DS7333 Unit 4 Case Study

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Modeling Runners' Times in the Cherry Blossom Race
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1 Introduction

The R code below was mainly developed in [Chapter 2] (http://rdatasciencecases.org/CherryBlossom/code.R) of the book by Deborah Nolan and Duncan Temple Lang called "Data Science in R: A Case Studies Approach to Computational Reasoning and Problem Solving" [1]. This original code was modified, as needed, in order to solve question (7) in the Exercises section.

2 Background

In this case study, authors [1] use the results (from 1999 to 2012) of the Cherry Blossom Ten Mile Run (Washington D.C.) in order to understand how people's physical performance changes as they age.

Publicly available race results can be found at: http://www.cherryblossom.org/

Although, data and formatting is not consitent year over year, generally speaking, each result file contains at minimum:

- Runner's finishing **place**
- **Name**
- **Age**
- **Hometown**
- **Time**

- **Figure 1:** Screen Shot of the 2011 Male Results

Question 7) Follow the approach developed in the section called [3.1] "Reading Tables of Race Results into R" to read the files for the female runners and then process them using the functions in the section called [3.2] "Data Cleaning and Reformatting Variables" to create a data frame for analysis. You may need to generalize the `createDF()` and `extractVariables()` functions to handle additional oddities in the raw text files.

3 Methods

In this section the code developed in Chapter 2 of NTL [1] is followed and modified as necessary in order to make it compatible to the female runners dataset.

3.1 Reading Tables of Race Results into R

```
In [1]: source_path = getwd()
```

- findColLocs (function)

  to find the starting and ending positions of the columns into a function. In the function, we safeguard against the last character in the row of '=' characters not being a blank, we add an additional element to the end of the vector of locations that is one character more than the length of the string [1].

```
In [2]: findColLocs = function(spacerRow) {

          spaceLocs = gregexpr(" ", spacerRow)[[1]]
          rowLength = nchar(spacerRow)

          if (substring(spacerRow, rowLength, rowLength) != " ")
            return( c(0, spaceLocs, rowLength + 1))
          else return(c(0, spaceLocs))
        }
```

- selectCols (function)

  to extract name, age, hometown, and all 3 times, i.e., gun time, net time, and time, and ignore the rest, e.g., place, div, and the 5-mile run time [1].

```
In [3]: selectCols = function(shortColNames, headerRow, searchLocs) {
          sapply(shortColNames, function(shortName, headerRow, searchLocs){

            startPos = regexpr(shortName, headerRow)[[1]]

            if (startPos == -1) return( c(NA, NA) )

            index = sum(startPos >= searchLocs)
            c(searchLocs[index] + 1, searchLocs[index + 1])
          },

          headerRow = headerRow, searchLocs = searchLocs )
        }
```

- extractVariables (function) - modified to locate footnote rows

  wrap up the process of extracting the columns into a function so we can apply it to each year's data [1].

```
In [4]: extractVariables =
          function(file, varNames =c("name", "home", "ag", "gun",
                                     "net", "time"))
          {
            eqIndex = grep("^===", file)

            spacerRow = file[eqIndex]
            headerRow = tolower(file[ eqIndex - 1 ])
            body = file[ -(1 : eqIndex) ]

            footnotes = grep("^[[:blank:]]*(\\*|\\#)", body)
            if ( length(footnotes) > 0 ) body = body[ -footnotes ]
            blanks = grep("^[[:blank:]]*$", body)
            if (length(blanks) > 0 ) body = body[ -blanks ]

            searchLocs = findColLocs(spacerRow)
            locCols = selectCols(varNames, headerRow, searchLocs)

            Values = mapply(substr, list(body), start = locCols[1, ],
                            stop = locCols[2, ])
            colnames(Values) = varNames

            return(Values)
          }
```

3.2 Data Cleaning and Reformatting Variables

- convertTime (function)

  Time is stored as a string in the format: `hh:mm:ss`. We want time in a numeric format so it can be more easily summarized and modeled. One possibility is to convert it to minutes, i.e., `hh * 60 + mm + ss/60`. To carry out this computation, we must split the time field up into its constituent pieces and convert each to numeric values. The `strsplit()` function can be very helpful for splitting strings at, e.g., colons [1].

```
In [5]: convertTime = function(time) {
          timePieces = strsplit(time, ":")
          timePieces = sapply(timePieces, as.numeric)
          sapply(timePieces, function(x) {
            if (length(x) == 2) x[1] + x[2]/60
            else 60*x[1] + x[2] + x[3]/60
          })
        }
```

- createDF (function)

  to apply to the character matrices in menResMat & womenResMat and return a data frame with variables for analysis. We have 6 variables: - runner's name - home town - age - 3 versions of time

In addition to the conversion of character strings to numeric, we also create two new variables, year and sex.

```
In [6]: createDF = function(Res, year, sex)
        {
          if ( !is.na(Res[1, 'net']) ) useTime = Res[ , 'net']
          else if ( !is.na(Res[1, 'gun']) ) useTime = Res[ , 'gun']
          else useTime = Res[ , 'time']

          useTime = gsub("[#\\*[:blank:]]", "", useTime)
          runTime = convertTime(useTime[ useTime != "" ])

          Res = Res[ useTime != "", ]
          age = gsub("X{2}\\s{1}?|\\s{3}?","0  ", Res[,'ag'])
          Res[, 'ag'] = age

          Results = data.frame(year = rep(year, nrow(Res)),
                               sex = rep(sex, nrow(Res)),
                               name = Res[ , 'name'], home = Res[ , 'home'],
                               age = as.numeric(Res[, 'ag']),
                               runTime = runTime,
                               stringsAsFactors = FALSE)
          invisible(Results)
        }
```

Load text files

```
In [7]: mfilenames = paste(source_path, "/Data/mens", 1999:2012, ".txt", sep = "")
        menFiles = lapply(mfilenames, readLines)
        names(menFiles) = 1999:2012

        wfilenames = paste(source_path, "/Data/womens", 1999:2012, ".txt", sep = "")
        womenFiles = lapply(wfilenames, readLines)
        names(womenFiles) = 1999:2012
```

Fix 2006 and then apply the *extractVariables()* function to menFiles and womenFiles to obtain a list of character matrices.

```
In [8]: separatorIdx = grep("^===", menFiles[["2006"]])
        separatorRow = menFiles[['2006']][separatorIdx]
        separatorRowX = paste(substring(separatorRow, 1, 63), " ",
                              substring(separatorRow, 65, nchar(separatorRow)),
                              sep = "")
        menFiles[['2006']][separatorIdx] = separatorRowX

        menResMat = sapply(menFiles, extractVariables)
        menDF = mapply(createDF, menResMat, year = 1999:2012,
                       sex = rep("M", 14), SIMPLIFY = FALSE)
```

```
separatorIdx = grep("^===", womenFiles[["2006"]])
separatorRow = womenFiles[['2006']][separatorIdx]
separatorRowX = paste(substring(separatorRow, 1, 63), " ",
                      substring(separatorRow, 65, nchar(separatorRow)),
                      sep = "")
womenFiles[['2006']][separatorIdx] = separatorRowX

womenFiles[[3]] = append(womenFiles[[3]], menFiles[[3]][4:5], after=3)

womenResMat = sapply(womenFiles, extractVariables)

womenDF = mapply(createDF, womenResMat, year = 1999:2012,
                 sex = rep("W", 14), SIMPLIFY = FALSE)
```

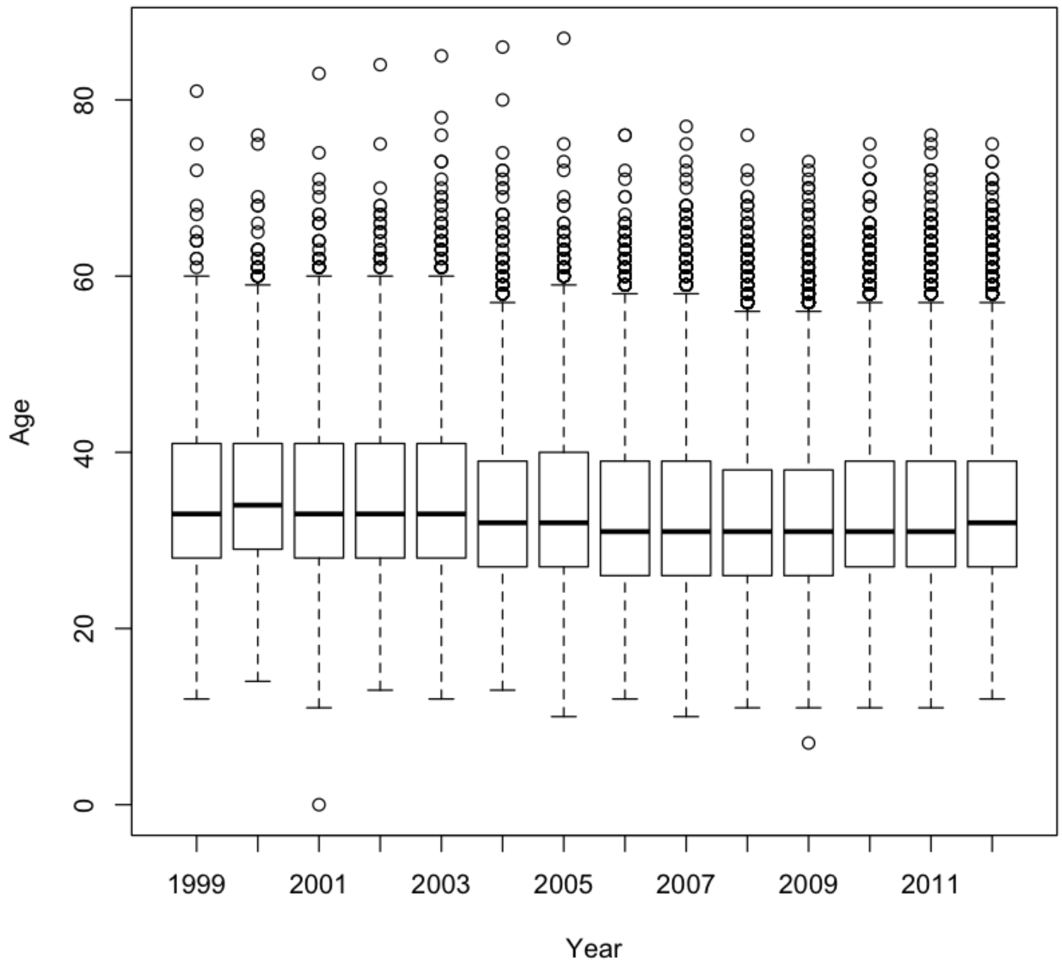
```
In [9]: sapply(womenResMat, nrow)
```

1999 2356 **2000** 2166 **2001** 2972 **2002** 3334 **2003** 3542 **2004** 3899 **2005** 4333 **2006** 5435 **2007** 5690 **2008** 6397 **2009** 8323 **2010** 8853 **2011** 9030 **2012** 9730

```
In [10]: age = sapply(womenResMat,
                      function(x) as.numeric(x[ , 'ag']))
```

```
Warning message in FUN(X[[i]], ...):
NAs introduced by coercion
```

```
In [11]: boxplot(age, ylab = "Age", xlab = "Year")
```



- **Figure 2:** Box Plot of Womens' Age by Year

Check the number of NA values for `age`

```
In [12]: sapply(age, function(x) sum(is.na(x)))
```

1999 4 **2000** 0 **2001** 0 **2002** 4 **2003** 0 **2004** 0 **2005** 8 **2006** 1 **2007** 2 **2008** 0 **2009** 2 **2010** 0 **2011** 0 **2012** 0
Check the number of NA values for `runTime`

```
In [13]: sapply(womenDF, function(x) sum(is.na(x$runTime)))
```

1999 0 **2000** 0 **2001** 0 **2002** 0 **2003** 0 **2004** 0 **2005** 0 **2006** 0 **2007** 0 **2008** 0 **2009** 0 **2010** 0 **2011** 0 **2012** 0

We combine the race results for all years and men into one data frame using the `do.call()` function to call `rbind()` with the list of data frames as input

```
In [14]: cbMen = do.call(rbind, menDF)
         cbWomen = do.call(rbind, womenDF)

         save(cbMen, file = paste(source_path, "/Data/Men.rda", sep = ""))
         save(cbWomen, file = paste(source_path, "/Data/Women.rda", sep = ""))
```

```
In [15]: dim(cbWomen)
```

1. 75972 2. 6

```
In [16]: head(cbWomen)
```

	year	sex	name	home	age	runTime
1999.1	1999	W	Jane Omoro	Kenya	26	53.61667
1999.2	1999	W	Jane Ngotho	Kenya	29	53.63333
1999.3	1999	W	Lidiya Grigoryeva	Russia	0	53.66667
1999.4	1999	W	Eunice Sagero	Kenya	20	53.91667
1999.5	1999	W	Alla Zhilyayeva	Russia	29	54.13333
1999.6	1999	W	Teresa Wanjiku	Kenya	24	54.16667

```
In [17]: summary(cbWomen)
```

```
      year          sex                 name                home
 Min.   :1999   Length:75972       Length:75972       Length:75972
 1st Qu.:2005   Class :character   Class :character   Class :character
 Median :2008   Mode  :character   Mode  :character   Mode  :character
 Mean   :2007
 3rd Qu.:2010
 Max.   :2012
      age          runTime
 Min.   : 0.00   Min.   : 51.73
 1st Qu.:27.00   1st Qu.: 88.53
 Median :32.00   Median : 97.33
 Mean   :33.84   Mean   : 98.09
 3rd Qu.:39.00   3rd Qu.:106.78
 Max.   :87.00   Max.   :177.52
```

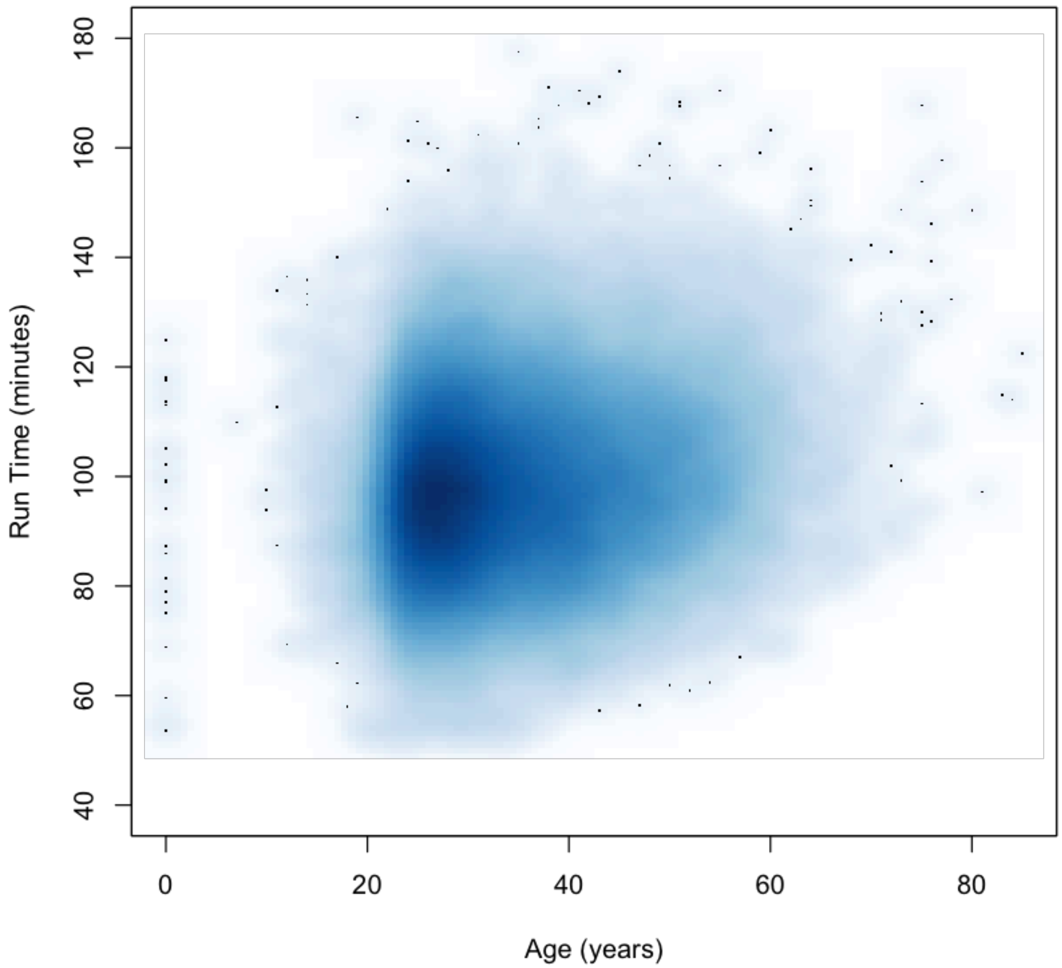
3.3 Exploring the Run Time for All Female Runners

3.3.1 Making Plots with Many Observations

Revised scatter plot with run time on the y-axis and age on the x-axis.

> `smoothScatter()` function provides a more formal approach to jittering and using transparency for visualizing the density of runner's time-age distribution. This function produces a smooth density representation of the scatter plot using color

```
In [18]: smoothScatter(y = cbWomen$runTime, x = cbWomen$age,
                       ylim = c(40, 180), xlim = c(0, 85),
                       xlab = "Age (years)", ylab = "Run Time (minutes)")
```



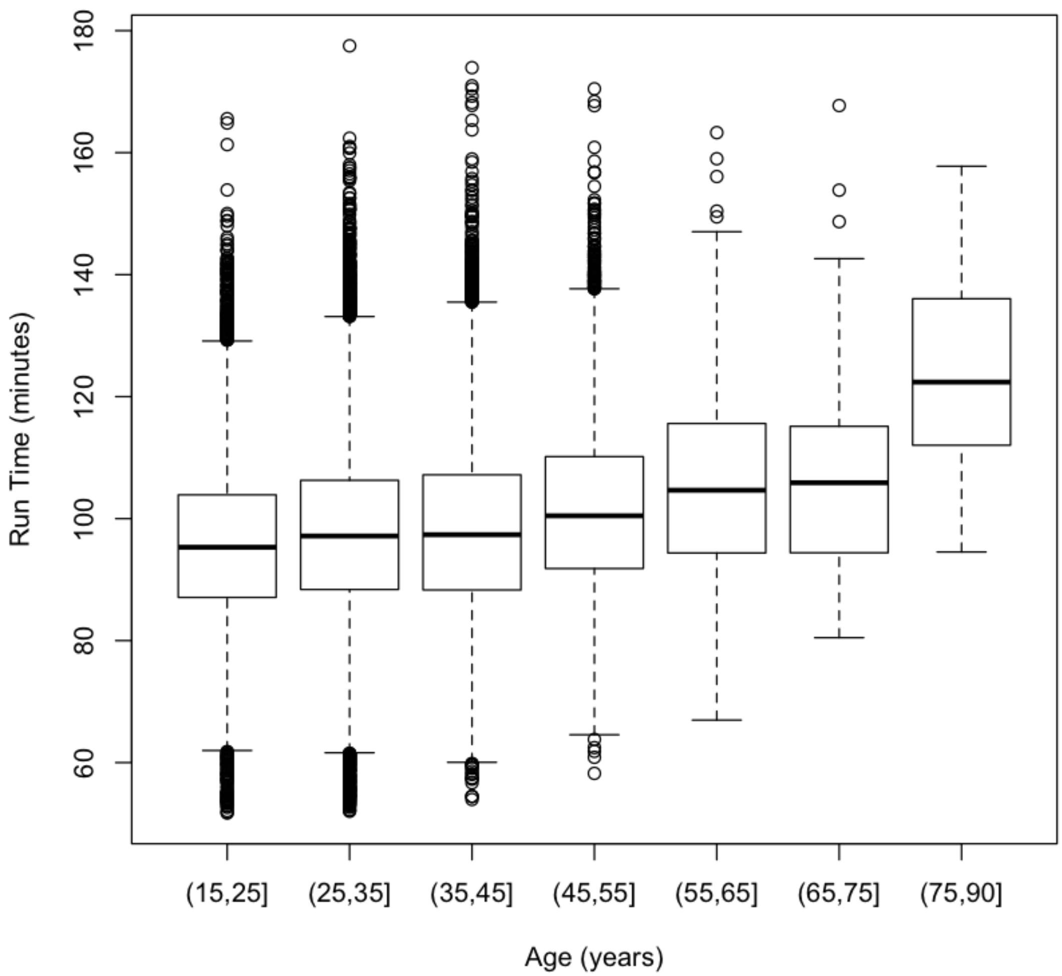
- **Figure 3:** Smoothed Scatter Plot for Run Time vs. Age for Female Runners.

  Graphically display summary statistics of run time for subgroups of runners with roughly the same age. Here, we group the runners into 10-year age intervals and plot the summaries for each subgroup in the form of a boxplot

```
In [19]: cbWomenSub = cbWomen[cbWomen$runTime > 30 & !is.na(cbWomen$age) & cbWomen$age > 15, ]
         ageCat = cut(cbWomenSub$age, breaks = c(seq(15, 75, 10), 90))
         table(ageCat)
```

```
ageCat
(15,25] (25,35] (35,45] (45,55] (55,65] (65,75] (75,90]
  12926   35815   17520    7515    1849     183      15
```

```
In [20]: plot(cbWomenSub$runTime ~ ageCat, xlab = "Age (years)", ylab = "Run Time (minutes)")
```



- **Figure 4:** Side-by-Side Boxplots of Female Runners' Run Time vs. Age

Similarly to the Men's boxplots, > We observe in this plot that the upper quartile increases faster with age than the median and lower quartile

3.3.2 Fitting Models to Average Performance

A simple linear model may be inadequate to describe this relationship. To see how well the simple linear model captures the relationship (or not) between run time and age, we fit the model with

```
In [21]: lmAge = lm(runTime ~ age, data = cbWomenSub)
         summary(lmAge)


Call:
lm(formula = runTime ~ age, data = cbWomenSub)

Residuals:
    Min      1Q  Median      3Q     Max
-46.093  -9.445  -0.648   8.639  79.208

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 91.330105   0.195631  466.85   <2e-16 ***
age          0.199396   0.005572   35.78   <2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 14.1 on 75821 degrees of freedom
Multiple R-squared:  0.01661,Adjusted R-squared:  0.01659
F-statistic:  1280 on 1 and 75821 DF,  p-value: < 2.2e-16
```

> To help us further discern any pattern in the residuals, we augment this residual plot with a smooth curve of local averages of the residuals from the fit. We fit the curve using `loess()` with

```
In [22]: resid.lo = loess(resids ~ age, data = data.frame(resids = residuals(lmAge),
                                                         age = cbWomenSub$age))
```

Based on `Figure 3`, we start by making a vector of age values from 20 to 80 and then, > We can obtain these predicted values from the `predict.loess()` function. This function takes the loess object from a fit, e.g., `resid.lo` and a data frame with variables matching those used in the loess curve fitting, in this case age.

> We consider two approaches to a more complex fit: a piecewise linear model and a nonparametric smooth curve. For the latter, we simply take local weighted averages of time as age varies, just as we smoothed the residuals from the linear fit. We use `loess()` again to do this with `womenRes.lo`, and then we make predictions for all ages ranges from 20 to 80 with `womenRes.lo.pr`

```
In [23]: age20to80 = 20:80

         resid.lo.pr = predict(resid.lo, newdata = data.frame(age = age20to80))

         womenRes.lo = loess(runTime ~ age, cbWomenSub)

         womenRes.lo.pr = predict(womenRes.lo, data.frame(age = age20to80))
```

In order to fit a piecewise linear model,

We place hinges at 30, 40, 50, and 60 and thus allow the slope of the line to change at these decade markers.

```
In [24]: decades = seq(30, 60, by = 10)
         overAge = lapply(decades,
                          function(x) pmax(0, (cbWomenSub$age - x)))
         names(overAge) = paste("over", decades, sep = "")
         overAge = as.data.frame(overAge)
         tail(overAge)
```

	over30	over40	over50	over60
75818	9	0	0	0
75819	10	0	0	0
75820	1	0	0	0
75821	25	15	5	0
75822	10	0	0	0
75823	8	0	0	0

For the piecewise model
$runTime = f(age, over30, over40, over50, over60)$

We find the least squares fit with

```
In [25]: lmPiecewise = lm(runTime ~ . , data = cbind(cbWomenSub[, c("runTime", "age")], overAge)
         summary(lmPiecewise)


Call:
lm(formula = runTime ~ ., data = cbind(cbWomenSub[, c("runTime",
    "age")], overAge))

Residuals:
    Min      1Q  Median      3Q     Max
-46.020  -9.435  -0.667   8.643  79.517

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 87.44984    0.67288 129.963   <2e-16 ***
age          0.35777    0.02490  14.370   <2e-16 ***
over30      -0.39439    0.03898 -10.117   <2e-16 ***
over40       0.38491    0.04218   9.125   <2e-16 ***
over50       0.10086    0.06885   1.465    0.143
over60      -0.02563    0.13087  -0.196    0.845
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 14.08 on 75817 degrees of freedom
Multiple R-squared:  0.01969,Adjusted R-squared:  0.01963
```

```
F-statistic: 304.6 on 5 and 75817 DF,  p-value: < 2.2e-16
```

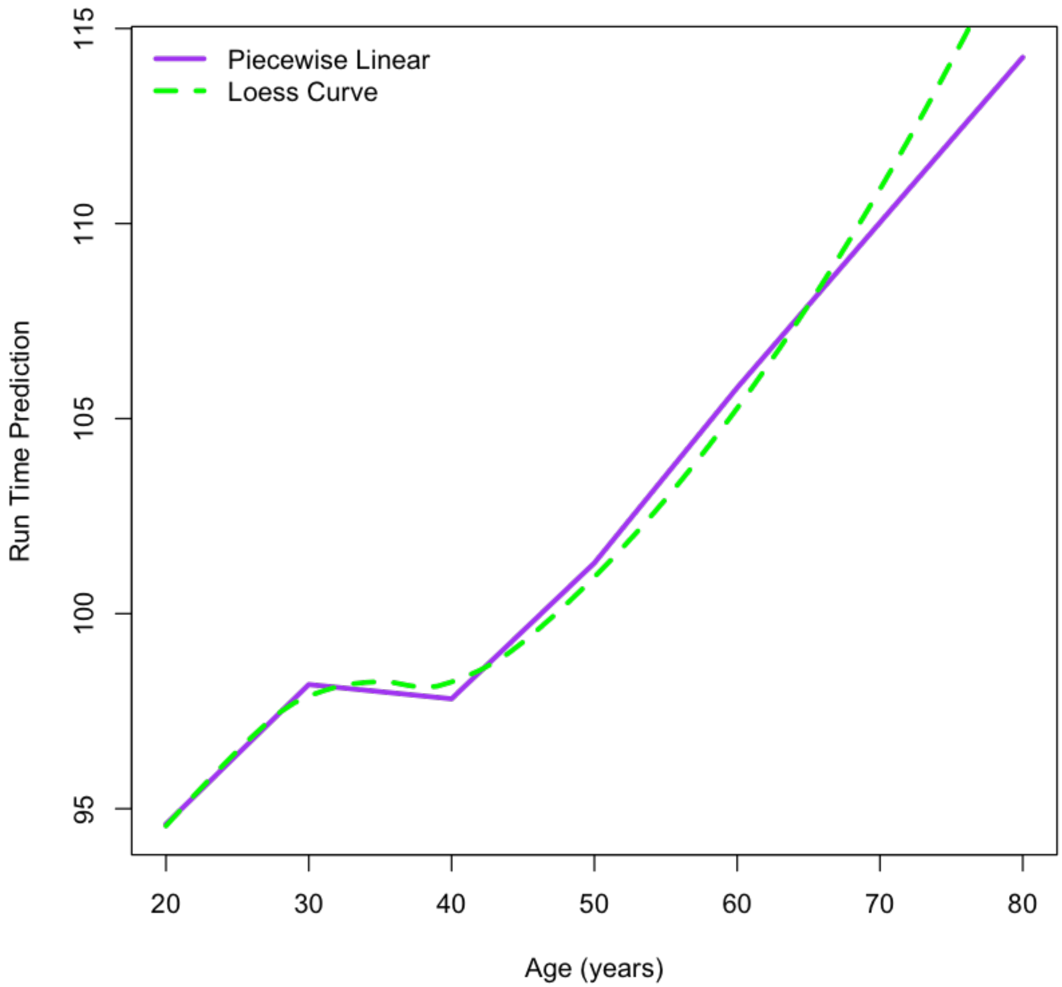
```
In [26]: overAge20 = lapply(decades, function(x) pmax(0, (age20to80 - x)))
         names(overAge20) = paste("over", decades, sep = "")
         overAgeDF = cbind(age = data.frame(age = age20to80), overAge20)
         tail(overAgeDF)
```

	age	over30	over40	over50	over60
56	75	45	35	25	15
57	76	46	36	26	16
58	77	47	37	27	17
59	78	48	38	28	18
60	79	49	39	29	19
61	80	50	40	30	20

```
In [27]: predPiecewise = predict(lmPiecewise, overAgeDF)
```

```
In [28]: plot(predPiecewise ~ age20to80, type = "l", col = "purple", lwd = 3,
              xlab = "Age (years)", ylab = "Run Time Prediction")

         lines(x = age20to80, y = womenRes.lo.pr, col = "green", lty = 2, lwd = 3)
         legend("topleft", col = c("purple", "green"), lty = c(1, 2), lwd= 3,
                legend = c("Piecewise Linear", "Loess Curve"), bty = "n")
```



- **Figure 5:** Piecewise Linear and Loess Curves Fitted to Run Time vs. Age

Figure 5 clearly shows that there is a changepoint at the age of 30 when run time deterioration slows down and another chagepoint at the age of 40 when run time deterioration accelerates dramatically.

4 Results

In this section, the analysis of female runners' run times as function of age is continued although the `changepoint` R package is utilized in the first subsection [4.1]. While in the subsequent subsection [4.2] the automatic LOESS R functions are applied.

4.1 Changepoint Detection

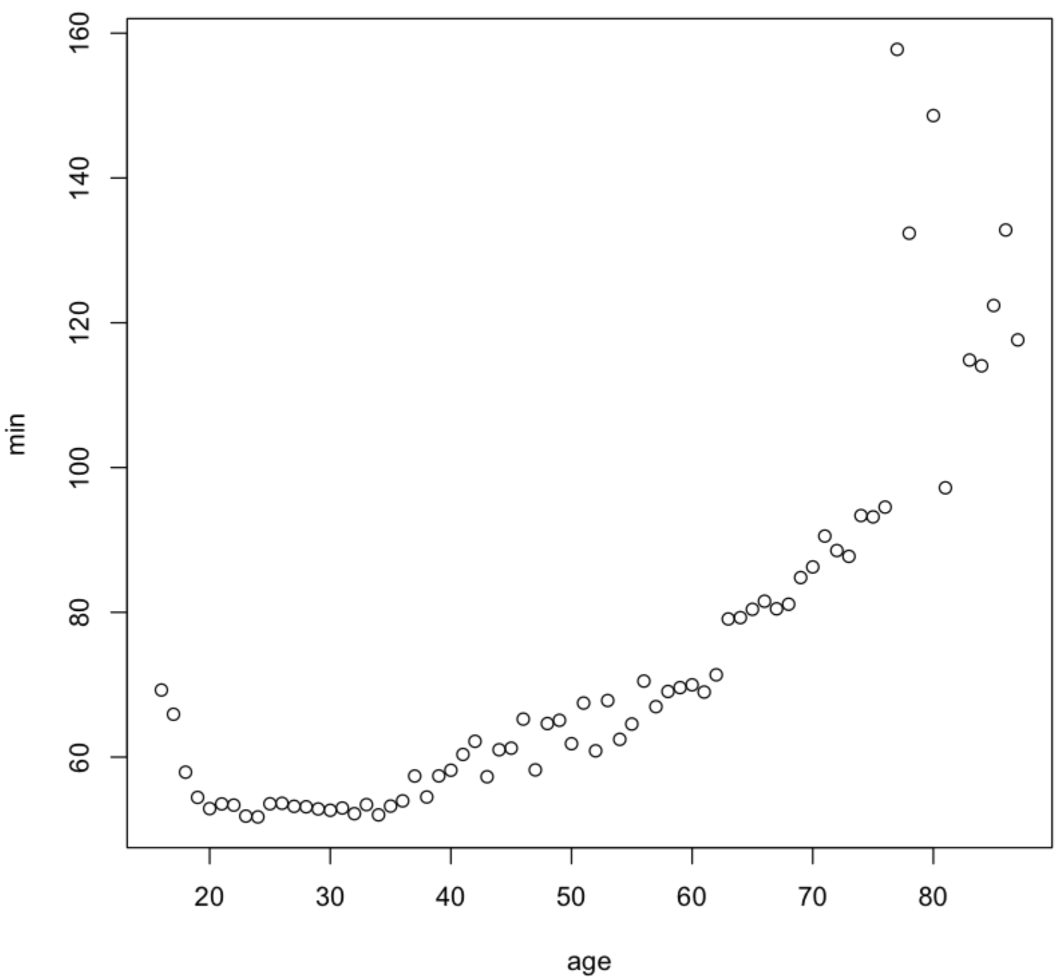
4.1.1 Data Preparation

In order to utilize the `changepoint` package data needs to be formatted as a quasi time series. Data was first summarized usin the mean function, but as it was detected in `Figure 4`, variance increases drastically after age 60. The median function yielded similar results. The best run time (minimum) provided a more 'stable' result.

```
In [29]: library(plyr)

In [30]: runTimebyage = ddply(cbWomenSub, ~ age, summarize, min = min(runTime))

In [31]: plot(min ~ age, data = runTimebyage)
```



- **Figure 6:** Scatter Plot of Age vs. Best (MIN) Run Time

```
In [32]: head(runTimebyage)
```

age	min
16	69.26667
17	65.91667
18	57.91667
19	54.43333
20	52.88333
21	53.53333

```
In [33]: 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
```

4.1.2 Changes in Mean

```
In [34]: m.pelt <- cpt.mean(runTimebyage$min, penalty = "Manual", pen.value = "50 * log(n)",
                            method = "PELT")
```

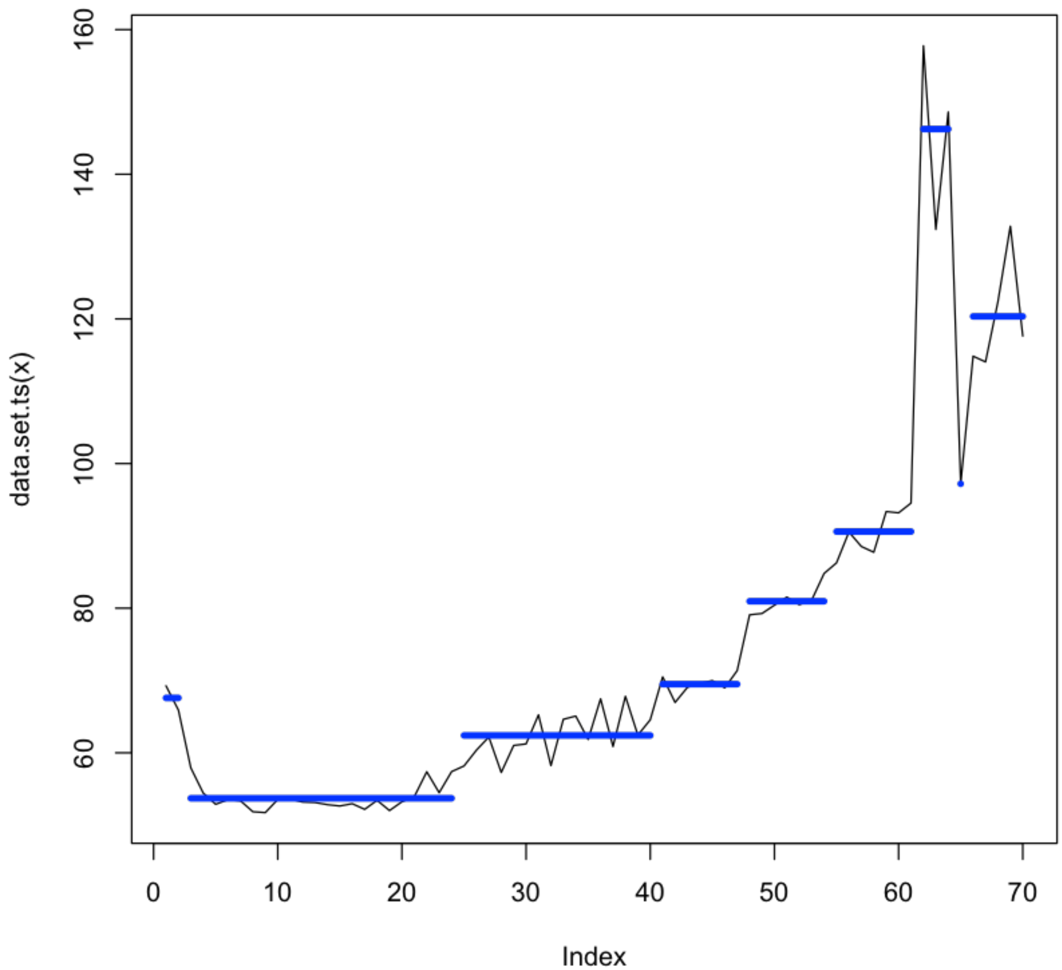
```
In [35]: m.pelt
```

```
Class 'cpt' : Changepoint Object
       ~~   : S4 class containing 12 slots with names
              cpttype date version data.set method test.stat pen.type pen.value minseglen cpts n

Created on  : Sun Feb  3 22:59:05 2019

summary(.)  :
----------
Created Using changepoint version 2.2.2
Changepoint type      : Change in mean
Method of analysis    : PELT
Test Statistic  : Normal
Type of penalty       : Manual with value, 212.4248
Minimum Segment Length : 1
Maximum no. of cpts   : Inf
Changepoint Locations : 2 24 40 47 54 61 64 65
```

```
In [36]: plot(m.pelt, type = "l", cpt.col = "blue", xlab = "Index", cpt.width = 4)
```



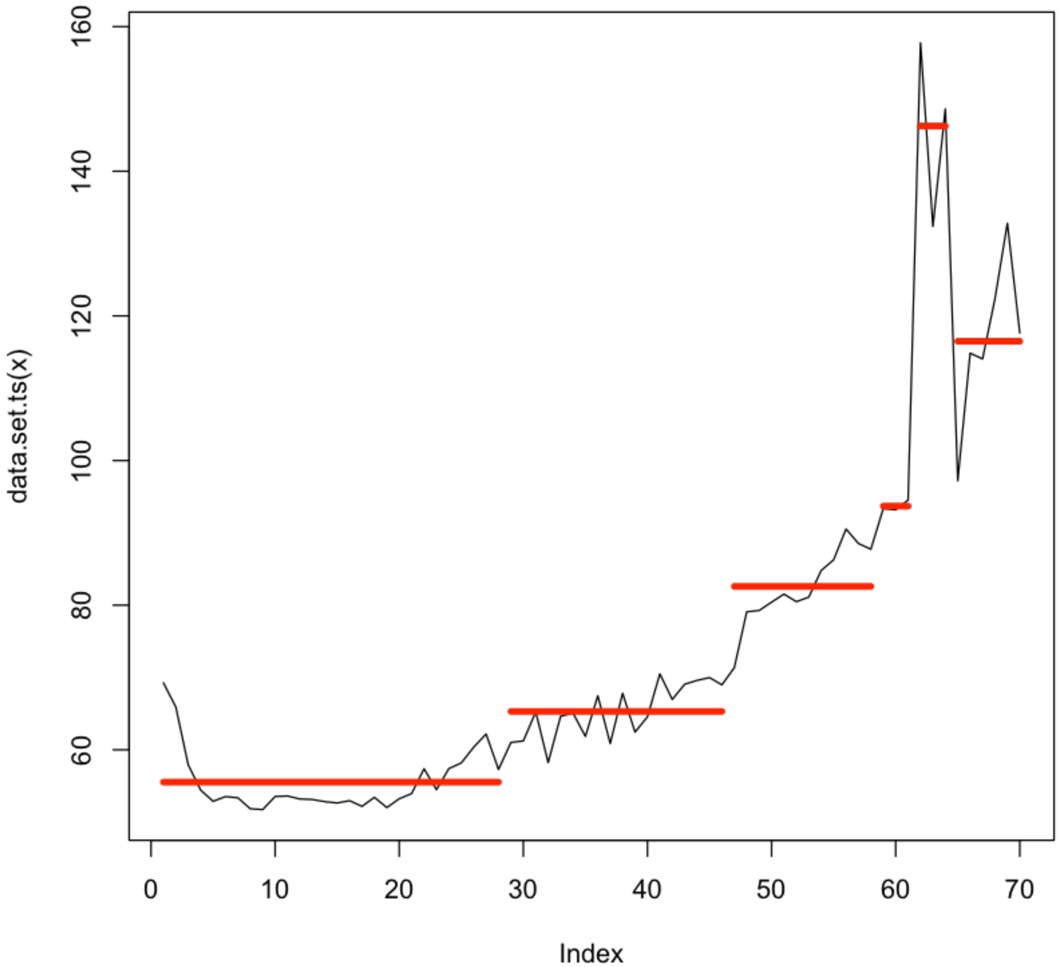
- **Figure 7:** PELT Changepoints of Run Time vs. Age (~Index)

After trying different values, results seem to be insensitive to the manual penalty applied `pen.value = "50 * log(n)`.

```
In [37]: m.binseg <- cpt.mean(runTimebyage$min, "Manual", pen.value = "50 * log(n)", method = "B

Warning message in BINSEG(sumstat, pen = pen.value, cost_func = costfunc, minseglen = minseglen,
The number of changepoints identified is Q, it is advised to increase Q to make sure changepoint

In [38]: plot(m.binseg, type = "l", xlab = "Index", cpt.width = 4)
```



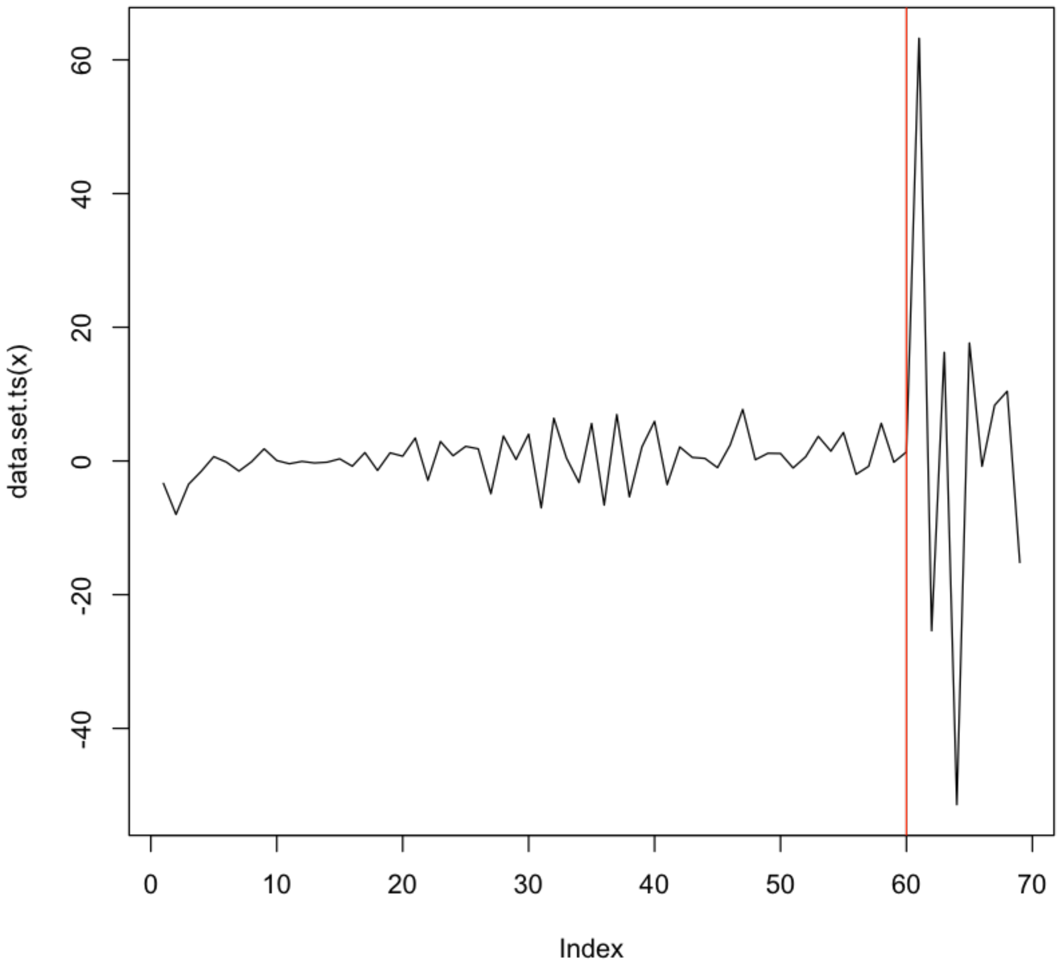
- **Figure 8:** Binary Segmentation Changepoints of Run Time vs. Age (~Index)

Binary Segmentation yields a lower number of changepoints (5 vs. 8) than the PELT method. Although it also seems to be insentive to the manual penalty applied.

4.1.3 Changes in Variance

```
In [39]: m.varPELT <- cpt.var(diff(runTimebyage$min), method = "PELT")
```

```
In [40]: plot(m.varPELT, xlab = "Index")
```



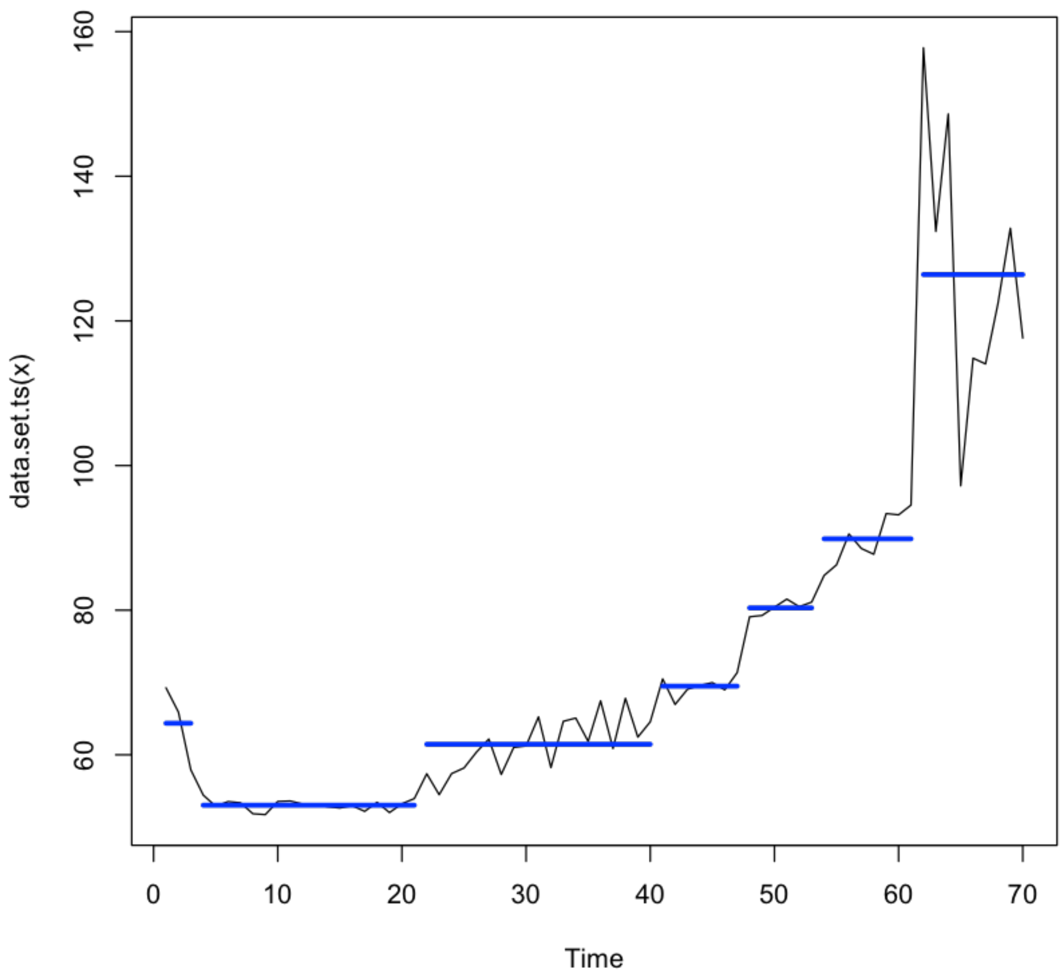
- **Figure 9:** Changes in Variance (PELT Method)

Both methods PELT and Binary Segmentation (not shown), yield only one variance change-point at the age of 60

4.1.4 Changes in Mean and Variance

```
In [41]: dis.pelt <- cpt.meanvar(runTimebyage$min, test.stat = "Normal", method = "PELT")
         cpts.ts(dis.pelt)
         plot(dis.pelt, cpt.col = "blue", cpt.width = 3)
```

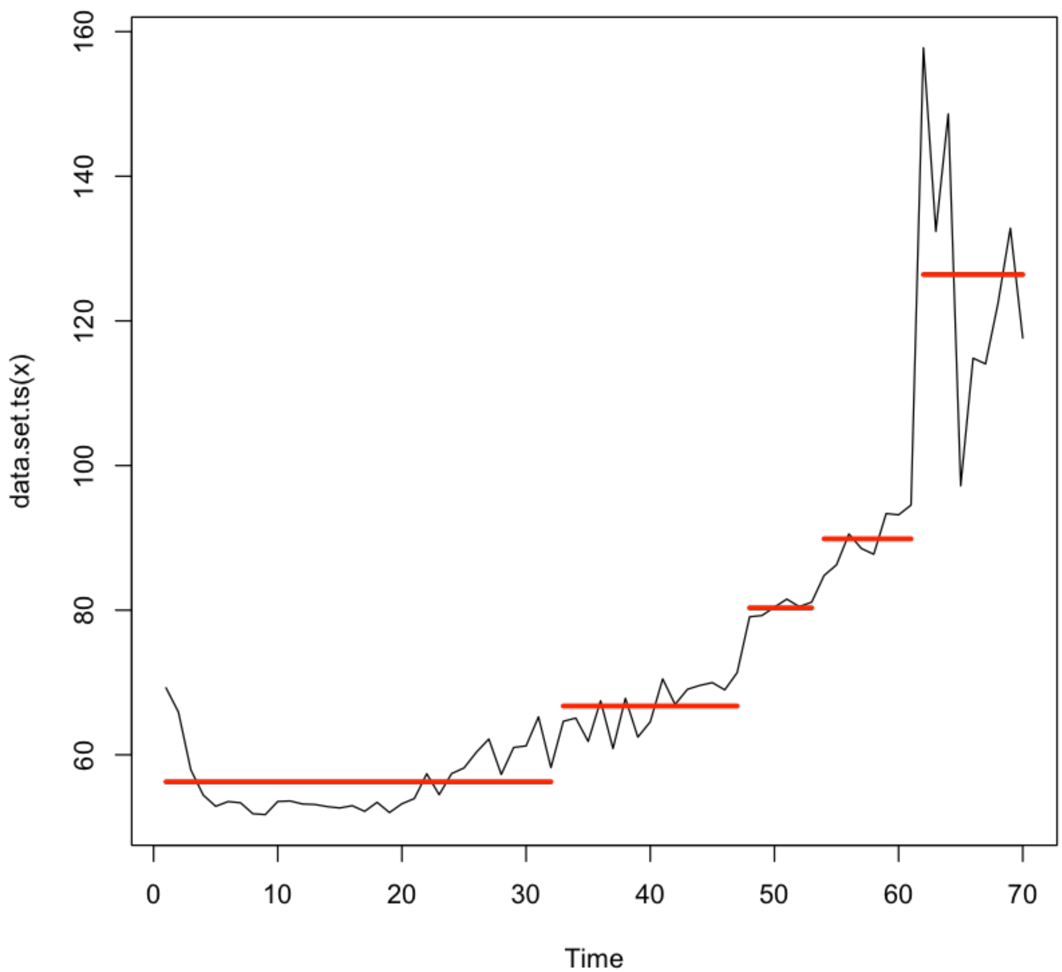
1. 3 2. 21 3. 40 4. 47 5. 53 6. 61



- **Figure 10:** Changes in Mean and Variance (PELT Method)

```
In [42]: dis.bs <- cpt.meanvar(runTimebyage$min, test.stat = "Normal", method = "BinSeg")
         cpts.ts(dis.bs)
         plot(dis.bs, cpt.col = "red", cpt.width = 3)
```

1. 32 2. 47 3. 53 4. 61



- **Figure 11:** Changes in Mean and Variance (Binary Segmentation Method)

Both methods, PELT (6 changepoints) and Binary Segmentation (4 changepoints), produce very similar results. The assumption of change in mean **and** variance despite of the method is the best course of action for this dataset.

4.2 LOESS

```
In [43]: library(ggplot2)
```

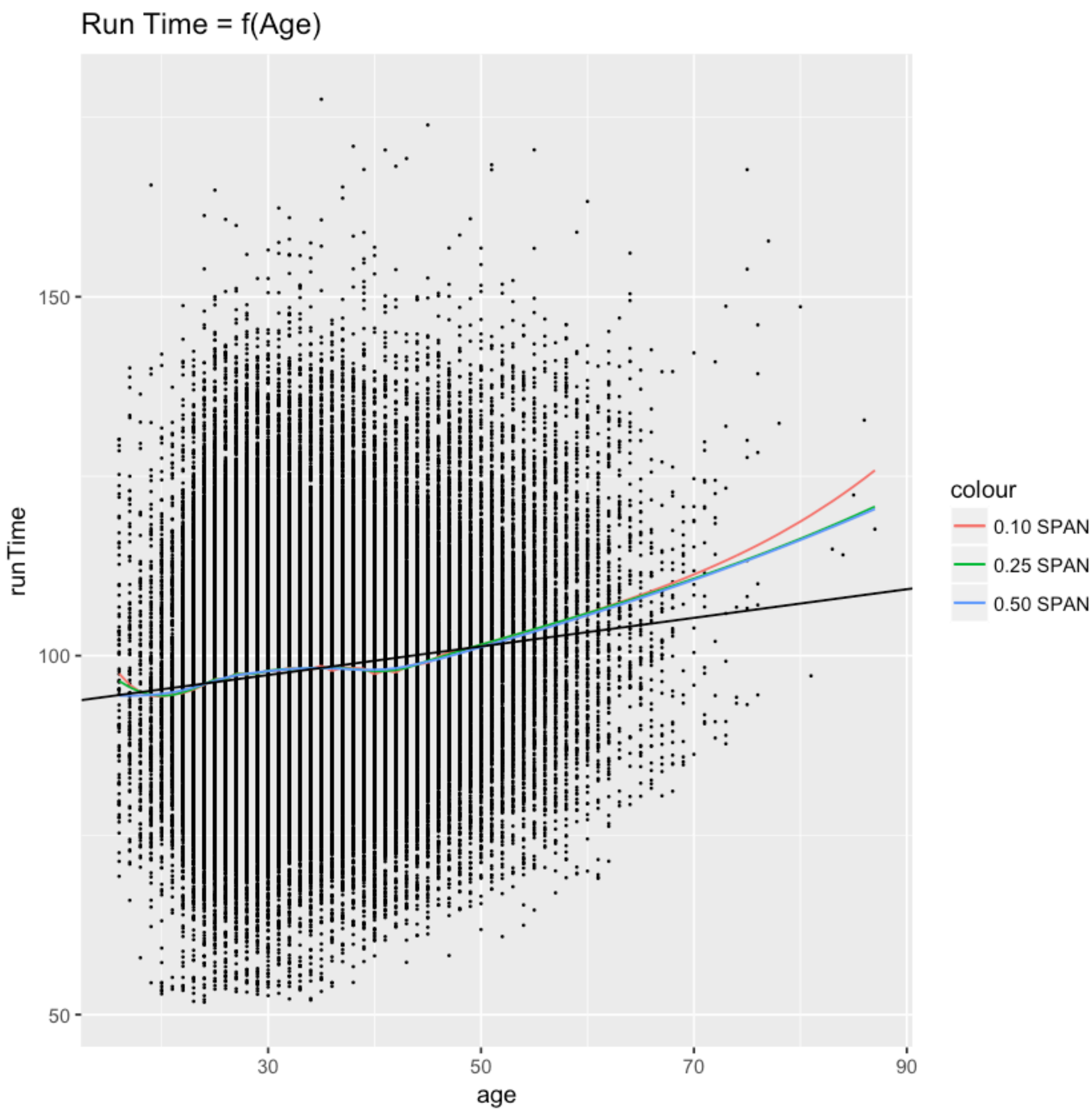
```
In [44]: loessresp10 <- loess(runTime ~ age, data = cbWomenSub, span = 0.10)
         smooth10 <- predict(loessresp10)
```

```
Warning message in simpleLoess(y, x, w, span, degree = degree, parametric = parametric, :
pseudoinverse used at 31Warning message in simpleLoess(y, x, w, span, degree = degree, parametri
neighborhood radius 1Warning message in simpleLoess(y, x, w, span, degree = degree, parametric =
reciprocal condition number  0Warning message in simpleLoess(y, x, w, span, degree = degree, par
There are other near singularities as well. 1
```

```
In [45]: loessresp25 <- loess(runTime ~ age, data = cbWomenSub, span = 0.25)
         smooth25 <- predict(loessresp25)
```

```
In [46]: loessresp50 <- loess(runTime ~ age, data = cbWomenSub, span = 0.50)
         smooth50 <- predict(loessresp50)
```

```
In [47]: loesspplot <- ggplot(data = cbWomenSub, aes(x = age, y = runTime)) +
         ggtitle("Run Time = f(Age)") +
         geom_point(size = 0.10) +
         geom_line(aes(y = smooth10, color = "0.10 SPAN")) +
         geom_line(aes(y = smooth25, color = "0.25 SPAN")) +
         geom_line(aes(y = smooth50, color = "0.50 SPAN")) +
         geom_abline(intercept = coef(lmAge)[1], slope = coef(lmAge)[2])
         loesspplot
```



- **Figure 12:** Simple Linear Model vs. LOESS with different Spans (0.10, 0.25, 0.50)

The results in `Figure 12` follow the same pattern as those in `Figure 5` where the authors developed a "manual" Piecewise linear model (i.e changepoints at 30 and 40). Although there seems to be a clear difference between span 0.10 and 0.25, 0.50 is virtually the same as 0.25.

5 Conclusions

- "The devil is in the details" when it comes to data transformation. Format and content changes make the data extraction an intricate and time consuming task
- Simple linear model is inadequate to describe the relationship of athletic performance (i.e. run times) vs. age because there is a clear changepoint (e.g. 40 years) where variance and performance deterioration accelerate

- The "manual" Piecewise linear model developed by the authors yields very similar results to the automatic LOESS function (i.e changepoints at 30 and 40), although results seem to be insensitive to the span after 0.25
- Changepoints detected by the `changepoint` package yield better results when we assume changes in mean and variance when applied to this particular dataset

6 References

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2. Brown, Zach, *Modeling Runners' Times in the Cherry Blossom Race*, https://rpubs.com/xzachx/351788

3. Killick, Rebecca, Eckley, Idris, Journal os Statistical Software, June 2014, Volume 58, Issue 3, *changepoint: An R Package for Changepoint Analysis*