Case_Study_4_Code

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Contents

```r
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.0 --

## v ggplot2 3.3.3     v purrr   0.3.4
## v tibble  3.0.4     v dplyr   1.0.2
## v tidyr   1.1.2     v stringr 1.4.0
## v readr   1.4.0     v forcats 0.5.0

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```r
library(hms)
library(rvest)
```

```
## Loading required package: xml2

##
## Attaching package: 'rvest'

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

## The following object is masked from 'package:readr':
##
##     guess_encoding
```

```r
library(lubridate)
```

```
##
## Attaching package: 'lubridate'

## The following object is masked from 'package:hms':
##
##     hms

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```r
library(foreach)
```

```
##
## Attaching package: 'foreach'

## The following objects are masked from 'package:purrr':
##
##     accumulate, when
```

```r
library(stringr)
library(iterators)
library(progress)
library(doParallel)
```

```
## Loading required package: parallel
```

```r
library(doSNOW)
```

```
## Loading required package: snow

##
## Attaching package: 'snow'

## The following objects are masked from 'package:parallel':
##
##     clusterApply, clusterApplyLB, clusterCall, clusterEvalQ,
##     clusterExport, clusterMap, clusterSplit, makeCluster, parApply,
##     parCapply, parLapply, parRapply, parSapply, splitIndices,
##     stopCluster
```

```r
library(dplyr)
library(states)
```

```
##
## Attaching package: 'states'
```

```
## The following object is masked from 'package:readr':
##
##     parse_date
```

```
library(ggplot2)
library(ggthemes)
library(SiZer)
library(plotly)
```

```
##
## Attaching package: 'plotly'

## The following object is masked from 'package:ggplot2':
##
##     last_plot

## The following object is masked from 'package:stats':
##
##     filter

## The following object is masked from 'package:graphics':
##
##     layout
```

```
years = c(1999:2012)
division = 'Overall+Women'
section = '10M'
sex = 'W'
```

Functions #The gen_Link function will generates the link with the query parameters for the searchable database

```
gen_Link = function(year,division,section,page=1,sex){

  paste0( 'http://www.cballtimeresults.org/performances'
          ,'?division=',division,'&page=',page,
          '&section=',section, '&sex=',sex,
          '&utf8=%E2%9C%93','&year=',year)
          #,'?utf8=%E2%9C%93&section=',section
          #,'&year=',year,'&division=',division,'&page=', page)

}
```

The gen__Table function will parse through the table of 20 records and 15 observations

and parse the table into its own data frame from xml2 read)html function and then use

the pipe operator to use rvest nodes to find the table structure

then the fucntion will insert the metadata for the query parameters of year, division, section, page, source link and sex

```
gen_Table = function(year,division,section,page, sex){


  #use gen_link function to get link to page
  genlink=gen_Link(year,division,section,page=page, sex=sex)

  #read the page, and grab to 'table' tag
  single_table = xml2::read_html(genlink) %>%
    rvest::html_nodes("table")  %>%
    rvest::html_table(fill=TRUE)

  #get the table and add metadata for the query parameters
  table_out = single_table[[1]] %>%
    mutate(year=year, divisionTitle=division, section=section, page=page, source=genlink, sex = sex)

}
```

This function will use all available cores on machine

It will process the years in parrell.

This code has been adapted from

https://github.com/ngupta23/ds7333_qtw/blob/master/case_study_2/submission_Kannan_Moro_Gupta/code/CS2_ETL.Rmd

https://cran.r-project.org/web/packages/doSNOW/doSNOW.pdf

https://stackoverflow.com/questions/36794063/r-foreach-from-single-machine-to-cluster

https://cran.r-project.org/web/packages/progress/progress.pdf

https://www.r-bloggers.com/2013/08/the-wonders-of-foreach/

```
scrapeTables  = function(years,division,section, sex,  max_itr = 500){


library(progress)
library(doParallel)
library(doSNOW)

    #Initialize Parrellel Process to detect number of cores
    #https://cran.r-project.org/web/packages/doSNOW/doSNOW.pdf
    #https://stackoverflow.com/questions/36794063/r-foreach-from-single-machine-to-cluster

    #Generate and register initial clusters based on cores, otherwise, this is a long process
    cl = makeCluster(detectCores())
    doSNOW::registerDoSNOW(cl)

    #Generate progress bar for the parallel loop based on number of years
    #https://cran.r-project.org/web/packages/progress/progress.pdf
    progBar = progress::progress_bar$new(total = length(years),format='[:bar] :percent :eta')
    progress = function(n) progBar$tick()

    #Initialize a parallel loop per each year
    #Intialize tableRaw as empty to loop to be populated as a table dataframe from gen_Table function
    tableRaw=NULL

    #tableRaw will now use for each using years as the iterator to use .combine to rbind
    #.export will do the gen_Table and gen_Link functions simultanlously and
```

```
    #options.snow will show the progress bar
    # the %dopar% will process all the years simultaneously.
    #https://www.r-bloggers.com/2013/08/the-wonders-of-foreach/
    tableRaw = foreach(y=years
                       ,.combine=rbind,.export=c('gen_Table','gen_Link')
                       ,.options.snow = list(progress=progress)) %dopar%
      {

        library(foreach)
        library(dplyr)
        #intialize isCompleted variable as FALSE for bool conditions to see if loop has been completed
        isCompleted=FALSE

        #Initiate loop since most pages are 487, we will only loop for the iterations for max_itr
        tableRaw=foreach(p=c(1:max_itr),.combine=rbind) %do%
          if(!isCompleted) {
            message('getting year:',y, ' page:',p,appendLF = F)
            #get the table of the current page
            table = gen_Table(year=y
                              ,division=division
                              ,section=section
                              ,page=p
                              ,sex=sex)
            message(' rows:',nrow(table))
            isCompleted = nrow(table)==0 #if there is record, we are at the last page, no need to read
            return(table)
          }
        return(tableRaw)
      }
    #Deactivate the cluster of cores
    stopCluster(cl)
    #save the raw data to rda format for later processing based on gender
    saveRDS(tableRaw,file=paste0('CB',sex,'tableRaw.rds'))

  return(tableRaw)
}
```

The purpose of this function is to transform the raw tables from the scrape

https://stackoverflow.com/questions/50040968/convert-a-duration-hms-to-seconds

https://stackoverflow.com/questions/10835908/is-there-a-way-to-convert-mmss-00-to-seconds-00

https://stackoverflow.com/questions/24173194/remove-parentheses-and-text-within-from-strings-in-r

```
tableTransform =function(data_df, cols_to_remove=NULL){
  dataDF = data_df %>%
    #Seperate Home town into seperate columns
    separate(col = 'Hometown', c('HomeTown', 'HomeState'), sep = ',', extra = 'merge', remove = TRUE, f
    #Seperate PiS/TiS into seperate columns
```

```
    separate(col='PiS/TiS',c('PiS','TiS'),sep='\\/'
             ,extra='drop',remove=TRUE) %>%
    #Seperate PiD/TiD into seperate columns
    separate(col='PiD/TiD',c('PiD','TiD'),sep='\\/'
             ,extra='drop',remove=TRUE) %>%
    #Trim the casted upper HomeTown strings of whitespace
    mutate(HomeTown = toupper(trimws(HomeTown))
           , HomeState = toupper(trimws(HomeState))
           , HomeTown = ifelse(HomeTown %in% c('NR', '', NULL), NA, toupper(trimws(HomeTown)))
           , HomeState = ifelse(HomeState %in% c('NR', '', NULL), NA, toupper(trimws(HomeState)))
           #Check if HomeState is in state.abb or DC and return USA else return the HomeTown as the Cou
           , HomeCountry = ifelse(HomeState %in% c(state.abb, "DC"), "USA", HomeTown)
           #Remove White Space
           , PiS = ifelse(trimws(PiS) %in% c('NR', '', NULL), NA, trimws(PiS))
           , TiS = ifelse(trimws(TiS) %in% c('NR', '', NULL), NA, trimws(TiS))
           , PiD = ifelse(trimws(PiD) %in% c('NR', '', NULL), NA, trimws(PiD))
           , TiD = ifelse(trimws(TiD) %in% c('NR', '', NULL), NA, trimws(TiD))
           , Division = ifelse(trimws(Division) %in% c('NR', '', NULL), NA, trimws(Division))
           # Normalize Time to seconds and minutes
           , RawTime = strptime(Time, format='%H:%M:%S')
           , RawTime_S = RawTime$hour * 3600 + RawTime$min * 60 + RawTime$sec
           , RawTime_M = as.numeric(RawTime_S)/60
           , RawPace = strptime(Pace, format = "%M:%OS")
           , RawPace_S = RawPace$min * 60 + RawPace$sec
           #Normalize Age where 'NR' as NA
           , Age = ifelse(Age %in% c("NR"), NA, Age)
           #Cast Variables as appropriate dtypes
           , Age = as.numeric(Age)
           , RawTime_S = as.numeric(RawTime_S)
           , RawPace_S = as.numeric(RawPace_S)
           , RawPace_M = as.numeric(RawPace_S)/60
           , year = as.factor(year)
           #Remove the (<Sex>) from the names
           #, Name = str_replace(Name, " \\s*\\([^\\)]+\\)", '')
           )
  #Remove columns we do not want
  dataDF = dataDF %>% select (-all_of(c(cols_to_remove)))

  return(dataDF %>% select(c( Age, year,  HomeTown, HomeState, HomeCountry, RawTime_S, RawTime_M, RawPa
}
```

Perform Scrape

Caution takes a long time without hexacore machine

```
#Women_table = scrapeTables(years=years,division = division,section=section,sex = sex, max_itr = 500)
```

```
#men_table = scrapeTables(years=years,division = 'Overall+Men',section=section,sex = "M", max_itr = 500
```

Load tables from file

```r
mens_table <- readRDS("/media/andrew/Seagate Backup Plus Drive/Documents/School/HomeWork/QTW/DS7333/CASE

womens_table <- readRDS("/media/andrew/Seagate Backup Plus Drive/Documents/School/HomeWork/QTW/DS7333/CA
```

Preview of raw table scrapes

```r
head(womens_table, n = 10)
```

```
##        Race                  Name Age    Time Pace PiS/TiS Division PiD/TiD
## 1  1999 10M        Jane Omoro (W)  26 0:53:37 5:22  1/2358    W2529   1/559
## 2  1999 10M       Jane Ngotho (W)  29 0:53:38 5:22  2/2358    W2529   2/559
## 3  1999 10M Lidiya Grigoryeva (W)  NR 0:53:40 5:22  3/2358       NR      NR
## 4  1999 10M     Eunice Sagero (W)  20 0:53:55 5:24  4/2358    W2024   1/196
## 5  1999 10M   Alla Zhilyayeva (W)  29 0:54:08 5:25  5/2358    W2529   3/559
## 6  1999 10M    Teresa Wanjiku (W)  24 0:54:10 5:25  6/2358    W2024   2/196
## 7  1999 10M     Elana Viazova (W)  38 0:54:29 5:27  7/2358    W3539   1/387
## 8  1999 10M      Gladys Asiba (W)  NR 0:54:50 5:29  8/2358       NR      NR
## 9  1999 10M      Nnenna Lynch (W)  27 0:55:39 5:34  9/2358    W2529   4/559
## 10 1999 10M   Margaret Kagiri (W)  30 0:55:43 5:34 10/2358    W3034   1/529
##       Hometown year divisionTitle section page
## 1        Kenya 1999 Overall+Women     10M    1
## 2        Kenya 1999 Overall+Women     10M    1
## 3       Russia 1999 Overall+Women     10M    1
## 4        Kenya 1999 Overall+Women     10M    1
## 5       Russia 1999 Overall+Women     10M    1
## 6        Kenya 1999 Overall+Women     10M    1
## 7      Ukraine 1999 Overall+Women     10M    1
## 8        Kenya 1999 Overall+Women     10M    1
## 9  Concord, MA 1999 Overall+Women     10M    1
## 10       Kenya 1999 Overall+Women     10M    1
##
## 1  http://www.cballtimeresults.org/performances?division=Overall+Women&page=1&section=10M&sex=W&utf8=
## 2  http://www.cballtimeresults.org/performances?division=Overall+Women&page=1&section=10M&sex=W&utf8=
## 3  http://www.cballtimeresults.org/performances?division=Overall+Women&page=1&section=10M&sex=W&utf8=
## 4  http://www.cballtimeresults.org/performances?division=Overall+Women&page=1&section=10M&sex=W&utf8=
## 5  http://www.cballtimeresults.org/performances?division=Overall+Women&page=1&section=10M&sex=W&utf8=
## 6  http://www.cballtimeresults.org/performances?division=Overall+Women&page=1&section=10M&sex=W&utf8=
## 7  http://www.cballtimeresults.org/performances?division=Overall+Women&page=1&section=10M&sex=W&utf8=
## 8  http://www.cballtimeresults.org/performances?division=Overall+Women&page=1&section=10M&sex=W&utf8=
## 9  http://www.cballtimeresults.org/performances?division=Overall+Women&page=1&section=10M&sex=W&utf8=
## 10 http://www.cballtimeresults.org/performances?division=Overall+Women&page=1&section=10M&sex=W&utf8=
##    sex
## 1    W
## 2    W
## 3    W
## 4    W
## 5    W
## 6    W
```

```
## 7    W
## 8    W
## 9    W
## 10   W
```

Perform the table transformation and remove metadata columns and other columns

```
cols_for_remove = c("divisionTitle", "source", "Pace", "Time", "RawTime", "RawPace", "page", "Race", "s
mens_table_T = tableTransform(mens_table, cols_to_remove = all_of(cols_for_remove))
```

```
## Warning: Expected 2 pieces. Missing pieces filled with `NA` in 3 rows [42230,
## 69995, 69996].
```

```
## Warning: Expected 2 pieces. Missing pieces filled with `NA` in 31 rows [1207,
## 2797, 7583, 9206, 9255, 10991, 12255, 13046, 14812, 15842, 21756, 21819, 22093,
## 22709, 23342, 23680, 25014, 25424, 25443, 25750, ...].
```

```
womens_table_T = tableTransform(womens_table, cols_to_remove = all_of(cols_for_remove))
```

```
## Warning: Expected 2 pieces. Missing pieces filled with `NA` in 20 rows [3, 8,
## 17, 2176, 7135, 7766, 8777, 9680, 10831, 18391, 18399, 18981, 19694, 20735,
## 21480, 22189, 28388, 29223, 38455, 47506].
```

Preview of the transformed table

```
head(womens_table_T, n = 10)
```

```
##    Age year HomeTown HomeState HomeCountry RawTime_S RawTime_M RawPace_S
## 1   26 1999    KENYA      <NA>       KENYA      3217  53.61667       322
## 2   29 1999    KENYA      <NA>       KENYA      3218  53.63333       322
## 3   NA 1999   RUSSIA      <NA>      RUSSIA      3220  53.66667       322
## 4   20 1999    KENYA      <NA>       KENYA      3235  53.91667       324
## 5   29 1999   RUSSIA      <NA>      RUSSIA      3248  54.13333       325
## 6   24 1999    KENYA      <NA>       KENYA      3250  54.16667       325
## 7   38 1999  UKRAINE      <NA>     UKRAINE      3269  54.48333       327
## 8   NA 1999    KENYA      <NA>       KENYA      3290  54.83333       329
## 9   27 1999  CONCORD        MA         USA      3339  55.65000       334
## 10  30 1999    KENYA      <NA>       KENYA      3343  55.71667       334
##    RawPace_M sex section PiS  TiS  PiD  TiD
## 1   5.366667   W     10M   1 2358    1  559
## 2   5.366667   W     10M   2 2358    2  559
## 3   5.366667   W     10M   3 2358 <NA> <NA>
## 4   5.400000   W     10M   4 2358    1  196
## 5   5.416667   W     10M   5 2358    3  559
## 6   5.416667   W     10M   6 2358    2  196
## 7   5.450000   W     10M   7 2358    1  387
## 8   5.483333   W     10M   8 2358 <NA> <NA>
## 9   5.566667   W     10M   9 2358    4  559
## 10  5.566667   W     10M  10 2358    1  529
```

```r
dim(womens_table_T)
```

```
## [1] 75866    15
```

```r
summary(womens_table_T)
```

```
##       Age             year         HomeTown          HomeState
##  Min.   : 7.00   2012   : 9727   Length:75866       Length:75866
##  1st Qu.:27.00   2011   : 9030   Class :character   Class :character
##  Median :32.00   2010   : 8853   Mode  :character   Mode  :character
##  Mean   :33.85   2009   : 8323
##  3rd Qu.:39.00   2008   : 6395
##  Max.   :87.00   2007   : 5532
##  NA's   :20      (Other):28006
##  HomeCountry          RawTime_S       RawTime_M        RawPace_S
##  Length:75866       Min.   : 3104   Min.   : 51.73   Min.   : 310.0
##  Class :character   1st Qu.: 5319   1st Qu.: 88.65   1st Qu.: 532.0
##  Mode  :character   Median : 5849   Median : 97.48   Median : 585.0
##                     Mean   : 5893   Mean   : 98.22   Mean   : 589.4
##                     3rd Qu.: 6418   3rd Qu.:106.97   3rd Qu.: 642.0
##                     Max.   :10651   Max.   :177.52   Max.   :1065.0
##
##    RawPace_M          sex              section              PiS
##  Min.   : 5.167   Length:75866       Length:75866       Length:75866
##  1st Qu.: 8.867   Class :character   Class :character   Class :character
##  Median : 9.750   Mode  :character   Mode  :character   Mode  :character
##  Mean   : 9.823
##  3rd Qu.:10.700
##  Max.   :17.750
##
##      TiS                PiD                TiD
##  Length:75866       Length:75866       Length:75866
##  Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character
##
##
##
##
```

Preview of NA columns

```r
columns = c("Age", "year",  "HomeTown", "HomeState", "HomeCountry", "RawTime_S", "RawTime_M", "RawPace_S

womens_table_T_na = womens_table_T %>% filter_at(vars(all_of(columns)),any_vars(is.na(.)))

head(womens_table_T_na, n = 10)
```

```
##    Age year  HomeTown HomeState HomeCountry RawTime_S RawTime_M RawPace_S
## 1   26 1999     KENYA      <NA>       KENYA      3217  53.61667       322
## 2   29 1999     KENYA      <NA>       KENYA      3218  53.63333       322
```

```
## 3   NA 1999    RUSSIA      <NA>      RUSSIA      3220  53.66667       322
## 4   20 1999     KENYA      <NA>       KENYA      3235  53.91667       324
## 5   29 1999    RUSSIA      <NA>      RUSSIA      3248  54.13333       325
## 6   24 1999     KENYA      <NA>       KENYA      3250  54.16667       325
## 7   38 1999   UKRAINE      <NA>     UKRAINE      3269  54.48333       327
## 8   NA 1999     KENYA      <NA>       KENYA      3290  54.83333       329
## 9   30 1999     KENYA      <NA>       KENYA      3343  55.71667       334
## 10  NA 1999 LANCASTER        PA         USA      3576  59.60000       358
##    RawPace_M sex section PiS  TiS  PiD  TiD
## 1   5.366667   W     10M   1 2358    1  559
## 2   5.366667   W     10M   2 2358    2  559
## 3   5.366667   W     10M   3 2358 <NA> <NA>
## 4   5.400000   W     10M   4 2358    1  196
## 5   5.416667   W     10M   5 2358    3  559
## 6   5.416667   W     10M   6 2358    2  196
## 7   5.450000   W     10M   7 2358    1  387
## 8   5.483333   W     10M   8 2358 <NA> <NA>
## 9   5.566667   W     10M  10 2358    1  529
## 10  5.966667   W     10M  17 2358 <NA> <NA>
```

```r
dim(womens_table_T_na)
```

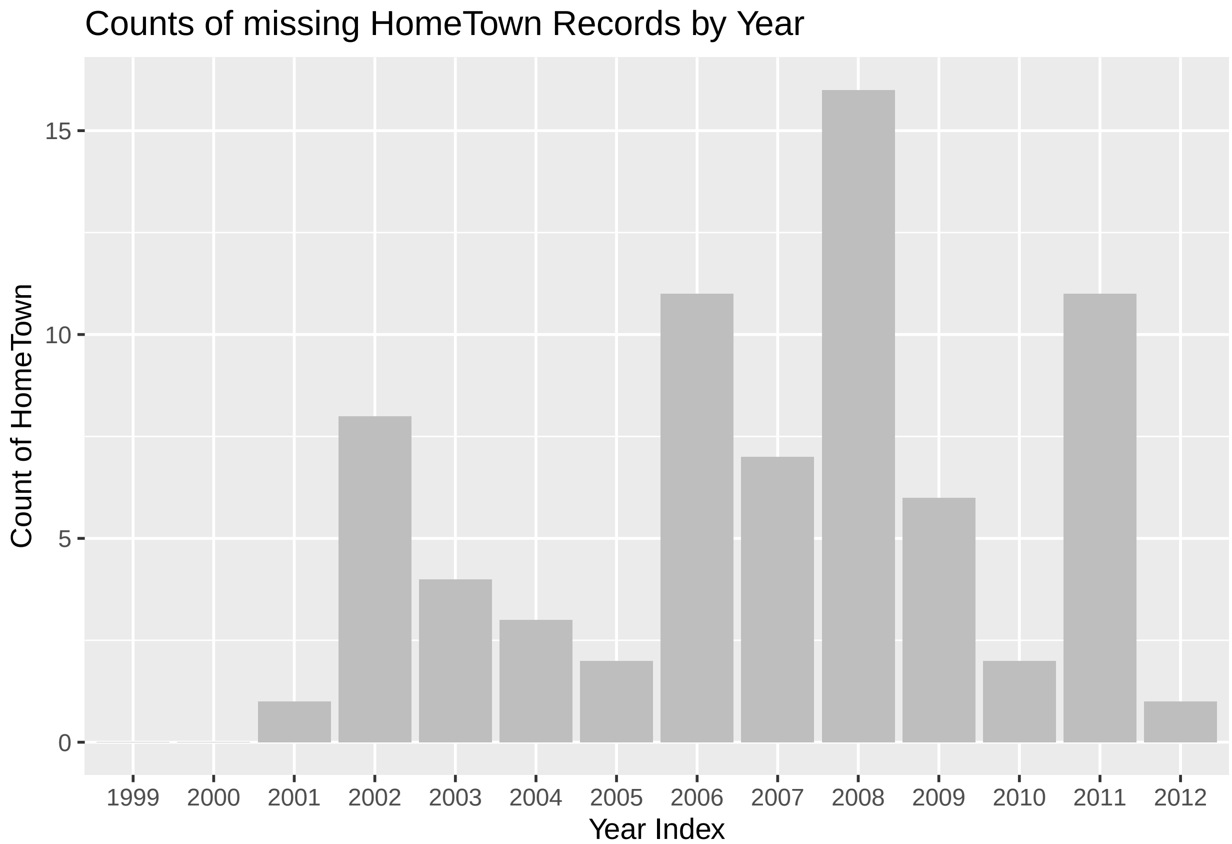
```
## [1] 262  15
```

Create a DF containing the NA counts of each feature

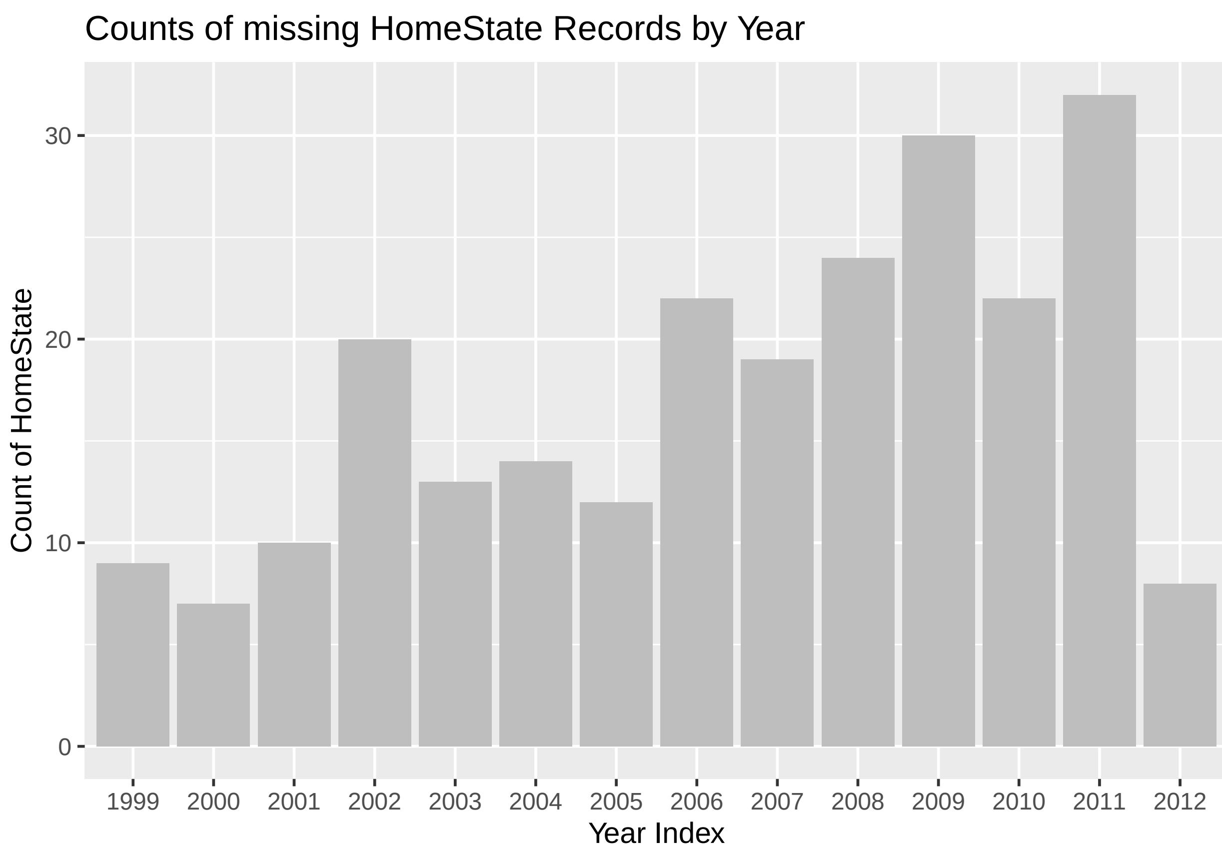
```r
na_df = data.frame(rowsum(+(is.na(womens_table_T)), womens_table_T$year))
na_df = cbind(year_idx = rownames(na_df), na_df)
```

Plots of prominate NA columns

```r
p1_na = ggplot(na_df, aes(x=year_idx, y=HomeTown)) + geom_bar(stat = "identity", fill = "grey") + labs(
p1_na
```




```
p2_na = ggplot(na_df, aes(x=year_idx, y=HomeState)) + geom_bar(stat = "identity", fill = "grey") +  labs

p2_na
```



We will remove NAs and only focus on completed records and rewmove NAs for further processing and reindex the table.

```
womens_table_T = womens_table_T[complete.cases(womens_table_T), ]
row.names(womens_table_T) = NULL
```

Final dataframe metadata

```
head(womens_table_T, n = 10)
```

```
##    Age year      HomeTown HomeState HomeCountry RawTime_S RawTime_M RawPace_S
## 1   27 1999       CONCORD        MA         USA      3339  55.65000       334
## 2   30 1999        EUGENE        OR         USA      3373  56.21667       337
## 3   37 1999   BLOOMINGTON        MN         USA      3443  57.38333       344
## 4   39 1999   ALBUQUERQUE        NM         USA      3444  57.40000       344
## 5   32 1999   CHAPEL HILL        NC         USA      3471  57.85000       347
## 6   30 1999    WASHINGTON        DC         USA      3485  58.08333       349
## 7   31 1999      COLUMBIA        MD         USA      3516  58.60000       352
## 8   25 1999    ALEXANDRIA        VA         USA      3582  59.70000       358
## 9   38 1999 SILVER SPRING        MD         USA      3588  59.80000       359
## 10  31 1999     ROCKVILLE        MD         USA      3630  60.50000       363
```

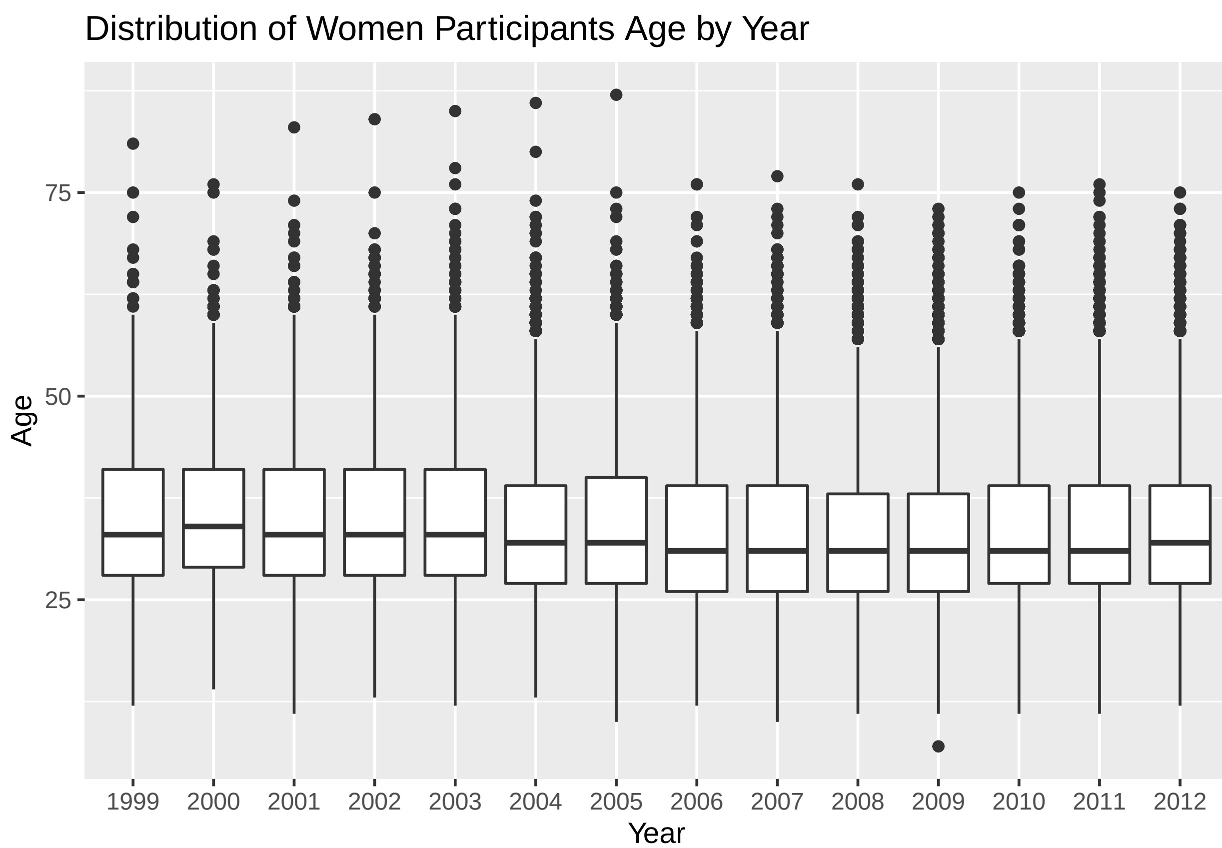
```
##    RawPace_M sex section PiS  TiS PiD TiD
## 1   5.566667   W     10M   9 2358   4 559
## 2   5.616667   W     10M  11 2358   2 529
## 3   5.733333   W     10M  12 2358   2 387
## 4   5.733333   W     10M  13 2358   3 387
## 5   5.783333   W     10M  14 2358   3 529
## 6   5.816667   W     10M  15 2358   4 529
## 7   5.866667   W     10M  16 2358   5 529
## 8   5.966667   W     10M  18 2358   5 559
## 9   5.983333   W     10M  19 2358   4 387
## 10  6.050000   W     10M  20 2358   6 529
```

```
Descriptions = c('Participant Age', 'Year of race', 'Participant Home Town', 'Participant Home State',
womensTableInfo = data.frame(Feature = names(womens_table_T), Description = Descriptions , Type = sappl
womensTableInfo
```

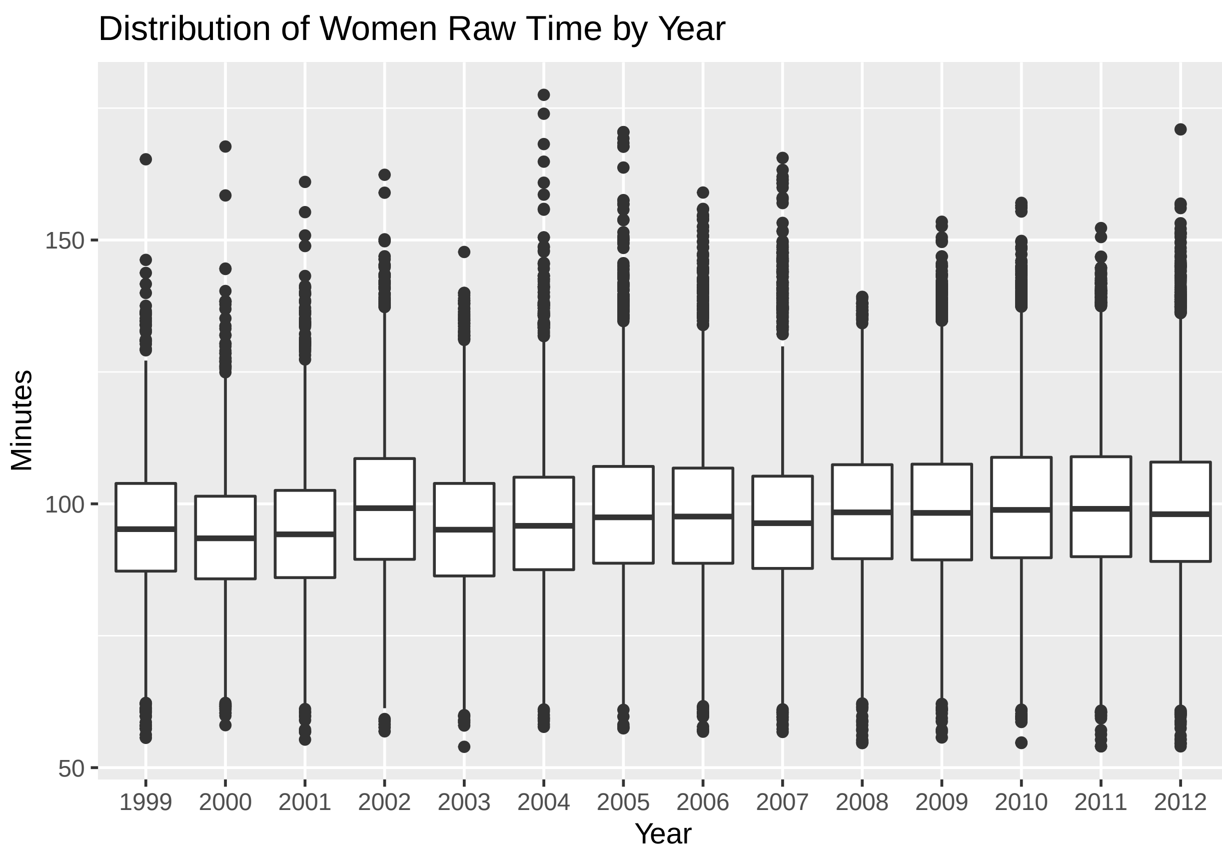
```
##        Feature                       Description      Type
## 1          Age                   Participant Age    double
## 2         year                      Year of race   integer
## 3     HomeTown             Participant Home Town character
## 4    HomeState            Participant Home State character
## 5  HomeCountry          Participant Home Country character
## 6    RawTime_S     Participant's Time in Seconds    double
## 7    RawTime_M     Participant's Time in Minutes    double
## 8    RawPace_S Participants Mile Pace in Seconds    double
## 9    RawPace_M Participants Mile Pace in Minutes    double
## 10         sex                            Gender character
## 11     section                  Participant Race character
## 12         PiS                   Position in Sex character
## 13         TiS                      Total in Sex character
## 14         PiD              Position in Division character
## 15         TiD                 Total in Division character
```

Generate plots of quick EDA for ages accross years

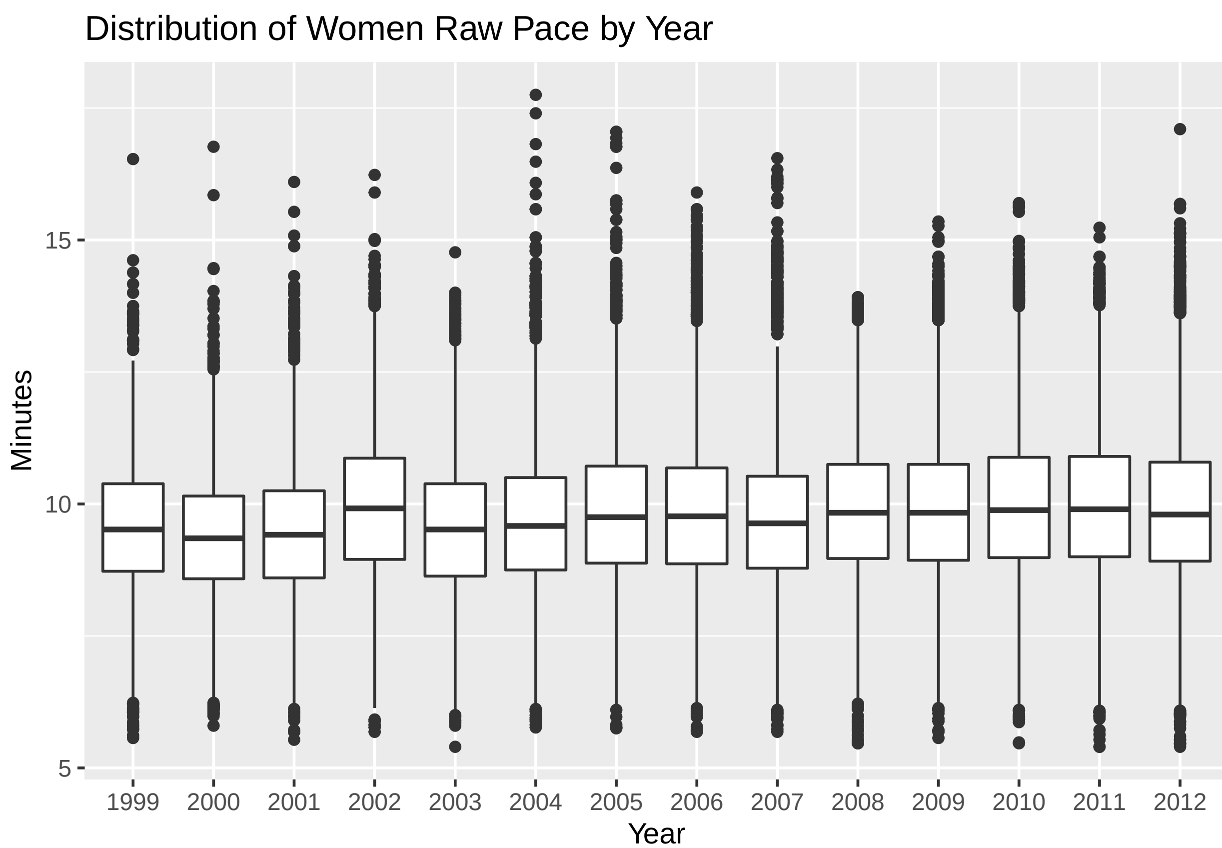
```
plot_data_age = ggplot(womens_table_T, aes(x = year, y = Age)) + geom_boxplot() + labs(title = "Distrib

plot_data_age
```




```
plot_data_time = ggplot(womens_table_T, aes(x = year, y = RawTime_M)) + geom_boxplot() + labs(title = "I

plot_data_time
```




```
plot_data_Pace = ggplot(womens_table_T, aes(x = year, y = RawPace_M)) + geom_boxplot() + labs(title = "I

plot_data_Pace
```



BRIAN GAITHER ##
##

Creating an age bin column for analysis

```
womens_table_T$AgeBin = cut(womens_table_T$Age, breaks=c(0,5,15,25,35,45,55,65,75,85,95),labels=c("1-5"
```

Creating a column to bin the pace in minutes for later analysis

```
womens_table_T$PaceBin = cut(womens_table_T$RawPace_M, breaks=c(0,5,5.5,6,6.5,7,7.5,8,8.5,9,9.5,10,10.5
                 labels=c("1-5","5.1-5.5","5.5-6","6-6.5","6.5-7","7-7.5","7.5-8","8-8.5","8.5-9","9-9.
```

write out the dataframe for later retrieval

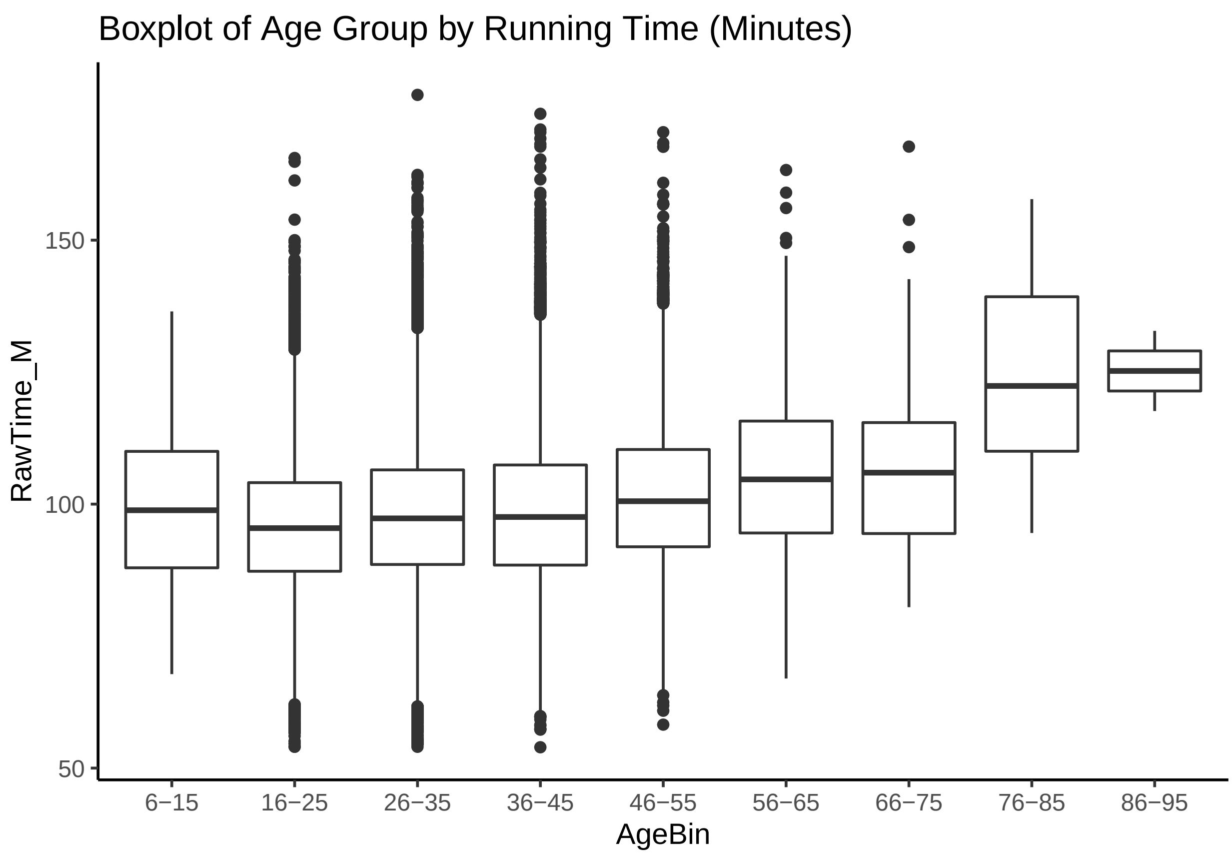
```
#write.csv(womens_table_T,"C:/Users/blgai/OneDrive/Documents/School/SMU/Spring 2021/Quantifying the Wor
```

read the data into dataframe

```
#womens_table_T = read.csv("C:/Users/blgai/OneDrive/Documents/School/SMU/Spring 2021/Quantifying the Wo
```

```
ggplot(womens_table_T, aes(x = Age, y=RawTime_M)) +
  geom_hex() +
  theme_bw() +
  labs(title="Scatter Plot of Female Runners:  Age vs Time in Minutes")
```


```r
f = ggplot(womens_table_T)
f + geom_boxplot(mapping = aes(x=AgeBin, y=RawTime_M)) + theme_classic() + labs(title="Boxplot of Age G
```



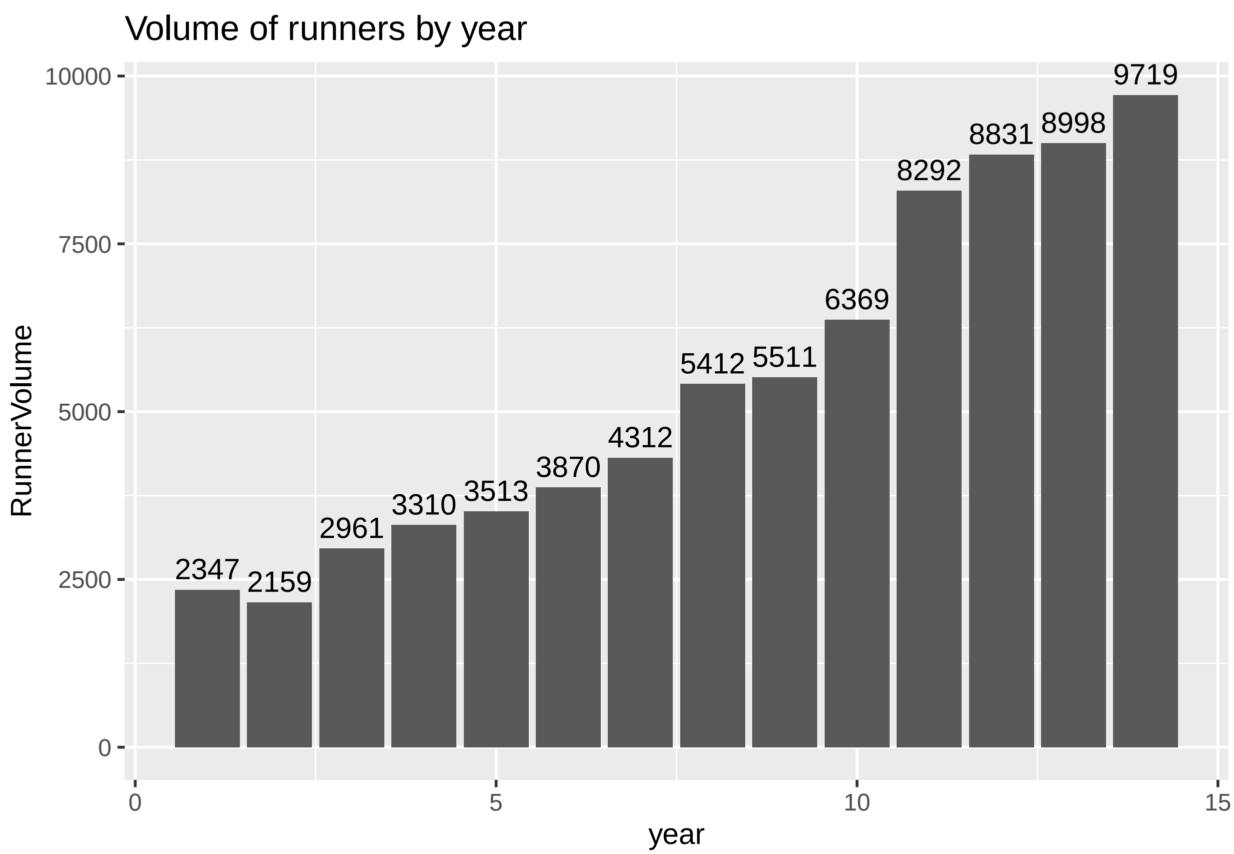
Let's examine overall runner volume

```
dfRunVol = womens_table_T %>% group_by(year) %>% tally()
dfRunVol$year = as.integer(dfRunVol$year)
names(dfRunVol)[2] <- "RunnerVolume"
head(dfRunVol)
```

```
## # A tibble: 6 x 2
##    year RunnerVolume
##   <int>        <int>
## 1     1         2347
## 2     2         2159
## 3     3         2961
## 4     4         3310
## 5     5         3513
## 6     6         3870
```

Plotting out volume of runners by year

```
ggplot(dfRunVol, aes(x=year, y=RunnerVolume)) +
  geom_col() +
  labs(title="Volume of runners by year") +
geom_text(aes(label = RunnerVolume), vjust = -0.5)
```



let's see how well we can predict the volume of racers in the 15th year

```
lmRunVol = lm(RunnerVolume ~ year, data = dfRunVol)
lmRunVol$coefficients
```

```
## (Intercept)        year
##    800.1978    613.3451
```

Below we see we have a statistically significant slope and intercept

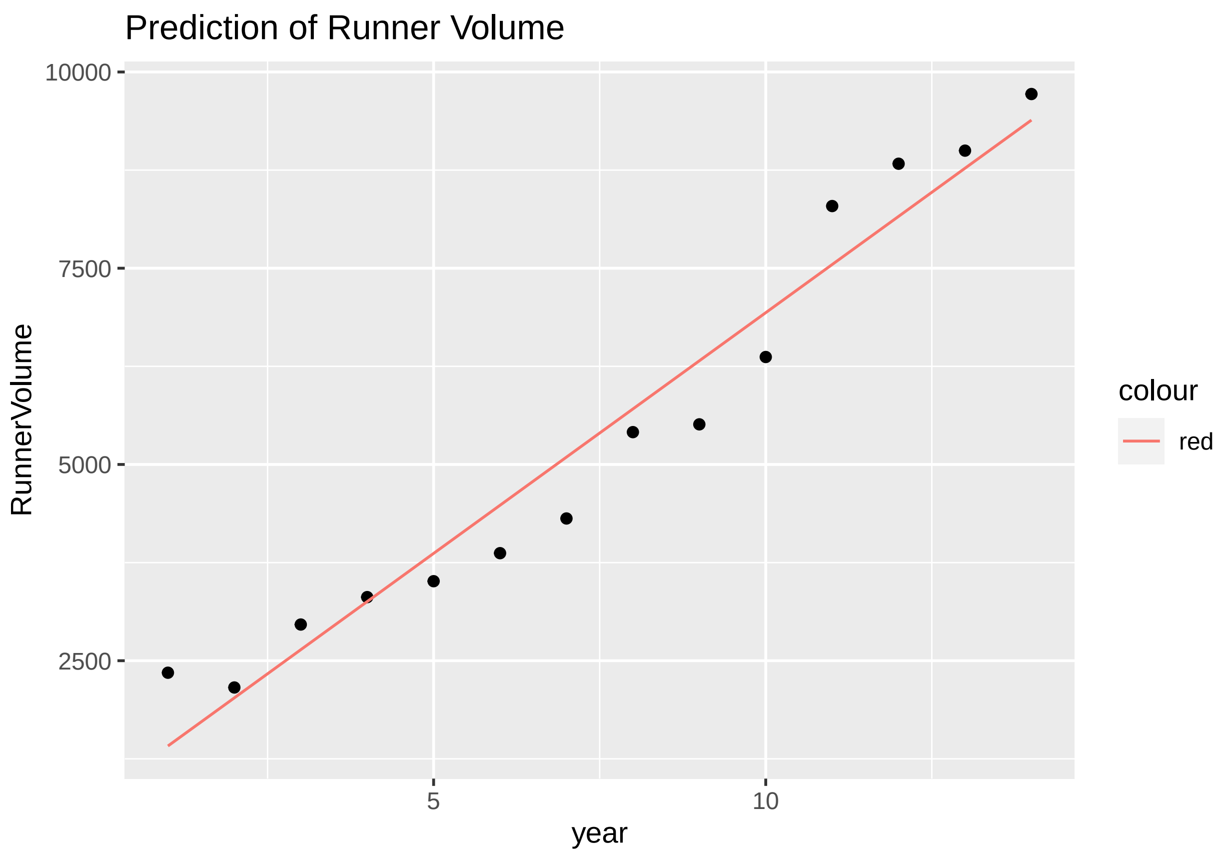
```
summary(lmRunVol)
```

```
##
## Call:
## lm(formula = RunnerVolume ~ year, data = dfRunVol)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -809.30 -511.97   94.27  329.17  933.46
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   800.20     339.09    2.36   0.0361 *
## year          613.35      39.82   15.40 2.87e-09 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 600.7 on 12 degrees of freedom
## Multiple R-squared:  0.9518, Adjusted R-squared:  0.9478
## F-statistic: 237.2 on 1 and 12 DF,  p-value: 2.872e-09
```

See how well our line fits

```r
preds = predict(lmRunVol)
ggplot(dfRunVol, aes(x=year, y=RunnerVolume)) + geom_point() + geom_line(dfRunVol, mapping = aes(x=year
```



How many runners are predicted to attend in 2013 (year 15)

```r
y_hat = 800.5 + (15*613.4)

print(paste0("Predicted volume of runners in 2013 is: ", y_hat))
```

```
## [1] "Predicted volume of runners in 2013 is: 10001.5"
```

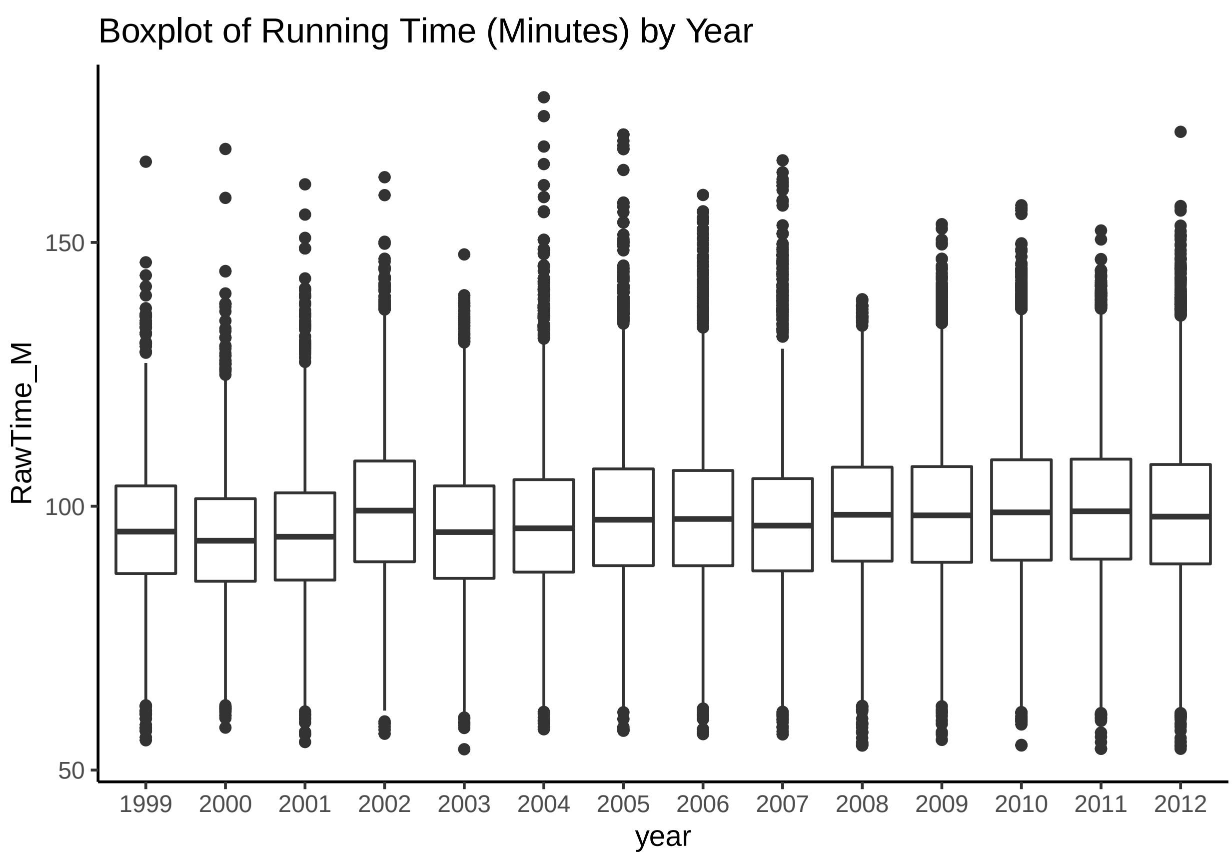
95% confidence intervals

```r
dfNew = data.frame(year=15)
predict(lmRunVol, newdata = dfNew, interval = 'confidence')
```

```
##        fit      lwr      upr
## 1 10000.37 9261.564 10739.18
```

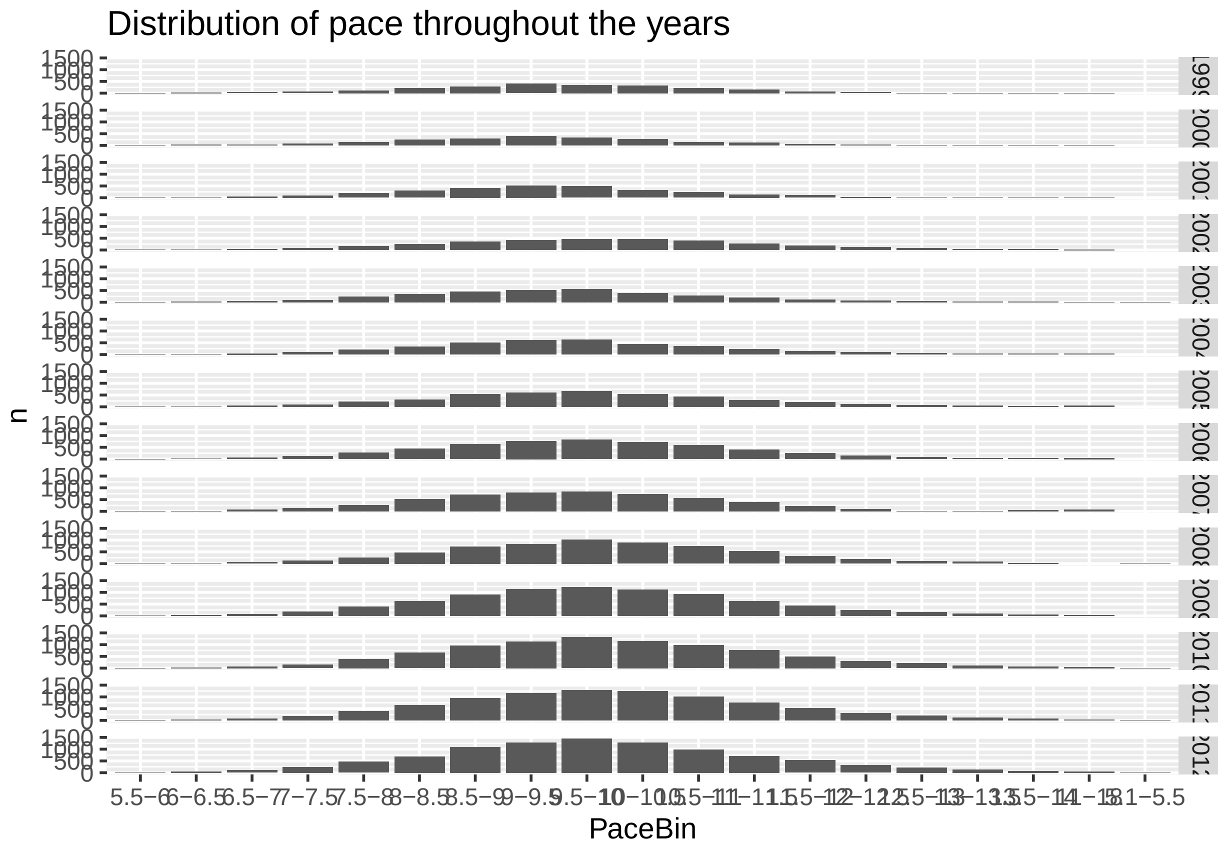
we can see below that the IQR of running times throughout the years has remained relatively constant. That means that

```
f = ggplot(womens_table_T)
f + geom_boxplot(mapping = aes(x=year, y=RawTime_M)) + theme_classic() + labs(title="Boxplot of Running
```



Let's look at the volume of runners by pace bin. We can see that the majority of runners are between 8-11 minute pace. This means that a large swell of runners will be running through the course together and race support must have enough volunteers to support the increase of runners as they make their way through the course.

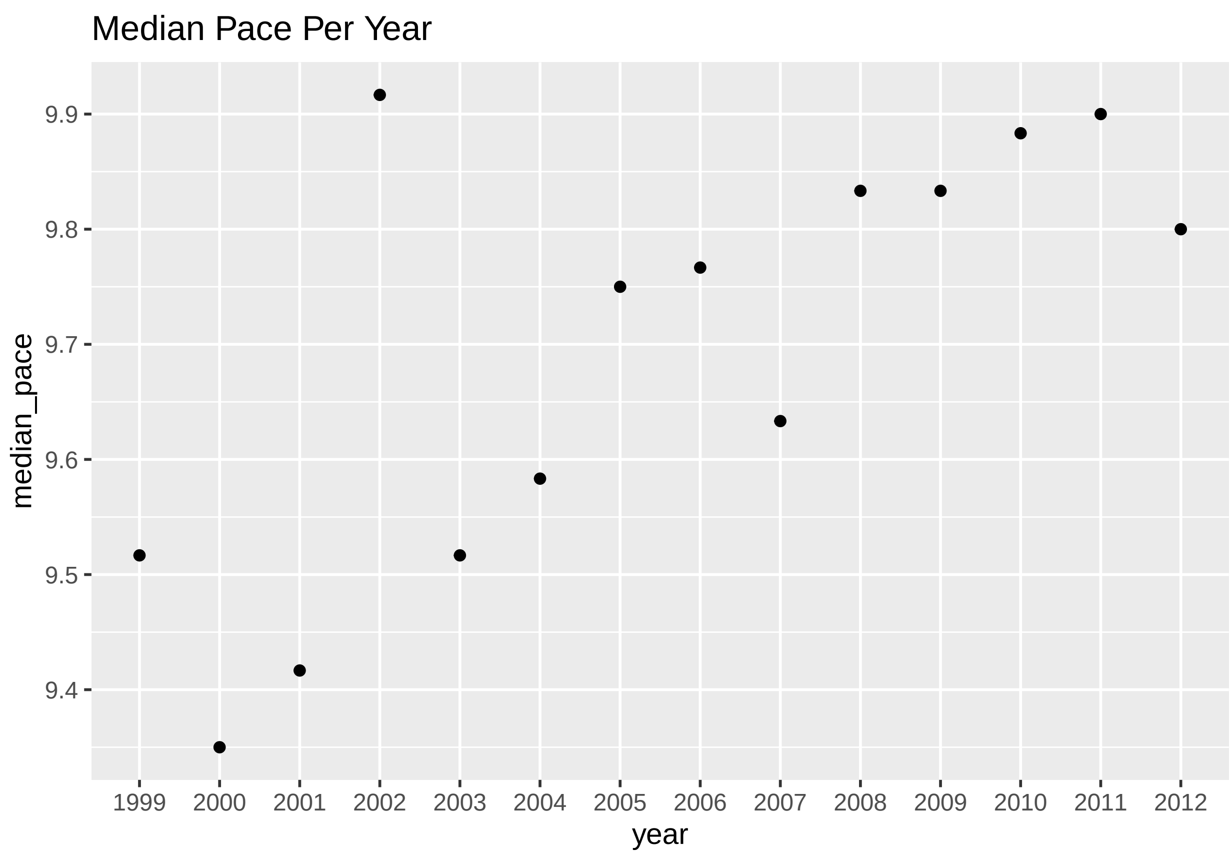
```
womens_table_T$PaceBin <- as.character(womens_table_T$PaceBin)
womens_table_T$PaceBin <- factor(womens_table_T$PaceBin, levels=unique(womens_table_T$PaceBin))

ggplot(womens_table_T %>% group_by(year, PaceBin) %>% tally()) +
  geom_col(mapping = aes(x=PaceBin, y=n)) +
  facet_grid(vars(year)) +
  labs(title="Distribution of pace throughout the years")
```



Let's take a look at the median pace per year.

```
womens_table_T %>% group_by(year) %>% dplyr::summarise(median_pace = median(RawPace_M)) %>% ggplot(aes(:
```

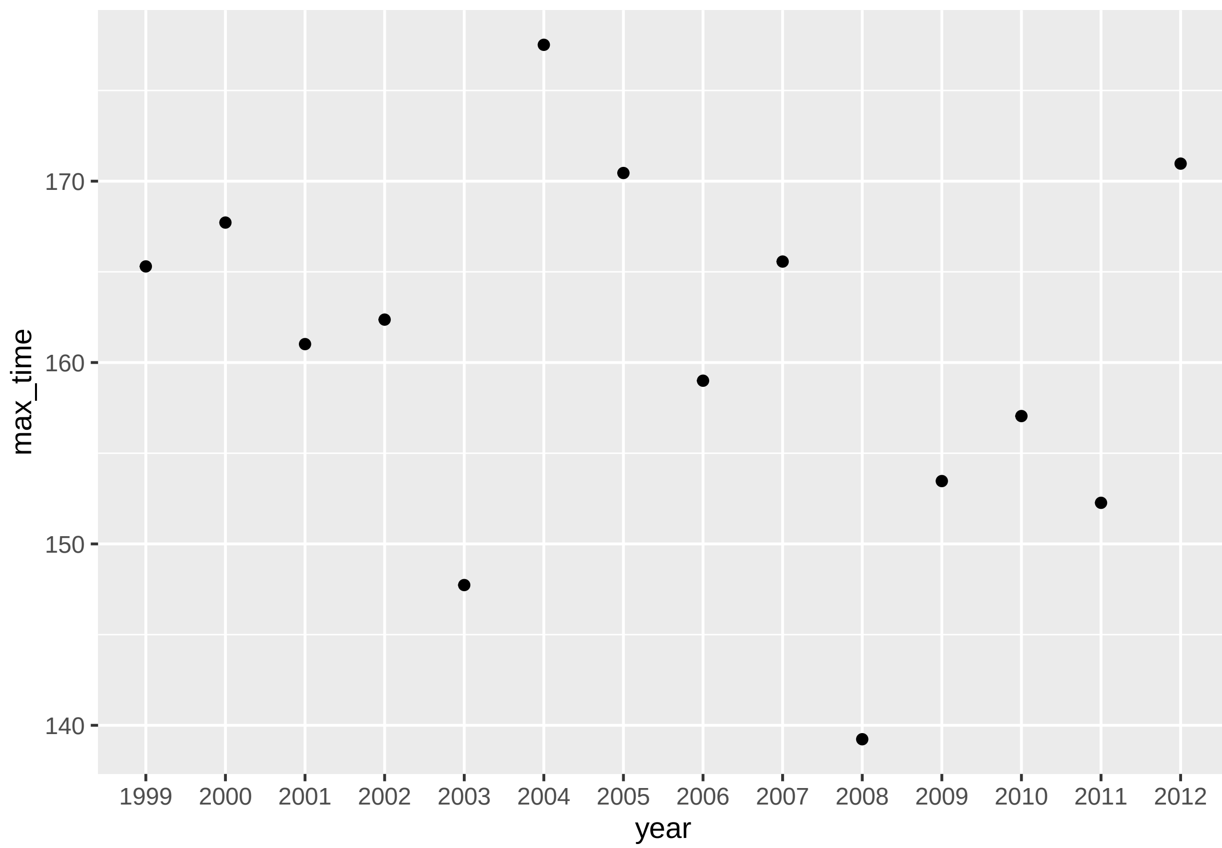
```
## `summarise()` ungrouping output (override with `.groups` argument)
```



If we look at the max times throughout the years, there isn't a consistent pattern observable, we'll revisit this after looking more at the age bins further

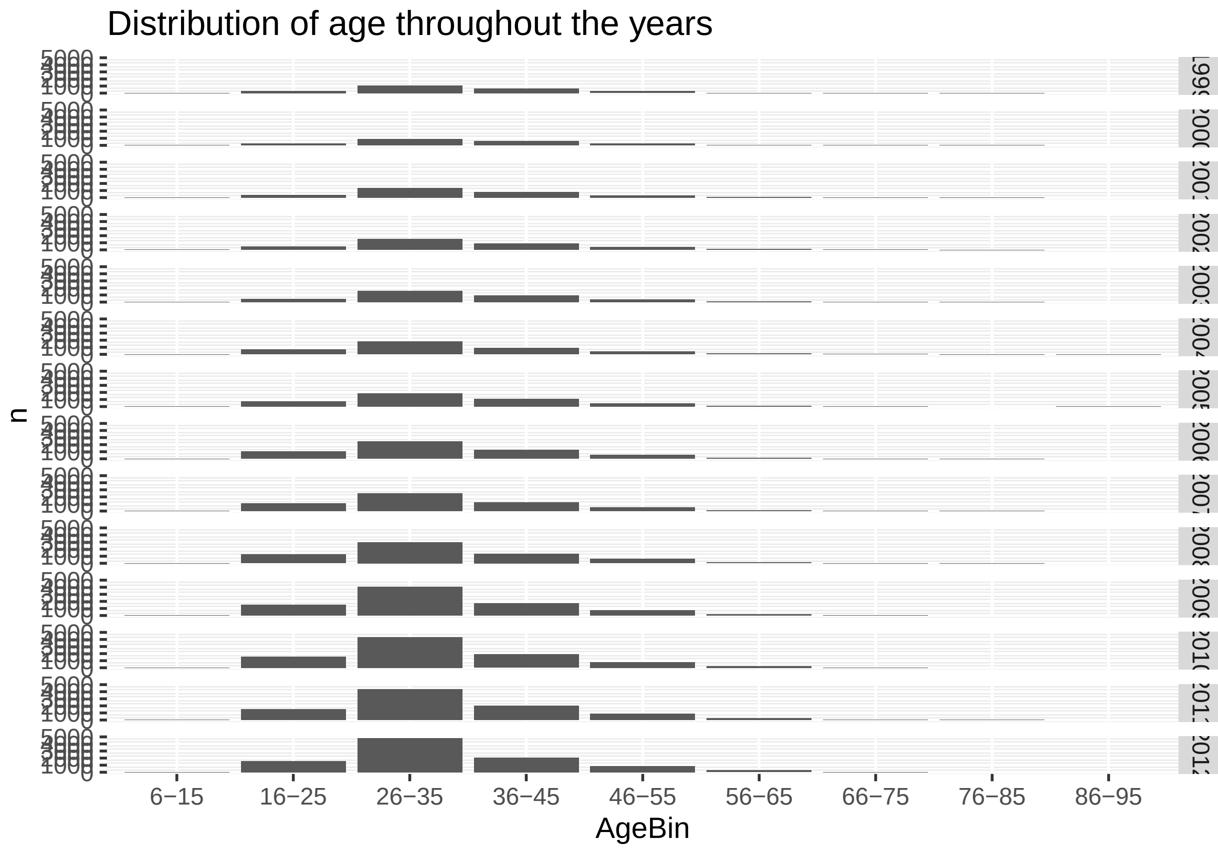
```
womens_table_T %>% group_by(year) %>% dplyr::summarise(max_time = max( RawTime_M )) %>% ggplot(aes(x=yea
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```



we see below that there has been a steady increase in 26-35 year old runners over the years

```
ggplot(womens_table_T %>% group_by(year, AgeBin) %>% tally()) +
  geom_col(mapping = aes(x=AgeBin, y=n)) +
  facet_grid(vars(year)) +
  labs(title="Distribution of age throughout the years")
```



Let’s take a closer look at the volume of runners in the 26-35 age category

```
dfRunAgeBinVol = womens_table_T %>% group_by(year, AgeBin) %>% dplyr::summarise(AgeBinVolume = n())

## `summarise()` regrouping output by 'year' (override with `.groups` argument)
```

```
head(dfRunAgeBinVol)

## # A tibble: 6 x 3
## # Groups:   year [1]
##   year  AgeBin AgeBinVolume
##   <fct> <fct>         <int>
## 1 1999  6-15              5
## 2 1999  16-25           286
## 3 1999  26-35          1086
## 4 1999  36-45           649
## 5 1999  46-55           273
## 6 1999  56-65            43
```

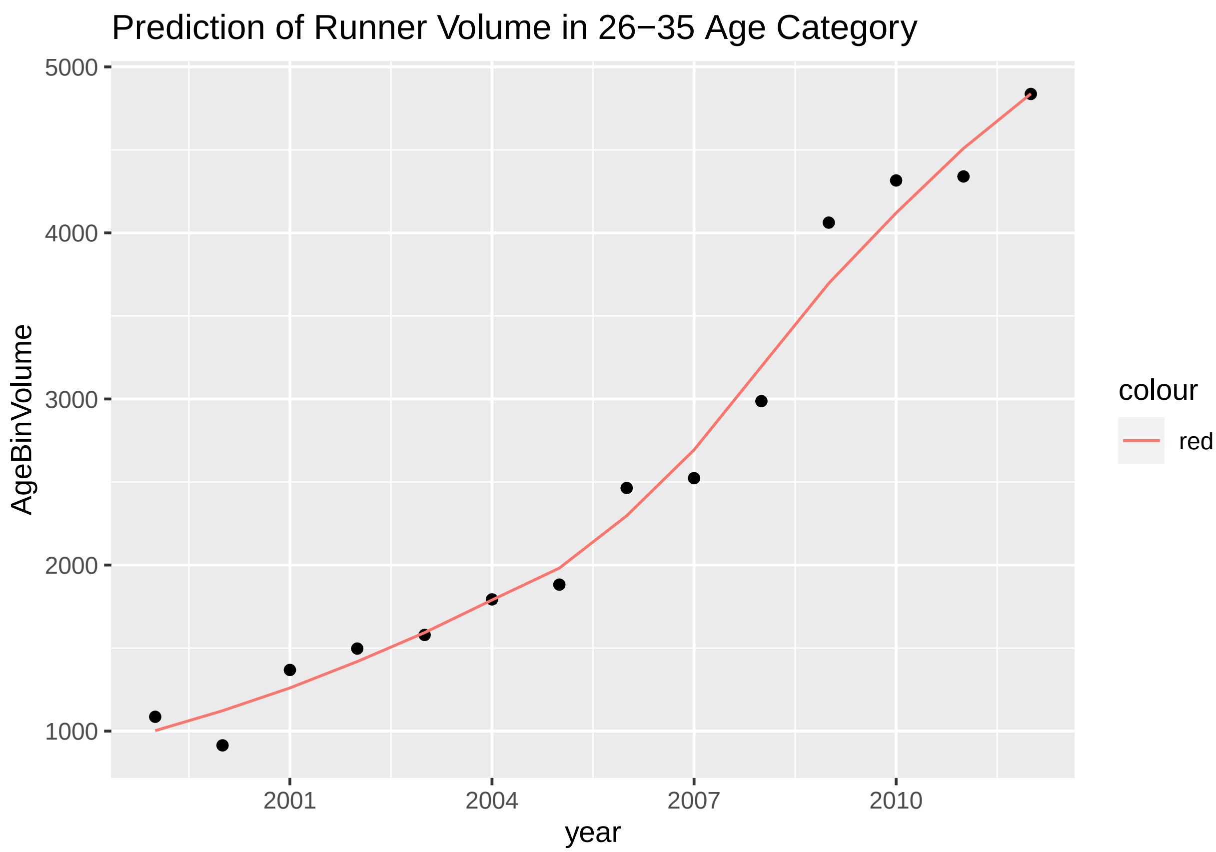
```
ggplot(dfRunAgeBinVol[dfRunAgeBinVol$AgeBin == '26-35',]) +
  geom_point(mapping = aes(x=year, y=AgeBinVolume)) +
  #facet_wrap(vars(year)) +
  labs(title="Increase in volume of 26-35 age group throughout the years")
```


```
dfRunAgeBinVol$year = as.numeric(as.character(dfRunAgeBinVol$year))
dfRunAgeBinVol[dfRunAgeBinVol$AgeBin == '26-35',]
```

```
## # A tibble: 14 x 3
## # Groups:   year [14]
##     year AgeBin AgeBinVolume
##    <dbl> <fct>         <int>
##  1  1999 26-35          1086
##  2  2000 26-35           914
##  3  2001 26-35          1368
##  4  2002 26-35          1497
##  5  2003 26-35          1579
##  6  2004 26-35          1793
##  7  2005 26-35          1882
##  8  2006 26-35          2464
##  9  2007 26-35          2523
## 10  2008 26-35          2987
## 11  2009 26-35          4062
## 12  2010 26-35          4316
## 13  2011 26-35          4340
## 14  2012 26-35          4837
```

Let's trend the volume of 26-35 year old runners using LOESS

```
df26 = dfRunAgeBinVol[dfRunAgeBinVol$AgeBin == '26-35',]
loessAge26 = loess(AgeBinVolume ~year, data=df26)
preds = predict(loessAge26)
ggplot(df26, aes(x=year, y=AgeBinVolume)) +
  geom_point() +
  geom_line(df26, mapping = aes(x=year, y=preds, col = "red")) +
  ggtitle("Prediction of Runner Volume in 26-35 Age Category")
```



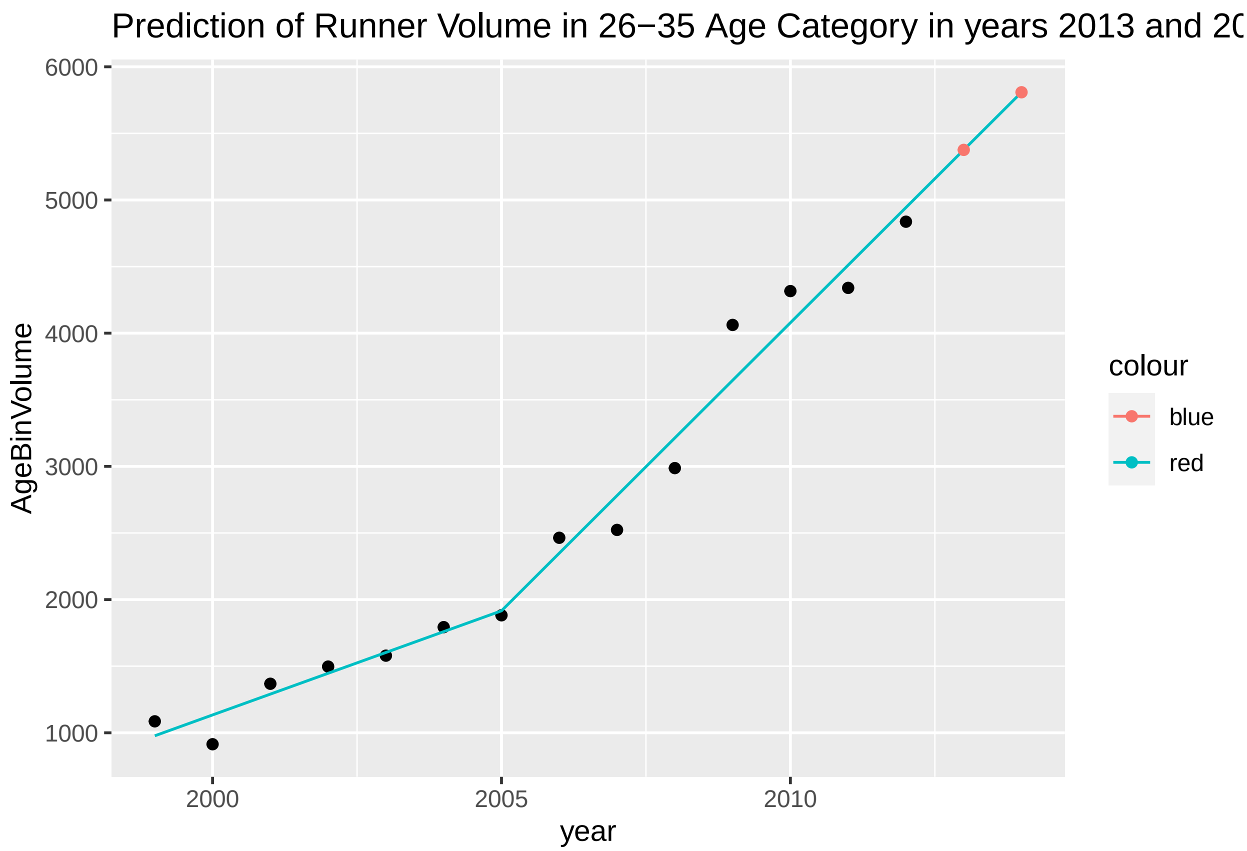
Let's now try to predict the volume of 26-35 year olds using a piece wise linear regression model

```
pw.model = piecewise.linear(df26$year, df26$AgeBinVolume, middle=1, CI=TRUE, sig.level = 0.05)
pw.model
```

```
## [1] "Threshold alpha: 2005.0000564959"
## [1] ""
## [1] "Model coefficients: Beta[0], Beta[1], Beta[2]"
##  (Intercept)            x            w
## -311648.2551     156.3910     276.1541
##       Change.Point Initial.Slope Slope.Change Second.Slope
## 2.5%      2003.007      81.99976     185.6956     369.3361
## 97.5%     2007.500     237.22169     570.7324     701.8154
```

Now that we have a piece wise linear model, let's predict the volume of 26-35 year olds in years 2013 and 2014

```r
preds = predict(pw.model,c(1999:2014))
predYears = c(1999:2014)
dfPreds = data.frame(year = predYears, predAgeBinVolume = predict(pw.model,predYears))
ggplot(df26, aes(x=year, y=AgeBinVolume)) +
  geom_point() +
  geom_line(dfPreds, mapping = aes(x=year, y=predAgeBinVolume, col = "red")) +
  geom_point(dfPreds[dfPreds$year %in% c(2013:2014), ], mapping = aes(x=year, y=predAgeBinVolume, col =
  ggtitle("Prediction of Runner Volume in 26-35 Age Category in years 2013 and 2014")
```



The actual predicted values for years 2013 and 2014. This is what we want to share with the race management team

```r
predict(pw.model,c(2013:2014))
```

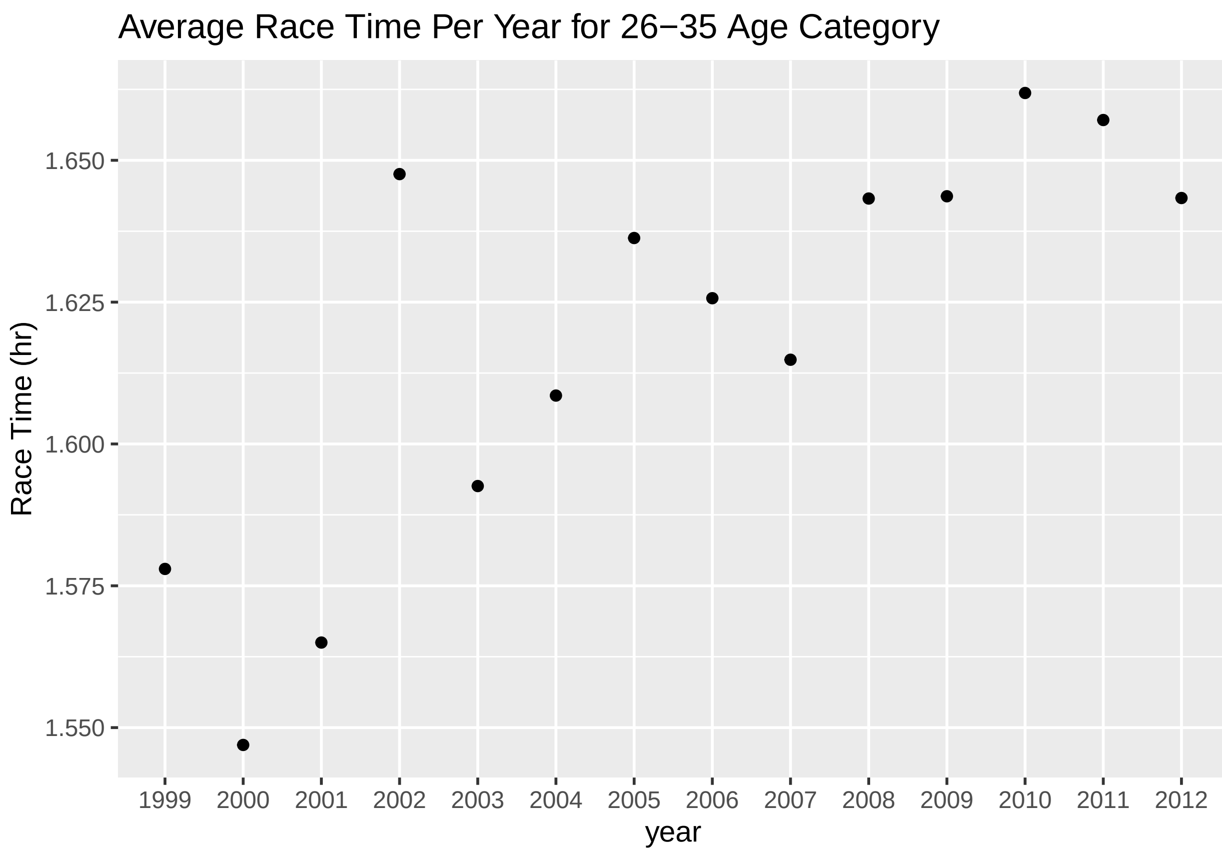
```
## [1] 5376.135 5808.681
```

Let's look at average times of age 25-36 year olds

```r
dfAvgTimes26 = womens_table_T %>% group_by(year, AgeBin) %>% dplyr::summarise(avgTime = mean(RawTime_M))
```

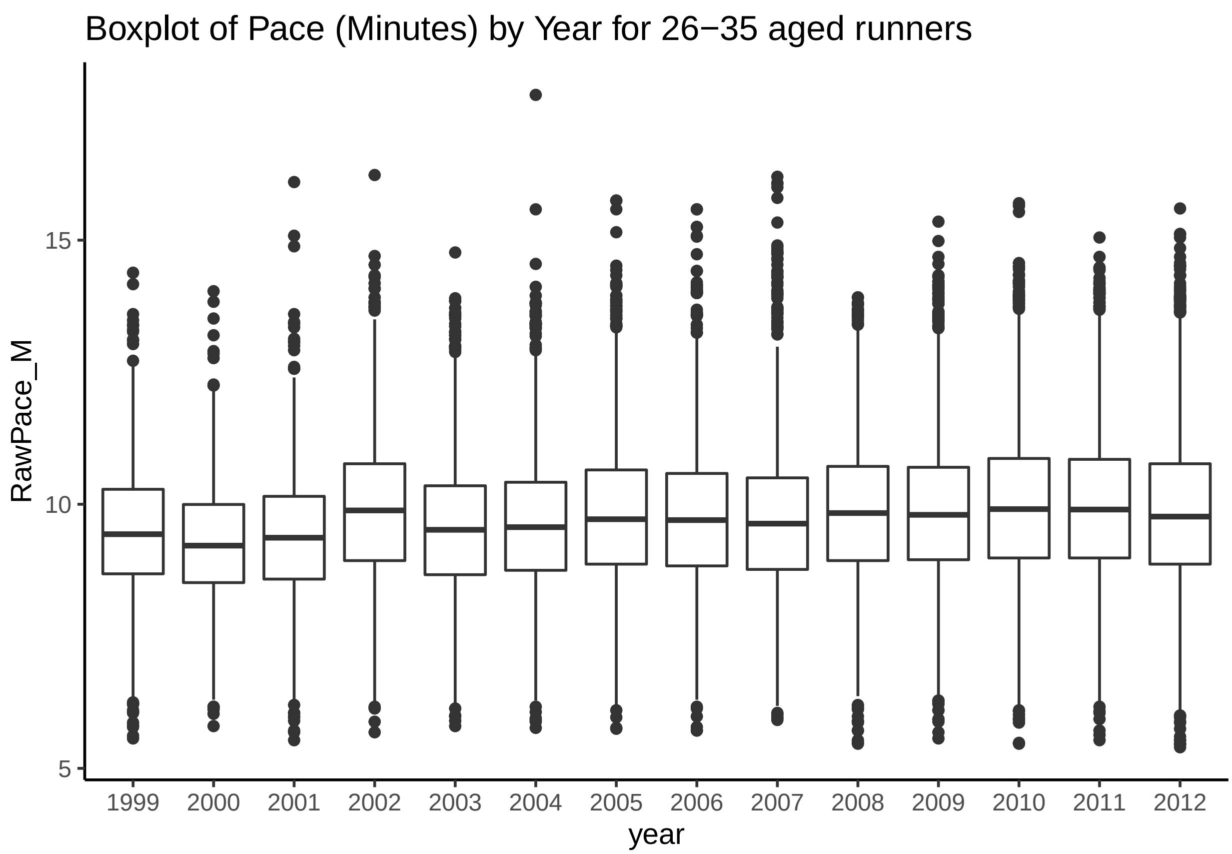
```
## `summarise()` regrouping output by 'year' (override with `.groups` argument)
```

```
dfAvgTimes26 = dfAvgTimes26[dfAvgTimes26$AgeBin == '26-35',]
dfAvgTimes26 %>% ggplot(aes(x=year, y=avgTime/60)) + geom_point() + ggtitle("Average Race Time Per Year
```



let's get a look at the pace of 26-35 year olds. over the years, they've held a pretty consistent pace. 50% are in the 9-10 minute pace group.

```
f = ggplot(womens_table_T %>% filter(womens_table_T$AgeBin == "26-35"))
f + geom_boxplot(mapping = aes(x=year, y=RawPace_M)) + theme_classic() + labs(title="Boxplot of Pace (M
```

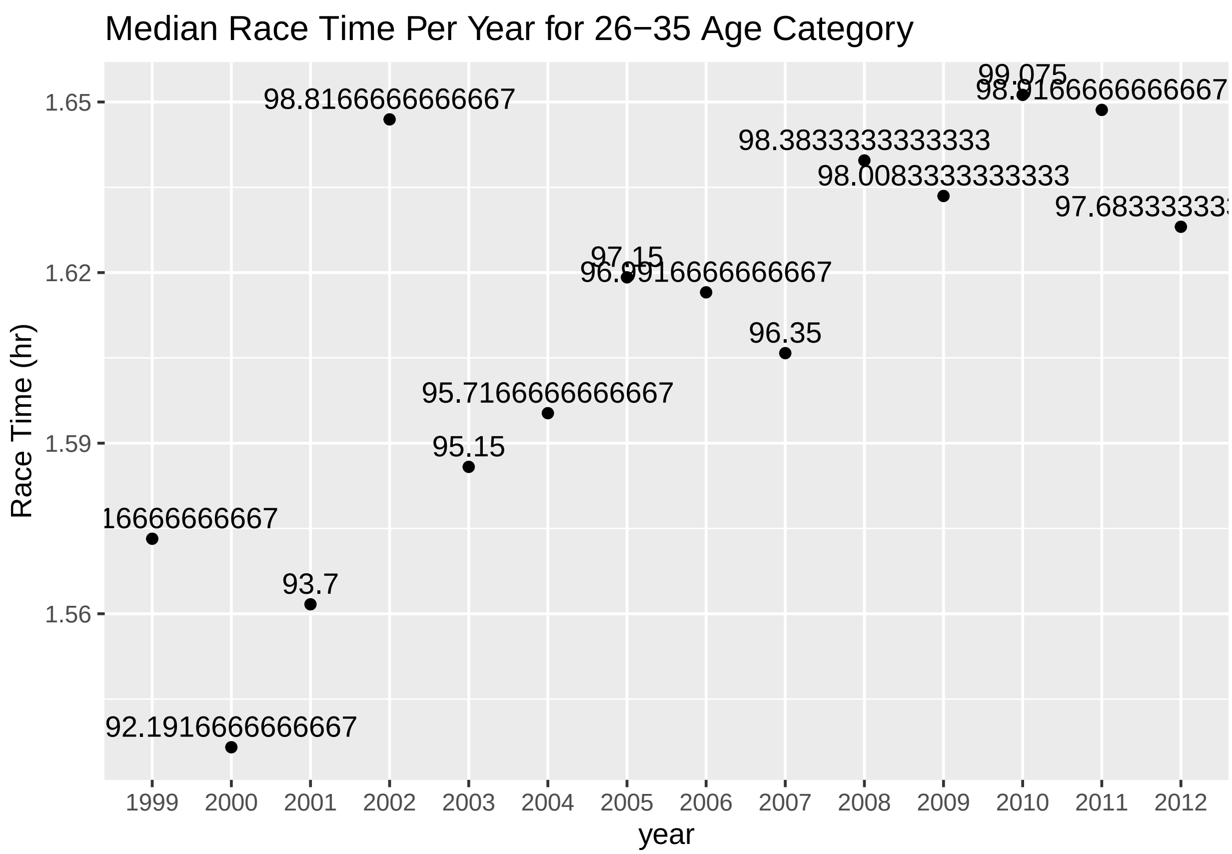


Let's look at median times of age 25-36 year olds

```
dfMedTimes26 = womens_table_T %>% group_by(year, AgeBin) %>% dplyr::summarise(medTime = median(RawTime_
```

```
## `summarise()` regrouping output by 'year' (override with `.groups` argument)
```

```
dfMedTimes26 = dfMedTimes26[dfMedTimes26$AgeBin == '26-35',]
dfMedTimes26 %>% ggplot(aes(x=year, y=medTime/60)) + geom_point() + ggtitle("Median Race Time Per Year 
geom_text(aes(label = medTime), vjust = -0.5)
```



Let's look at the proportion the 26-35 year olds make up of the total runners over the years. As of 2012, this age group makes up about 50% of all runners.

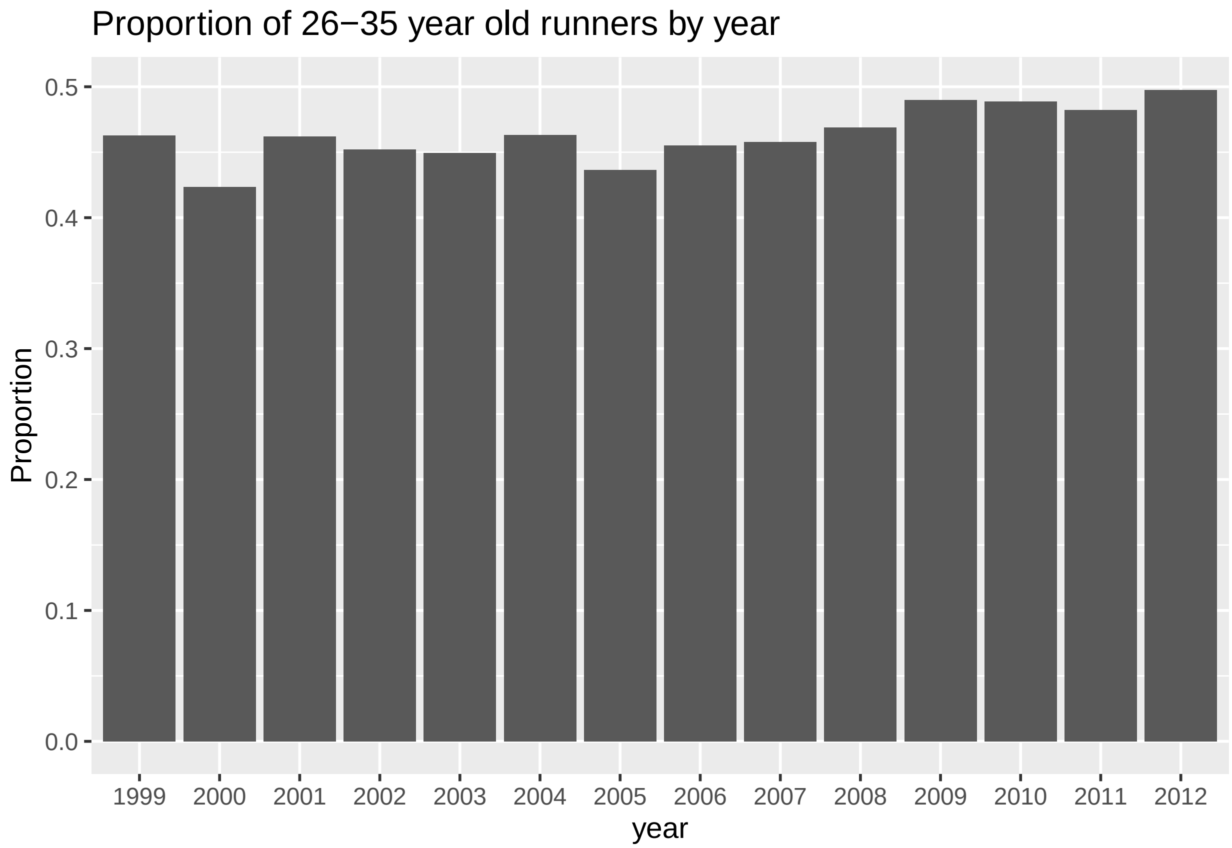
```
dfAgg = womens_table_T %>% filter(womens_table_T$AgeBin == "26-35") %>% group_by(year, AgeBin) %>% dply
```

```
## `summarise()` regrouping output by 'year' (override with `.groups` argument)
```

```
dfAgg$TotalRunners = (womens_table_T %>% group_by(year) %>% dplyr::summarise(TotalRunners = n()))$Total
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
dfAgg$Proportion = dfAgg$AgeBinVolume / dfAgg$TotalRunners

ggplot(dfAgg, aes(x=year, y=Proportion)) +
  geom_col() +
  labs(title="Proportion of 26-35 year old runners by year")
```

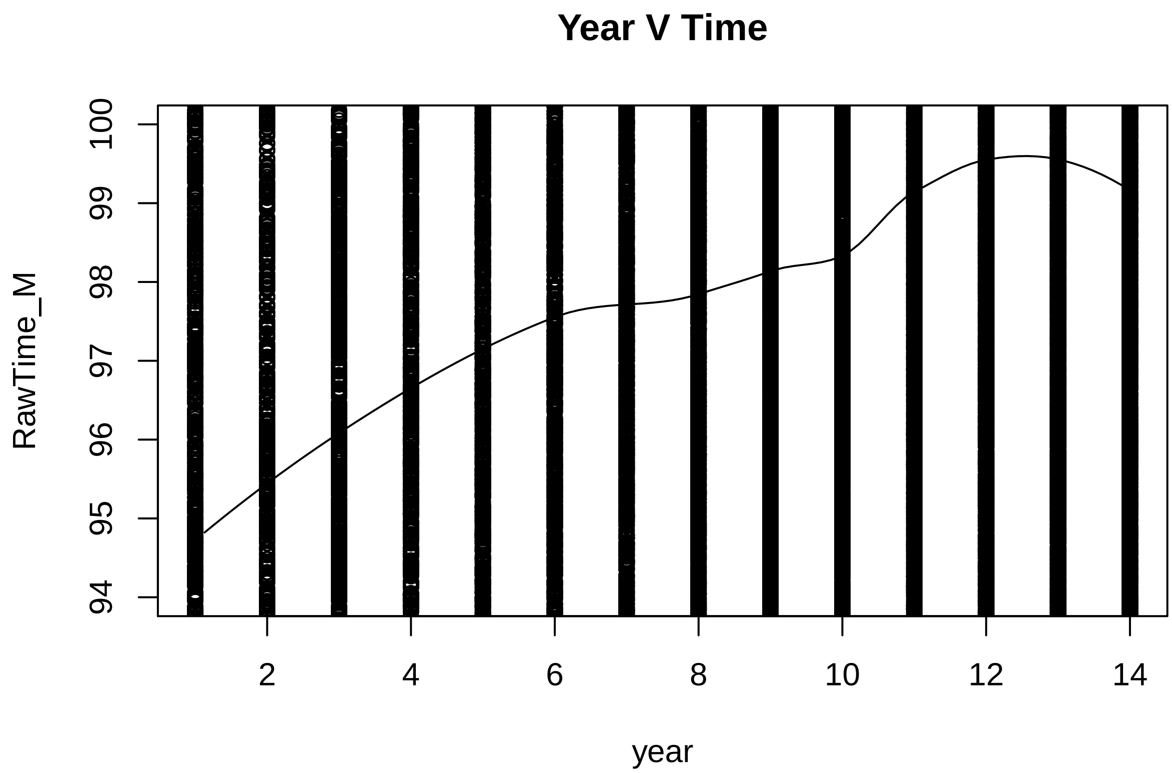


So to summarize, it's expected that 50% of the runners will be in the 26-35 year old age group in 2013. The median race time will be 97-98 minutes or approximately 9.7 minute pace.

##########################Sabrina add on#################################

When we consider how things have changed, we were asked to look at the average racer time. For that, we are going to first consider a LOESS prediction. Because this is a nonparametric method, and will weight itself relative to time, we feel like this should give indication of whether or not the average runner is getting faster or slower.

```
#Predict LOESS on time
womens_table_T$RawTime_M = as.numeric(womens_table_T$RawTime_M) #need data to be numeric for LOESS
womens_table_T$year = as.numeric(womens_table_T$year)  #need data to be numeric for LOESS
plot(RawTime_M~year, ylim = c(94,100), data=womens_table_T, main="Year V Time")
out <- loess(RawTime_M~year, data=womens_table_T)
curve(predict(out, newdata=data.frame(year = x)), add=TRUE)
```



As shown above average time actually increased across the 14 year window, but did show a downturn in 2011 and 2012. This indicates that the finishers may in fact be speeding back up again.

Our next objective is to determine if anywhere along the way the average time has sectioned off in a way that indicates multiple trends. For that, we will run a changepoint evaluation on the average.

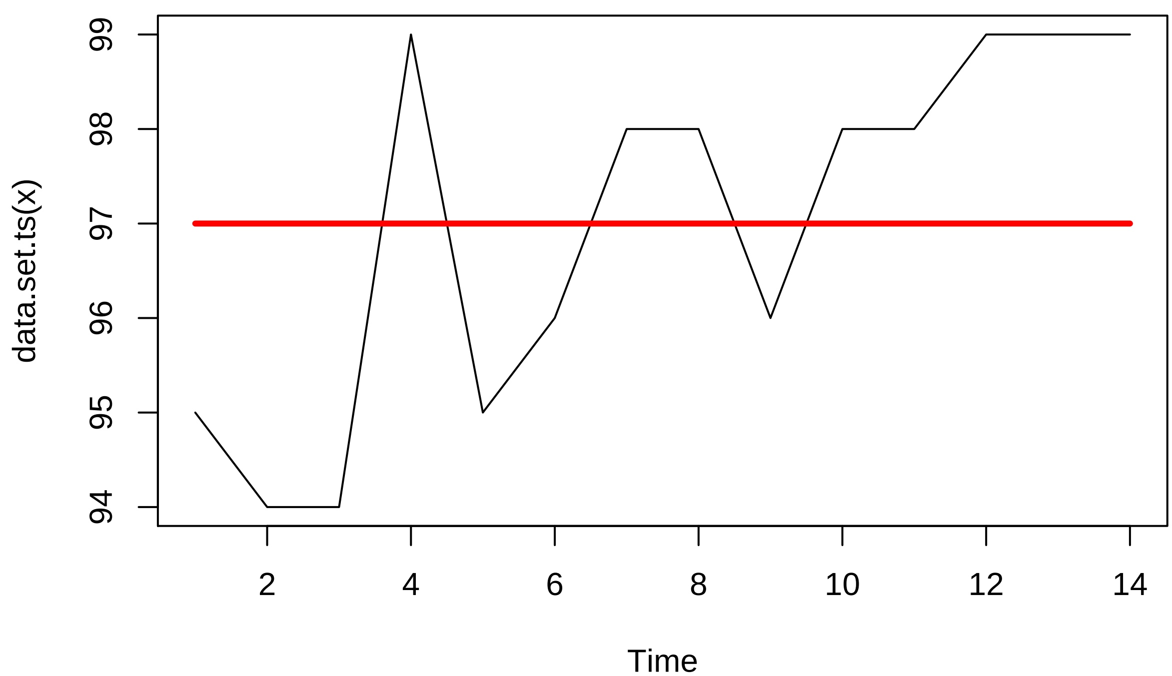
```
#Run a piecewise fit next
plotdata = womens_table_T %>%
 group_by(year)   %>%
  summarise(average = mean(RawTime_M), .groups = "keep")

plotdata$average = as.integer(plotdata$average)
plotdata$average = as.ts(plotdata$average)

library(changepoint)
```

```
## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

## Successfully loaded changepoint package version 2.2.2
##  NOTE: Predefined penalty values changed in version 2.2.  Previous penalty values with a postfix 1 i
```

```r
dis.bs <- cpt.meanvar(plotdata$average, test.stat = "Poisson", method = "BinSeg")
cpts.ts(dis.bs)
```

```
## numeric(0)
```

```r
plot(dis.bs, cpt.width = 3)
```



You can see that this produced a single average. This could be appropriately stating that nothing has statistically changed. More likely, we do not have enough data points to find clean break points.

Conclusion / Recommendations

As mentioned in previous sections, the average age of the female runner has decreased in the last 14 years. The average race time of participants has slowed, and the distribution has formed a wider, more even presentation. From this, we conclude that participation in this race has become more popular, and likely as much a social event as a competitive one. As you look to advertise in the future, you should consider expansion of advertising into social media platforms, where you are likely to connect the most effectively with the demographic described above.

As with any expansion, planning must be taken into consideration for an enjoyable event. In the 14 years we evaluated, your race participation size in females quadrupled. We predict you will see over 10,000 female participants in the next year's event. You will need to consider the logistics in organizing to that scale. You should anticipate needing 10% more staff on race day. Volunteers to pass out water, hand out medals, and manage bag checks are one part of that increase. You'll also need additional police to help maintain crowd control. If you provide pace runners, you should consider that in some of your highest volume pace groups, you may need an additional runner per assigned segment to ensure your participants are able to manage their positions.

Your site provides contact information for hotel accommodations booked at group rates. In the last four years, out of state participation has doubled (based on excluding DC, VA, and MD). Knowing that we expect participation to be higher next year, you should factor this into any hotel negotiations for the next event. You must also ensure that you have sufficient parking, or shuttle service in place if you unable to allow participants and fans to park directly adjacent to the starting line.

```
# looking at counts with division splits too
plotdata = womens_table_T %>% filter(HomeState != "VA") %>% filter(HomeState != "MD") %>% filter(HomeSta
  group_by(year, HomeState) %>%
  summarise(count = n())
```

```
## `summarise()` regrouping output by 'year' (override with `.groups` argument)
```

```
p = plotdata %>%
  ggplot(aes(x = year, y = count, fill = HomeState)) +
  geom_bar(stat = "identity", position = "stack")
ggplotly(p)
```

Finally, we recommend that you have contingencies for the unexpected. A myriad of situations could cause this event to be delayed, postponed and even cancelled. Coordinating 10,000 people converging on Washington DC is no small feat, and that is only your female participation. Should you encounter a situation that makes it unsafe to gather, you need to have options available to participants. If you entertain hosting a virtual run in lieu of gathering in person, you must consider the supply chain impacts of needing to distribute race swag and medals. Ordering well in advance, and in bulk since you know your expected participation, will allow you the time needed to handle everyone's participation memorabilia one extra time.