

School of Mathematics and Statistics
MAST90083: Computational Statistics and Data Science

Assignment 1

Due date: No later than 11:59pm on Monday 5th September 2022

Weight: 15%

Question 1: Linear Regression

This question relates to the methods used to resolve the issues present in linear regression by doing variable selection so that predictors that fail to significantly explain the response can be dropped. However you will find that ridge regression although penalizes the coefficients, still fails to do variable selection. Lasso on other hand resolves this issue by only shrinking the insignificant coefficients towards zero. This question makes use of the Hitters dataset.

1. Load the Hitters dataset. Remove all those rows from Hitters dataset that have entry NA in the "salary" column
2. For a design matrix construction, use function "model.matrix" to read all variables in Hitters dataset excluding the salary and store them in variable \mathbf{x} . Also, read the salary variable and store it in variable \mathbf{y} . Generate a sequence of 100 values of λ between 10^{10} and 10^{-2} and call the function "glmnet" from glmnet library. You can generate the sequence as $10\Lambda seq(10, -2, length = 100)$, where Λ is a "raised to" sign. For glmnet, set $\alpha = 0$, and estimate ridge coefficients for 100 λ values. Then, observe the set of coefficients for two extreme values of λ i.e. 10^{10} and also for 10^{-2} . For which value of λ among these two, the coefficient values are more close to zero?
3. Now, draw a plot of l_2 -norm of coefficient values (excluding the intercept's coefficient value) against the logarithm of the λ values. Can you say from this plot that you cannot really decide the optimal λ value between 10^{10} and 10^{-2} , better is to use the mean square error (MSE) plot against the λ values? Explain how can you say that?
4. The glmnet library already has a function "cv.glmnet" that performs ten fold cross validation (CV). You are going to use this function to select an optimal λ . Now, first you need to set the seed equal to 10 for random number generator. Then randomly pick 131 samples from \mathbf{x} for all variables and also the corresponding samples from \mathbf{y} to construct a training dataset. The rest of the samples can be saved for testing dataset. Using this training dataset, plot the cross validation results, and find the best λ (the one that results in smallest CV error) value and its corresponding test MSE value (MSE value obtained using testing dataset and best λ), you may want to use "predict" function here. Now refit the ridge regression model on the full data set using the λ chosen by CV. Examine the coefficients are they all present, similar to the linear regression case?

5. This time we set $\alpha = 1$ (Lasso case) and again plot the cross validation results, and find the best λ value (using training set) and its corresponding MSE value (using testing set). Now predict the coefficients again using the best λ that we just selected. Were all coefficients selected again? Well most of them are zero, are they not?

Question 2: Model Selection

In this question we consider the analysis of three model selection criteria for selecting the order p of the following model

$$y_t = \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} + \eta_t \quad t = p+1, \dots, n \quad y_t \in R$$

where η_t are independent identically distributed (i.i.d.) from $N(0, \sigma^2)$. The criteria we consider are

$$IC_1 = \log(\hat{\sigma}_p^2) + \frac{2(p+1)}{T}$$

$$IC_2 = \log(\hat{\sigma}_p^2) + \frac{T+p}{T-p-2}$$

$$IC_3 = \log(\hat{\sigma}_p^2) + \frac{p \log(T)}{T}$$

where $\hat{\sigma}_p^2 = \frac{\text{RSS}_p}{T} = \frac{\|\mathbf{y} - \hat{\mathbf{y}}\|^2}{T}$.

1. In the IC 's given above, T represents the number of effective samples. In the case of the model of order p above what is T ?
2. Find the least square estimator of $\boldsymbol{\phi} = (\phi_1, \dots, \phi_p)^\top$
3. Provide the expression of $\hat{\sigma}_p^2$
4. Generate two sets of 100 samples using the models

$$M1 : \quad y_t = 0.434y_{t-1} + 0.217y_{t-2} + 0.145y_{t-3} + 0.108y_{t-4} + 0.087y_{t-5} + \eta_t \quad \eta_t \sim N(0, 1)$$

$$M2 : \quad y_t = 0.682y_{t-1} + 0.346y_{t-2} + \eta_t \quad \eta_t \sim N(0, 1)$$

5. Using these two sets, compute the values of IC_1 , IC_2 and IC_3 for $p = 1, \dots, 10$ for models M_1 and M_2 . For each model provide a figure illustrating the variations of IC_1 , IC_2 and IC_3 (plot the three criteria in a single figure for each model).
6. Using model M_1 generate 1000 sets (vectors) of size 100 and provide a table of counts of the selected model by IC_1 , IC_2 and IC_3
7. Using model M_1 generate 1000 sets of size 15 and provide a table of counts of the selected model by IC_1 , IC_2 and IC_3

8. Repeat questions 6 and 7 using model M_2 .
9. What do you observe from these tables?
10. Derive expressions for the probabilities of overfitting for the model selection criteria IC_1 , IC_2 and IC_3 . For the derivation you will assume the true model to be p_0 and consider overfitting by L extra parameters.
11. Provide tables of the calculated probabilities for M_1 in the cases $n = 25$ and $n = 100$ with $L = 1, \dots, 8$.
12. What are the important remarks that can be made from these probability tables?
13. The tables obtained from question 11 provide overfitting information as a function of the sample size. We are now interested in the case of large sample size or when $n \rightarrow \infty$ (p_0 & L fixed). Derive the expressions of the probabilities of overfitting in this case.
14. What is the important observation that you can make?

Grading:

- Total: 15 points
- Question 1: 5 points
- Question 2: 10 points

The assignment is to be submitted via LMS