predictFinish

David Wihl

November 24, 2015

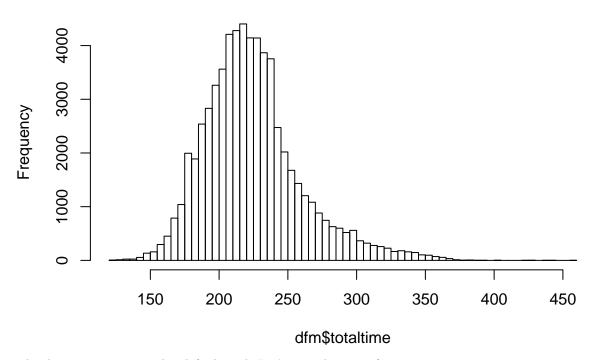
First let's read in the data and calculate finish times:

```
dfm <- read.csv("Previous Boston Marathon study/BAA data.txt",header=T,sep=" ")
times = as.matrix(dfm[,7:15], ncol=9)
dfm$totaltime = rowSums(times)</pre>
```

Some preliminary EDA of the data:

hist(dfm\$totaltime,breaks=50, main="Boston Marathon Finish Time (min) Distribution for '10, '11, '13")

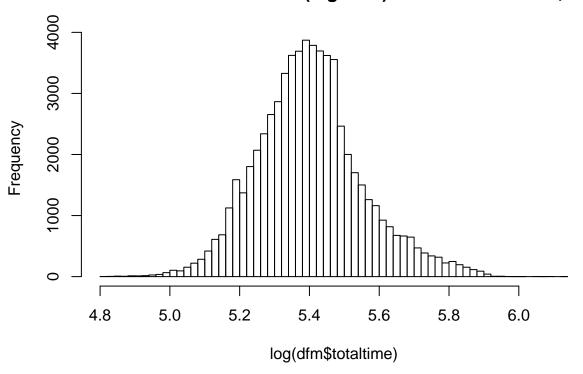
Boston Marathon Finish Time (min) Distribution for '10, '11, '13



The data appears somewhat left skewed. Let's try a log transform:

hist(log(dfm\$totaltime),breaks=50, main="Boston Marathon Finish Time (log-min) Distribution for '10, '1

Boston Marathon Finish Time (log-min) Distribution for '10, '11, '13



That seems better.

Let's try a multiple regression on the non-log data:

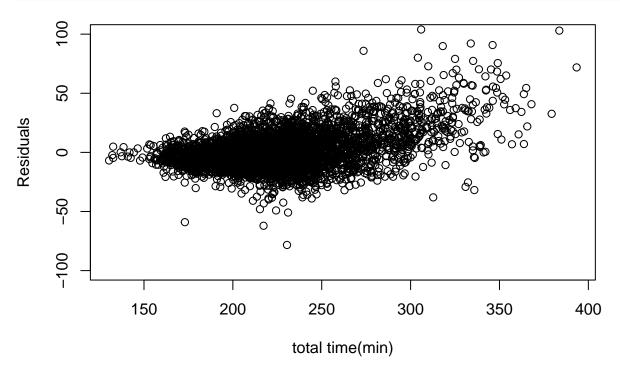
```
dfms = dfm[!is.na(dfm$totaltime), ]
dfms = dfms[order(dfms$totaltime),]
model = lm(totaltime~Age+Gender1F2M+K0.5, data=dfms)
summary(model)
```

```
##
## Call:
## lm(formula = totaltime ~ Age + Gender1F2M + K0.5, data = dfms)
## Residuals:
##
      Min
                1Q
                   Median
                                30
                                       Max
                     -2.64
  -376.18
            -9.26
                              6.48
                                   187.43
##
## Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
## (Intercept) -24.640157
                            0.595532
                                      -41.38
                                               <2e-16 ***
                 0.073888
                            0.006227
                                       11.87
                                               <2e-16 ***
## Age
## Gender1F2M
                 2.847267
                            0.139233
                                       20.45
                                               <2e-16 ***
## KO.5
                 9.703124
                            0.020687
                                      469.03
                                               <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 15.43 on 64163 degrees of freedom
## Multiple R-squared: 0.8097, Adjusted R-squared: 0.8097
## F-statistic: 9.103e+04 on 3 and 64163 DF, p-value: < 2.2e-16
```

```
model.resid = resid(model)
```

Let's plot the residuals

```
#plot(dfms$totaltime, model.resid, ylim=c(-100,100))
xydata = data.frame(x=dfms$totaltime, y=model.resid)
xydata = xydata[sample(1:nrow(xydata), 5000, replace=FALSE),]
plot(xydata$x,xydata$y,ylim=c(-100,100), xlab="total time(min)", ylab="Residuals")
```



This appears to be spreading out and trending up.

Let's try a polynomial transformation on the 5k time to see if that improves things:

```
bestresidsum = 9e9
bestpoly = 0
for (i in seq(from=1.0, to= 2.5, by=0.1)){
    dfms$k5xform = dfms$K0.5 ^ i
    model = lm(totaltime~Age+Gender1F2M+k5xform, data=dfms)
    model.residsum = sum(resid(model)^2)
    if (model.residsum < bestresidsum) {
        bestresid = resid(model)
        bestresidsum = model.residsum
        bestpoly = i
    }
}
cat("total error went from ",sum(model.resid^2), " (untransformed) to ", bestresidsum," (transformed)\n</pre>
```

total error went from 15271875 (untransformed) to 15261576 (transformed)

```
#plot(dfms$totaltime,bestresid,ylim=c(-100,100))
xydata = data.frame(x=dfms$totaltime, y=bestresid)
xydata = xydata[sample(1:nrow(xydata), 5000, replace=FALSE),]
plot(xydata$x,xydata$y,ylim=c(-100,100), xlab="total time(min)", ylab="Residuals")
```

