Predicting Boston Marathon Cutoff Times

Sam McGee

2022-09-17

Predicting Boston Marathon Cutoff Times

Historically, the Boston Marathon is one of the more fabled marathons for runners to participate in. Part of this is the long lasting legacy of the race, while another part is the selective qualification process. Unlike the other 5 World Major Marathons, Boston does not have a lottery entry system, and participants must complete a prior marathon under a specified time in order to qualify, known as a "Boston Qualifying time" or "BQ." The following table outlines the current 2022 BQ standards;

Age Group	Men's BQ	Women's BQ
18-34	3:00:00	3:30:00
35-39	3:05:00	3:35:00
40-44	3:10:00	3:40:00
45-49	3:20:00	3:50:00
50-54	3:25:00	3:55:00
55-59	3:35:00	4:05:00
60-64	3:50:00	4:20:00
65-69	4:05:00	4:35:00
70-74	4:20:00	4:50:00
75-79	4:35:00	5:05:00
80+	4:50:00	5:20:00

Despite the large field size for Boston Marathon and the level of athleticism required to BQ, in recent years the Boston Marathon has had to limit the accepted entries by imposing an additional "cutoff time" to the BQ standards in order to meet field size requirements. To accomplish this, Boston Marathon admits the fastest marathon entry times first until the allotted field size is at capacity. This means that the BQ standard is made more stringent by shortening the maximum time a successfully admitted participant could have finished their entry-marathon in. For example, in 2014 the cutoff time was 1:38, meaning the maximum accepted time for any age group was 1:38 *faster* than the BQ Standard.

Over the years, this cutoff time has been influenced largely by the number of entrants who had run a BQ time during the qualification window, as well as the allotted field size for the Boston Marathon. Knowing this, we may be able to use data from previous years to develop a model to predict the cutoff time based on the total number of runners with a BQ standard, the field size capacity for the given year, and the number of qualifiers not accepted (as a proxy estimate for the proportion of entrants with BQ standards).

Additional information can be found here;

https://www.baa.org/races/boston-marathon/qualify

Previous years' data (2012 through 2020)

The cutoff time was initially implemented in 2012, at 1:14, and prevented 3,228 athletes with the BQ standard from being registered due to the field size of 27,000 that year. The table of all current cutoff time information is shown below;

```
website <- read_html('https://www.baa.org/races/boston-marathon/qualify')
tab <- html_table(website)
Cutoff_info_unformatted <- tab[[2]]
# convert columns 2 & 4 to numeric objects, convert column 3 to date-time object
Cutoff_info <- as.data.frame(matrix(NA,
                                    nrow=nrow(Cutoff_info_unformatted),
                                    ncol=ncol(Cutoff_info_unformatted)))
Cutoff_info[,1] <- Cutoff_info_unformatted[,1]
for (i in 1:nrow(Cutoff_info_unformatted)) {
  Cutoff_info[i,2] <- Cutoff_info_unformatted[i,2] %>%
    str_replace_all(',','') %>%
    as.numeric()
  Cutoff_info[i,3] <- format(as.POSIXct(as.character(Cutoff_info_unformatted[i,3]),
                                                      format='%M:%OS'),
                             '%M:%OS')
  Cutoff_info[i,4] <- Cutoff_info_unformatted[i,4] %>%
    str_replace_all(',','') %>%
    as.numeric()
}
```

```
## Warning in Cutoff_info_unformatted[i, 4] %>% str_replace_all(",", "") %>% : NAs
## introduced by coercion
```

```
colnames(Cutoff_info) <- c('Year','FieldSize','Cutoff','NotAccepted')

Cutoff_info
```

```
##    Year FieldSize Cutoff NotAccepted
## 1  2012     27000  01:14        3228
## 2  2014     36000  01:38        2976
## 3  2015     30000  01:02        1947
## 4  2016     30000  02:28        4562
## 5  2017     30000  02:09        2957
## 6  2018     30000  03:23        5062
## 7  2019     30000  04:52        7248
## 8  2020     31500  01:39        3161
## 9  2021     20000  07:47        9215
## 10 2022     30000  00:00          NA
```

The field size for 2021 was heavily restricted due to the COVID-19 pandemic. For our analyses, the data for that year will be removed.

Webscrape information for marathon finishers that met BQ standard

Because so many marathons of varying sizes are run each year, we will use a selection of the 30 marathons each year that garnered the most BQs. These data are curated and made available by www.marathonguide.com which will also aid our analyses.

Here, we will pull the years needed for our analyses as well as clean up the tables to coerce the columns into the correct data format.

```
BQ_years <- c('2011','2012','2014','2015','2016','2017','2018','2019','2020','2022')

for (i in BQ_years) {
  website <- read_html(paste0('http://www.marathonguide.com/races/BostonMarathonQualifyingRaces.cfm?Yea
  tab <- html_table(website)
  # assign to temporary table
  temp_BQ_tab <- tab[[15]]
  # clean up "BQers" column to remove commas and assert as numeric
  BQers_cleaned <- temp_BQ_tab
  BQers_cleaned[,4] <- NA
  for(j in 1:nrow(temp_BQ_tab)) {
    BQers_cleaned[j,4] <- temp_BQ_tab[j,4] %>%
      str_replace_all(',','') %>%
      as.numeric()
  }
  assign(paste('BQ_Total_',i,sep=''),BQers_cleaned,envir = .GlobalEnv)
}
```

Testing the theory that "More BQ Runners" yields "Stricter Cutoff Times"

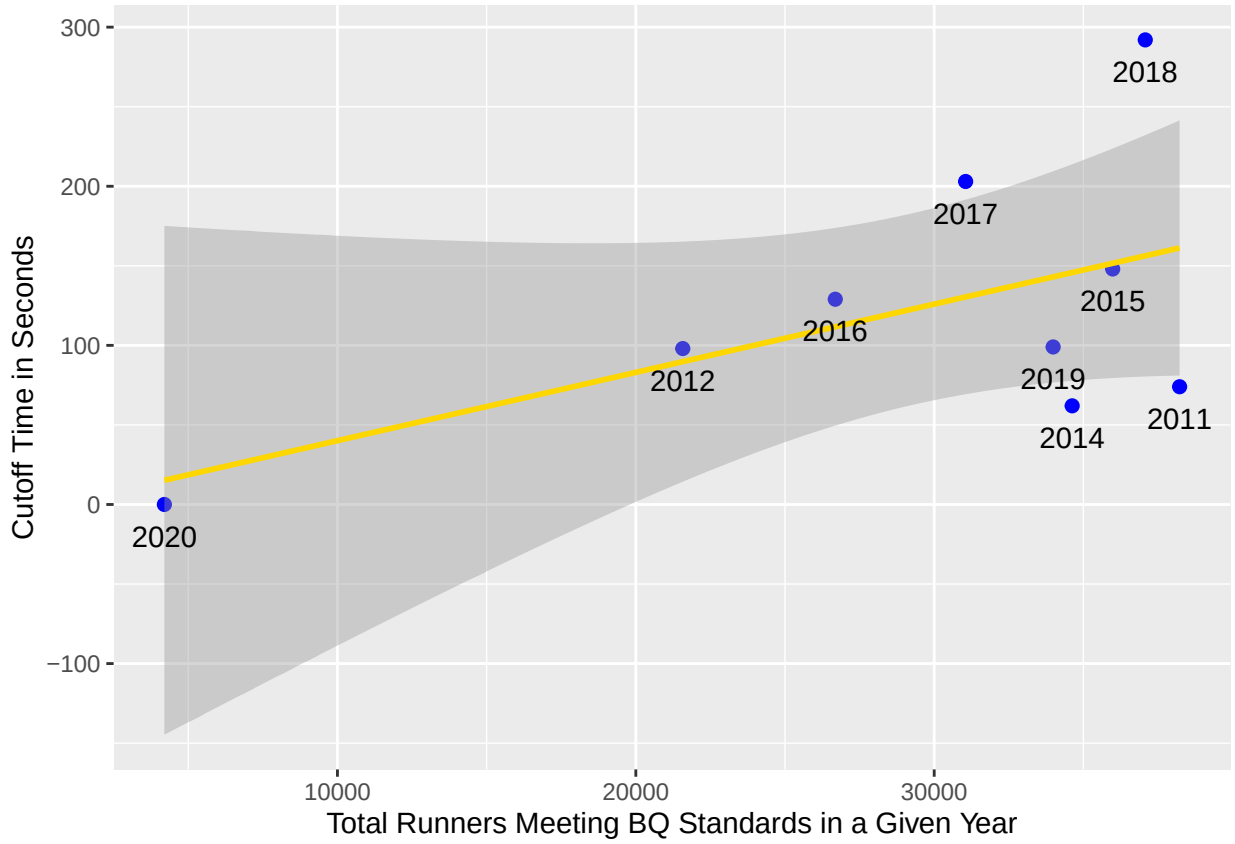
We should first look to see if there may be a correlation between the number of runners meeting the BQ standard and the ensuing cutoff time for that year.

Bear in mind; the number of runners in a given year are those who would run the following year for the Boston Marathon, so our information between "BQers in a given year" and the "Cutoff Time" needs to be staggered to account for this.

```
BQ_Total_v_Cutoff <- as.data.frame(matrix(nrow=length(BQ_years),ncol=3))
rownames(BQ_Total_v_Cutoff) <- BQ_years
colnames(BQ_Total_v_Cutoff) <- c('BQers','Cutoff','Seconds')

for (i in 1:length(BQ_years)) {
  cur_year <- BQ_years[i]
  BQ_Total_v_Cutoff[as.character(cur_year), 'BQers'] <-
    sum(get(paste0('BQ_Total_',cur_year,sep=''))[,4])
  if (cur_year == '2022') {
    break
  } else {
    cuttime_formatted <- as.POSIXct(Cutoff_info[(Cutoff_info[,1] == BQ_years[i+1]), 3], format='%M:%OS'

  BQ_Total_v_Cutoff[as.character(cur_year), 'Cutoff'] <- format(cuttime_formatted, '%M:%OS')
  BQ_Total_v_Cutoff[as.character(cur_year), 'Seconds'] <-
    (as.integer(format(cuttime_formatted, '%M'))*60) + as.integer(format(cuttime_formatted, '%OS'))
  }
}

# compare cutoff time in seconds to number of BQers
      # removing year 2022 because that cutoff time has not been determined yet
BQ_pre2022 <- subset(BQ_Total_v_Cutoff, rownames(BQ_Total_v_Cutoff) != '2022')
```

```
ggplot(BQ_pre2022,
       aes(x=BQers,y=Seconds,
           label=rownames(BQ_pre2022))) +
  geom_point(color='blue', size=2) +
  geom_smooth(method='lm', color='gold') +
  xlab('Total Runners Meeting BQ Standards in a Given Year')+
  ylab('Cutoff Time in Seconds') +
  geom_text(vjust=2)
```

```
## `geom_smooth()` using formula 'y ~ x'
```



Here we can see that there *may* be a moderate relationship between the number of runners with the BQ standard and the stringency of the ensuing cutoff time. The number of BQers and the ensuing cutoff time for 2020 was very likely influenced by the COVID-19 pandemic, as there were not many opportunities to achieve a BQ standard throughout 2020 due to the cancellation of so many races.

```
cor(BQ_pre2022$Seconds, BQ_pre2022$BQers)
```

```
## [1] 0.5444581
```

The correlation between these two variables supports our assumption that any relationship between these variables is moderate at best. Given this relationship, our resulting predictions will likely need to be treated with tempered caution.

BQ Cutoff Time, Total BQers Only

Our first model will try to predict the Boston Cutoff time (in Seconds) using only the total number of runners who achieved the BQ standard in the previous year.

```
BQfit <- lm(Seconds ~ BQers, data=BQ_pre2022)
summary(BQfit)
```

```
##
## Call:
## lm(formula = Seconds ~ BQers, data = BQ_pre2022)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -87.223 -44.031  -3.597  17.306 135.717
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.825731  77.444516  -0.036    0.972
## BQers        0.004292   0.002499   1.717    0.130
##
## Residual standard error: 76.4 on 7 degrees of freedom
## Multiple R-squared:  0.2964, Adjusted R-squared:  0.1959
## F-statistic: 2.949 on 1 and 7 DF,  p-value: 0.1296
```

The F-statistic for this regression is not significant, and therefore the cutoff score is likely influenced by other variables rather than the number of runners with a BQ standard during a given year. The R^2 value is fairly low as well, at about 0.3, so this model doesn't have a whole lot of predictive ability either. However, for the sake of this project, we'll continue to see if we can come close to predicting the 2022 cutoff time.

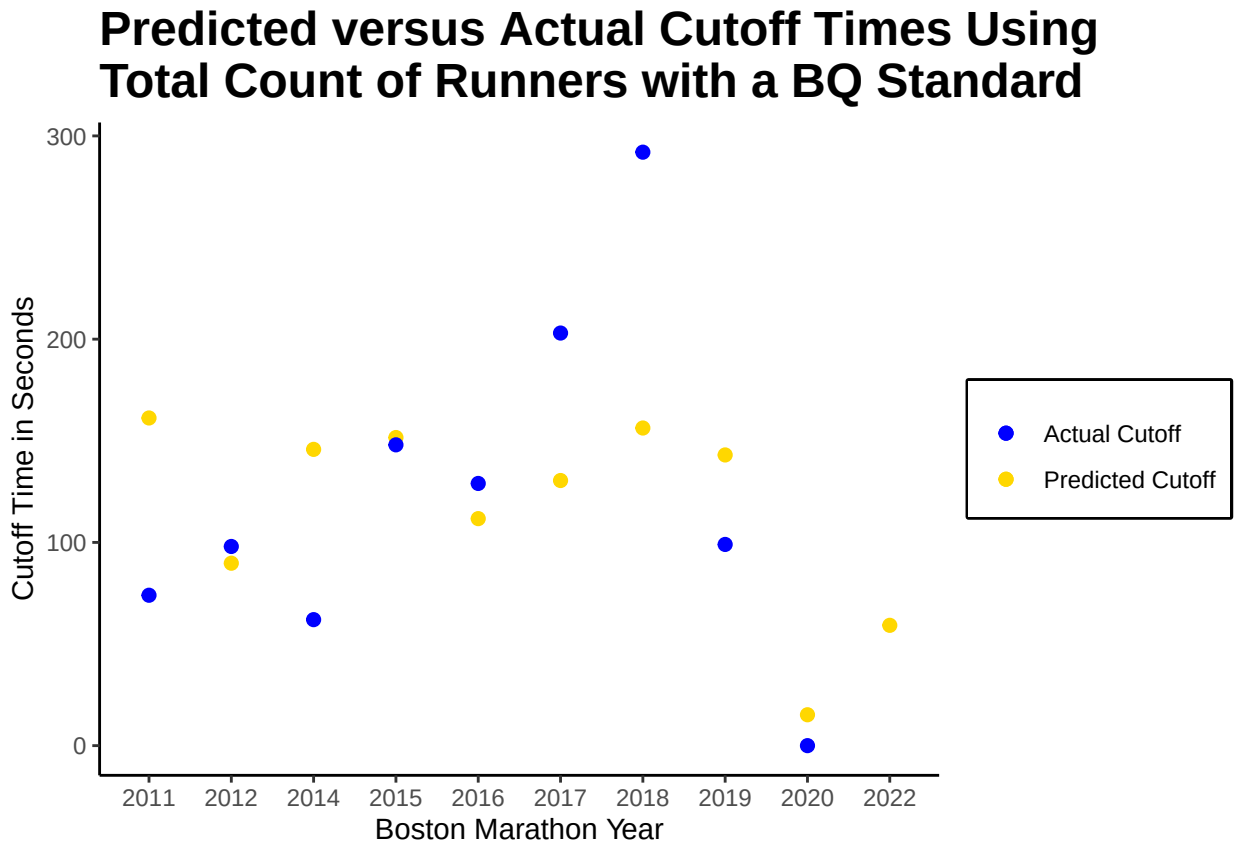
```
CutoffPredicted <- as.data.frame(predict(BQfit, newdata=BQ_Total_v_Cutoff))

colnames(CutoffPredicted) = 'PredictedCutoff'
CutoffPredicted$ActualCutoff <- BQ_Total_v_Cutoff$Seconds
CutoffPredicted
```

```
##      PredictedCutoff ActualCutoff
## 2011       161.22287           74
## 2012        89.76006           98
## 2014       145.76901           62
## 2015       151.59693          148
## 2016       111.69415          129
## 2017       130.44391          203
## 2018       156.28330          292
## 2019       143.03101           99
## 2020        15.19876            0
## 2022        59.20426           NA
```

```
ggplot(CutoffPredicted, aes(x=rownames(CutoffPredicted),y=value)) +
  geom_point(aes(y=PredictedCutoff, color='Predicted Cutoff'),size= 2) +
  geom_point(aes(y=ActualCutoff, color='Actual Cutoff'),size= 2) +
  xlab('Boston Marathon Year') +
```

```
  ylab('Cutoff Time in Seconds') +
  ggtitle('Predicted versus Actual Cutoff Times Using\nTotal Count of Runners with a BQ Standard') +
  theme(panel.background = element_rect(fill='white', color=NA),
        axis.line = element_line(color='black',size=.5),
        plot.title = element_text(size=18, face='bold'),
        legend.title = element_blank(),
        legend.box.background = element_rect(color='black',size=1),
        legend.key = element_rect(fill='white',color=NA)) +
  scale_color_manual(values = c('blue','gold'))
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```



It looks like this model really doesn't do well, and aside from the 2020 predicted Cutoff value, seems to predict a cutoff score around 110 seconds. Let's see if adding more information about the allotted Field Size can improve our predictions.

Predicting Cutoff Times using Number of Runners with BQ Standard and Boston Marathon Field Size

For this second model, we can include information about the allotted Boston Marathon Field Size. Generally, this number has been near 30,000 runners per year, although certain years have had more or less. Given that a larger Field Size would allow for more runners with the BQ standard to register, we should expect that years with a larger Field Size will have a less stringent Cutoff time.

```
BQ_field_cutoff <- as.data.frame(matrix(NA, nrow = nrow(BQ_pre2022), ncol=3))
BQ_field_cutoff[,1] <- BQ_pre2022$BQers
BQ_field_cutoff[,2] <- Cutoff_info[1:nrow(BQ_field_cutoff),2]
BQ_field_cutoff[,3] <- BQ_pre2022$Seconds
colnames(BQ_field_cutoff) <- c('BQers','FieldSize','Cutoff')
rownames(BQ_field_cutoff) <- rownames(BQ_pre2022)

BQfit_field <- lm(Cutoff ~ (BQers + FieldSize), data=BQ_field_cutoff)
summary(BQfit_field)
```

```
##
## Call:
## lm(formula = Cutoff ~ (BQers + FieldSize), data = BQ_field_cutoff)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -82.11 -48.39  -0.95  13.16 139.16
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -90.103958 202.016427  -0.446    0.671
## BQers         0.003561   0.003068   1.161    0.290
## FieldSize     0.003697   0.007819   0.473    0.653
##
## Residual standard error: 81.03 on 6 degrees of freedom
## Multiple R-squared:  0.3217, Adjusted R-squared:  0.09562
## F-statistic: 1.423 on 2 and 6 DF,  p-value: 0.3121
```

Our F-statistic here is even smaller than before, and thus our model may not be improved with the additional information. The R^2 value is only slightly improved to 0.32, but this model still does not have a great deal of predictive ability and we should take these values with a serious grain of caution. Nonetheless, we'll try to predict the 2022 cutoff time using this model.

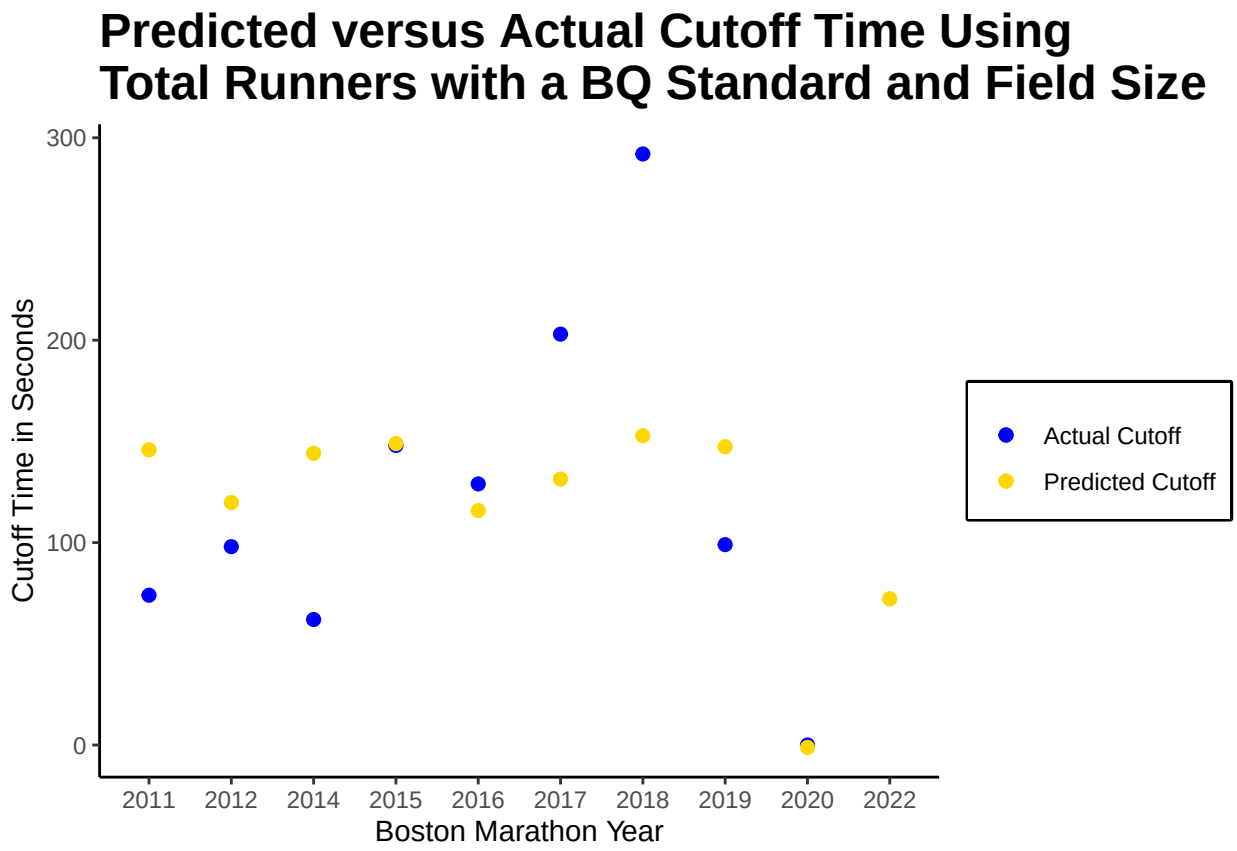
```
BQ_Total_w_Field <- BQ_Total_v_Cutoff
BQ_Total_w_Field$FieldSize <- Cutoff_info[,2]

FieldCutoffPredicted <- predict(BQfit_field, newdata = BQ_Total_w_Field)
FieldCutoffPredicted
```

```
##       2011       2012       2014       2015       2016       2017       2018
## 145.844330 119.825954 144.114020 148.949663 115.840823 131.398203 152.838118
##       2019       2020       2022
## 147.388361  -1.199473  72.287991
```

Once again, our model doesn't do a great job of predicting the cutoff times historically, and therefore we should not put too much faith into the predicted 72 second cutoff time for 2022. In terms of pure "gut-check" feeling with these results, 72 seconds or 1:12 does not seem out of place for what we might expect, so the model may be capturing some of the variance and explaining it here, but there are likely other factors we have not considered here that contribute to the final cutoff time. Out of curiosity however, we'll overlay our model's predicted cutoff time over the observed cutoff times for each year.

```r
ModelvReality <- as.data.frame(matrix(NA, nrow=10, ncol=2))
ModelvReality[,1] <- BQ_Total_v_Cutoff$Seconds
ModelvReality[,2] <- FieldCutoffPredicted
colnames(ModelvReality) <- c('ActualCutoff','PredictedCutoff')
rownames(ModelvReality) <- rownames(BQ_Total_v_Cutoff)

ggplot(ModelvReality, aes(x=rownames(ModelvReality),y=value)) +
  geom_point(aes(y=ActualCutoff, color = 'Actual Cutoff'),size= 2) +
  geom_point(aes(y=PredictedCutoff, color = 'Predicted Cutoff'),size= 2) +
  xlab('Boston Marathon Year') +
  ylab('Cutoff Time in Seconds') +
  ggtitle('Predicted versus Actual Cutoff Time Using\nTotal Runners with a BQ Standard and Field Size')+
  theme(panel.background = element_rect(fill='white', color=NA),
        axis.line = element_line(color='black',size=.5),
        plot.title = element_text(size=18, face='bold'),
        legend.title = element_blank(),
        legend.box.background = element_rect(color='black',size=1),
        legend.key = element_rect(fill='white',color=NA)) +
  scale_color_manual(values=c('blue','gold'))
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```



Conclusion

In short, this model does not appear to perform very well with the available data, and there are likely other factors not included in these data contributing to the final Boston Cutoff times. Additional methods could be considered to try to better predict the Cutoff time using these data, for instance Bayesian inference may be well-suited to this given the small sample size available. However, for our purposes today with the announcement of the official 2022 Boston Cutoff time coming soon now that registration has closed, *and* given this is a low-stakes analysis, we might consider a Cutoff near 72 seconds, or 1:12, as being one likely 2022 Boston Marathon Cutoff time.