

ISLR | Chapter 6 Exercises

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Conceptual

1

- **A.** For a model with k predictors, Best Subset Selection will always have the best *training* RSS. The reason for this is, given a fixed k , there are $\binom{p}{k}$ possible models, and Best Subset Selection considers all of those $\binom{p}{k}$ possibilities.

In Forward Stepwise Selection, of the total $\binom{p}{k}$ possible models, only the models that contain the $(k - 1)$ model produced by Forward Stepwise Selection will be considered for the “best” k -variable model.

In Backward Stepwise Selection, of the total $\binom{p}{k}$ possible models, the predictors in the “best” k -variable model *must* be a subset of the model with $(k + 1)$ predictors.

In short, Best Subset Selection will have the best (lowest) *training* RSS for a model with k predictors because it considers **all** the possible $\binom{p}{k}$ models, whereas Forward and Backward Stepwise Selection only consider a **subset** of all the possible $\binom{p}{k}$ models.

- **B.** There is no definitive answer for which subset selection method will have the lowest *testing* RSS (overfitting). If there is a large number of predictors, Best Subset Selection has the possibility of finding a model that has a low training RSS but a high testing RSS. Cross validation could be used to estimate the testing error of three models (one for Best Subset Selection, one for Forward Stepwise Selection and one for Backward Stepwise Selection) and a decision on which model has the lowest testing RSS could be made in consideration of the CV results.
- **C.**
 - i.* True.
 - ii.* True.
 - iii.* False, the predictors in the k -variable model identified by Backward Subset Selection are **not** a subset of the predictors in the $(k + 1)$ -variable model identified by Forward Subset Selection.
 - iv.* False, the predictors in the k -variable model identified by Forward Stepwise Selection are **not** a subset of the predictors in the $(k + 1)$ -variable model identified by Backward Stepwise Selection.
 - v.* False, the predictors in the k -variable model identified by Best Subset Selection are **not necessarily** a subset of the predictors in the $(k + 1)$ -variable model identified by Best Subset Selection.

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- **A.** The lasso, relative to least squares is, *iii*, less flexible and hence will give improved prediction accuracy when its increase in bias is less than its decrease in variance.
- **B.** Ridge Regression, relative to least squares is, *iii*, less flexible and hence will give improved prediction accuracy when its increase in bias is less than its decrease in variance.
- **C.** Non-linear methods, relative to least squares are, *ii*, more flexible and hence will give improved prediction accuracy when their increase in variance is less than their decrease in bias.

3

In the (alternate) equation for the Lasso...

$$\sum_{i=1}^n \left(y_k - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right) \text{ subject to } \sum_{j=1}^p |\beta_j| \leq s$$

As we increase s from 0...

- **A.** ...the training RSS will, *iv*, steadily decrease. As the budget (s) for the sum of the regression coefficients increases from 0, each β_j will approach the value it would reach in ordinary least squares regression (no constraint). Therefore, without a constraint, we are letting the regression coefficients “roam freely” to reach their ordinary least squares values. Using the constraint, we are “lassoing” them in (pun intended).
- **B.** ...the testing RSS will, *ii*, decrease initially, and then eventually start increasing in a U shape. When s is 0, all the regression coefficients are 0, and the “model” is simply the intercept, β_0 , the mean of the response (highly biased, very low variance). As s increases from 0, the model becomes more flexible, allowing for an increasingly better fit to the data up to a point (bottom of the U). Once this point is reached, the model becomes **overly** flexible, overfitting the training data and leading to an increase in the test error (right side of U).
- **C.** ...variance will, *iii*, steadily increase. As s increases from 0, the model becomes more and more flexible, and as we know, more flexible models have a higher variance and lower bias. The model will be more influenced by the data it is trained on.
- **D.** ...(squared) bias will, *iv*, steadily decrease. As s increases from 0, the model becomes more and more flexible, and as we know, more flexible models have a higher variance and lower bias. The model will have a better chance of representing the *true* relationship between the predictors and the response.
- **E.** ...the irreducible error will, *v*, remain constant. The irreducible error is just that, **irreducible**.

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In the equation for Ridge Regression...

$$\sum_{i=1}^n \left(y_k - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p \beta_j^2$$

...as we increase λ from 0...

- **A.** ...the training RSS will, *iii*, steadily increase. As λ increases from 0, more “weight” is given to the second term in the cost function, thus penalizing large regression coefficients more and more. Increasing λ from 0 restricts the regression coefficients more and more.
- **B.** ...the testing RSS will, *ii*, decrease initially, and then eventually start increasing in a U shape. As λ increases from 0, increasingly strict restrictions are put on the magnitude that the regression coefficients can grow too. This has the affect of making the model less flexible and more generalizable, **up to a point**. The left side of the U represents the model’s increase in bias being less than it’s decrease in variance, and the right side of the U represents the decrease in variance no longer being worth the increase in bias.
- **C.** ...the variance will, *iv*, steadily decrease. As λ increases from 0, increasingly strict limits are placed on the regression coefficients, making it less flexible.

- **D.** ...the (squared) bias will, *iii*, steadily increase. As λ increases from 0, increasingly strict limits are placed on the regression coefficients, making it less flexible. This will make it increasingly harder for the model to estimate the true relationship between the response and the predictors.
- **E.** ...the irreducible error will, *v*, remain constant. The irreducible error is just that, **irreducible**.