

ECE 625
Instructor: Di Niu
Assignment 1

Due date: see the course website

- You must use either Word or Latex to write up your assignment. Hand written assignments are not accepted.
- Include all necessary R outputs in your answers.
- In addition, email me and the marking TA all your R code in one zip file named ECE625_Assign1_FirstName_LastName.zip. The subject of the email should be “ECE 625 Assignment 1 R code.”
- In the zip file, you need to have an individual file named Assign1_Q#.R for each question that needs R code, e.g., Assign1_Q9.R.

You may lose marks if you do not follow the instructions above or the requested format.

Q1.

We now revisit the bias-variance decomposition.

- (a) Provide a sketch of typical (squared) bias, variance, training error, test error, and Bayes (or irreducible) error curves, on a single plot, as we go from less flexible statistical learning methods towards more flexible approaches. The x -axis should represent the amount of flexibility in the method, and the y -axis should represent the values for each curve. There should be five curves. Make sure to label each one.
- (b) Explain why each of the five curves has the shape displayed in part (a).

Q2.

What are the advantages and disadvantages of a very flexible (versus a less flexible) approach for regression or classification? Under what circumstances might a more flexible approach be preferred to a less flexible approach? When might a less flexible approach be preferred?

Q3.

This exercise relates to the `College` data set, which can be found in the file `College.csv`. It contains a number of variables for 777 different universities and colleges in the US. The variables are

- `Private` : Public/private indicator
- `Apps` : Number of applications received
- `Accept` : Number of applicants accepted
- `Enroll` : Number of new students enrolled
- `Top10perc` : New students from top 10 % of high school class
- `Top25perc` : New students from top 25 % of high school class
- `F.Undergrad` : Number of full-time undergraduates
- `P.Undergrad` : Number of part-time undergraduates
- `Outstate` : Out-of-state tuition
- `Room.Board` : Room and board costs
- `Books` : Estimated book costs
- `Personal` : Estimated personal spending
- `PhD` : Percent of faculty with Ph.D.'s
- `Terminal` : Percent of faculty with terminal degree
- `S.F.Ratio` : Student/faculty ratio
- `perc.alumni` : Percent of alumni who donate
- `Expend` : Instructional expenditure per student
- `Grad.Rate` : Graduation rate

Before reading the data into `R`, it can be viewed in Excel or a text editor.

- (a) Use the `read.csv()` function to read the data into `R`. Call the loaded data `college`. Make sure that you have the directory set to the correct location for the data.
- (b) Look at the data using the `fix()` function. You should notice that the first column is just the name of each university. We don't really want `R` to treat this as data. However, it may be handy to have these names for later. Try the following commands:

```
> rownames(college)=college[,1]  
> fix(college)
```

You should see that there is now a `row.names` column with the name of each university recorded. This means that R has given each row a name corresponding to the appropriate university. R will not try to perform calculations on the row names. However, we still need to eliminate the first column in the data where the names are stored. Try

```
> college=college[,-1]  
> fix(college)
```

Now you should see that the first data column is `Private`. Note that another column labeled `row.names` now appears before the `Private` column. However, this is not a data column but rather the name that R is giving to each row.

- (c) i. Use the `summary()` function to produce a numerical summary of the variables in the data set.
- ii. Use the `pairs()` function to produce a scatterplot matrix of the first ten columns or variables of the data. Recall that you can reference the first ten columns of a matrix `A` using `A[,1:10]`.
- iii. Use the `plot()` function to produce side-by-side boxplots of `Outstate` versus `Private`.
- iv. Create a new qualitative variable, called `Elite`, by *binning* the `Top10perc` variable. We are going to divide universities into two groups based on whether or not the proportion of students coming from the top 10% of their high school classes exceeds 50%.

```
> Elite=rep("No",nrow(college))
> Elite[college$Top10perc >50]="Yes"
> Elite=as.factor(Elite)
> college=data.frame(college,Elite)
```

Use the `summary()` function to see how many elite universities there are. Now use the `plot()` function to produce side-by-side boxplots of `Outstate` versus `Elite`.

- v. Use the `hist()` function to produce some histograms with differing numbers of bins for a few of the quantitative variables. You may find the command `par(mfrow=c(2,2))` useful: it will divide the print window into four regions so that four plots can be made simultaneously. Modifying the arguments to this function will divide the screen in other ways.
- vi. Continue exploring the data, and provide a brief summary of what you discover.

Q4.

Suppose we have a data set with five predictors, $X_1 = \text{GPA}$, $X_2 = \text{IQ}$, $X_3 = \text{Gender}$ (1 for Female and 0 for Male), $X_4 = \text{Interaction between GPA and IQ}$, and $X_5 = \text{Interaction between GPA and Gender}$. The response is starting salary after graduation (in thousands of dollars). Suppose we use least squares to fit the model, and get $\hat{\beta}_0 = 50$, $\hat{\beta}_1 = 20$, $\hat{\beta}_2 = 0.07$, $\hat{\beta}_3 = 35$, $\hat{\beta}_4 = 0.01$, $\hat{\beta}_5 = -10$.

- (a) Which answer is correct, and why?
- For a fixed value of IQ and GPA, males earn more on average than females.

- ii. For a fixed value of IQ and GPA, females earn more on average than males.
 - iii. For a fixed value of IQ and GPA, males earn more on average than females provided that the GPA is high enough.
 - iv. For a fixed value of IQ and GPA, females earn more on average than males provided that the GPA is high enough.
- (b) Predict the salary of a female with IQ of 110 and a GPA of 4.0.
- (c) True or false: Since the coefficient for the GPA/IQ interaction term is very small, there is very little evidence of an interaction effect. Justify your answer.

Q5.

This question involves the use of simple linear regression on the `Auto` data set.

- (a) Use the `lm()` function to perform a simple linear regression with `mpg` as the response and `horsepower` as the predictor. Use the `summary()` function to print the results. Comment on the output. For example:
 - i. Is there a relationship between the predictor and the response?
 - ii. How strong is the relationship between the predictor and the response?
 - iii. Is the relationship between the predictor and the response positive or negative?
 - iv. What is the predicted `mpg` associated with a `horsepower` of 98? What are the associated 95 % confidence and prediction intervals?
- (b) Plot the response and the predictor. Use the `abline()` function to display the least squares regression line.
- (c) Use the `plot()` function to produce diagnostic plots of the least squares regression fit. Comment on any problems you see with the fit.

Q6.

This question should be answered using the `Carseats` data set.

- (a) Fit a multiple regression model to predict `Sales` using `Price`, `Urban`, and `US`.

- (b) Provide an interpretation of each coefficient in the model. Be careful—some of the variables in the model are qualitative!
- (c) Write out the model in equation form, being careful to handle the qualitative variables properly.
- (d) For which of the predictors can you reject the null hypothesis $H_0 : \beta_j = 0$?
- (e) On the basis of your response to the previous question, fit a smaller model that only uses the predictors for which there is evidence of association with the outcome.
- (f) How well do the models in (a) and (e) fit the data?
- (g) Using the model from (e), obtain 95 % confidence intervals for the coefficient(s).
- (h) Is there evidence of outliers or high leverage observations in the model from (e)?

Q7.

It is well-known that ridge regression tends to give similar coefficient values to correlated variables, whereas the lasso may give quite different coefficient values to correlated variables. We will now explore this property in a very simple setting.

Suppose that $n = 2$, $p = 2$, $x_{11} = x_{12}$, $x_{21} = x_{22}$. Furthermore, suppose that $y_1 + y_2 = 0$ and $x_{11} + x_{21} = 0$ and $x_{12} + x_{22} = 0$, so that the estimate for the intercept in a least squares, ridge regression, or lasso model is zero: $\hat{\beta}_0 = 0$.

- (a) Write out the ridge regression optimization problem in this setting.
- (b) Argue that in this setting, the ridge coefficient estimates satisfy $\hat{\beta}_1 = \hat{\beta}_2$.
- (c) Write out the lasso optimization problem in this setting.
- (d) Argue that in this setting, the lasso coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$ are not unique—in other words, there are many possible solutions to the optimization problem in (c). Describe these solutions.

Q8.

In this exercise, we will generate simulated data, and will then use this data to perform best subset selection.

- (a) Use the `rnorm()` function to generate a predictor X of length $n = 100$, as well as a noise vector ϵ of length $n = 100$.
- (b) Generate a response vector Y of length $n = 100$ according to the model

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 X^3 + \epsilon,$$

where $\beta_0, \beta_1, \beta_2$, and β_3 are constants of your choice.

- (c) Use the `regsubsets()` function to perform best subset selection in order to choose the best model containing the predictors X, X^2, \dots, X^{10} . What is the best model obtained according to C_p , BIC, and adjusted R^2 ? Show some plots to provide evidence for your answer, and report the coefficients of the best model obtained. Note you will need to use the `data.frame()` function to create a single data set containing both X and Y .
- (d) Repeat (c), using forward stepwise selection and also using backwards stepwise selection. How does your answer compare to the results in (c)?
- (e) Now fit a lasso model to the simulated data, again using X, X^2, \dots, X^{10} as predictors. Use cross-validation to select the optimal value of λ . Create plots of the cross-validation error as a function of λ . Report the resulting coefficient estimates, and discuss the results obtained.
- (f) Now generate a response vector Y according to the model

$$Y = \beta_0 + \beta_7 X^7 + \epsilon,$$

and perform best subset selection and the lasso. Discuss the results obtained.

Q9.

In this exercise, we will predict the number of applications received using the other variables in the `College` data set.

- (a) Split the data set into a training set and a test set.

- (b) Fit a linear model using least squares on the training set, and report the test error obtained.
- (c) Fit a ridge regression model on the training set, with λ chosen by cross-validation. Report the test error obtained.
- (d) Fit a lasso model on the training set, with λ chosen by cross-validation. Report the test error obtained, along with the number of non-zero coefficient estimates.
- (e) Comment on the results obtained. How accurately can we predict the number of college applications received? Is there much difference among the test errors resulting from these three approaches?

Q10.

Suppose we collect data for a group of students in a statistics class with variables X_1 = hours studied, X_2 = undergrad GPA, and Y = receive an A. We fit a logistic regression and produce estimated coefficient, $\hat{\beta}_0 = -6, \hat{\beta}_1 = 0.05, \hat{\beta}_2 = 1$.

- (a) Estimate the probability that a student who studies for 40 h and has an undergrad GPA of 3.5 gets an A in the class.
- (b) How many hours would the student in part (a) need to study to have a 50 % chance of getting an A in the class?