

Longley

DP

September 6, 2016

To avoid filling up the handout with long summaries I'll use a shortened version, which I call `look()`. The code is hidden in the pdf file, but is viewable in the Rmd file.

The famous Longley dataset

```
data(longley) # we now have a 16 by 7 data frame called longley
# Also look at pairs(longley)
```

```
##      GNP.deflator GNP Unemployed Armed.Forces Population Year Employed
## 1947          83.0 234           236           159         108 1947    60.3
## 1948          88.5 259           232           146         109 1948    61.1
## 1949          88.2 258           368           162         110 1949    60.2
```

Longley used this small set of data to illustrate the potentially nasty effects of round-off errors when working with predictors that are “almost linearly dependent”. I'll use it to illustrate the effects that small changes can have on a least squares fit when the matrix of predictors is “ill-conditioned”.

```
out0 <- lm(Employed ~. , data = longley) ; look(out0)
```

```
## Residuals:
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -0.410 -0.158 -0.028  0.000  0.102  0.455
## Rsquared:  0.995
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3482.259   890.420  -3.911  0.004
## GNP.deflator    0.015     0.085   0.177  0.863
## GNP             -0.036     0.033  -1.070  0.313
## Unemployed     -0.020     0.005  -4.136  0.003
## Armed.Forces   -0.010     0.002  -4.822  0.001
## Population     -0.051     0.226  -0.226  0.826
## Year           1.829     0.455   4.016  0.003
```

A lot of the work is being done by `1` (a column of ones) and the `longley$Year` predictor:

```
outYear <- lm(Employed ~ Year, data = longley) ; look(outYear) #summary(outYear)
```

```
## Residuals:
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.310 -0.709  0.210  0.000  0.424  1.470
## Rsquared:  0.943
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1335.105   91.607  -14.6    0
## Year         0.717     0.047   15.3    0
```

The other predictors improved the fit by only a small amount. Compare $\text{totalSS} = \sum_i (y_i - \bar{y})^2$ with the sum of squared residuals for both fits:

```
## totalSS outYearSS resOSS
## 185.009 10.457 0.836
```

Remove time trend from five predictors

Replace the columns “GNP.deflator”, “GNP”, “Unemployed”, “Armed.Forces”, and “Population” by their components orthogonal to 1 and “Year”.

```
L1 <- longley
for (nn in names(longley)[1:5]){
  L1[[nn]] <- lm(longley[[nn]] ~ longley[["Year"]])$residual
}
out1 <- lm(Employed ~ . , L1)
```

Look at `pairs(L1)` to see the effect. Then compare residuals and coefficients with `out0`:

```
##      Min. 1st Qu.  Median Mean 3rd Qu.  Max.
## out1 -0.41 -0.158 -0.0282  0  0.102 0.455
## out0 -0.41 -0.158 -0.0282  0  0.102 0.455

##      (Intercept) GNP.deflator      GNP Unemployed Armed.Forces Population
## out1      -1335      0.0151 -0.0358   -0.0202   -0.0103   -0.0511
## out0     -3482      0.0151 -0.0358   -0.0202   -0.0103   -0.0511
##      Year
## out1 0.717
## out0 1.829
```

The least squares fitted vector is the same but some of the coefficients have changed. Why?

Effect of small perturbations

Now I’ll make some small changes that, I hope, will have a bad effect on the `bhat`. Manufacture a small perturbation as suggested on the SVD.pdf handout:

```
Xsvd <- svd(L1[,1:5])
U <- Xsvd$u; U5 <- U[,5]
V <- Xsvd$v; V5 <- V[,5]

E <- U5 %*% t(V5) ; dimnames(E) <- dimnames(longley[,1:5])
yincr <- U5 %*% t(U5) %*% y
```

```
L3 <- L2 <- L1 # make changes on copies
L2[,1:5] <- L1[,1:5] - E
L3[,1:5] <- L1[,1:5] - 2*E
L4 <- L2; L4$Employed <- y + yincr
L5 <- L3; L5$Employed <- y + 2*yincr
# compare:
# round(L,2); round(LL,2)
```

```

out2 <- lm(Employed ~. , data = L2)
out3 <- lm(Employed ~. , data = L3)
out4 <- lm(Employed ~. , data = L4)
out5 <- lm(Employed ~. , data = L5)

```

Compare the original longley data with the fake data set obtained by applying the L5 perturbations to longley. Do you think any of the differences are particularly noteworthy?

```

##           1947  1948  1949  1950  1951  1952  1953  1954
## GNP.deflator 83.0  88.5  88.2  89.5  96.2  98.1  99.0 100.0
## fake_GNP.d   82.9  88.4  88.2  89.7  96.4  98.1  98.8  99.9
## GNP          234.3 259.4 258.1 284.6 329.0 347.0 365.4 363.1
## fake_GNP     234.3 259.5 258.1 284.5 328.9 347.0 365.5 363.2
## Unemployed   235.6 232.5 368.2 335.1 209.9 193.2 187.0 357.8
## fake_Unemp   235.6 232.5 368.2 335.1 209.9 193.2 187.0 357.8
## Armed.Forces 159.0 145.6 161.6 165.0 309.9 359.4 354.7 335.0
## fake_Armed   159.0 145.6 161.6 165.0 309.9 359.4 354.7 335.0
## Population   107.6 108.6 109.8 110.9 112.1 113.3 115.1 116.2
## fake_Popul   107.4 108.1 109.7 111.5 112.8 113.4 114.3 115.9
## Employed     60.3  61.1  60.2  61.2  63.2  63.6  65.0  63.8
## fake_Emplo   60.3  61.1  60.2  61.2  63.3  63.6  64.9  63.7

```

```

##           1955  1956  1957  1958  1959  1960  1961  1962
## GNP.deflator 101.2 104.6 108.4 110.8 112.6 114.2 115.7 116.9
## fake_GNP.d   101.4 104.6 108.3 110.8 112.8 114.2 115.6 116.8
## GNP          397.5 419.2 442.8 444.6 482.7 502.6 518.2 554.9
## fake_GNP     397.4 419.2 442.8 444.6 482.6 502.6 518.2 554.9
## Unemployed   290.4 282.2 293.6 468.1 381.3 393.1 480.6 400.7
## fake_Unemp   290.4 282.2 293.6 468.1 381.3 393.1 480.6 400.7
## Armed.Forces 304.8 285.7 279.8 263.7 255.2 251.4 257.2 282.7
## fake_Armed   304.8 285.7 279.8 263.7 255.2 251.4 257.2 282.7
## Population   117.4 118.7 120.4 122.0 123.4 125.4 127.8 130.1
## fake_Popul   118.2 118.9 120.1 121.8 124.1 125.4 127.5 129.8
## Employed     66.0  67.9  68.2  66.5  68.7  69.6  69.3  70.5
## fake_Emplo   66.1  67.9  68.2  66.5  68.7  69.6  69.3  70.5

```

Then compare their least squares fits. Larger values in the last column of the coefficients dispaly suggest we should not take a coefficient too seriously. (More about that idea soon.) First longley then fake:

```

## Residuals:
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -0.410 -0.158 -0.028  0.000  0.102  0.455
## Rsquared:  0.995
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3482.259   890.420  -3.911  0.004
## GNP.deflator    0.015     0.085   0.177  0.863
## GNP             -0.036     0.033  -1.070  0.313
## Unemployed     -0.020     0.005  -4.136  0.003
## Armed.Forces   -0.010     0.002  -4.822  0.001
## Population     -0.051     0.226  -0.226  0.826
## Year            1.829     0.455   4.016  0.003

```

```

## Residuals:
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -0.410 -0.158 -0.028   0.000   0.102   0.455
## Rsquared:  0.995
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3894.072  1055.762  -3.688  0.005
## GNP.deflator   0.083    0.126   0.657  0.528
## GNP            -0.068    0.055  -1.226  0.251
## Unemployed    -0.024    0.008  -3.221  0.010
## Armed.Forces  -0.011    0.002  -4.805  0.001
## Population     0.202    0.416   0.486  0.638
## Year           2.028    0.532   3.815  0.004

```

The point is that some of the coefficients are very sensitive to changes in the data almost at the level of round-off error.

Just for the comparison, here are the coefficients for the fits with time trends removed:

```

##           (Intercept) GNP.deflator  GNP Unemployed Armed.Forces Population
## longley      -3482         0.02 -0.04    -0.02    -0.01    -0.05
## L1          -1335         0.02 -0.04    -0.02    -0.01    -0.05
## L2          -1335        -0.02 -0.02    -0.02    -0.01    -0.18
## L3          -1335         0.04 -0.05    -0.02    -0.01     0.06
## L4          -1335        -0.07  0.00    -0.02    -0.01    -0.35
## L5          -1335         0.08 -0.07    -0.02    -0.01     0.20
##           Year
## longley     1.83
## L1          0.72
## L2          0.72
## L3          0.72
## L4          0.72
## L5          0.72

```

You might also find it interesting to look at the least squares in more detail.

```
#look(out0);look(out1);look(out2);look(out3);look(out4);look(out5)
```