Variable Selection

PYJ

Variable Selection

- Core: Mean Squared Error: $\mathrm{MSE}(\hat{\beta}) = E[(\hat{\beta} \beta)^2]$
 - MSE = Variance + $(Bias)^2$
 - When we miss necessary predictors: gain a smaller variance (intuitively, deleting variables cannot increase the variance); also get a biased estimates (how large is the bias depends on what's the X_i
 - Variance-Bias Trade-off: compare the increment in $(Bias)^2$ and the reduction in variance, vice versa.
- Model Comparison Methods
 - Nested model: F test -> they follow F distribution
 - * Example:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$$

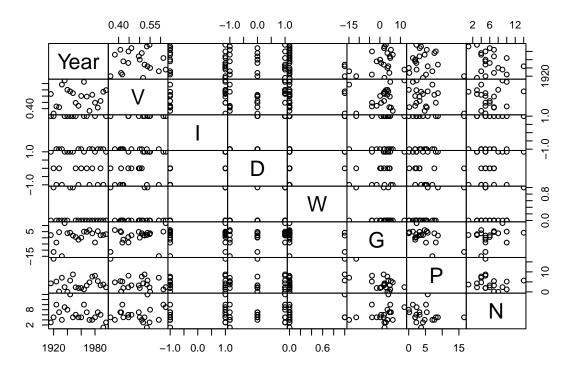
- Any two models w/ the same response
 - * Similar to nested, but not nested
 - · MSE (SSE/(n-p-1))
 - · AIC (Akaike) = $nlog_e(SSE_n/n) + 2p$
 - · BIC (Bayesian) = $n \log_e(SSE_p/n) + p \log_e(n)$
- Any two models w/ the same response but possibly differently transformed
 - * Example: $log(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$, $\sqrt{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$
- Forward Selection (FS): \$2^q\$ subsets

• Stepwise Selection (SW): each iteration choose the lowest AIC or BIC; stop when no candidate can lower the score

Coding Example

```
p160 = read.table("P160.txt", h = T)
```

```
pairs(p160, gap = 0, oma = c(2, 2, 2, 2))
```



quick visualization of how variables correlated

```
# BE, include everything at the beginning step(lm(V \sim I + D + W + G + P + N, data = p160), test = "F")
```

```
Start: AIC=-104.98
V ~ I + D + W + G + P + N

Df Sum of Sq RSS AIC F value Pr(>F)
```

```
1 0.0044157 0.077119 -105.75 0.8503 0.3721
                   0.072704 -104.98
<none>
      1 0.0101039 0.082808 -104.25 1.9456 0.1848
- D
Step: AIC=-106.98
V \sim I + D + W + G + P
      Df Sum of Sq RSS AIC F value Pr(>F)
- I
       1 0.0000436 0.072755 -108.97 0.0090 0.9257
– W
       1 0.0001396 0.072851 -108.94 0.0288 0.8675
- G
       1 0.0016497 0.074361 -108.51 0.3403 0.5683
– P
       1 0.0048827 0.077594 -107.62 1.0073 0.3315
                   0.072712 -106.98
<none>
- D
      1 0.0101469 0.082859 -106.24 2.0933 0.1685
Step: AIC=-108.97
V \sim D + W + G + P
      Df Sum of Sq RSS AIC F value Pr(>F)
       1 0.0001571 0.072912 -110.92 0.0346 0.85488
- W
       1 0.0016185 0.074374 -110.51 0.3559 0.55912
- G
- P
       1 0.0050355 0.077791 -109.56 1.1074 0.30829
<none>
                   0.072755 - 108.97
– D
    1 0.0245242 0.097280 -104.87 5.3932 0.03373 *
___
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
Step: AIC=-110.92
V \sim D + G + P
      Df Sum of Sq RSS AIC F value Pr(>F)
- G
       1 0.0017808 0.074693 -112.42 0.4152 0.52794
                   0.072912 -110.92
<none>
- P
       1 0.0110706 0.083983 -109.95 2.5812 0.12655
- D
       1 0.0270882 0.100001 -106.29 6.3158 0.02234 *
___
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
Step: AIC=-112.42
V \sim D + P
                    RSS AIC F value Pr(>F)
      Df Sum of Sq
                  0.074693 -112.42
<none>
```

```
- P 1 0.0099223 0.084616 -111.80 2.3911 0.13943
```

- D 1 0.0255565 0.100250 -108.24 6.1588 0.02317 *

Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1

Call:

 $lm(formula = V \sim D + P, data = p160)$

Coefficients:

(Intercept) D P 0.514022 0.043134 -0.006017

we are using F test here to compare current model with the potential model, the score is s

BE stops when there's only D and P included in this model.

```
summary(lm(V \sim D + P, data = p160))
```

Call:

 $lm(formula = V \sim D + P, data = p160)$

Residuals:

Min 1Q Median 3Q Max -0.101121 -0.036838 -0.006987 0.019029 0.163250

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 0.514022 0.022793 22.552 1.2e-14 ***

D 0.043134 0.017381 2.482 0.0232 *

P -0.006017 0.003891 -1.546 0.1394

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06442 on 18 degrees of freedom Multiple R-squared: 0.3372, Adjusted R-squared: 0.2636

F-statistic: 4.579 on 2 and 18 DF, p-value: 0.02468

```
# Forward selection
step(lm(V ~ 1, data = p160), scope = V ~ I + D + W + G + P + N, direction = "forward", test
Start: AIC=-107.78
V ~ 1
      Df Sum of Sq
                        RSS
                                AIC F value Pr(>F)
+ D
        1 0.0280805 0.084616 -111.80 6.3054 0.02124 *
+ I
        1 0.0135288 0.099167 -108.47 2.5921 0.12389
+ P
        1 0.0124463 0.100250 -108.24 2.3589 0.14106
                   0.112696 -107.78
+ G
        1 0.0060738 0.106622 -106.94 1.0824 0.31123
+ N
        1 0.0024246 0.110271 -106.24 0.4178 0.52579
+ W
        1 0.0009518 0.111744 -105.96 0.1618 0.69197
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Step: AIC=-111.8
V ~ D
      Df Sum of Sq RSS AIC F value Pr(>F)
+ P
        1 0.0099223 0.074693 -112.42 2.3911 0.1394
<none>
                   0.084616 -111.80
+ W
      1 0.0068141 0.077801 -111.56 1.5765 0.2253
+ I
        1 0.0012874 0.083328 -110.12 0.2781 0.6044
        1 0.0006325 0.083983 -109.95 0.1356 0.7170
+ G
+ N
        1 0.0000033 0.084612 -109.80 0.0007 0.9793
Step: AIC=-112.42
V \sim D + P
                         RSS
                                 AIC F value Pr(>F)
      Df Sum of Sq
<none>
                    0.074693 -112.42
+ G
        1 0.00178078 0.072912 -110.92 0.4152 0.5279
+ W
        1 0.00031940 0.074374 -110.51 0.0730 0.7903
+ N
        1 0.00018496 0.074508 -110.47 0.0422 0.8397
+ I
        1 0.00002633 0.074667 -110.42 0.0060 0.9392
Call:
lm(formula = V \sim D + P, data = p160)
```

```
0.514022
               0.043134
                           -0.006017
Only D and P included in the model.
# stepwise
step(lm(V ~ D + W, data = p160), scope = V~ I + D + W + G + P + N, direction = "both", test
Start: AIC=-111.56
V \sim D + W
                                AIC F value Pr(>F)
      Df Sum of Sq
                        RSS
- W
        1 0.006814 0.084616 -111.80 1.5765 0.22532
<none>
                   0.077801 -111.56
+ P
        1 0.003428 0.074374 -110.51 0.7835 0.38843
+ N
        1 0.000374 0.077428 -109.66 0.0820 0.77802
+ I
        1 0.000178 0.077623 -109.61 0.0391 0.84567
+ G
        1 0.000011 0.077791 -109.56 0.0023 0.96213
- D
        1 0.033943 0.111744 -105.96 7.8529 0.01178 *
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
Step: AIC=-111.8
V ~ D
      Df Sum of Sq
                        RSS
                                AIC F value Pr(>F)
+ P
        1 0.0099223 0.074693 -112.42 2.3911 0.13943
<none>
                   0.084616 -111.80
+ W
        1 0.0068141 0.077801 -111.56 1.5765 0.22532
+ I
        1 0.0012874 0.083328 -110.12 0.2781 0.60439
+ G
        1 0.0006325 0.083983 -109.95 0.1356 0.71703
+ N
        1 0.0000033 0.084612 -109.80 0.0007 0.97928
- D
        1 0.0280805 0.112696 -107.78 6.3054 0.02124 *
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
Step: AIC=-112.42
V \sim D + P
```

Coefficients: (Intercept)

Df Sum of Sq

D

AIC F value Pr(>F)

RSS

```
0.074693 -112.42
<none>
- P
        1 0.0099223 0.084616 -111.80 2.3911 0.13943
+ G
        1 0.0017808 0.072912 -110.92 0.4152 0.52794
+ W
        1 0.0003194 0.074374 -110.51 0.0730 0.79026
+ N
        1 0.0001850 0.074508 -110.47 0.0422 0.83968
        1 0.0000263 0.074667 -110.42 0.0060 0.93919
+ I
- D
        1 0.0255565 0.100250 -108.24 6.1588 0.02317 *
Signif. codes:
               0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Call:
lm(formula = V \sim D + P, data = p160)
Coefficients:
(Intercept)
                       D
  0.514022
                0.043134
                            -0.006017
```

Difference between using AIC and BIC in programming: substitute 2 to $\log_e(n)$, therefore, need to specify $k = \log(n)$ as last command.

FS, BE, SW may not choose the same model: Highly correlated predictors can cause variables to appear significant in one method but not in another; order dependency exists.