Lab #6 - Predictive Regression II

Econ 224

September 11th, 2018

College Football Rankings and Market Efficiency

This example is based on the paper "College Football Rankings and Market Efficiency" by Ray Fair and John F. Oster (*Journal of Sports Economics*, Vol. 8 No. 1, February 2007, pp. 3-18) and the related discussion in Chapter 10 of *Predicting Presidential Elections and Other Things* by Ray Fair. The data used in this exercise are courtesy of Professor Fair. For convenience I have posted a copy on the course website which can be read into R as follows:

```
library(tidyverse)
football <- read_csv('http://ditraglia.com/econ224/fair_football.csv')
football
```

```
# A tibble: 1,582 x 10
   SPREAD     H   MAT   SAG   BIL   COL   MAS   DUN   REC    LV
    <int> <int> <int> <int> <int> <int> <int> <int> <dbl> <dbl>
 1     34     1     7    31    28    17    38    14  0     24
 2     29    -1    34    29    10    41    26    18 33.3   13.5
 3     10    -1   -16   -23   -33     5   -12   -25  8.33 -10.5
 4    -11     1     2    -8    -8    -7    -2    -4  0      3
 5     35    -1    35    35    38    25    25    28 25      5
 6     -2     1    29    36    17    25    20    11 33.3   11.5
 7     11     1    35    39    28    40    30    34 41.7   10
 8     20     1    29    13    12    37    13    26 25      7.5
 9      7     1    40    41    -7    45    36    43 66.7   11.5
10     20    -1    61    37    36    80    51    35 75     11
# ... with 1,572 more rows
```

Each row of the tibble `football` contains information on a single division I-A college football game. All of these games were played in 1998, 1999, 2000, or 2001. We have ten weeks of data for each year, beginning in week 6 of the college football season.

Response Variable: `SPREAD`

Our goal is to predict `SPREAD`, the *point spread* in a given football game. This variable is constructed as follows. For each game, one of the two teams is *arbitrarily* designated "Team A" and the other "Team B." The point spread is defined as A's final score minus B's final score. For example, in the first row of `football` the value of `SPREAD` is 34. This means that team A scored 34 more points than team B. Again, the designations of A and B are *completely arbitrary*, so `SPREAD` can be positive or negative. The value of `-2` for `SPREAD` in row 6 indicates that the team designated A in that game scored two points *fewer* than team designated B.

Predictor Variables

Home Field Indicator: `H`

The predictor `H` is a categorical variable that equals `1` if team A was the home team, `-1` if team B was the home team, and `0` if neither was the home team as in, e.g. the Rose Bowl.

Computer Ranking Systems: (`MAT, SAG, BIL, COL, MAS, DUN`)

Our next set of predictors is constructed from the following computer ranking systems:

1. Matthews/Scripps Howard (MAT)
2. Jeff Sagarin's *USA Today* (SAG)
3. Richard Billingsley (BIL)
4. *Atlanta Journal-Constitution* Colley Matrix (COL)
5. Kenneth Massey (MAS)
6. Dunkel (DUN)

Fair and Oster (2007) describe these as follows:

> Each week during a college football season, there are many rankings of the Division I-A teams. Some rankings are based on the votes of sports writers, and some are based on computer algorithms ... The algorithms are generally fairly complicated, and there is no easy way to summarize their main differences.

The predictors `MAT, SAG, BIL, COL, MAS` and `DUN` are constructed as the *difference* of rankings for team A minus team B in the week when the corresponding game is scheduled to occur. Suppose, for example, that in a week when Stanford is schedule to play UCLA, Richard Billingsley has Stanford #10 and UCLA #22. The *difference* of ranks is 11. So if Stanford is team A, `BIL` will equal `11` and if Stanford is team B, `BIL` will equal `-11`. To be clear, each of these predictors will be *positive* when the team designated A is *more highly ranked*.

Win-Loss Record: `REC`

Continuing their discussion of computer ranking systems, Fair and Oster (2007) write:

> Each system more or less starts with a team's win-loss record and makes adjustments from there. An interesting system to use as a basis of comparison is one in which only win-loss records are used ... denoted `REC`.

The predictor `REC` is constructed differently from `MAT, SAG, BIL, COL, MAS` and `DUN`. This predictor equals the difference in *percentage of games won* for team A minus team B. For example, returning to the Stanford versus UCLA example, suppose that Stanford has won 80% of its games thus far while UCLA has won 50%. Then `REC` will equal `30` if Stanford is team A and `-30` if Stanford is team B.

Las Vegas Point Spread: `LV`

Our final predictor is `LV`: the Las Vegas line point spread. ESPN defines a point spread as follows:

> Also known as the line or spread, it [a point spread] is a number chosen by Las Vegas and overseas oddsmakers that will encourage an equal number of people to wager on the underdog as on the favorite. If fans believe that Team A is two touchdowns better than Team B, they may bet them as 14-point favorites. In a point spread, the negative value (-14) indicates the favorite and the positive value (+14) indicates the underdog. Betting a -14 favorite means the team must win by at least 15 points to cover the point spread. The +14 underdog team can lose by 13 points and still cover the spread.

For example, the value of 24 for `LV` row 1 of `football` indicates that fans believe team A is 24 points better than team B. The fact that a point spread is an *equilibrium value* chosen to balance the quantity of bets for and against a given team has some important economic implications that we will explore below.

Exercises

1. Calculate the *home field advantage*. How often does the home team win? How many more point, on average, does the home team score?
2. Run a linear regression *without an intercept* that uses `H` to predict `SPREAD`. Interpret the coefficient estimates, carry out appropriate inference, and summarize the model fit. Why *doesn't* it make sense to include an intercept in this regression, or indeed in *any* regression predicting `SPREAD`?
3. Install the R package `GGally` and use the function `ggpairs` to make a pairs plot of the columns `MAT, SAG, BIL, COL, MAS, DUN,` and `REC`. Summarize your results.
4. Run a regression *without an intercept* using `H`, `REC` and the six computer ranking systems (`MAT, SAG, BIL, COL, MAS,` and `DUN`) to predict `SPREAD`. Do all of the ranking systems add additional predictive information beyond that contained in `H` and the other ranking systems? Carry out appropriate statistical inference to make this determination. If, based on your results, some predictors appear to be redundant, re-estimate your regression dropping these. Based on your results from part 4 of this question, is it possible to make better predictions of college football games than the *best* of the seven computer systems?
5. Run a regression *without an intercept* that predicts `SPREAD` using `LV`, `H` and whichever of the seven ranking systems you found to contain independent information in part 4 above. Does `H` or any of the ranking systems contain additional predictive information beyond that contained in `LV`? Carry out appropriate statistical inference to make this determination.
6. What do your findings from part 5 above have to do with the concept of market efficiency? If betting markets are efficient, what should be the slope and intercept in a regression that uses `LV` *alone* to predict `SPREAD`? Can you statistically reject these values for the regression coefficients? How accurately does `LV` alone predict `SPREAD`?

Solutions

Exercise #1

```
# In games with a home team (i.e. not bowl games) how often does the home
# team win?
football %>%
  filter(H != 0) %>%
  mutate(Hwin = SPREAD * H > 0) %>%
  summarize(mean(Hwin))
```

```
# A tibble: 1 x 1
  `mean(Hwin)`
         <dbl>
1        0.586
```

```
# In games with a home team (i.e. not bowl games) how many more points does the
# home team score on average?
football %>%
  filter(H != 0) %>%
  summarize(mean(SPREAD * H))
```

```
# A tibble: 1 x 1
  `mean(SPREAD * H)`
               <dbl>
1               4.86
```

```r
# Regression to predict SPREAD using H *without* a constant
reg1 <- lm(SPREAD ~ H - 1, football)
summary(reg1)
```

```
Call:
lm(formula = SPREAD ~ H - 1, data = football)

Residuals:
    Min      1Q  Median      3Q     Max 
-61.143  -6.143   6.143  17.857  68.143 

Coefficients:
  Estimate Std. Error t value Pr(>|t|)    
H    4.857      0.537   9.044   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 20.66 on 1581 degrees of freedom
Multiple R-squared:  0.04919,   Adjusted R-squared:  0.04859 
F-statistic:  81.8 on 1 and 1581 DF,  p-value: < 2.2e-16
```

Explain why it makes sense *not* to include a constant. Hint: which team was designated A and which was designated B was *arbitrary*. How does it affect the regression prediction?

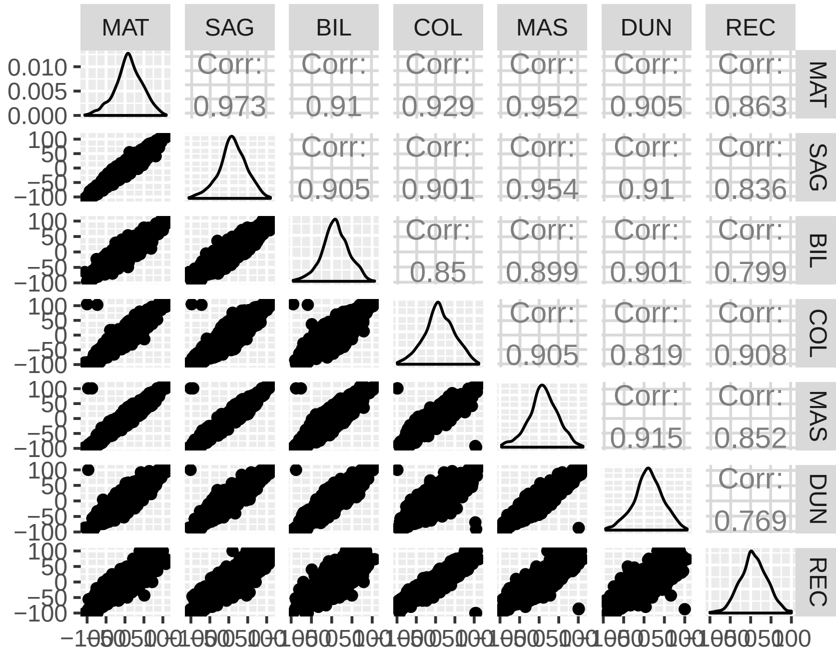
```r
# Plot each of the seven systems one another using ggpairs
library(GGally)
```

```
Attaching package: 'GGally'

The following object is masked from 'package:dplyr':

    nasa
```

```r
football %>%
  select(MAT:REC) %>%
  ggpairs
```




```
# Does each ranking system contain independent information?
# (Regression *without* an intercept)
reg1 <- lm(SPREAD ~ H + MAT + SAG + BIL + COL + MAS + DUN + REC - 1, football)
summary(reg1)
```

```
Call:
lm(formula = SPREAD ~ H + MAT + SAG + BIL + COL + MAS + DUN +
    REC - 1, data = football)

Residuals:
    Min      1Q  Median      3Q     Max
-53.542  -9.134   2.150  11.736  56.963

Coefficients:
     Estimate Std. Error t value Pr(>|t|)
H    4.267073   0.436668   9.772  < 2e-16 ***
MAT -0.099306   0.060804  -1.633 0.102624
SAG  0.248165   0.054817   4.527 6.43e-06 ***
BIL  0.080436   0.034244   2.349 0.018953 *
COL -0.062588   0.035894  -1.744 0.081410 .
MAS -0.007075   0.044624  -0.159 0.874047
DUN  0.118512   0.033769   3.509 0.000462 ***
REC  0.080412   0.030460   2.640 0.008374 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 16.53 on 1574 degrees of freedom
Multiple R-squared:  0.3942,    Adjusted R-squared:  0.3911
F-statistic:   128 on 8 and 1574 DF,  p-value: < 2.2e-16
```

```r
# Neither MAT nor MAS are significant individually. What about jointly?
library(car)
```

```

Attaching package: 'car'


The following object is masked from 'package:dplyr':

    recode


The following object is masked from 'package:purrr':

    some
```

```r
linearHypothesis(reg1, c('MAT = 0', 'MAS = 0'))
```

```

Linear hypothesis test

Hypothesis:
MAT = 0
MAS = 0

Model 1: restricted model
Model 2: SPREAD ~ H + MAT + SAG + BIL + COL + MAS + DUN + REC - 1

  Res.Df    RSS Df Sum of Sq      F Pr(>F)
1   1576 430638
2   1574 429879  2    758.07 1.3878 0.2499
```

```r
# The preceding results suggest that MAT and MAS do not add additional predictive
# information beyond that contained in the other predictors, so it makes sense
# to try a regression that doesn't include them:
reg2 <- lm(SPREAD ~ H + SAG + BIL + COL + DUN + REC - 1, football)
summary(reg2)
```

```


Call:
lm(formula = SPREAD ~ H + SAG + BIL + COL + DUN + REC - 1, data = football)

Residuals:
    Min      1Q  Median      3Q     Max
-53.379  -9.159   2.226  11.953  60.007

Coefficients:
    Estimate Std. Error t value Pr(>|t|)
H    4.31812    0.43495   9.928  < 2e-16 ***
SAG  0.18662    0.03809   4.899 1.06e-06 ***
BIL  0.07203    0.03387   2.127 0.033587 *
COL -0.08575    0.03279  -2.615 0.009014 **
DUN  0.10866    0.03151   3.449 0.000578 ***
REC  0.07666    0.03017   2.541 0.011141 *
```

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

Residual standard error: 16.53 on 1576 degrees of freedom
Multiple R-squared:  0.3932,    Adjusted R-squared:  0.3908
F-statistic: 170.2 on 6 and 1576 DF,  p-value: < 2.2e-16
```

```r
# The preceding results suggest that MAT and MAS do not add additional predictive
# information beyond that contained in the other predictors, so it makes sense
# to try a regression that doesn't include them:
reg2 <- lm(SPREAD ~ H + SAG + BIL + COL + DUN + REC - 1, football)
summary(reg2)
```

```
Call:
lm(formula = SPREAD ~ H + SAG + BIL + COL + DUN + REC - 1, data = football)

Residuals:
    Min      1Q  Median      3Q     Max 
-53.379  -9.159   2.226  11.953  60.007 

Coefficients:
    Estimate Std. Error t value Pr(>|t|)    
H    4.31812    0.43495   9.928  < 2e-16 ***
SAG  0.18662    0.03809   4.899 1.06e-06 ***
BIL  0.07203    0.03387   2.127 0.033587 *  
COL -0.08575    0.03279  -2.615 0.009014 ** 
DUN  0.10866    0.03151   3.449 0.000578 ***
REC  0.07666    0.03017   2.541 0.011141 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 16.53 on 1576 degrees of freedom
Multiple R-squared:  0.3932,    Adjusted R-squared:  0.3908
F-statistic: 170.2 on 6 and 1576 DF,  p-value: < 2.2e-16
```

```r
# Once we add the Las Vegas line point spread (LV) nothing else is significant!
reg3 <- lm(SPREAD ~ LV + H + SAG + BIL + COL + DUN + REC - 1, football)
summary(reg3)
```

```
Call:
lm(formula = SPREAD ~ LV + H + SAG + BIL + COL + DUN + REC - 
    1, data = football)

Residuals:
    Min      1Q  Median      3Q     Max 
-60.379  -8.469   1.564  11.285  54.636 

Coefficients:
     Estimate Std. Error t value Pr(>|t|)    
LV   1.051782   0.076071  13.826   <2e-16 ***
H    0.729503   0.485981   1.501    0.134    
```

```
SAG  0.018065   0.037994   0.475    0.635
BIL -0.027867   0.032797  -0.850    0.396
COL -0.005476   0.031518  -0.174    0.862
DUN -0.024891   0.031290  -0.795    0.426
REC  0.018585   0.028804   0.645    0.519
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 15.61 on 1575 degrees of freedom
Multiple R-squared:  0.4588,    Adjusted R-squared:  0.4564
F-statistic: 190.8 on 7 and 1575 DF,  p-value: < 2.2e-16
```

```r
linearHypothesis(reg3, c('H = 0', 'SAG = 0', 'BIL = 0', 'COL = 0', 'DUN = 0',
                         'REC = 0'))
```

```
Linear hypothesis test

Hypothesis:
H = 0
SAG = 0
BIL = 0
COL = 0
DUN = 0
REC = 0

Model 1: restricted model
Model 2: SPREAD ~ LV + H + SAG + BIL + COL + DUN + REC - 1

  Res.Df    RSS Df Sum of Sq      F Pr(>F)
1   1581 385883
2   1575 384026  6    1856.8 1.2692 0.2684
```

```r
# How well does LV predict on its own? Can we reject the null that the coef is 1?
# What would it mean for this coef to equal 1? Make a plot.
reg4 <- lm(SPREAD ~ LV - 1, football)
summary(reg4)
```

```
Call:
lm(formula = SPREAD ~ LV - 1, data = football)

Residuals:
    Min      1Q  Median      3Q     Max
-61.244  -9.065   1.043  10.910  54.234

Coefficients:
   Estimate Std. Error t value Pr(>|t|)
LV  1.01436    0.02785   36.42   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 15.62 on 1581 degrees of freedom
Multiple R-squared:  0.4562,    Adjusted R-squared:  0.4559
F-statistic:  1326 on 1 and 1581 DF,  p-value: < 2.2e-16
```

```r
linearHypothesis(reg4, c('LV = 1'))
```

```
Linear hypothesis test

Hypothesis:
LV = 1

Model 1: restricted model
Model 2: SPREAD ~ LV - 1

  Res.Df    RSS Df Sum of Sq      F Pr(>F)
1   1582 385948
2   1581 385883  1    64.908 0.2659 0.6061
```

```r
ggplot(football, aes(x = LV, y = SPREAD)) +
  geom_point() +
  geom_smooth(method = 'lm')
```