Statistics 452: Statistical Learning and Prediction

Chapter 6, Part 1: Linear Model Selection

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Introduction

Alternatives to Least Squares

- We have used least squares to fit the linear model

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_p X_p + \epsilon. \tag{1}$$

- In this chapter we consider alternative methods of fitting the model, with the goal of better prediction accuracy and model interpretability when p is large.
  - Prediction accuracy: Unless n is much larger than p there is a tendancy to overfit, leading to poor predictions on the test set. In case $p > n$ there is no unique least squares solution.
  - Model interpretability: It is often the case that only a small subset of the predictors is truly associated with the response. The model is more interpretable without irrelevant variables.

Approaches in this Chapter

- Each of the following can be thought of as a strategy to reduce variance, with (hopefully) minimal increase in bias.
- Subset selection: Forward, backward, stepwise and all subsets selection to identify truly associated model terms.
- Shrinkage (regularization): Shink estimated coefficients toward zero.
- Dimension reduction: Find a low-dimension representation of the predictors, and use these as predictors.

Subset Selection

Best (All) Subset Selection

- Straightforward idea: Consider all 2^p possible models (p of with one predictor, $\binom{p}{2} = p(p-1)/2$ with two predictors, etc.) and choose the one with the best estimated test set error.
  - Can use cross validation to estimate test set error, or computationally cheaper alternatives (C_p, BIC – to be discussed).
- Break the exhaustive search for the best of all models into two steps:
  1. Fit all $\binom{p}{k}$ models with k predictors and select the one, call it $\mathcal{M}_k$, with the smallest RSS.
  2. Select the best model from $\mathcal{M}_0, \ldots, \mathcal{M}_p$ based on estimated test set error.
- See Algorithm 6.1 in test for a complete algorithm.

Drawback of All Subsets

- Computational: 2^p becomes very large as p increases.

```
p<-10; 2^p
```

```
## [1] 1024
```

```
p<-20; 2^p
```

```
## [1] 1048576
```

Example of All Subsets

```r
uu <- url("http://www-bcf.usc.edu/~gareth/ISL/Credit.csv")
Credit <- read.csv(uu,row.names=1)
head(Credit,n=3)
```

```
##    Income Limit Rating Cards Age Education Gender Student Married
## 1  14.891  3606    283     2  34        11   Male      No     Yes
## 2 106.025  6645    483     3  82        15 Female     Yes     Yes
## 3 104.593  7075    514     4  71        11   Male      No      No
##   Ethnicity Balance
## 1 Caucasian     333
## 2     Asian     903
## 3     Asian     580
```

```r
library(leaps) # contains regsubsets()
cfits <- regsubsets(Balance ~ ., data=Credit,nvmax=11)
cfits.sum <- summary(cfits)
```

```
cfits.sum$which
```

```
##    (Intercept) Income Limit Rating Cards   Age Education GenderFemale
## 1         TRUE  FALSE FALSE   TRUE FALSE FALSE     FALSE        FALSE
## 2         TRUE   TRUE FALSE   TRUE FALSE FALSE     FALSE        FALSE
## 3         TRUE   TRUE FALSE   TRUE FALSE FALSE     FALSE        FALSE
## 4         TRUE   TRUE  TRUE  FALSE  TRUE FALSE     FALSE        FALSE
## 5         TRUE   TRUE  TRUE   TRUE  TRUE FALSE     FALSE        FALSE
## 6         TRUE   TRUE  TRUE   TRUE  TRUE  TRUE     FALSE        FALSE
## 7         TRUE   TRUE  TRUE   TRUE  TRUE  TRUE     FALSE         TRUE
## 8         TRUE   TRUE  TRUE   TRUE  TRUE  TRUE     FALSE         TRUE
## 9         TRUE   TRUE  TRUE   TRUE  TRUE  TRUE     FALSE         TRUE
## 10        TRUE   TRUE  TRUE   TRUE  TRUE  TRUE     FALSE         TRUE
## 11        TRUE   TRUE  TRUE   TRUE  TRUE  TRUE      TRUE         TRUE
##    StudentYes MarriedYes EthnicityAsian EthnicityCaucasian
## 1       FALSE      FALSE          FALSE              FALSE
## 2       FALSE      FALSE          FALSE              FALSE
## 3        TRUE      FALSE          FALSE              FALSE
## 4        TRUE      FALSE          FALSE              FALSE
## 5        TRUE      FALSE          FALSE              FALSE
## 6        TRUE      FALSE          FALSE              FALSE
## 7        TRUE      FALSE          FALSE              FALSE
## 8        TRUE      FALSE           TRUE              FALSE
## 9        TRUE       TRUE           TRUE              FALSE
## 10       TRUE       TRUE           TRUE               TRUE
## 11       TRUE       TRUE           TRUE               TRUE
```

```r
cfits.sum$rss
```

```
##  [1] 21435122 10532541  4227219  3915058  3866091  3821620  3810759
##  [8]  3804746  3798367  3791345  3786730
```

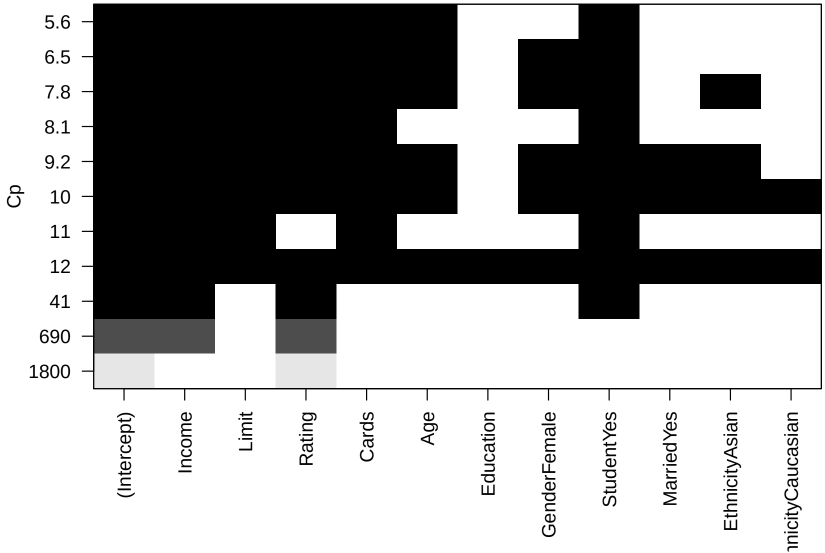
```r
cfits.sum$rsq
```

```
##  [1] 0.7458484 0.8751179 0.9498788 0.9535800 0.9541606 0.9546879 0.9548167
##  [8] 0.9548880 0.9549636 0.9550468 0.9551016
```

```r
cfits.sum$cp
```

```
##  [1] 1800.308406  685.196514   41.133867   11.148910    8.131573
##  [6]    5.574883    6.462042    7.845931    9.192355   10.472883
## [11]   12.000000
```

```r
plot(cfits,scale="Cp")
```



RSS and R^2 for Model Selection

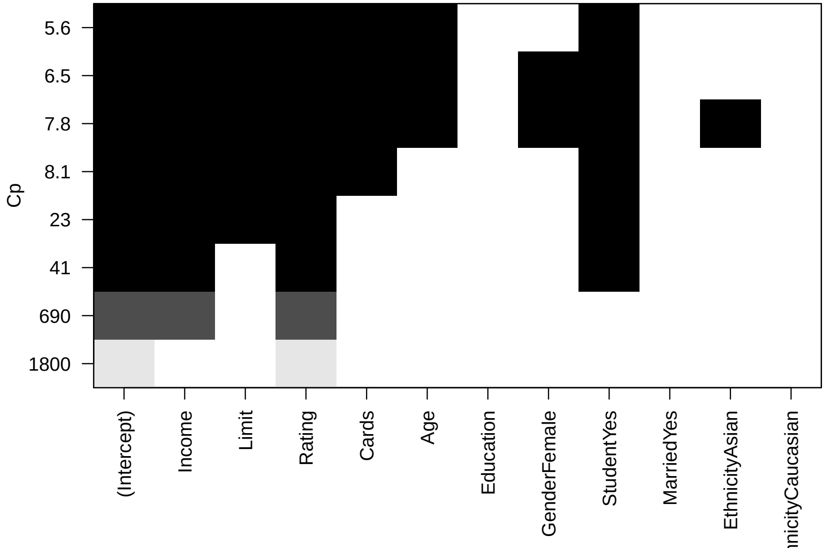
- RSS always decreases when we add predictors, even if the added predictors are, in fact, unrelated to the response.
  - k predictors: Least squares finds the coefficients $\hat{\beta}_0, \ldots, \hat{\beta}_k$ that minimize RSS.
  - $k + 1$ predictors: Least squares can reduce RSS compared to coefficients $\hat{\beta}_0, \ldots, \hat{\beta}_k, 0$.
- Similarly, $R^2 = 1 - RSS/TSS$ always increases.
- Neither is useful for comparing models of different size.
  - Will define C_p and other measures soon.

Forward Selection

- Select the best model of each size through the following restricted search:
  - Start with the null model, $\mathcal{M}_0$, that contains no predictors.
  - Consider the best model, $\mathcal{M}_1$ with 1 predictor.
  - Consider the best model, $\mathcal{M}_2$ obtained by adding one of the $p-1$ terms **not** in $\mathcal{M}_1$.
  - Consider the best model, $\mathcal{M}_3$ obtained by adding one of the $p-2$ terms **not** in $\mathcal{M}_2$.
  - And so on.
- Then use the estimated test set error to select the best from $\mathcal{M}_0, \ldots, \mathcal{M}_p$.
- See Algorithm 6.2.

Example Forward Selection

```
cfits.fwd <- regsubsets(Balance ~ .,data=Credit,
                        method="forward")
plot(cfits.fwd,scale="Cp")
```



Advantages and Disadvantages of Forward Selection

- Advantages:
  - Far less computation. Can show forward selection only fits $1 = p(p+1)/2$ models. With $p = 20$, $2^p = 1048686$ while \$1+p(p+1)/2 = 211.
  - Can be applied even when $p > n$.
- Disadvantage:
  - Not guaranteed to find the best model.

Backward Selection

- Reverse of forward selection: Start with the largest model and remove the least predictive predictor one at a time.
  - Start with the full model $\mathcal{M}_p$.
  - Consider the best model, $\mathcal{M}_{p-1}$, obtained by removing one of the p terms in $\mathcal{M}_p$.
  - Consider the best model, $\mathcal{M}_{p-2}$ obtained by removing one of the $p-1$ terms in $\mathcal{M}_{p-1}$.
  - And so on.
- Then use the estimated test set error to select the best from $\mathcal{M}_0, \ldots, \mathcal{M}_p$.
- See Algorithm 6.3.

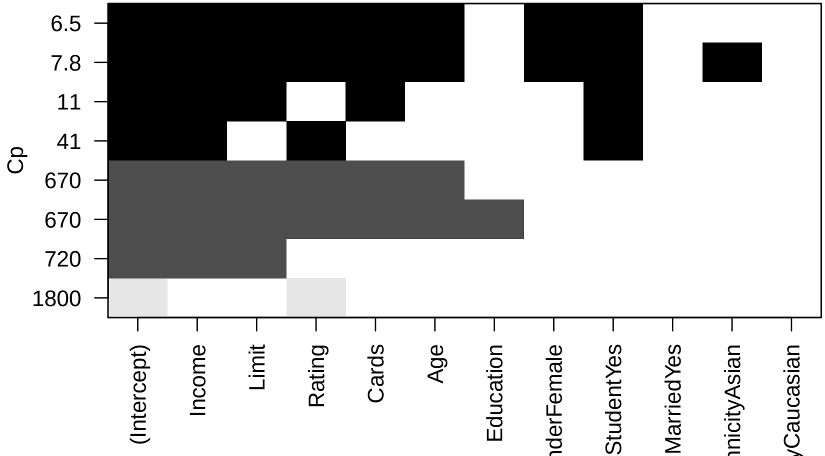
Advantages and Disadvantages of Backward Selection

- Advantage:
  - Same computation as forward selection. Only fits $1 + p(p+1)/2$ models.
- Disadvantage:
  - Not guaranteed to find the best model.

Hybrid Stepwise Selection

- Iterate between adding and deleting model terms in the search for a best model.

```
cfit.hybrid <- regsubsets(Balance ~ ., data=Credit,
                          method="seqrep")
plot(cfit.hybrid,scale="Cp")
```



Model Comparisons and Estimated Test Error

- Estimated test error is a basis for model comparison.
- Methods for estimating test error are classified as indirect or direct.
- Indirect methods estimate the "optimism", which is roughly the difference between the test and training errors.
  - That is, test error = training error + optimism
    and estimated test error = training error + estimated optimism
- Direct methods use validation or cross-validation.

Indirect methods

- C_p, AIC and BIC are in this class.
- C_p for a model with d (subset of p) predictors is defined as

$$C_p = \frac{1}{n}(\mathrm{RSS} + 2d\hat{\sigma}^2)$$

or

$$C_p' = \frac{1}{n\hat{\sigma}^2}(\mathrm{RSS} + 2d\hat{\sigma}^2)$$

where $\hat{\sigma}^2$ is an estimate of σ^2 from a low-bias model.
- The form of C_p is RSS plus penalty.

AIC

- AIC stands for Akaike Information Criterion.
- AIC can be defined for many models fit by maximum likelihood.
- For linear regression with Gaussian errors AIC is essentially C_p'.
  - A small difference is that $\hat{\sigma}^2$ in AIC is usually taken to be the estimate from the current model, rather than a fixed low-bias model.

BIC

- BIC stands for Bayesian Information Criterion and is a.k.a Schwartz's criterion.
- BIC is defined as

$$\mathrm{BIC} = \frac{1}{n\hat{\sigma}^2}(\mathrm{RSS} + \log_e(N)d\hat{\sigma}^2)$$

  where N is the sample size.

  - As with AIC $\hat{\sigma}^2$ in BIC is usually taken to be the estimate from the current model.

- Compared to AIC, BIC has a stricter penalty term because of the $\log_e(N)$ term in place of 2.
  - $\log_e(N) > 2$ for $N > 7$.

Direct Methods

- Can use validation or cross-validation to directly estimate the test error.
  - Takes a little programming – see week 6 exercises.