STAT406- Methods of Statistical Learning Lecture 3

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```
int getRandomNumber()
{
return 4; // chosen by fair dice roll.
// guaranteed to be random.
}
```

Cross validation

We can show that

$$\begin{split} E_{\mathsf{data},Y|\mathbf{X}_0} & \left[\left(Y - \hat{f}(\mathbf{X}_0) \right)^2 \right] \\ &= V(\hat{f}(\mathbf{X}_0)) + B^2 \left(\hat{f}(\mathbf{X}_0) \right) + V(\epsilon) \,, \end{split}$$

where V denotes variance and

$$B^{2}\left(\hat{f}(\mathbf{X}_{0})\right) = \left[E_{\mathsf{data}}\left(\hat{f}(\mathbf{X}_{0}) - f(\mathbf{X}_{0})\right)\right]^{2}.$$

is the squared bias:

Activity!

Cross validation

- Conservative lower bound for MSPE
- Discussion
- Proper way of using CV



• Simple example:

```
set.seed(123)
x1 <- rnorm(506)
x2 <- rnorm(506, mean=2, sd=1)
x3 <- rexp(506, rate=1)
x4 <- x2 + rnorm(506, sd=.1)
x5 <- x1 + rnorm(506, sd=.1)
x6 <- x1 - x2 + rnorm(506, sd=.1)
x7 <- x1 + x3 + rnorm(506, sd=.1)
y <- x1*3 + x2/3 + rnorm(506, sd=2.2)</pre>
```

• Variables X_1 and X_2 are clearly important. But they are also highly correlated to X_4 , X_5 , X_6 and X_7 .

 However, nothing is significant? > summary(lm(v~., data=x)) Call: $lm(formula = v \sim ., data = x)$ Residuals: Min 10 Median 30 Max -6.882 -1.474 -0.033 1.415 5.823 Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 0.03457 0.23018 0.150 0.8807 x 1 3.22612 1.68088 1.919 0.0555 . x2 0.23867 1.39355 0.171 0.8641 -0.35926 0.98680 -0.364 0.7160 x3 x4 -0.69359 0.99025 -0.700 0.4840 0.09271 0.91162 0.102 0.9190 x 5 -0.73887 1.01114 -0.731 0.4653 x 6 x7 0.31651 0.98610 0.321 0.7484 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Residual standard error: 2.148 on 498 degrees of freedom Multiple R-squared: 0.6353, Adjusted R-squared: 0.6302 F-statistic: 123.9 on 7 and 498 DF, p-value: < 2.2e-16

But...

```
> summary(lm(v \sim x1 + x2, data=x))
Call:
lm(formula = v \sim x1 + x2, data = x)
Residuals:
   Min 10 Median 30
                                 Max
-6.9303 -1.5736 -0.0068 1.3840 5.9567
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.00733 0.20900 0.035 0.97204
x1
           2.89168 0.09806 29.490 < 2e-16 ***
x2
            0.27903 0.09249 3.017 0.00268 **
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 2.141 on 503 degrees of freedom
Multiple R-squared: 0.6343, Adjusted R-squared: 0.6328
F-statistic: 436.2 on 2 and 503 DF, p-value: < 2.2e-16
```

Even worse...

```
> summary (lm(v \sim x1 + x2 + x4, data=x))
Call:
lm(formula = v \sim x1 + x2 + x4, data = x)
Residuals:
   Min 10 Median 30
                                 Max
-6.8064 -1.5229 -0.0308 1.4226 5.8861
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0001127 0.2093588 0.001 1.000
        2.8964461 0.0983390 29.454 <2e-16 ***
×1
         0.9740807 0.9917783 0.982 0.326
x2
×4
          -0.6934442 0.9851714 -0.704 0.482
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
Residual standard error: 2.142 on 502 degrees of freedom
Multiple R-squared: 0.6347, Adjusted R-squared: 0.6325
F-statistic: 290.7 on 3 and 502 DF, p-value: < 2.2e-16
```

Discussion points

- Correlated covariates are now prevalent
- Researchers can (and do) collect data "blindly"
- Sometimes, data are collected without a specific question in mind

Discussion points

- Correlated covariates:
- Mask each other when included simultaneously in a model
- May reduce prediction accuracy

One strategy:

- (1): Select models to be considered
- (2): Select a quantitative criterion to compare them (e.g. AIC, C_p , CV-based $\widehat{\mathsf{MSPE}}$)
- (3): Choose a strategy to explore the models under consideration

For example:

- (1): Consider all possible models
- (2): Use AIC to compare them
- (3): Best subset search (2^p fits!)
- (3'): Stepwise search

• Is this strategy prediction-based?

AIC?

Why not compare models using residual sum of squares, or R^2 ?