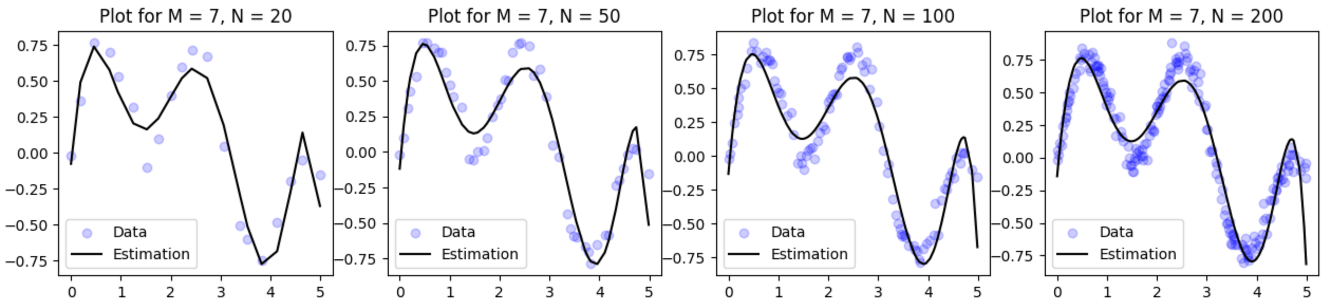
Akshat Meena (CS19B052)
Rohit Bhagat (CS19B038)

## A. Regression

1. **1D Dataset**

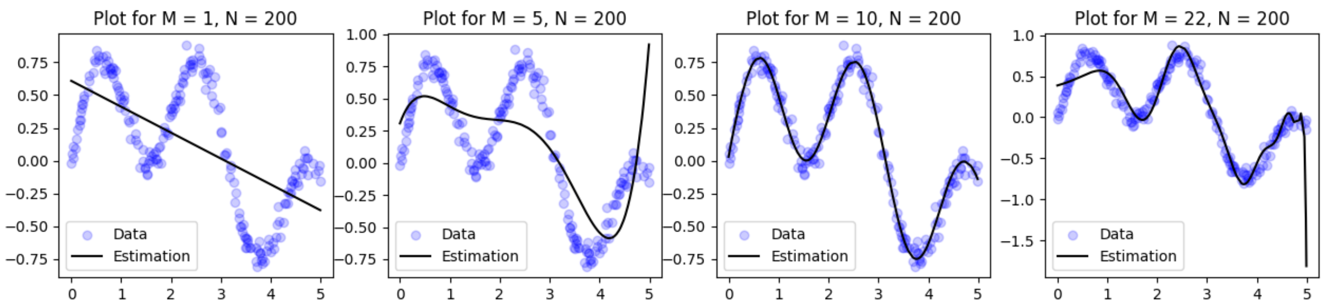
   - **Least square regression**
     We experiment with different sample size keeping the complexity constant. We plot the least square regression for N = 20, 50, 100, 200 and M = 7. We observe that for lower value of N, the curve isn't smooth and may over-fit too depending on M. As we start increasing N, the curve starts getting smoother.

Figure 1: Plots for N = 20, 50, 100, 200 and M = 7.



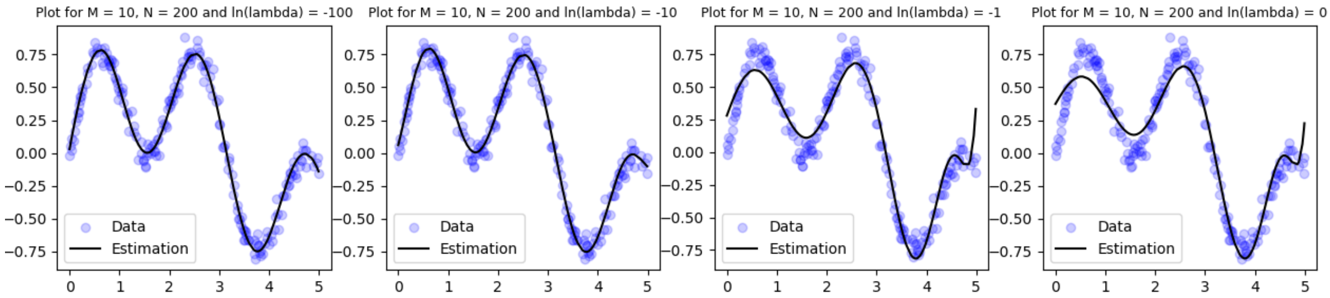

Then we experiment with different model complexity keeping the size same.We plot the least square regression for M = 1, 5, 10 ,22 and N = 1000. We observe the for low model complexity the curve is not able to fit properly but as the M increase it starts fitting the data, if we increase the model complexity more then the curve start over-fitting.

Figure 2: Plots for M = 1, 5, 10, 22 and N = 200.



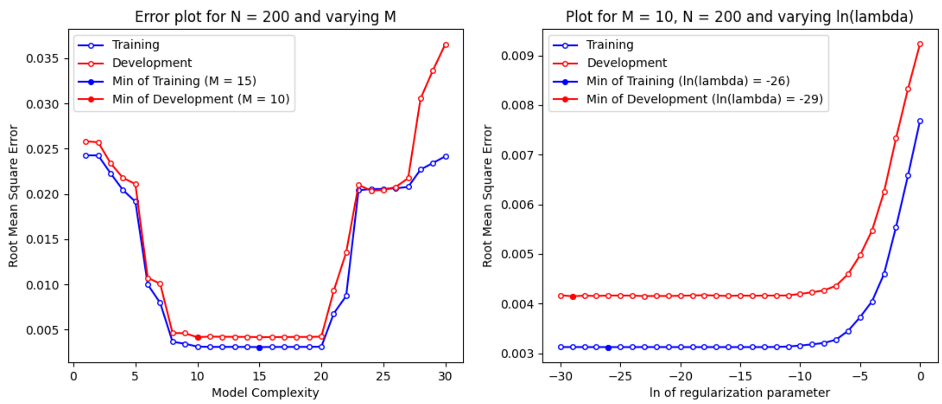

   - **Ridge regression**
     We experiment with different regularization parameter($\lambda$) keeping the M and N constant. We plot the Ridge regression for ln($\lambda$) = -100, -10, -1, 0. The regularization parameter helps dealing with over-fitting.
   - **Error plots**
     We also plot the error of our model for training and development sets vs model complexity and

Figure 3: Plots for ln($\lambda$) = -100, -10, -1, 0 and M = 10 and N = 200.




the regularization parameter. In the plot with varying M we see that initially the error decreases but later due to over-fitting it starts increasing. Similarly in the plot with varying regularization parameter however the plot shifts from over-fit to under-fit.

Figure 4: Error plots

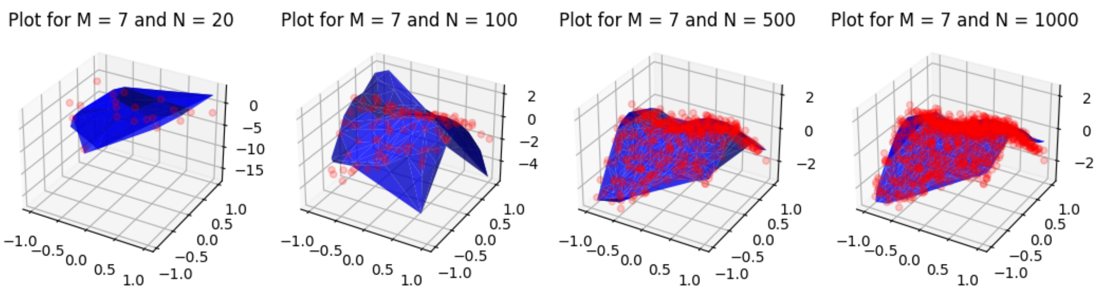



We can see that we can get best trained model for Model complexity(M) = 10 and regularization parameter($\lambda$) = $e^{-29}$

## 2. 2D Dataset

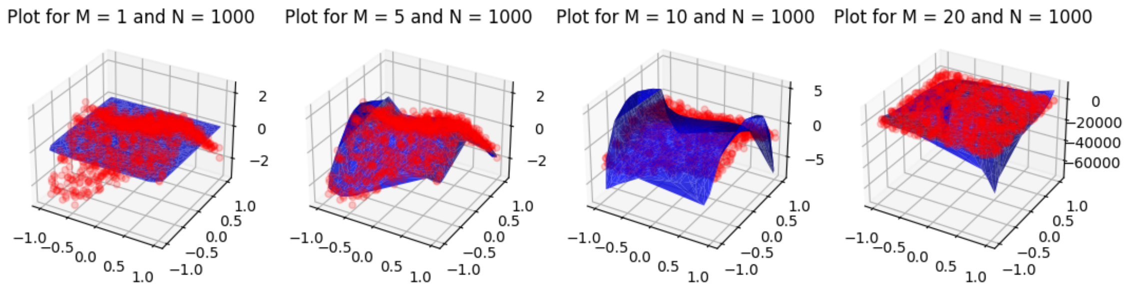
- **Least square regression**
  We experiment with different sample size keeping the complexity constant. We plot the least square regression for N = 20, 100, 500, 1000 and M = 7. We observe that for lower value of N, the curve isn't smooth and may over-fit too depending on M. As we start increasing N, the curve starts getting smoother.

Figure 5: Plots for N = 20, 100, 500, 1000 and M = 7.




Then we experiment with different model complexity keeping the size same.We plot the least square regression for M = 1, 5, 10 ,20 and N = 1000. We observe the for low model complexity the curve is not able to fit properly but as the M increase it starts fitting the data, if we increase the model

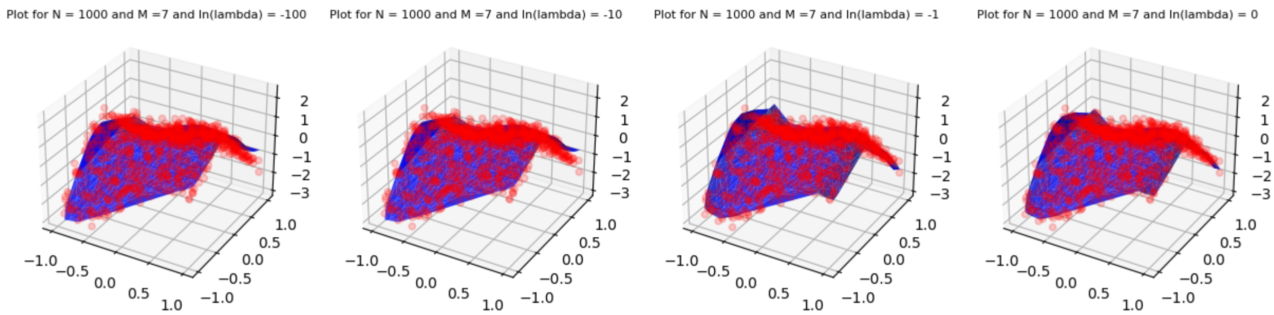
Figure 6: Plots for M = 1, 5, 10, 20 and N = 200.




complexity more then the curve start over-fitting.

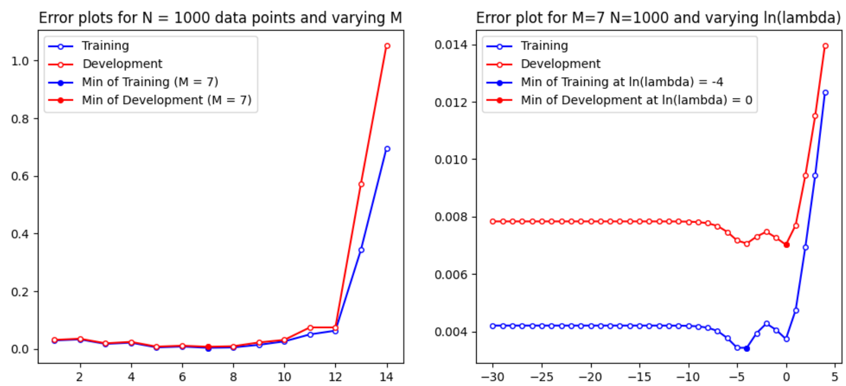
- **Ridge regression**
  We experiment with different regularization parameter($\lambda$) keeping the M and N constant. We plot the Ridge regression for ln($\lambda$) = -100, -10, -1, 0. The regularization parameter helps dealing with over-fitting.

Figure 7: Plots for ln($\lambda$) = -100, -10, -1, 0 and M = 7 and N = 1000.




- **Error plots**
  We also plot the error of our model for training and development sets vs model complexity and the regularization parameter. In the plot with varying M we see that initially the error decreases but later due to over-fitting it starts increasing. Similarly in the plot with varying regularization parameter however the plot shifts from over-fit to under-fit.

Figure 8: Error plots




We can see that we can get best trained model for Model complexity(M) = 7 and regularization parameter($\lambda$) = $e^0$