Boston Marathon Finish Time Predictions

Harvard Stats E139 Fall 2015

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Abstract

We want to build a reasonably accurate model for predicting Boston Marathon finish times based on gender, age on 5k split times. We will build a baseline using untransformed linear regression. Then, we will analyze the data and perform appropriate transformations. After transforming the data, we will cluster the data into different subgroups using unsupervised learning algorithms. Finally, we will run different regression algorithms on the transformed and subsetted data to see our improvements over the baseline.

Baseline

We obtained the following data: *fill in here*

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$totaltime = rowSums(times)
dfm = dfm[!is.na(dfm$totaltime), ]
```

Step 1: Baseline Regression

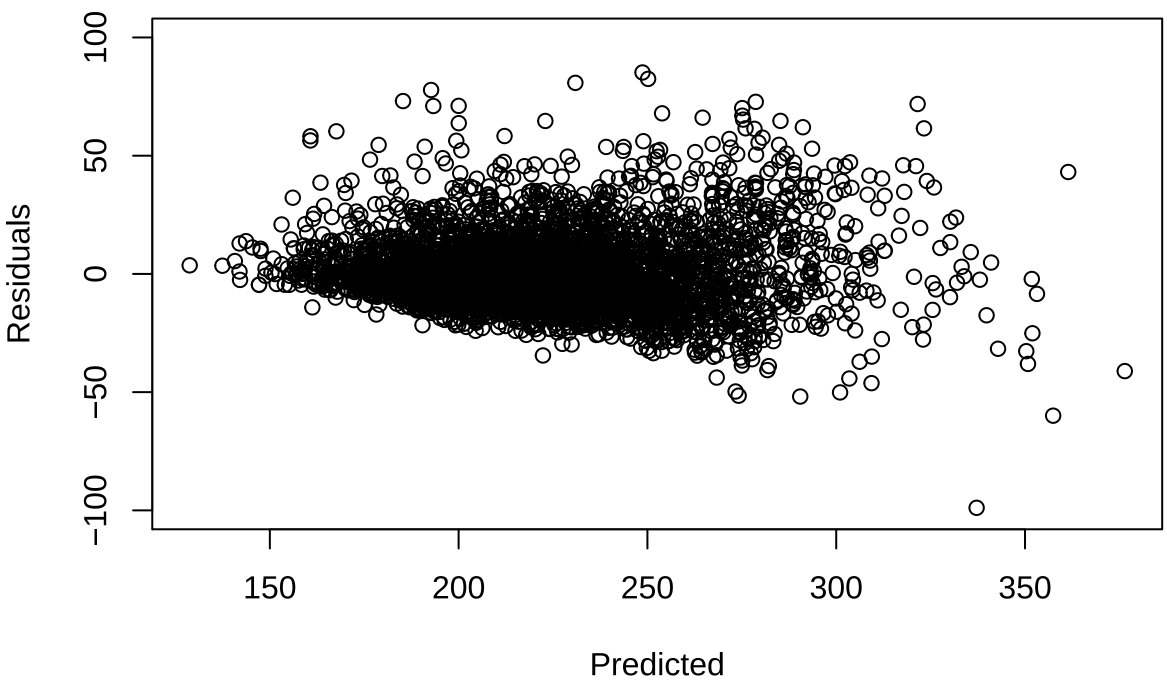
```
base.mod = lm(totaltime~Age+Gender1F2M+K0.5,data=dfm)
summary(base.mod)
```

```
##
## Call:
## lm(formula = totaltime ~ Age + Gender1F2M + K0.5, data = dfm)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -376.18   -9.26   -2.64    6.48  187.43
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept) -24.640157   0.595532  -41.38   <2e-16 ***
## Age           0.073888   0.006227   11.87   <2e-16 ***
## Gender1F2M    2.847267   0.139233   20.45   <2e-16 ***
## K0.5          9.703124   0.020687  469.03   <2e-16 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 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
```

Our baseline mean error is 15.4273139, or approximately 15 minutes.

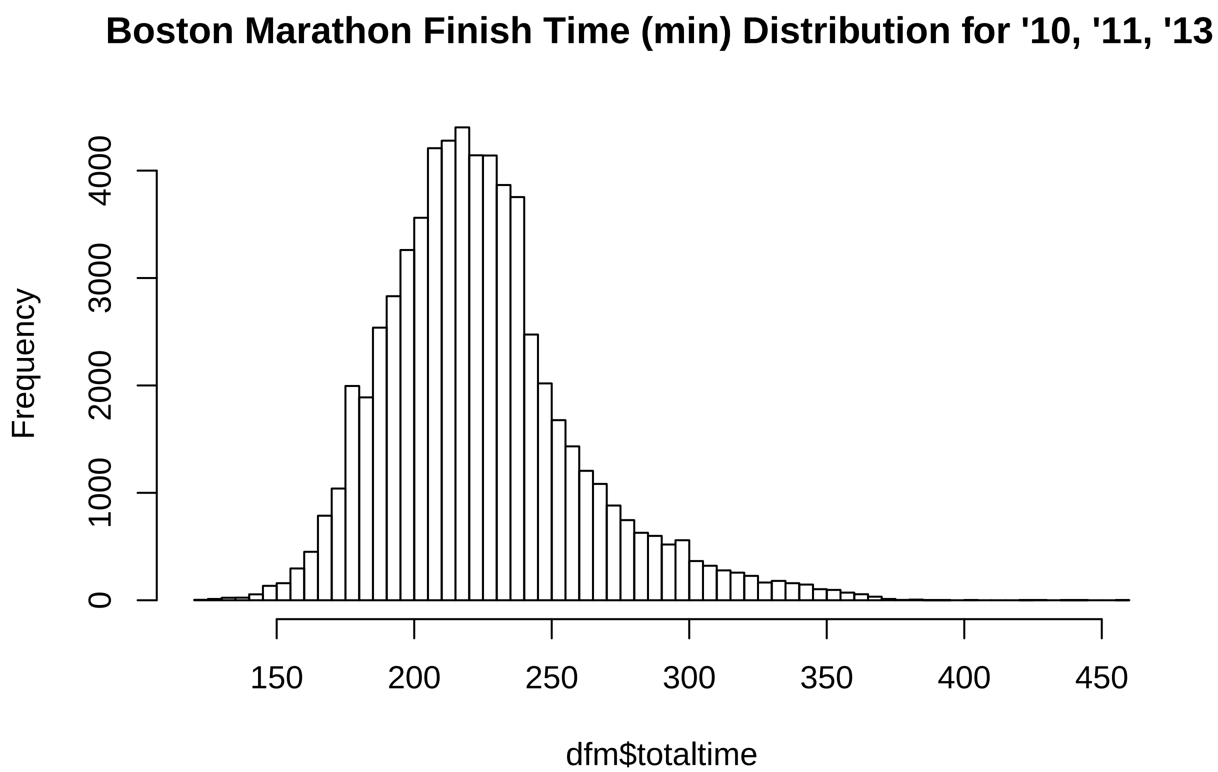
```r
y.hat = predict(base.mod)
xydata = data.frame(x=y.hat, y=resid(base.mod))
xydata = xydata[sample(1:nrow(xydata), 5000, replace=FALSE),]
plot(xydata$x,xydata$y,ylim=c(-100,100), xlab="Predicted", ylab="Residuals")
```



Step 2: Examination of the data and transformations.

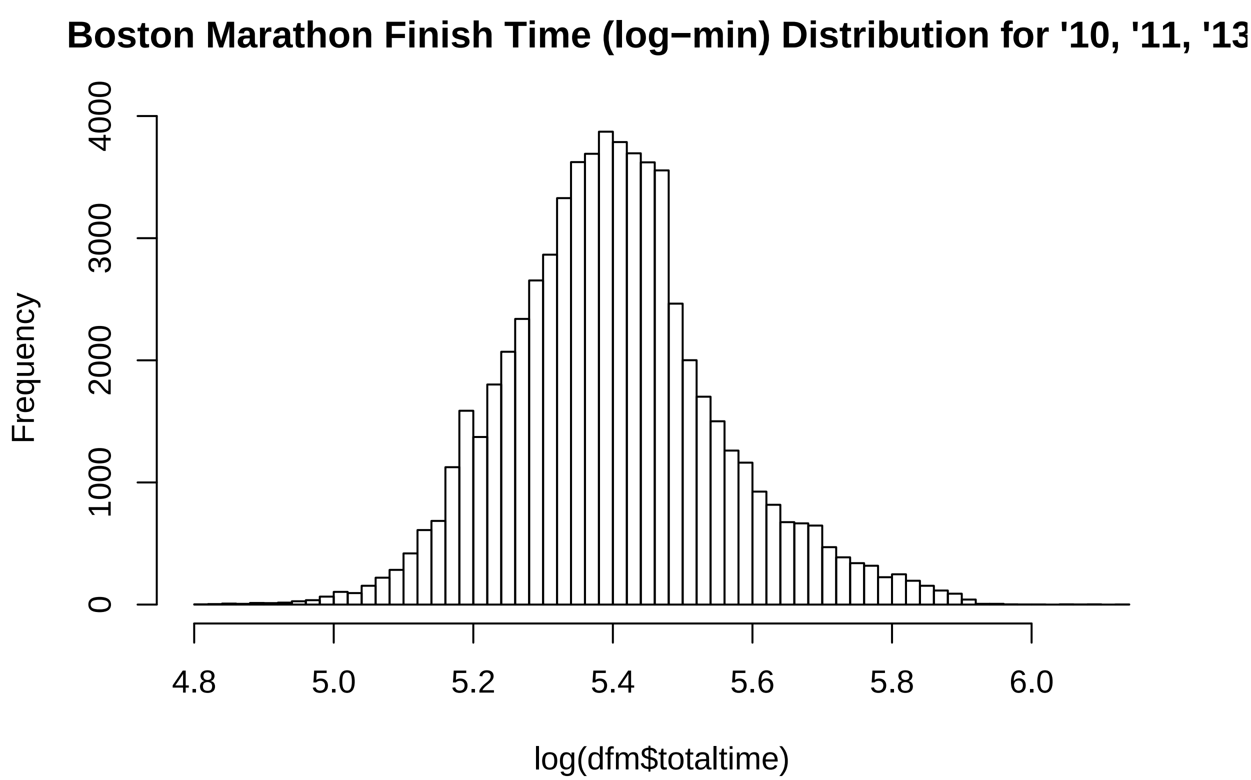
Some preliminary EDA of the data:

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



The data appears somewhat right skewed. Let's try a log transform of the predicted variable:

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



That seems better.

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

```
tx.mod = lm(log(totaltime)~Age+Gender1F2M+K0.5, data=dfm)
summary(tx.mod)
```

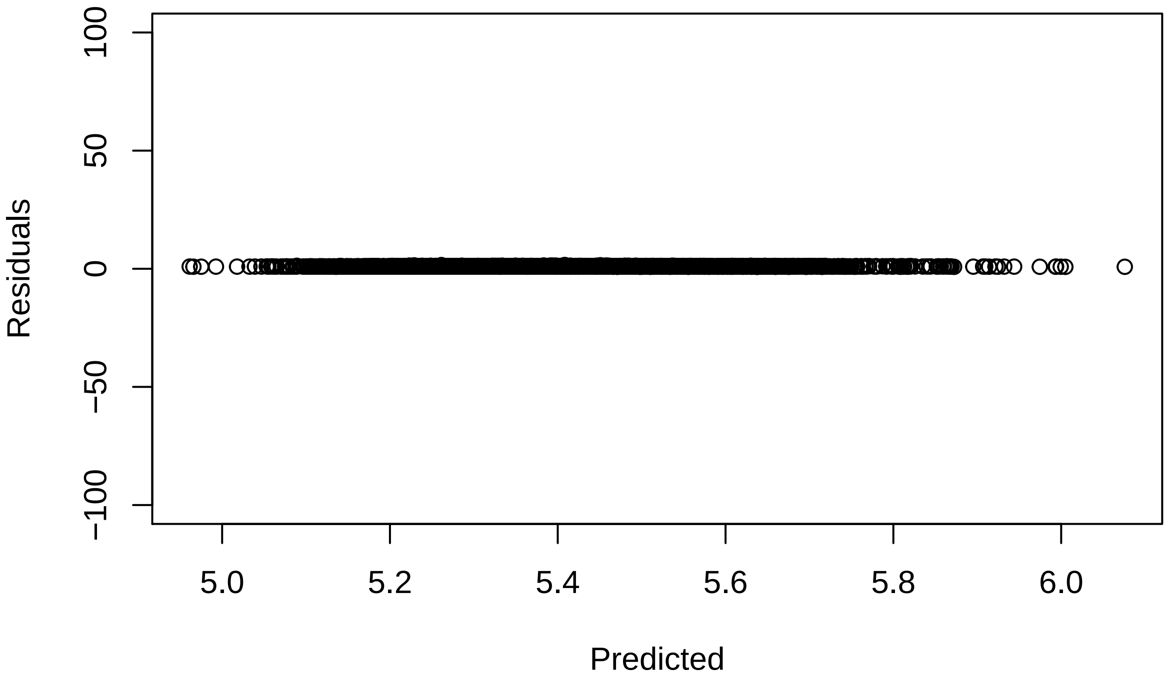
```
##
## Call:
## lm(formula = log(totaltime) ~ Age + Gender1F2M + K0.5, data = dfm)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.64168 -0.04097 -0.01051  0.03117  0.66161
##
## Coefficients:
##              Estimate Std. Error  t value Pr(>|t|)
## (Intercept) 4.341e+00  2.469e-03 1757.820  < 2e-16 ***
## Age         7.015e-04  2.582e-05   27.169  < 2e-16 ***
## Gender1F2M  2.568e-03  5.773e-04    4.449 8.66e-06 ***
## K0.5        4.131e-02  8.578e-05  481.571  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.06397 on 64163 degrees of freedom
## Multiple R-squared:  0.8232, Adjusted R-squared:  0.8231
## F-statistic: 9.955e+04 on 3 and 64163 DF,  p-value: < 2.2e-16
```

Our transformed mean error is 1.0042766

NOTE: I know this is wrong :)

Let's plot the residuals vs predicted

```
#plot(dfms$totaltime,model.resid,ylim=c(-100,100))
y.hat = predict(tx.mod)
xydata = data.frame(x=y.hat, y=exp(resid(tx.mod)))
xydata = xydata[sample(1:nrow(xydata), 5000, replace=FALSE),]
plot(xydata$x,xydata$y,ylim=c(-100,100), xlab="Predicted", 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)\
#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")
```

Step 3: Clustering the Data into Subgroups

Let's try subsetting the data set in subgroups using an unsupervised learning algorithm.

Note to Pooja and Nathaniel: I'm using the untransformed data set because the transformation part is not complete. When we've completed the transformations, we'll change this to use the transformed data.

```r
# Code inspired from https://datayo.wordpress.com/2015/05/06/using-k-means-to-cluster-wine-dataset/
columnstokeep <- c("totaltime","Age","Gender1F2M","K0.5")
dfm2<- dfm[columnstokeep]

# Warning: using NbClust never finished even when I tried 2-4 instead of 2-15 clusters.
# install.packages("NbClust")
#library(NbClust)
#nc <- NbClust(data=dfm2,
#              min.nc=2, max.nc=4,
#              method="kmeans")
#barplot(table(nc$Best.n[1,]),
#        xlab="Numer of Clusters",
#        ylab="Number of Criteria",
#        main="Number of Clusters Chosen by 26 Criteria")


for (num_clusters in c(4,8,10,20)) {
  fit.km <- kmeans(dfm2, num_clusters)


  cluster.resid = c()

  cat ("Number of clusters:",num_clusters,"\n")
  for (i in 1:num_clusters){
    df = dfm2[ fit.km$cluster == i, ]
    mod = lm(totaltime~Age+Gender1F2M+K0.5,data=df)
    cluster.resid[i] = sqrt(mean(mod$residuals^2))
    cat("For cluster ",i," the mean error is ", cluster.resid[i], "\n")
  }
  cat ("Mean error rate overall:", mean(cluster.resid),"\n\n")
}
```

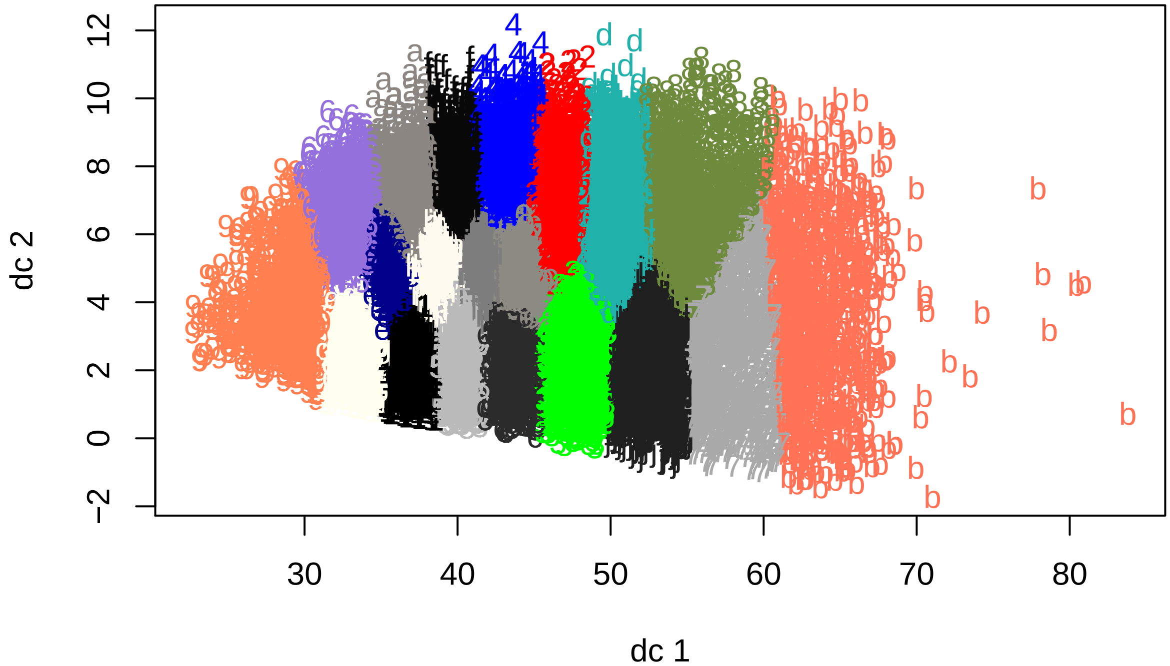
```
## Number of clusters: 4
## For cluster  1  the mean error is  19.91593
## For cluster  2  the mean error is  6.640114
## For cluster  3  the mean error is  10.80318
## For cluster  4  the mean error is  7.411255
## Mean error rate overall: 11.19262
##
## Number of clusters: 8
## For cluster  1  the mean error is  5.491411
## For cluster  2  the mean error is  15.96396
## For cluster  3  the mean error is  9.844832
## For cluster  4  the mean error is  5.893997
## For cluster  5  the mean error is  7.367676
## For cluster  6  the mean error is  5.21441
## For cluster  7  the mean error is  5.306092
## For cluster  8  the mean error is  7.563495
## Mean error rate overall: 7.830734
##
## Number of clusters: 10
## For cluster  1  the mean error is  4.808299
## For cluster  2  the mean error is  9.368798
```

```
## For cluster  3  the mean error is  5.193474
## For cluster  4  the mean error is  4.827317
## For cluster  5  the mean error is  15.21307
## For cluster  6  the mean error is  4.94271
## For cluster  7  the mean error is  7.196038
## For cluster  8  the mean error is  6.894591
## For cluster  9  the mean error is  6.321289
## For cluster  10  the mean error is  5.807631
## Mean error rate overall: 7.057322
```

```
## Warning: did not converge in 10 iterations
```

```
## Number of clusters: 20
## For cluster  1  the mean error is  4.35205
## For cluster  2  the mean error is  4.814349
## For cluster  3  the mean error is  6.350111
## For cluster  4  the mean error is  4.698862
## For cluster  5  the mean error is  4.195343
## For cluster  6  the mean error is  3.994331
## For cluster  7  the mean error is  8.459383
## For cluster  8  the mean error is  9.239134
## For cluster  9  the mean error is  4.79938
## For cluster  10  the mean error is  4.20755
## For cluster  11  the mean error is  4.059902
## For cluster  12  the mean error is  13.34765
## For cluster  13  the mean error is  5.11153
## For cluster  14  the mean error is  5.936961
## For cluster  15  the mean error is  3.65115
## For cluster  16  the mean error is  4.164899
## For cluster  17  the mean error is  4.505002
## For cluster  18  the mean error is  3.684103
## For cluster  19  the mean error is  3.734284
## For cluster  20  the mean error is  7.667055
## Mean error rate overall: 5.548652
```

```r
# Warning: this takes awhile to run because it includes all data points
# install.packages("fpc")
library(fpc)
plotcluster(dfm2, fit.km$cluster)
```



Note: as you can see, the unsupervised learning found groupings that would have difficult if not impossible to us to find on our own

Conclusion

By transforming and subsetting the data we were able to bring down the size of the residuals significantly and improve the accuracy of the model…