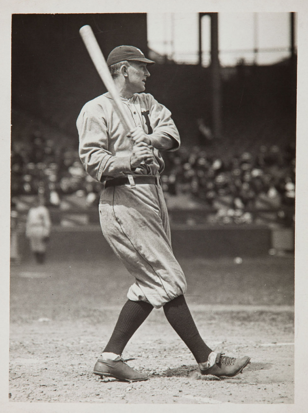
THE UNIVERSITY OF TEXAS AT AUSTIN
McCOMBS SCHOOL OF BUSINESS

Model Building - Part 2

Lecture 15

STA 371G

Predicting Baseball Player Batting Averages



- load baseball.csv
- install the packages car, leaps, and corrplot if you haven't already

What predicts a player’s batting average

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- We are going to explore this dataset with best subsets regression

The 10 potential x variables

- YEAR: Year this entry calculated for
- LG: League, either NL or AL
- AVG: Batting average
- OBP: On base percentage
- SLG: Slugging average
- EXP: Years of experience
- PAYR: Plate appearances per year
- MLAVG: Batting average for the leauge for the year
- MLOBP: On base percentage for the leaugue for the year
- MLSLG: Slugging percentage for the leaugue for the year
- AVGcumLag1: Player's cumulative batting average for previous years
- OBPcumLag1: Player's cumulative on base percentage for previous years
- SLGcumLag1: Player's cumulative slugging percentage for previous years
- G: Games played (must have been at least 98)
- YRINDEX: Number of years since 1958

Build model full and check for multicollinearity

```
full <- lm(AVG ~ OBP + SLG + EXP + PAYR + MLAVG
+ MLOBP + MLSLG + AVGcumLag1 + OBPcumLag1
+ SLGcumLag1 + G + YRINDEX, data=baseball)

round(vif(full),2)

       OBP        SLG        EXP       PAYR      MLAVG      MLOBP
      3.71       4.32       1.20       1.37      11.07      12.69
     MLSLG AVGcumLag1 OBPcumLag1 SLGcumLag1          G    YRINDEX
      7.39       2.09       3.95       3.82       1.12       2.18
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```

Uh oh. Houston, we have a problem!

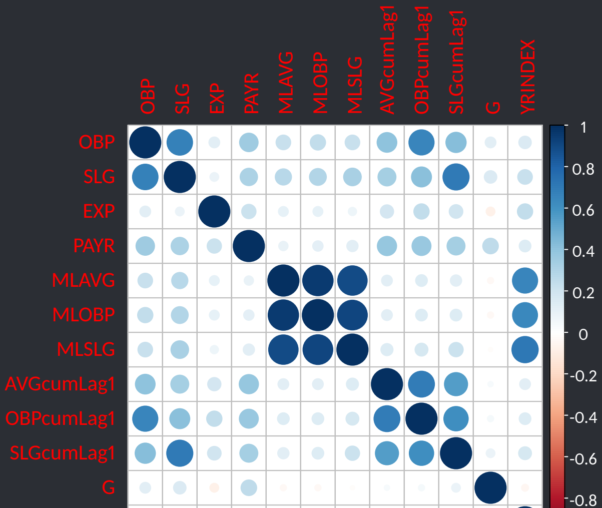
Look at the correlations to find the problem

This matrix is hard to read

```
numericpredictors <- baseball[,8:19]
M <- round(cor(numericpredictors),2) # calculate correlations

# print M by just typing M

# This table is confusing!
# There is a much better way to see this using corrplot
# So make the library available
library(corrplot)
```

Plot the correlations to better see the problem

```r
corrplot(M, method = "circle") #plot matrix
```



Reduce multicollinearity by dropping variables

- The Major League averages are highly correlated with each other
- Let's keep just MLAVG and drop MLOBP and MLSLG

```
full <- lm(AVG ~ OBP + SLG + EXP + PAYR + MLAVG
+ AVGcumLag1 + OBPcumLag1
+ SLGcumLag1 + G + YRINDEX, data=baseball)

round(vif(full), 2)
```

```
       OBP        SLG        EXP       PAYR      MLAVG AVGcumLag1 
      3.62       4.29       1.16       1.37       1.86       2.09 
OBPcumLag1 SLGcumLag1          G    YRINDEX 
      3.92       3.79       1.12       1.85 
```

Much better!

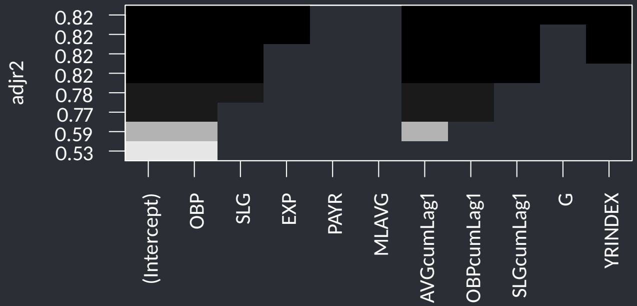
Run resubsets to get a sense of the best predictors

```
library(leaps)
bestsubsets <- regsubsets(AVG ~ OBP + SLG + EXP + PAYR + MLAVG
+ AVGcumLag1 + OBPcumLag1
+ SLGcumLag1 + G + YRINDEX, data=baseball)
```

Now let’s plot and identify the important predictors

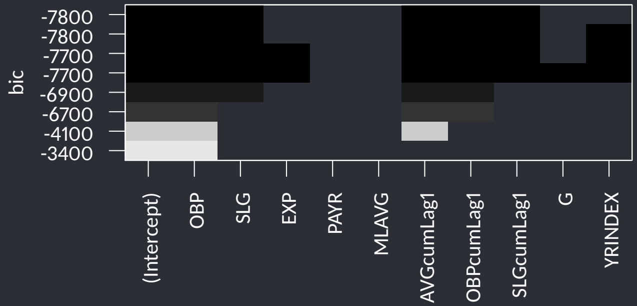
Use Adj R^2 to compare models

```
plot(bestsubsets, scale="adjr2")  # use adjusted R^2
```



Use BIC to compare models

```r
plot(bestsubsets, scale="bic")  # use BIC
```



Generate the best candidate model

```
model <- lm(AVG ~ OBP + SLG + AVGcumLag1 + OBPcumLag1
+ SLGcumLag1, data=baseball)

summary(model)
```

```
Call:
lm(formula = AVG ~ OBP + SLG + AVGcumLag1 + OBPcumLag1 + SLGcumLag1,
    data = baseball)

Residuals:
      Min        1Q    Median        3Q       Max
-0.056014 -0.007723  0.000263  0.008180  0.040508

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.027871   0.002497   11.16   <2e-16 ***
OBP          0.498209   0.009089   54.81   <2e-16 ***
SLG          0.160826   0.004697   34.24   <2e-16 ***
AVGcumLag1   0.880348   0.011950   73.67   <2e-16 ***
OBPcumLag1  -0.476261   0.012105  -39.34   <2e-16 ***
SLGcumLag1  -0.171831   0.005547  -30.98   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01213 on 4529 degrees of freedom
Multiple R-squared:  0.821,Adjusted R-squared:  0.8208
F-statistic:  4154 on 5 and 4529 DF,  p-value: < 2.2e-16
```

Does the National League’s Designated Hitter Rule matter?

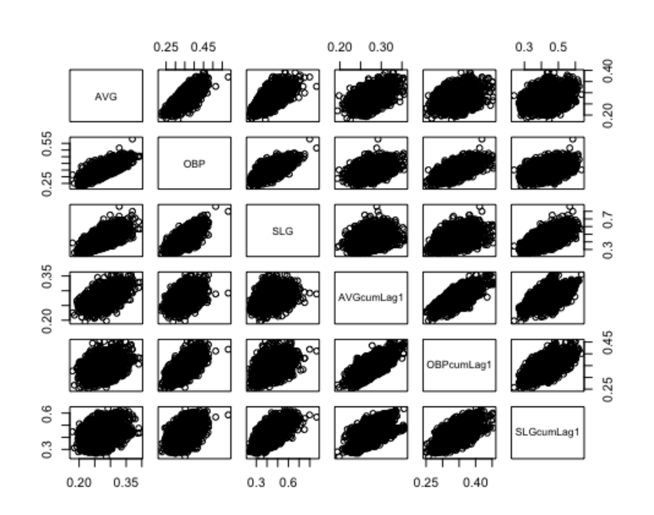
```
#Add a the categorical variable LG and find out!

model <- lm(AVG ~ OBP + SLG + AVGcumLag1 + OBPcumLag1
+ SLGcumLag1 + LG, data=baseball)
```

Does the National League's Designated Hitter Rule Matter?

```r
# Find the rows in baseball where LG is not either NL or AL
# and remove them so we can focus on the difference
# between NL and AL

base1 <- baseball[baseball$LG == "NL" | baseball$LG == "AL",]

modelLG <- lm(AVG ~ OBP + SLG + AVGcumLag1 + OBPcumLag1
+ SLGcumLag1 + LG, data=base1)

# Look at the summary, LG is not statistically significant
```

Check for linear relationships

```
# Depending on your computer, this command may run slowly
#pairs(~ AVG + OBP + SLG + AVGcumLag1 + OBPcumLag1 + SLGcumLag1, data=baseball)
```



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- If you omit some important variables or fail to use data transformations when they are needed, or if the assumption of linear or linearizable relationships is simply wrong, the model is a bad one, no matter what the R^2.

Is this model really useful?

- Automated regression model selection methods cannot make something out of nothing.
- If you omit some important variables or fail to use data transformations when they are needed, or if the assumption of linear or linearizable relationships is simply wrong, the model is a bad one, no matter what the R^2.
- Use your own judgment and intuition about your data to try to fine-tune whatever the computer comes up with.

A challenge

```
# Load the dataset challenge and run the following regression

model <- lm(y ~ x1 + x2 + x3 + x4 + x5 + x6 + x7
     + x8 + x9 + x10 + x11 + x12, data=challenge)

    # Generate a summary and examine R^2
    # 0.21 of the variance is explained
```

Surprise!

```
# I created this data with a random number generator
# You may have to run it a couple of times to get significance

 y <- rnorm(100)
 x1 <- rnorm(100)
 x2 <- rnorm(100)
 x3 <- rnorm(100)
 x4 <- rnorm(100)
 x5 <- rnorm(100)
 x6 <- rnorm(100)
 x7 <- rnorm(100)
 x8 <- rnorm(100)
 x9 <- rnorm(100)
 x10 <- rnorm(100)
 x11 <- rnorm(100)
 x12 <- rnorm(100)
 summary(lm(y ~ x1 + x2 + x3 + x4 + x5 + x6 + x7
 + x8 + x9 + x10 + x11 + x12))


Call:
lm(formula = y ~ x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 +
    x10 + x11 + x12)
```

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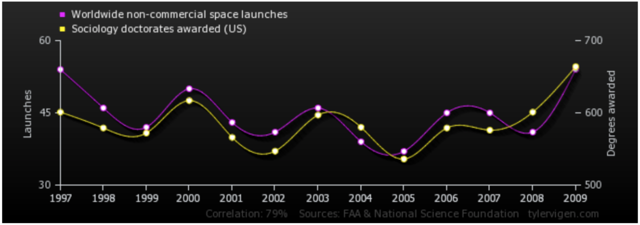
- If you have more than 1 predictor for 10-15 y values, you are likely to see spurious correlations.
- If you fit models with meaningless variables, you are fitting noise and will end up with an overfitted model that is not predictive going forward.
- You could even end up int he American Statistical Association's Hall of Shame!

www.tylervigen.com/spurious-correlations

Worldwide non-commercial space launches
correlates with
Sociology doctorates awarded (US)



	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Worldwide non-commercial space launches *Launches (FAA)*	54	46	42	50	43	41	46	39	37	45	45	41	54
Sociology doctorates awarded (US) *Degrees awarded (National Science Foundation)*	601	579	572	617	566	547	597	580	536	579	576	601	664

Correlation: 0.78915

- Don't fall for these!
- Have a great spring break!