Exploratory Data Analysis on Examining the Impact of Environmental and Demographic Factors on Marathon Performance

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Introduction

In recent years, marathon participation and performance have seen a marked increase, prompting a deeper exploration into the factors influencing outcomes in these endurance events. In collaboration with Dr. Brett Romano Ely and Dr. Matthew Ely from the Department of Health Sciences at Providence College, this study aims to assess the impact of environmental condition like temperature, humidity, solar radiation, and wind speed on marathon performance in both male and female marathon runners.

This study will focus on **three aims**. The first aim is to examine the effects of increasing age on marathon performance in men and women. Our second aim is to explore the impacts of environmental conditions on marathon performance, and whter the impact differs across age and gender. The last aim is to identify (WBGT, Flag conditions, temperature, etc) that have the largest impact on marathon performance. I hypothesize that increasing environmental temperatures and unfavorable weather conditions will have a

negative impact on marathon performance. Specifically, endurance exercise performance tends to degrade with rising temperatures, and this decline is likely to be exacerbated in longer-distance events, such as marathons, due to the greater physiological demands placed on athletes over extended periods of time.

Begin with an exploratory analysis to identify patterns and relationships among key variables. During data preprocessing, note that `Race (0=Boston, 1=Chicago, 2=NYC, 3=TC, 4=D)` corresponds to the `Race`variable in the *course_record* dataset. Also, the `Sex (0=F, 1=M)` variable also corresponds to the `Gender` in the course_record dataset. To have these two variables to match, I rename these variables to `Race` and `Gender`. After further reviewing the data, I noticed that some of the marathon races were denoted differently,like `0` while the other data set indicates race as `B` to indicate Boston's marathon. To enhance consistency of the variables, we changed the marathon races from `0` to `B`, `1` to `C`, `3` to `TC`, and `4` to `D`. I also changed the binary outcomes of the `Gender` variables to match where `0 = M` to indicate male and `1` for female.Once that is done, I decided to renamed all the variable names for better understanding and to correlate to code sheet. Once this stage of processing is done, I merged the data by `Race`, `Gender`, and `Year`. This merge was able to keep variables to the left and implemented the other variables that weren't in common. In the course_record variable, the data gives us the course records, but project 1 gives us the percentage off the course record.Because we want to measure the`Run Times` accuractely, I first converted the course records into seconds and then created a variable to get the actual runtime and marathon time for a participant in seconds. `(Runtimes = Race_Seconds * (1 +` (Percent CR‘ / 100))

Exploratory Analysis and Data Preprocessing: An initial exploratory analysis was conducted to identify patterns and relationships among key variables. During preprocessing, it was observed that `Race (0=Boston, 1=Chicago, 2=NYC, 3=TC, 4=D)` corresponds to the `Race` variable in the *course_record* dataset, while `Sex (0 = F, 1 = M)` corresponds to the `Gender` variable. To ensure consistency, the `Sex` and `Race` variables were renamed to `Gender` and `Race`, respectively.

Further review revealed discrepancies in how some marathon races were coded. For instance, while one dataset used numeric codes (e.g., `0` for Boston), another dataset used letter codes (e.g., `B` for Boston). To standardize these variables, the race codes were recoded from `0` to `B`, `1` to `C`, `3` to `TC`, and `4` to `D`. Additionally, the binary outcomes for `Gender` were modified to align across datasets, with `0` recoded as `M` for male and `1` as `F` for female.

Variable names were then systematically renamed for clarity and consistency with the codebook. After completing these preprocessing steps, the data were merged by `Race`, `Gender`, and `Year`, ensuring that variables from the left dataset were retained, while integrating other variables that were not common across datasets.

To begin with, we will observe the data and notice any commonalities within the variables. We begin our data preprocessing by noticing that`Race (0=Boston, 1=Chicago, 2=NYC, 3=TC, 4=D)` corresponds to the `Race` variables in the course_record data set.

The raw data used for this analysis consisted of 11,564 rows and 14 columns. The data was then processed to observed the missing data to further our analysis. To begin this analysis, I got the sum of missing values from the data set by columns. From this analysis, I noticed that the variables **Flag, Dry bulb Temp C, Wet bulb Temp C, Percent Relative Humidity , Black Globe Temp C, Dew Point in C, Wind Speed, and Wet Culb Globe Temp** has missing data. I observed the missing the data using the `naniar package` in r to find the percentage missing and available in the data. Following this procedure,we found the the number of missing values from each of these columns were 491, making it a grand total 4419 missing values. I observed that missing data only represents 2.2% on the data while we still have a high representation of the data being represented at 97.2%. Therefore, we will remove those irrelevant variables.

The raw dataset used for this analysis consisted of 11,564 observations across 14 variables. An initial review of the data was conducted to assess missing values, which would guide subsequent analysis. The sum of missing values was calculated for each variable. From this assessment, it was observed that the variables Flag, Dry Bulb Temp C, Wet Bulb Temp C, Percent Relative Humidity, Black Globe Temp C, Dew Point in C, Wind Speed, and Wet Bulb Globe Temp contained missing values.

To further quantify the extent of missingness, the naniar package in R was employed to calculate the

percentage of missing and available data. The analysis revealed that each of these variables had 491 missing values, contributing to a total of 4,419 missing entries across the dataset. However, these missing values accounted for only 2.2% of the total dataset, leaving 97.8% of the data intact and available for analysis.

Given the relatively small proportion of missing data, it was determined that the variables with missing values would be removed, as their exclusion would not significantly impact the overall representation or integrity of the dataset.

Lastly, in Aim 3, we include the two other data sets marathon_dates and aqi_values. In the marathon_dates dataset, ot provided the race, race I changed the marathon race names to correspond to current flow of variables. Then

Missing Data Attributes

Possibly Meet Completely at random because the the course_record wasn't dependent on the project 1 data. They carried some of the same attributes and shared covariates the we can't say one is dependent of the other.

```
## [1] 4419
```

In the course record data we have Pecent CR which give percentages by gender In the project 1 data we have course record overall has race seconds

Results

Aim 1: Examine effects of increasing age on marathon performance in men and women

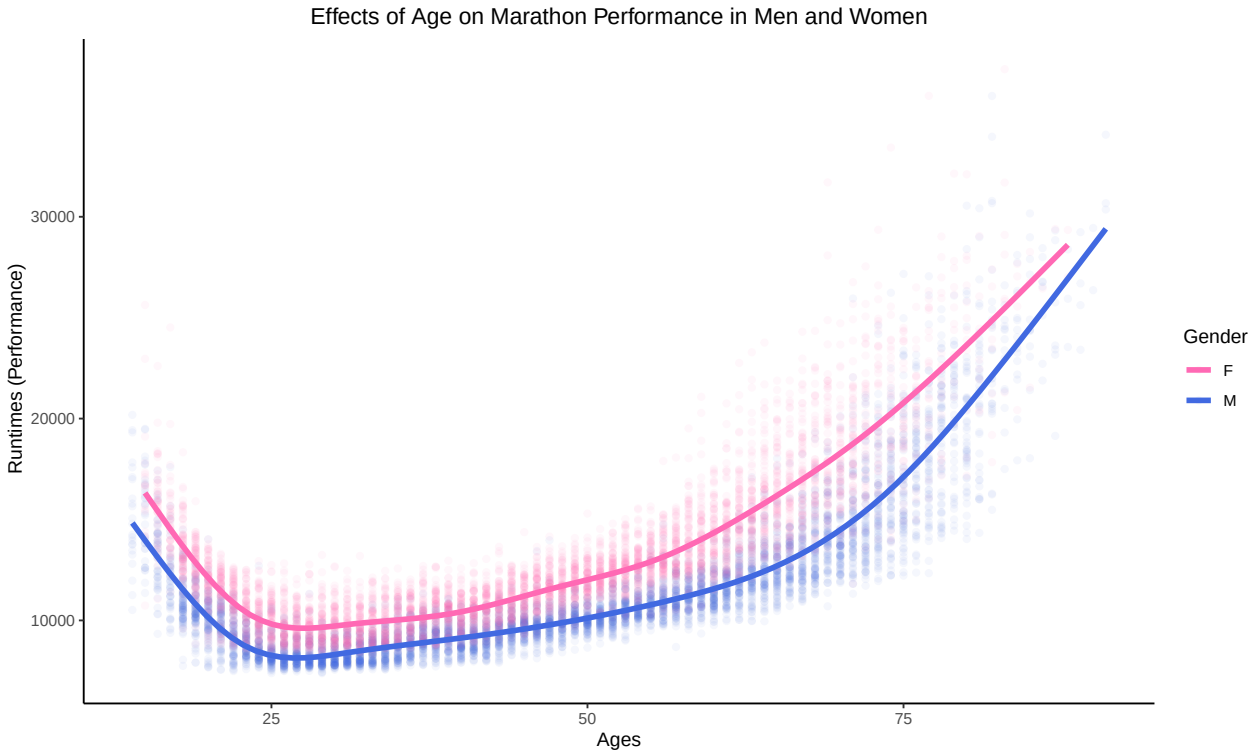
In the **Effects of Age on Marathon Performance in Men and Women** visualization, we observe the marathon performance (measured in runtimes) of men and women across a wide age range, from 14 to 91 years. Based on the data, there is a clear decrease in runtimes up to approximately 25 years of age, indicating improved performance in both men and women during their younger years, with peak performance typically occurring in the mid-twenties. This pattern signifies that younger participants, particularly those in their mid-twenties or younger, perform better in marathons compared to older participants.

After reaching this peak, there is a noticeable and steady increase in runtimes, suggesting a decline in performance as age advances. When comparing genders, men consistently demonstrate faster runtimes across all ages. While both men and women exhibit similar trends in declining performance with age, the slope of decline is steeper for women, particularly around the ages of 60-65. This indicates that the negative effects of aging on marathon performance are more pronounced in women during later life stages.

Overall, the performance gap between genders widens with increasing age, with men generally maintaining faster runtimes compared to women, especially in older age groups. This widening gap highlights the greater impact of aging on female marathon runners in terms of performance decline.

Table 1: Marathon Runners' Data Description

Variables	Missing Data	Type	Description
Age (yr)	0	Numeric	Age (yr) represents the ages of the participants.
Black Globe Temp C	491	Numeric	Black Globe Temp Celcius indicates how hot it feels in direct sunlight.It considers temperature, humidity, wind speed, sun angle, and cloud cover to provide a holistic view of the stress placed on the body in hot environments.
CR	0	HMS/Numeric	CR is the course record for each marathon.
Dew Point in C	491	Numeric	Dew Point in Celcius is the temperature the air needs to be cooled to (at constant pressure) in order to achieve a relative humidity (RH) of 100%. At this point the air cannot hold more water in the gas form. If the air were to be cooled even more, water vapor would have to come out of the atmosphere in the liquid form, usually as fog or precipitation.
Dry bulb Temp C	491	Numeric	Dry bulb Temp Celcius is the air temperature without taking into account of the humidity or any moisture.
Flag	491	Character	Flag WBGT Thresholds. White= WBGT < 10C, Green= WBGT 10-18C, Yellow=WBGT >18-23C, Red= WBGT >23-28C, and Black= WBGT > 28C
Gender	0	Character	Gender is represented by F= Female and M= Male.
Percent CR	0	Numeric	Percent CR is the percent off current course record for gender.
Percent Relative Humidity	491	Numeric	Percent Relative Humidity how much moisture is in the air compared to the maximum amount of moisture the air can hold at a given temperature. Gives an idea of how humid it feels outside.
Race	0	Character	Race represents the marathons the participants competed, including the B=Boston Marathon, C= Chicago Marathon, NY= New York City Marathon,T= Twin Cities Marathon (Minneapolis,MN), D= Grandma's Marathon (Duluth, MN).
Race_Seconds	0	Numeric	Race_Seconds is the course record measured in seconds.
Runtimes	0	Numeric	Runtimes is the converted gender percentage into seconds.
Solar Radiation	491	Numeric	Solar Radiation in Watts per meter squared is the energy emitted by the sun, which travels through space and reaches the Earth as light and heat.
Wet Bulb Globe Temp	491	Numeric	Wet Bulb Globe Temp measures the combined effect of temperature, humidity, wind speed, and solar radiation on humans. Formula WBGT= 0.7 x Tw + 0.2 x Tg+ 0.1 xTd.
Wet bulb Temp C	491	Numeric	Wet bulb Temp Celcius is a measure of temperature that reflects both the heat and humidity in the air. Wet bulb temperature gives you an idea of how temperature feels when you take humidity into account.
Wind Speed	491	Numeric	Wind Speed in Km/hr.
Year	0	Numeric	Years represented in the dataset ranging from 1993-2016.

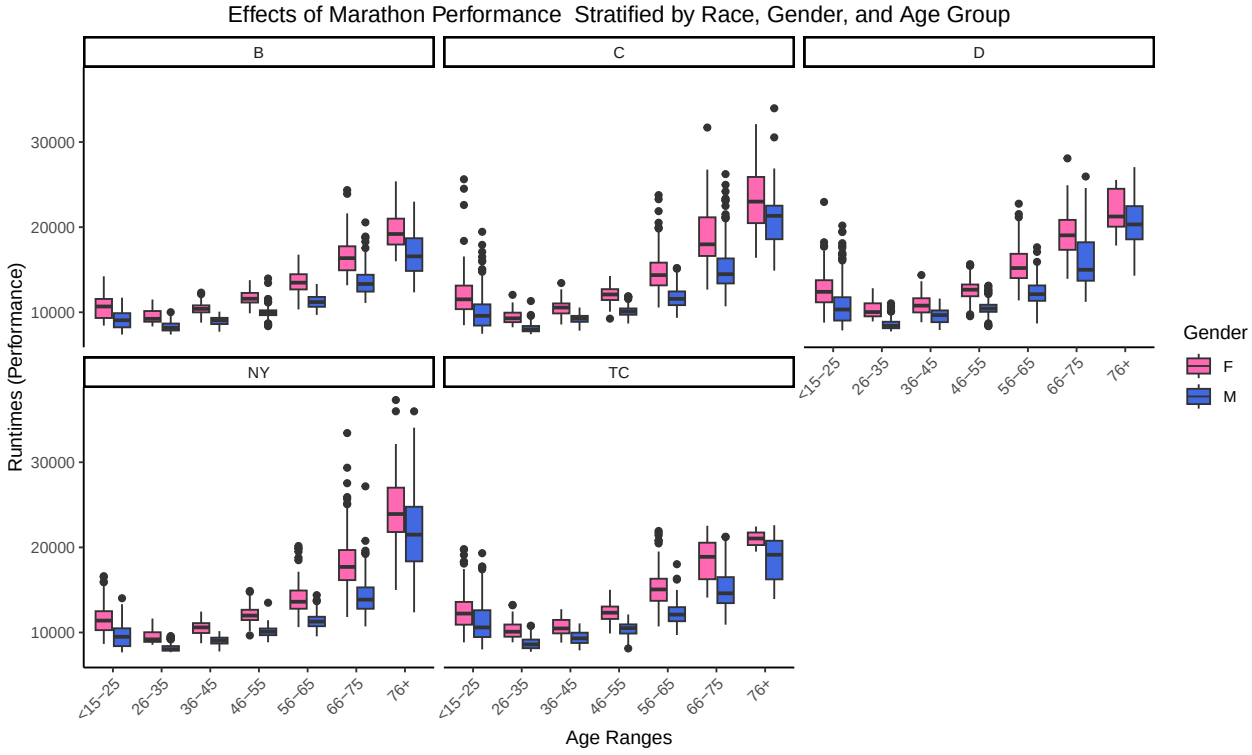


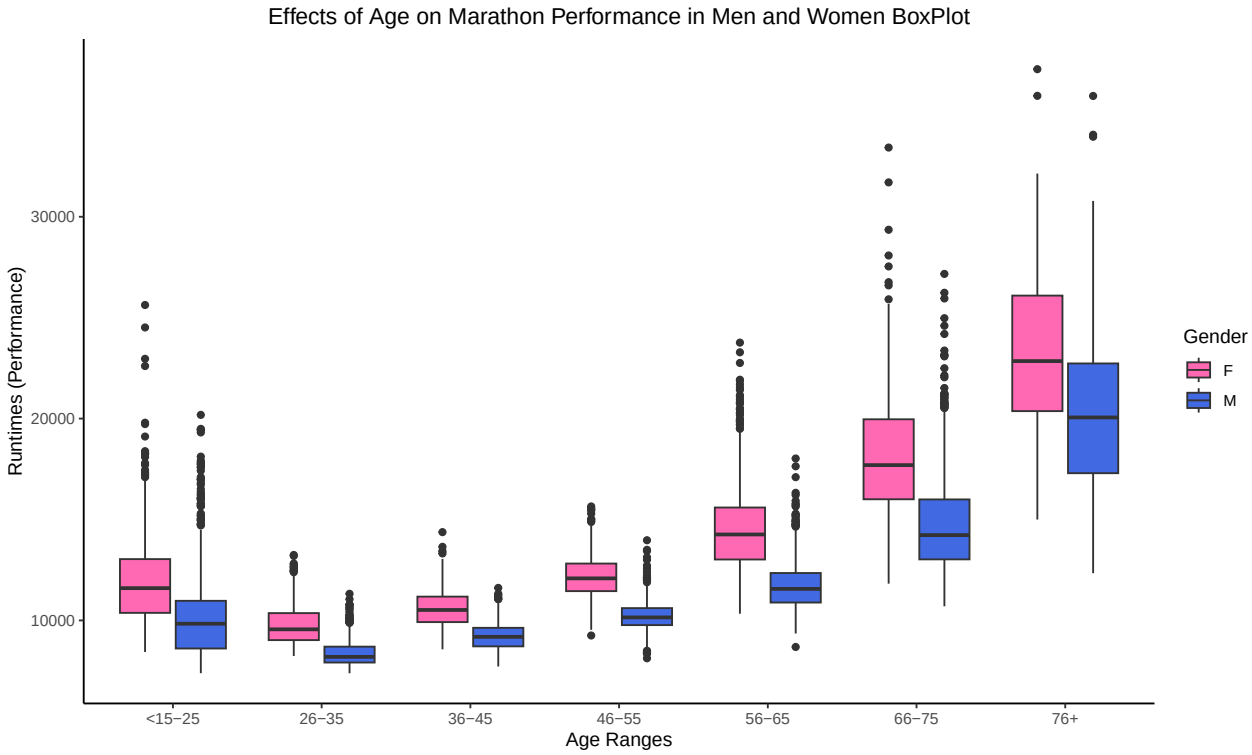
In the **Marathon Performance Summary Table by Age Ranges** and the **Effects of Age on Marathon Performance in Men and Women**, we noticed some summary statistics of the boxplot measurements of the marathon runners runtimes based upon their age ranges. The marathon runners were broken up into seven age groups where we noticed a somewhat balance number of people in each group. From the box plot, younger runners **<15–25** tend to perform better, with lower runtimes, as evidenced by lower median values and a tighter interquartile range (IQR). This age group shows more variability (outliers) in performance for both genders.In the summary table, the mean runtime for this group is 11,039, with a median of 10,626. This group performs significantly better than older age groups, with a relatively smaller IQR of 2,917. The **26–35** and **36–45** age groups demonstrate the best overall marathon performance. From the box plot, both men and women in these groups have lower runtimes and reduced variability (indicated by shorter whiskers and fewer outliers). The table shows a continued decline in median runtimes as runners transition from 26–35 (median: 8,896) to 36–45 (median: 9,774). The IQR for both groups remains relatively small (~1,500), indicating more consistent performance in this age range. Men tend to outperform women in these age groups, as seen by the lower median runtimes in the blue box plots. The oldest age groups **66–75** and **76+** exhibit the largest runtimes and widest performance variability. The box plots show much larger IQRs, particularly for women, reflecting significant variation in performance. In the table, the mean and median runtimes increase sharply for the **66–75** (mean: 16,156; median: 15,552) and 76+ (mean: 21,032; median: 20,688) groups. The IQR also expands dramatically, especially for the 76+ group (IQR: 5,687), indicating a broad range of abilities within this age range.The box plot demonstrates that men, even in older age groups, continue to have better performance (lower runtimes) than women. However, the performance gap between genders widens significantly after age 66, particularly in the 76+ group.

Marathon Performance Summary by Age Range

Age Ranges	Marathon Runners	Mean Runtimes	1Q	Median Runtimes	3Q	IQR

<15-25	1736	11,039	9,332	10,626	12,248	2,917
26-35	1840	9,064	8,194	8,896	9,684	1,491
36-45	1840	9,881	9,092	9,774	10,589	1,498
46-55	1840	11,174	10,131	10,968	12,112	1,981
56-65	1820	13,125	11,494	12,664	14,374	2,880
66-75	1463	16,156	13,700	15,552	17,964	4,264
76+	534	21,032	17,924	20,688	23,611	5,687





Explore the impact of environmental conditions on marathon performance, and whether the impact differs across age and gender.

Higher temperatures lead to slower times stratify by gender age

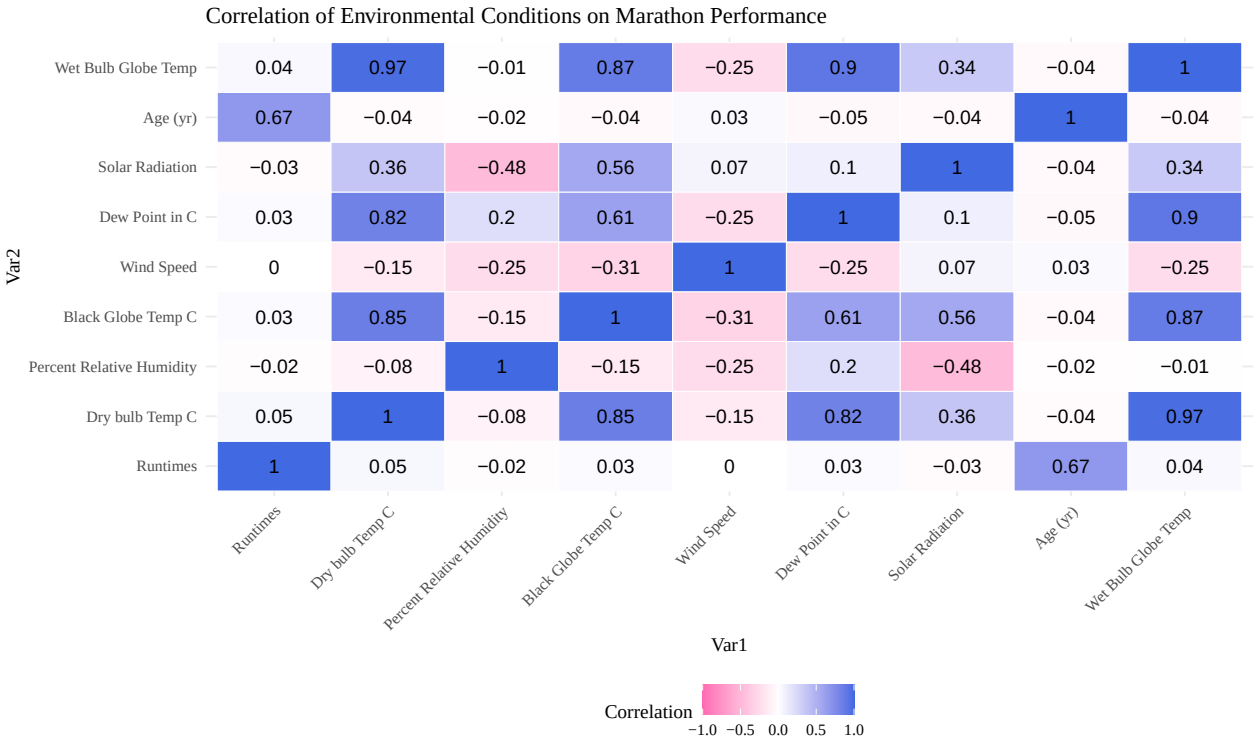
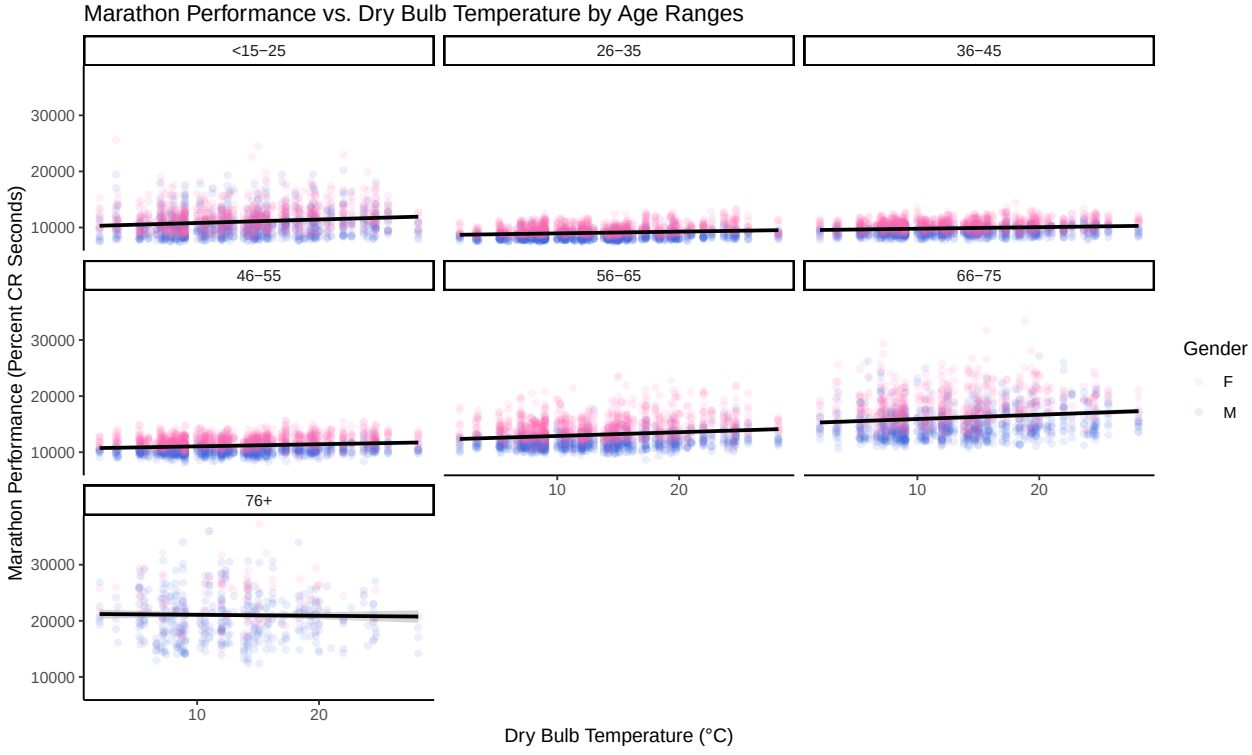
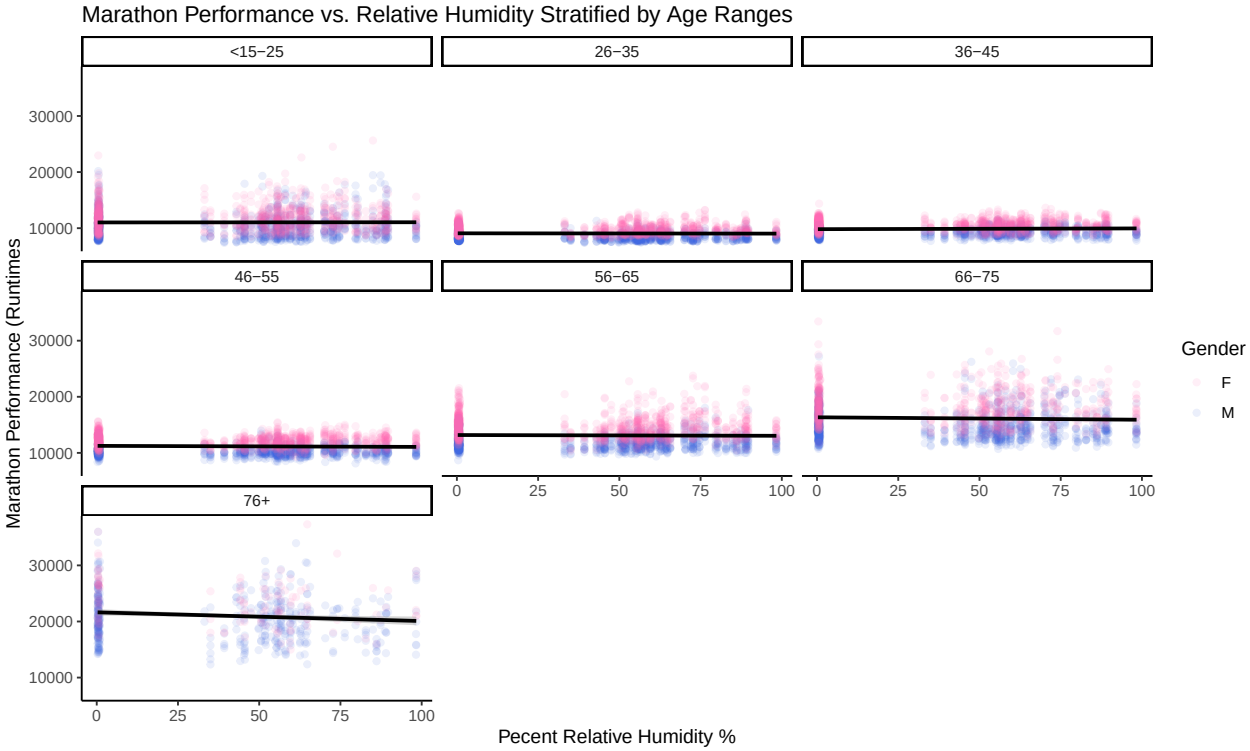
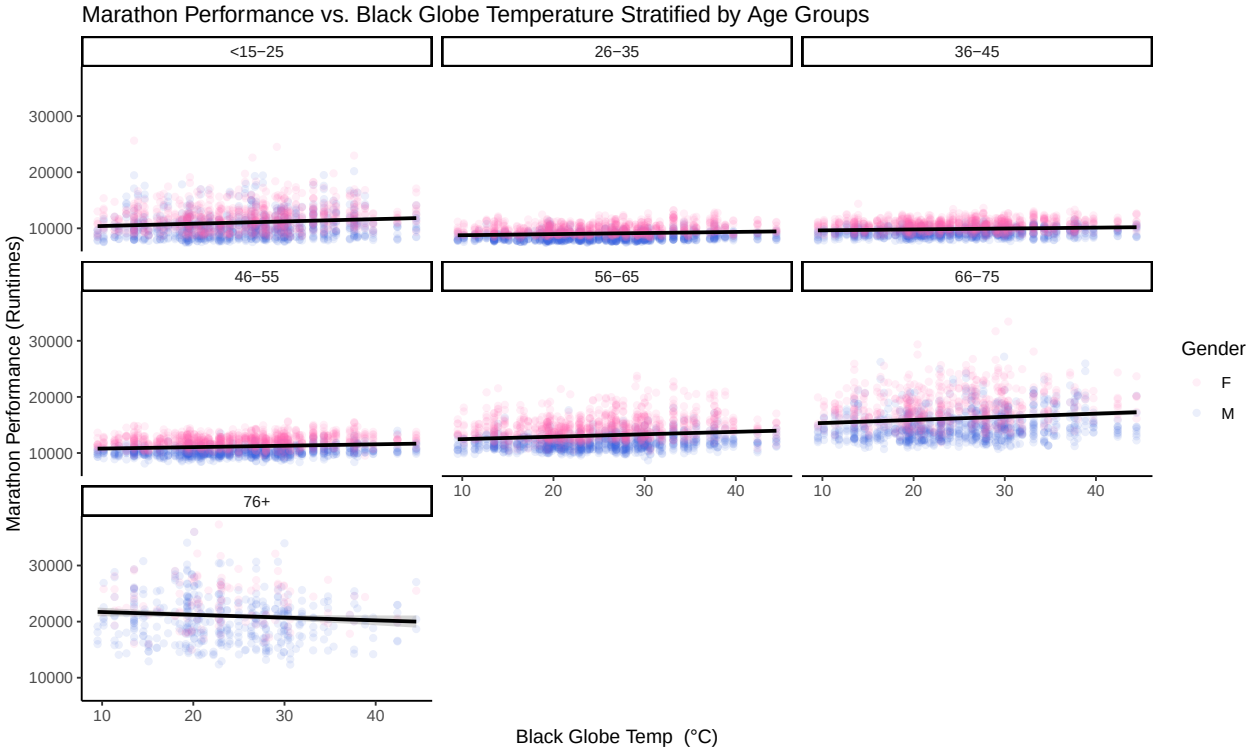


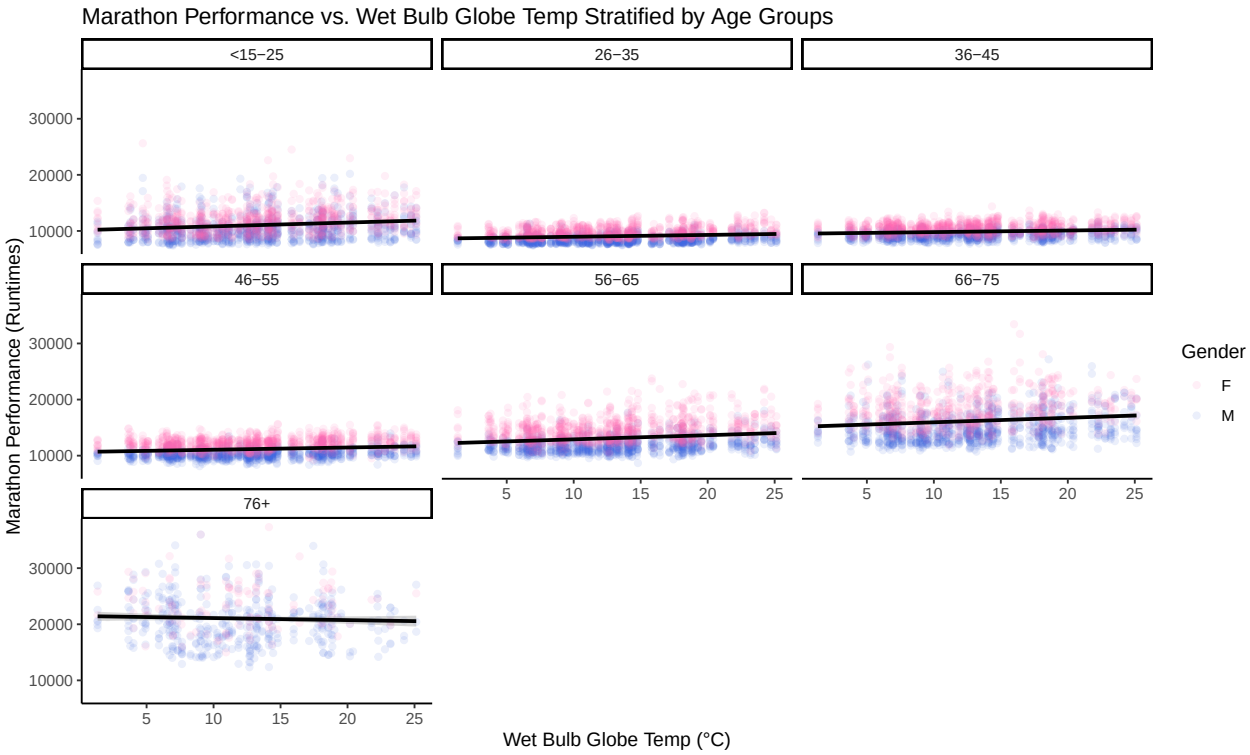
Table 3: Impact of Environmental Conditions on Marathon Performance by Age and Gender

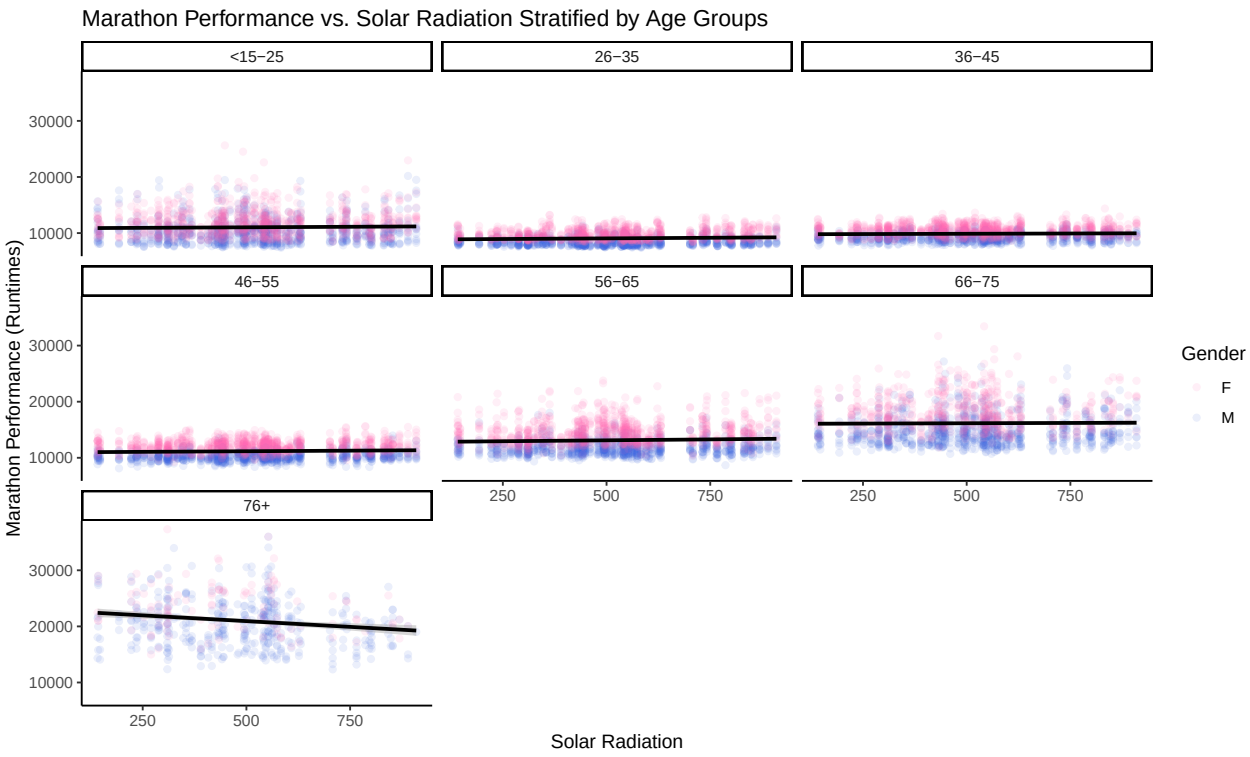
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	**2411.77125**	**578.71285**	**4.16747**	**0.00003**
‘Dry bulb Temp C‘	**-552.88575**	**122.75832**	**-4.50386**	**0.00001**
‘Percent Relative Humidity‘	**21.06573**	**2.97023**	**7.09228**	**0.00000**
‘Black Globe Temp C‘	**-270.50909**	**65.07994**	**-4.15657**	**0.00003**
‘Wind Speed‘	-24.68197	21.22259	-1.16301	0.24485
‘Dew Point in C‘	**-313.60541**	**92.41151**	**-3.39358**	**0.00069**
‘Solar Radiation‘	**4.71062**	**0.57781**	**8.15250**	**0.00000**
‘Age (yr)‘	**221.49195**	**11.16442**	**19.83909**	**0.00000**
‘Wet Bulb Globe Temp‘	**1288.98835**	**290.41680**	**4.43841**	**0.00001**
GenderM	**-1890.99700**	**419.11095**	**-4.51192**	**0.00001**
‘Dry bulb Temp C‘:‘Age (yr)‘	**10.39954**	**2.40581**	**4.32268**	**0.00002**
‘Percent Relative Humidity‘:‘Age (yr)‘	**-0.55316**	**0.05694**	**-9.71409**	**0.00000**
‘Black Globe Temp C‘:‘Age (yr)‘	**4.72352**	**1.28324**	**3.68095**	**0.00023**
‘Wind Speed‘:‘Age (yr)‘	0.31655	0.40853	0.77485	0.43845
‘Dew Point in C‘:‘Age (yr)‘	**4.88779**	**1.81383**	**2.69473**	**0.00706**
‘Solar Radiation‘:‘Age (yr)‘	**-0.12420**	**0.01132**	**-10.97440**	**0.00000**
‘Age (yr)‘:‘Wet Bulb Globe Temp‘	**-21.46104**	**5.70079**	**-3.76457**	**0.00017**
‘Age (yr)‘:GenderM	**-6.54622**	**2.73514**	**-2.39338**	**0.01671**
‘Dry bulb Temp C‘:GenderM	-36.56022	85.61722	-0.42702	0.66937
‘Percent Relative Humidity‘:GenderM	**4.82247**	**2.04912**	**2.35344**	**0.01862**
‘Black Globe Temp C‘:GenderM	-24.62302	45.15141	-0.54534	0.58553
‘Wind Speed‘:GenderM	7.71624	14.53336	0.53093	0.59548
‘Dew Point in C‘:GenderM	-33.38632	64.05318	-0.52123	0.60222
‘Solar Radiation‘:GenderM	0.65298	0.39924	1.63557	0.10196
‘Wet Bulb Globe Temp‘:GenderM	84.32974	202.04485	0.41738	0.67641

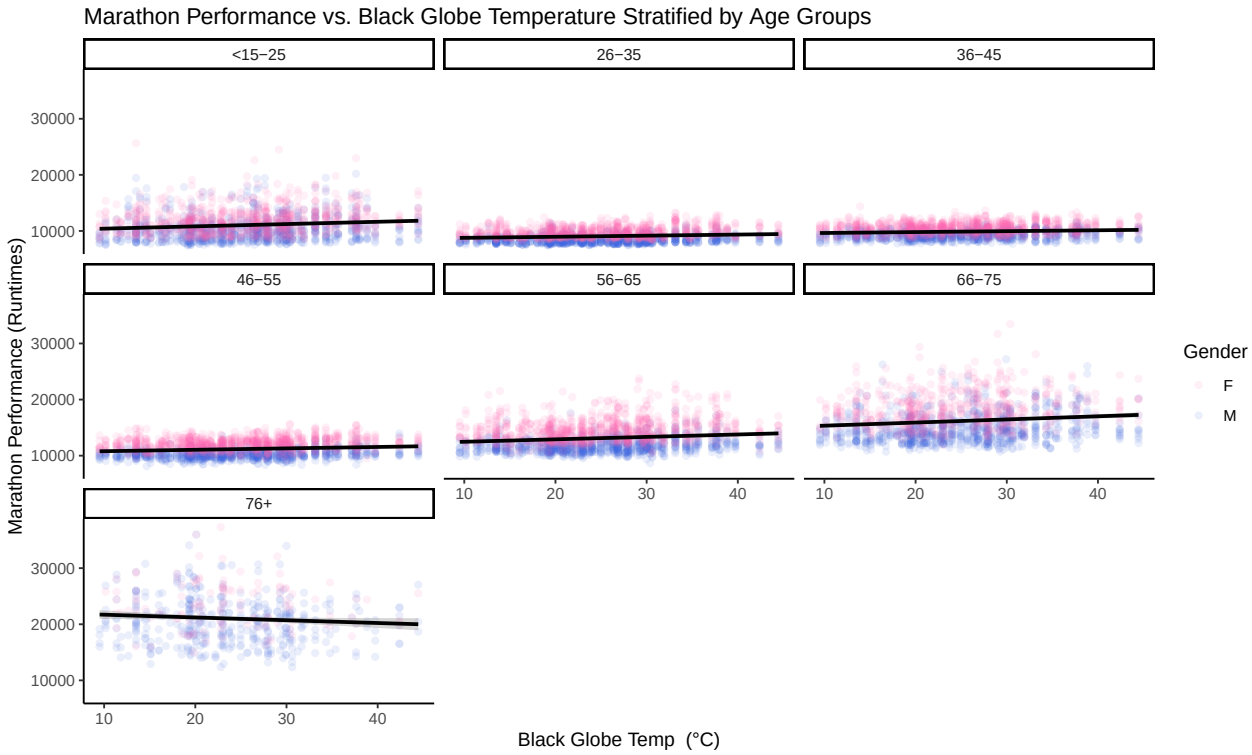



Marathon Performance vs. Relative Humidity Stratified by Age Ranges
<15–25
26–35
36–45
46–55
56–65
66–75
76+
Marathon Performance (Runtimes
30000
20000
10000
0
25
50
75
100
Pecent Relative Humidity %
Gender
F
M

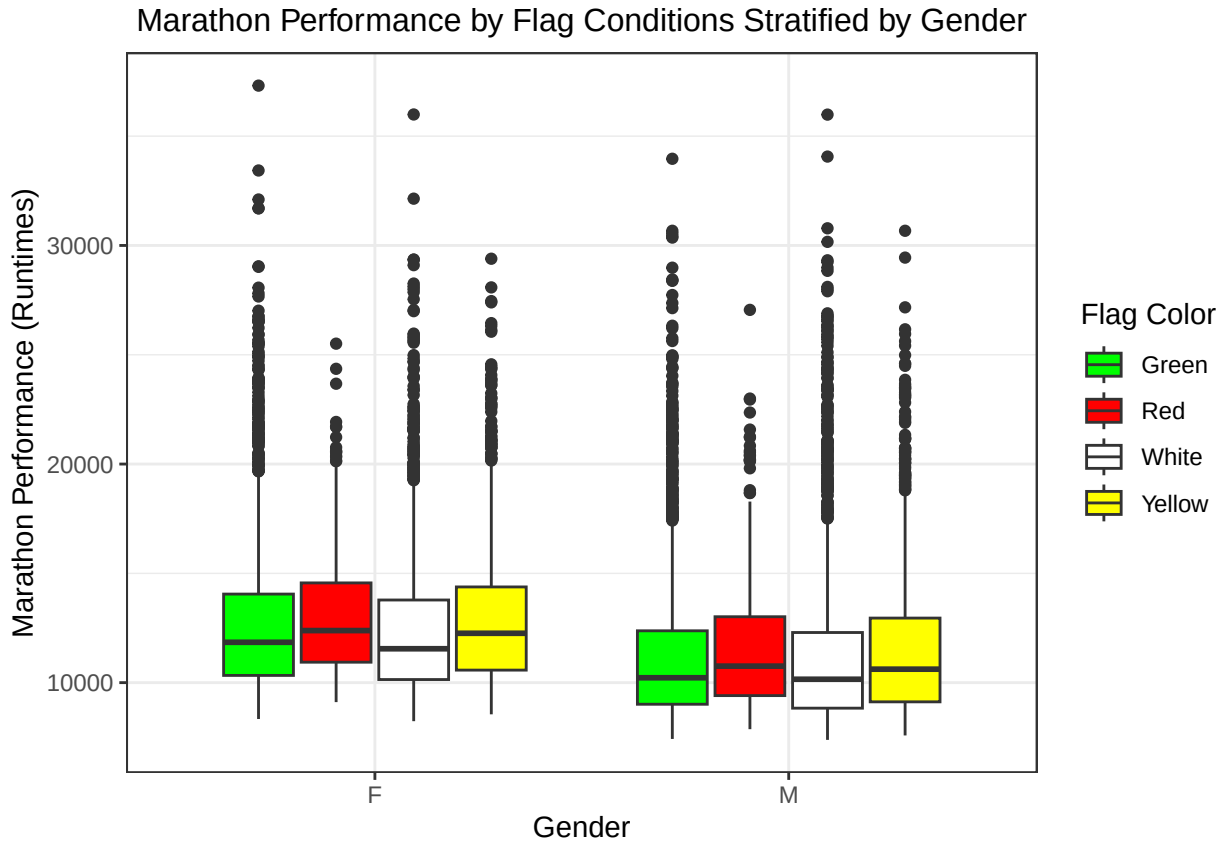

Marathon Performance vs. Black Globe Temperature Stratified by Age Groups
<15–25
26–35
36–45
46–55
56–65
66–75
76+
Marathon Performance (Runtimes)
30000
20000
10000
10
20
30
40
Black Globe Temp (°C)
Gender
F
M

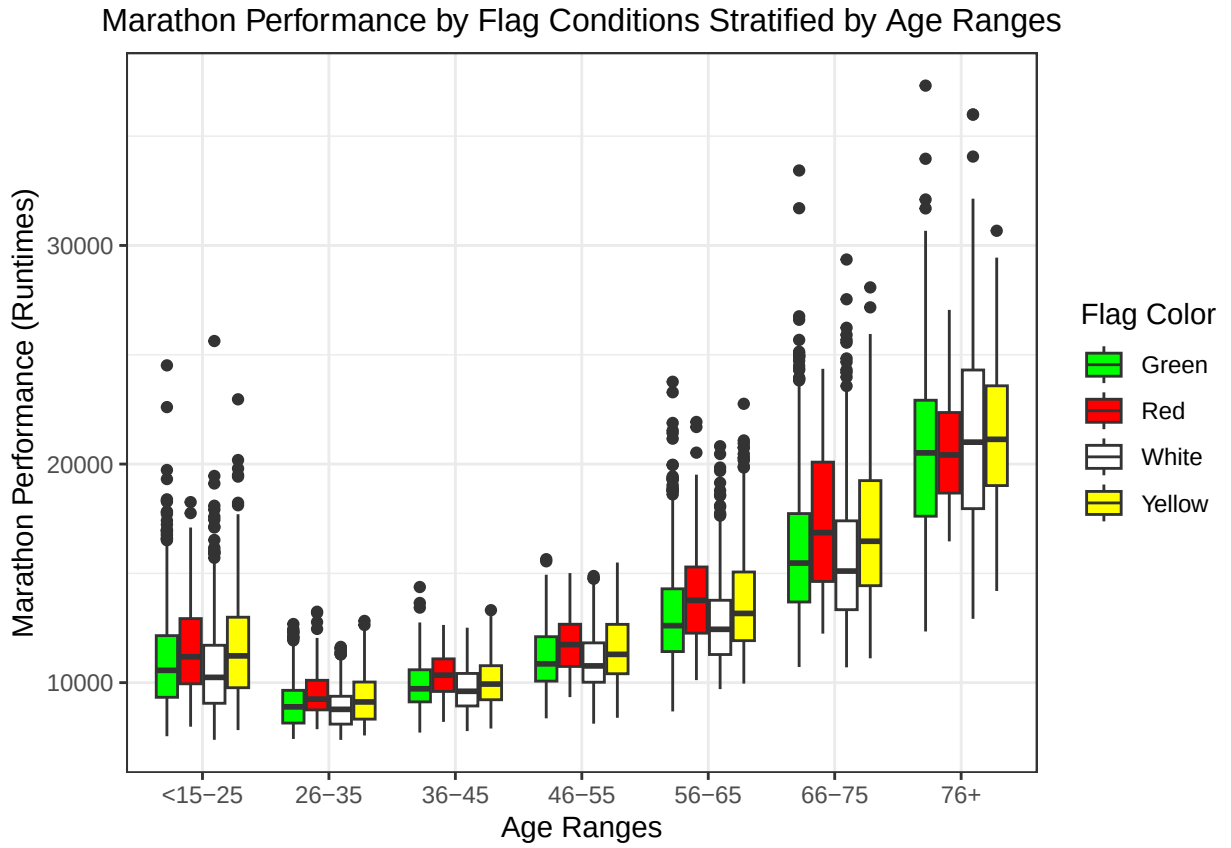

Marathon Performance vs. Wet Bulb Globe Temp Stratified by Age Groups
<15–25
26–35
36–45
46–55
56–65
66–75
76+
Marathon Performance (Runtimes)
Wet Bulb Globe Temp (°C)
Gender
F
M

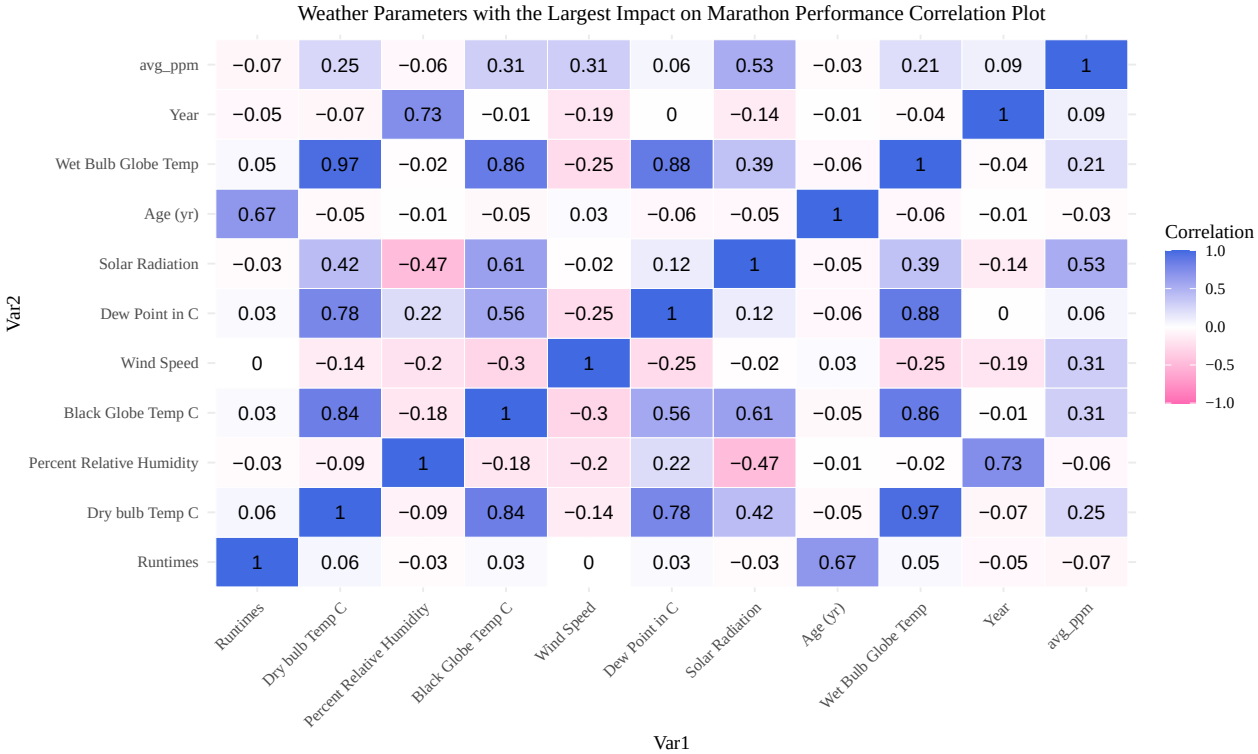

Marathon Performance vs. Solar Radiation Stratified by Age Groups
<15–25
26–35
36–45
46–55
56–65
66–75
76+
Marathon Performance (Runtimes)
Solar Radiation
Gender
F
M



Aim 3: Identify the weather parameters (WBGT, Flag conditions, temperature, etc) that have the largest impact on marathon performance.







Code Appendix

```r
knitr::opts_chunk$set(warning = FALSE,
                      message = FALSE,
                      echo = FALSE,
                      fig.align = "center")




#Data
library(readr)
marathon_dates <- read_csv("marathon_dates.csv")
course_record <- read_csv("course_record.csv")
aqi_values <- read_csv("aqi_values.csv")
project1 <- read_csv("project1.csv")
#Packages
library(lubridate)
library(tidyverse)
library(tidyr)
library(dplyr)
library(naniar)
library(visdat)
library(kableExtra)
library(knitr)
library(gridExtra)
library(ggridges)
library(gt)
library(ggwordcloud)
library(ggplot2)
library(magick)
library(ggplot2)
library(corrplot)
library(reshape2)



# Path to your image
fig_path <- "/Users/diahminhawkins/Documents/GitHub/Project1/weather.png"

# Load the image using magick
img <- image_read(fig_path)

# Convert image to raster for use in ggplot
img_raster <- as.raster(img)


# Example data
words <- c("Boston", "New York City", "Minneapolis", "Grandma's", "Chicago",
           "Race", "Age", "Gender", "Weather", "Performance",
           "Wet Bulb Globe Temperature", "Humidity")

frequencies <- c(1, 1, 1, 1, 1, 1, 5, 1, 4, 15, 3, 14)

new_frame <- data.frame(words, frequencies)
```

```r
# Generate the word cloud on top of the image background
ggplot(new_frame, aes(label = words, size = frequencies)) +
  # Add the image background
  annotation_raster(img_raster, xmin = -Inf, xmax = Inf, ymin = -Inf, ymax = Inf) +

  # Generate the word cloud
  geom_text_wordcloud(aes(color = frequencies)) +
  scale_size_area(max_size = 10) +

  # Customize the colors of the words
  scale_color_gradient(low = "yellow", high = "red") +

  # Remove axis titles and labels since we want the word cloud only
  theme_void()


# Currently, there has been an increase in marathon participation and performance in the past two decad
#Course Record  Data Management
course_record<- course_record%>%
  mutate(Race_Seconds= as.numeric(hms(course_record$CR)))

#Change column names from Sex... to Gender to match project1 dataset
colnames(course_record)[colnames(course_record) == "Sex (0=F, 1=M)"] ="Gender"


# Change the Race variable to a character variable
course_record <- course_record %>%
  mutate(Race = as.character(Race))



# Project 1 Data Management
#Change colnames for a more readable and understanding approach
colnames(project1)[colnames(project1) == "Sex (0=F, 1=M)"] ="Gender"
colnames(project1)[colnames(project1) == "Race (0=Boston, 1=Chicago, 2=NYC, 3=TC, 4=D)"] ="Race"
colnames(project1)[colnames(project1) == "Td, C"] ="Dry bulb Temp C"
colnames(project1)[colnames(project1) == "Tw, C"] ="Wet bulb Temp C"
colnames(project1)[colnames(project1) == "%rh"] ="Percent Relative Humidity"
colnames(project1)[colnames(project1) == "Tg, C"] ="Black Globe Temp C"
colnames(project1)[colnames(project1) == "SR W/m2"] ="Solar Radiation"
colnames(project1)[colnames(project1) == "DP"] ="Dew Point in C"
colnames(project1)[colnames(project1) == "Wind"] ="Wind Speed"
colnames(project1)[colnames(project1) == "WBGT"] ="Wet Bulb Globe Temp"
colnames(project1)[colnames(project1) == "%CR"] ="Percent CR"
#change gender if 0 to F to represent female
project1$Gender<-ifelse(project1$Gender== "0","F","M")  #change gender if 0 to F to represent female el


# Mutate the Race names from numbers to the marathon cities for better understanding
project1 <- project1 %>%
  mutate(Race = case_when(
    Race == "0" ~ "B",
    Race == "1" ~ "C",
```

```
    Race == "2" ~ "NY",
    Race == "3" ~ "TC",
    Race == "4" ~ "D"))


#Change the Race variable to a character variable
project1 <- project1 %>%
  mutate(Race = as.character(Race))

# Merge the two dataframes
course_record_project1<-left_join(project1,course_record,
                                  by= c("Race","Gender", "Year"))

# Change the Course Percentage %CR into course seconds
course_record_project1 <- course_record_project1 %>%
  mutate(Runtimes = Race_Seconds * (1 + (`Percent CR` / 100)))
#Get the sum on NA's to get assumptions  (MCAR)
sum_of_na<-sum(is.na(course_record_project1))
#Examine the data
course_record_project1%>% vis_dat()
vis_miss(course_record_project1)
course_record_project1%>% glimpse()

#Calculate all the missing data
sum(is.na(course_record_project1))

#Get all the missing data from each column
Missing_Data<- sapply(course_record_project1, function(x) sum(is.na(x)))
# Convert to dataframe
Missing_Data_df <- data.frame(ColumnName = names(Missing_Data), `Missing Data` = Missing_Data)

# Set names for the dataframe columns if necessary
names(Missing_Data_df) <- c("Variables", "Missing Data")

#Create variable table dataframe with description of the Marathon Dat
Variables_table<- data_frame(
  Variables= c("Race", "Year", "Gender", "Flag", "Age (yr)",
               "Percent CR", "Dry bulb Temp C","Wet bulb Temp C",
               "Percent Relative Humidity", "Black Globe Temp C","Solar Radiation",
               "Dew Point in C", "Wind Speed" ,"Wet Bulb Globe Temp","CR",
               "Race_Seconds","Runtimes"),
  Type= c("Character", "Numeric", "Character", "Character","Numeric",
          "Numeric","Numeric", "Numeric", "Numeric","Numeric","Numeric","Numeric",
          "Numeric","Numeric", "HMS/Numeric", "Numeric","Numeric"),
  Description= c("Race represents the marathons the participants competed, including the B=Boston Marath
                 C= Chicago Marathon, NY= New York City Marathon,T= Twin Cities Marathon (Minneapolis,M
                 D= Grandma's Marathon (Duluth, MN).",
                 "Years represented in the dataset ranging from 1993-2016.",
                 "Gender is represented by F= Female and M= Male.",
                 "Flag WBGT Thresholds. White= WBGT < 10C, Green= WBGT 10-18C, Yellow=WBGT >18-23C,
                 Red= WBGT >23-28C, and Black= WBGT > 28C",
                 "Age (yr) represents the ages of the participants.",
                 "Percent CR is the percent off current course record for gender.",
```

```
                "Dry bulb Temp Celcius is the air temperature without taking into account of the humidi
                moisture.",
                "Wet bulb Temp Celcius is a measure of temperature that reflects both the heat and humi
                "Percent Relative Humidity how much moisture is in the air compared to the maximum amou
                "Black Globe Temp Celcius  indicates how hot it feels in direct sunlight.It considers t
                "Solar Radiation in Watts per meter squared is the energy emitted by the sun, which tra
                "Dew Point in Celcius is the temperature the air needs to be cooled to (at constant pre
                "Wind Speed in Km/hr.",
                "Wet Bulb Globe Temp measures the combined effect of temperature, humidity, wind speed
                "CR is the course record for each marathon.",
                "Race_Seconds is the course record  measured in seconds.",
                "Runtimes is the converted gender percentage into seconds."
                )
)

Missing_Data_df$Variables <- as.character(Missing_Data_df$Variables)
Variables_table$Variables <- as.character(Variables_table$Variables)
merged_df <- merge(Missing_Data_df, Variables_table, by = "Variables", all = TRUE)


# Create the table with kable and customize with kableExtra
kable(merged_df, "latex", booktabs = TRUE, caption = "Marathon Runners' Data Description") %>%
  kable_styling(latex_options = c("striped", "scale_down")) %>%
  column_spec(1, width = "3cm") %>%
  column_spec(2, width = "2cm") %>%
  column_spec(3, width = "2cm") %>%
  column_spec(4, width = "8cm")


course_record_project1<-na.omit(course_record_project1)

#Find the minimum age
minimimum_age<-min(course_record_project1$`Age (yr)`)

#Find the maximum age
maximum_age<-max(course_record_project1$`Age (yr)`)

#Create Age Ranges/ Age Breaks to Categorize the groups
course_record_project1$age_ranges<- cut(
  course_record_project1$`Age (yr)`,
  breaks = c(0, 25, 35, 45, 55, 65, 75, Inf),  # Custom breaks for the new age ranges
  labels = c("<15-25", "26-35", "36-45", "46-55", "56-65", "66-75", "76+")

)

#Get Counts By Age Group to see balance
age_range_counts <- course_record_project1 %>%
  group_by(age_ranges)%>%
  summarise(count=n())


#Marathon Performance by age by Race
marathon_performance_by_age<- course_record_project1%>%
```

```
  select(Race,Year, Gender, age_ranges, Runtimes, `Age (yr)`)%>%
  group_by(Race, Gender, age_ranges)




#Get the best course_record from each race
best_course_race<- course_record_project1 %>%
  filter(Runtimes <= Race_Seconds)%>%
  group_by(Race, Gender, age_ranges)%>%
  summarise(count=n())


# Rename some of the column names
best_course_race <- best_course_race %>%
  rename(
    `Marathon` = Race,          # Rename 'Race' to 'Race Name'
    `Gender` = Gender,           # Keep the 'Gender' column as is (optional)
    `Age Range` = age_ranges,    # Rename 'age_ranges' to 'Age Range'
    `Number of Participants` = count  # Rename 'count' to 'Number of Participants'
  )
# Create the table with the new column names and specified styling
best_course_race %>%
  kbl(caption = "<div style='text-align:center; font-size:24px; font-weight:bold;'>Marathon Runners wit
  kable_classic(full_width = F, html_font = "Cambria", font_size = 20) %>%
  kable_styling(position = "center", font_size = 16)


worst_course_race <- course_record_project1 %>%
  filter(Runtimes >= Race_Seconds) %>%
  group_by(Race,Gender, age_ranges)%>%
  summarise(count=n())



just_gender_age_ranges<- course_record_project1 %>%
  filter(Runtimes >= Race_Seconds) %>%
  group_by(Gender, age_ranges)%>%
  summarise(count=n())

worst_course_race %>%
  kbl(caption = "Number of Marathon Runners that Did not beat the Course Record by Race, Gender, and Ag
  kable_classic(full_width = F, html_font = "Times New Roman", font_size= 20)


# Create bar plot od the Worst Course Race varaiable for easier read
ggplot(worst_course_race, aes(x = Race, y = count, fill = Gender)) +
  geom_bar(stat = "identity", position = "dodge") +  # Create a bar plot, grouped by Gender
  labs(title = "Number of Marathon Runners that Did not beat the Course Record by Race, Gender, and Age
       x = "Race",
       y = "Marathon Runners") +
  scale_fill_manual(values = c("F" = "hotpink", "M" = "royalblue")) +  # colors pink for F and blue for
  facet_wrap(~ age_ranges) +
```

```
  theme_minimal()


# Line plot of the Marathon Runners Performance by Age
age_plot<-ggplot(marathon_performance_by_age, aes(x = `Age (yr)`, y = Runtimes, color = Gender)) +
  geom_point(alpha = 0.05) +
  geom_smooth(se = FALSE, linewidth = 1.5) +
  labs(title = "Effects of Age on Marathon Performance in Men and Women",
       x = "Ages",
       y = " Runtimes (Performance)") +
  scale_color_manual(values = c("F" = "hotpink", "M" = "royalblue")) +
  theme_classic()+
  theme(plot.title = element_text(hjust = 0.5) )



age_plot

#Create summary statistics table
marathon_performance_summary_table <-marathon_performance_by_age%>%
  group_by(age_ranges) %>%
  summarise(
    Count=n(),
    Mean= mean(Runtimes),
    Q1_Runtime = quantile(Runtimes, 0.25, na.rm = TRUE),
    Median_Runtime = median(Runtimes, na.rm = TRUE),       # Median of Runtimes
     # Lower quartile (25th percentile)
    Q3_Runtime = quantile(Runtimes, 0.75, na.rm = TRUE),    # Upper quartile (75th percentile)
    IQR_Runtime = IQR(Runtimes, na.rm = TRUE) # IQR of Runtimes
  )

marathon_performance_summary_table %>%
  gt() %>%
  tab_header(
    title = "Marathon Performance Summary by Age Range"
  ) %>%
  cols_label(
    age_ranges = "Age Ranges",
    Count = "Marathon Runners",
    Mean = "Mean Runtimes",
     Q1_Runtime = "1Q",
    Median_Runtime = "Median Runtimes",
    Q3_Runtime = "3Q",
    IQR_Runtime = "IQR"
  ) %>%
  fmt_number(
    columns = vars(Mean, Median_Runtime, Q1_Runtime, Q3_Runtime, IQR_Runtime),
    decimals = 0 # Set decimal places for summary statistics
  )


# Create boxplot stratified by diffferent Races
ggplot(marathon_performance_by_age, aes(x = age_ranges, y = Runtimes, fill = Gender)) +
```

```
  geom_boxplot() +
  facet_wrap(~ Race) +  # Facet by Race to create separate plots for each race
  labs(title = "Effects of Marathon Performance  Stratified by Race, Gender, and Age Group",
       x = "Age Ranges",
       y = "Runtimes (Performance)") +
  theme_classic()+
  scale_fill_manual(values = c("F" = "hotpink", "M" = "royalblue"))+
  theme(axis.text.x= element_text(angle =45, vjust= 1, hjust = 1),
        plot.title = element_text(hjust = 0.5) )



# Create the boxplot to visualize the grouping
age_boxplot<-ggplot(marathon_performance_by_age, aes(x = age_ranges, y =Runtimes, fill = Gender)) +
  geom_boxplot() +
  labs(title = "Effects of Age on Marathon Performance in Men and Women BoxPlot",
       x = "Age Ranges",
       y = "Runtimes (Performance)") +
   scale_fill_manual(values = c("F" = "hotpink", "M" = "royalblue"))+
  theme_classic()+
  theme(
  plot.title = element_text(hjust = 0.5))


age_boxplot


 # Create Dataframe to allocate for other environmental conditions
 environmental_conditions <- course_record_project1 %>%
  select(Race, Gender, `Age (yr)`, Runtimes, `Dry bulb Temp C`, `Wet bulb Temp C`,
  `Percent Relative Humidity`, `Black Globe Temp C`, `Solar Radiation`,`Dew Point in C`,
  `Wind Speed`, `Wet Bulb Globe Temp`, age_ranges) %>%
  group_by( Gender, `Age (yr)`)

#Observing the linear model approach to see the impact on performance due to weather conditions and
# observer the difference in gender and age
# Linear to evaluate statistical significance
model <- lm(Runtimes ~ `Dry bulb Temp C` + `Percent Relative Humidity` + `Black Globe Temp C` +
         `Wind Speed` + `Dew Point in C` + `Solar Radiation` + `Age (yr)` + `Wet Bulb Globe Temp` + Gen
         `Dry bulb Temp C`:`Age (yr)` + `Percent Relative Humidity`:`Age (yr)` +
         `Black Globe Temp C`:`Age (yr)` +`Wind Speed`:`Age (yr)` + `Dew Point in C`:`Age (yr)` +
         `Solar Radiation`:`Age (yr)` + `Wet Bulb Globe Temp`:`Age (yr)` + Gender:`Age (yr)` +
         `Dry bulb Temp C`:Gender + `Percent Relative Humidity`:Gender + `Black Globe Temp C`:Gender +
          `Wind Speed`:Gender + `Dew Point in C`:Gender + `Solar Radiation`:Gender +
          `Wet Bulb Globe Temp`:Gender, data = environmental_conditions)

model_table <- round(summary(model)$coefficients, 5)

# Use kable to create the summary table
model_table %>%
  kbl(caption = "Impact of Environmental Conditions on Marathon Performance by Age and Gender",
      booktabs = TRUE, escape = FALSE, align = "c") %>%
  kable_styling(full_width = FALSE, latex_options = c('hold_position'))%>%
```

```
  column_spec(1, bold = TRUE, color="black", border_right = TRUE)%>%
  row_spec(1, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(2, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(3, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(4, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(6, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(7, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(8, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(9, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(10, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(11, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(12, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(13, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(15, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(16, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(17, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(18, bold = TRUE, color="black", background = "#87CEEB")%>%
  row_spec(20, bold = TRUE, color="black", background = "#87CEEB")


#Create Correlation plot
# Observing  and Including all the numeric variables
numeric_data <- course_record_project1%>%
  select(Runtimes, `Dry bulb Temp C` , `Percent Relative Humidity` , `Black Globe Temp C` ,
       `Wind Speed` , `Dew Point in C` ,`Solar Radiation` , `Age (yr)` ,`Wet Bulb Globe Temp`)

# Compute the correlation matrix using complete observations
cor_matrix <- cor(numeric_data, use = "complete.obs")  # Use complete.obs to ignore NAs

# Melt the correlation matrix for ggplot2
cor_data <- melt(cor_matrix)

#Environmental conditions correlation plot
environmental_conditions_plot<-ggplot(data = cor_data, aes(x = Var1, y = Var2, fill = value)) +
  geom_tile(color = "white") +
  geom_text(aes(label = round(value, 2)), color = "black", size = 4) +
  scale_fill_gradient2(low = "hotpink", high = "royalblue", mid = "white",
                       midpoint = 0, limit = c(-1, 1), space = "Lab",
                       name = "Correlation") +
  labs(title = "Correlation of Environmental Conditions on Marathon Performance") +
  theme_minimal(base_family = "Times") +
  theme(axis.text.x = element_text(angle = 45, vjust = 1, hjust = 1),
        legend.position = "bottom")
environmental_conditions_plot



# Dry bulb plot
 dry_bulb_plot<-ggplot(environmental_conditions, aes(x = `Dry bulb Temp C`, y = Runtimes, color = Gende
  geom_point(alpha=.1) +  # Scatter plot
  geom_smooth(method = "lm", formula = y ~ x, color = "black") +  # Linear regression line with confide
  facet_wrap(~ age_ranges) +  # Facet the plot by age_ranges
  theme_classic() +
```

```
  labs(title = "Marathon Performance vs. Dry Bulb Temperature by Age Ranges",
       x = "Dry Bulb Temperature (°C)",
       y = "Marathon Performance (Percent CR Seconds)")+
  scale_color_manual(values = c("M" = "royalblue", "F" = "hotpink"))


  dry_bulb_plot


# Humidity Percentages Plot
relative_percent_humidity<- ggplot(environmental_conditions, aes(x = `Percent Relative Humidity`,
                            y = Runtimes, color = Gender)) +
                            geom_point(alpha=.1) +  # Scatter plot
                            geom_smooth(method = "lm", formula = y ~ x, color = "black") +
                            # Linear regression line with confidence interval
                            facet_wrap(~ age_ranges) +  # Facet the plot by age_ranges
                            theme_classic() +
                            labs(title = "Marathon Performance vs. Relative Humidity Stratified by Age
                                    x = "Pecent Relative Humidity %",
                                    y = "Marathon Performance (Runtimes")+
                            scale_color_manual(values = c("M" = "royalblue", "F" = "hotpink"))

relative_percent_humidity

 # Black Globe Temperature
black_globe_temp_graph<- ggplot(environmental_conditions, aes(x = `Black Globe Temp C`,
                          y = Runtimes, color = Gender)) +
                          geom_point(alpha=.1) +  # Scatter plot
                          geom_smooth(method = "lm", formula = y ~ x, color = "black") +
                          # Linear regression line with confidence interval
                          facet_wrap(~ age_ranges) +  # Facet the plot by age_ranges
                          theme_classic() +
                          labs(title = "Marathon Performance vs. Black Globe Temperature Stratified by
                          x = "Black Globe Temp  (°C)",
                          y = "Marathon Performance (Runtimes)")+
                          scale_color_manual(values = c("M" = "royalblue", "F" = "hotpink"))

black_globe_temp_graph


 # Wet Bulb Temperature
 wet_bulb_graph<-ggplot(environmental_conditions, aes(x = `Wet Bulb Globe Temp`,
                       y = Runtimes, color = Gender)) +
                       geom_point(alpha=.1) +
                       geom_smooth(method = "lm", formula = y ~ x, color = "black") +
                       # Linear regression line with confidence interval
                       facet_wrap(~ age_ranges) +  # Facet the plot by age_ranges
                       theme_classic() +
  labs(title = "Marathon Performance vs. Wet Bulb Globe Temp Stratified by Age Groups",
       x = "Wet Bulb Globe Temp (°C)",
       y = "Marathon Performance (Runtimes)")+
  scale_color_manual(values = c("M" = "royalblue", "F" = "hotpink"))
```

```
 wet_bulb_graph

 #Solar Radiation Graph
 solar_radiation_graph<-ggplot(environmental_conditions, aes(x = `Solar Radiation`,
                     y = Runtimes, color = Gender)) +
                     geom_point(alpha=.1) +  # Scatter plot
                     geom_smooth(method = "lm", formula = y ~ x, color = "black") +
                    # Linear regression line with confidence interval
                     facet_wrap(~ age_ranges) +  # Facet the plot by age_ranges
                     theme_classic() +
                     labs(title = "Marathon Performance vs. Solar Radiation Stratified by Age Groups",
                     x = "Solar Radiation",
                     y = "Marathon Performance (Runtimes)")+
                     scale_color_manual(values = c("M" = "royalblue", "F" = "hotpink"))

solar_radiation_graph


black_globe_temp_graph <- ggplot(environmental_conditions, aes(x = `Black Globe Temp C`, y = Runtimes,
  geom_point(alpha=.1) +  # Scatter plot
  geom_smooth(method = "lm", formula = y ~ x, color = "black") +  # Linear regression line with confide
  facet_wrap(~ age_ranges) +  # Facet the plot by age_ranges
  theme_classic() +
  labs(title = "Marathon Performance vs. Black Globe Temperature Stratified by Age Groups",
       x = "Black Globe Temp  (°C)",
       y = "Marathon Performance (Runtimes)") +
    # Use scale_color_manual to set custom colors for Male and Female
  scale_color_manual(values = c("M" = "royalblue", "F" = "hotpink"))

black_globe_temp_graph

#Data Management of the marathon data set and air quality
#Change Race Names
marathon_dates <- marathon_dates %>%
   mutate(marathon = case_when(
     marathon == "NYC" ~ "NY",
     marathon == "Grandmas" ~ "D",
     marathon == "Boston" ~ "B",
     marathon == "Twin Cities" ~"TC"
  ))

#Change column names to match course_record_project column names
colnames(marathon_dates)[colnames(marathon_dates) == "marathon"] ="Race"
colnames(marathon_dates)[colnames(marathon_dates) == "year"] ="Year"

# Change formatting  of the dates
marathon_dates <- marathon_dates %>%
 mutate(date = as.Date(date, format = "%Y-%m-%d"))

# Combine the marathon dates datframe to my current dataframe by using left_join
course_record_project1 <- course_record_project1%>%
    left_join(marathon_dates, by = c("Race", "Year"))
```

```r
# Change the marathon variable to Race to match corresponding data and change race names
aqi_values <- aqi_values %>%
   rename(Race = marathon) %>%
     mutate(
     Race = case_when(
     Race == "NYC" ~ "NY",
     Race == "Grandmas" ~ "D",
     Race == "Boston" ~ "B",
     Race == "Twin Cities" ~"TC"
  ),
    date = as.Date(date_local, format = "%Y-%m-%d"),
    Year = as.numeric(format(date, "%Y"))
      ) %>%
   select(-date_local) #Remove the date_local variable


# calculate average ozone ppm (8-hour avg)
avg_ppm <- aqi_values %>%
   filter(units_of_measure == "Parts per million",
          sample_duration == "8-HR RUN AVG BEGIN HOUR") %>%
          group_by(Race, Year, date) %>%
          summarize(avg_ppm = mean(arithmetic_mean, na.rm = T)) %>%
          ungroup()



# Merge data_frame to current dataframe
 course_record_project1 <-  course_record_project1 %>%
   left_join(avg_ppm, by = c("Race", "Year", "date"))


weather_parameters<-course_record_project1%>%
  select(Gender, `Age (yr)`, Runtimes, `Dry bulb Temp C`, `Wet bulb Temp C`,
  `Percent Relative Humidity`, `Black Globe Temp C`, `Solar Radiation`,`Dew Point in C`,
  `Wind Speed`, `Wet Bulb Globe Temp`, age_ranges, Flag)


# Create the box plot with custom Flag colors and filled boxplots
flag_exam <- ggplot(weather_parameters, aes(x = Gender, y = Runtimes, fill = Flag)) +
  geom_boxplot() +  # Use geom_boxplot for creating a boxplot
  theme_bw() +      # Black and white theme for a clean plot
  scale_fill_manual(values = c(
    "White" = "white",   # Replace these with the Flag categories and the colors you want to assign
    "Green" = "green",
    "Black" = "black",
    "Yellow" = "yellow",  # Add more colors for other Flag categories as needed
    "Red" = "red"
  )) +
  labs(
    title = "Marathon Performance by Flag Conditions Stratified by Gender",
    x = "Gender",
    y = "Marathon Performance (Runtimes)",
    fill = "Flag Color"  # Title for the legend
```

```
  ) +
  theme((legend.position = "right"),
    plot.title = element_text(hjust = 0.5, size = 12)) # Center and set title size to 12


flag_exam


flag_age_ranges<- ggplot(weather_parameters, aes(x = age_ranges, y = Runtimes, fill = Flag)) +
  geom_boxplot() +  # Use geom_boxplot for creating a boxplot
  theme_bw() +      # Black and white theme for a clean plot
  scale_fill_manual(values = c(
    "White" = "white",   # Replace these with the Flag categories and the colors you want to assign
    "Green" = "green",
    "Black" = "black",
    "Yellow" = "yellow",  # Add more colors for other Flag categories as needed
    "Red" = "red"
  )) +
  labs(
    title = "Marathon Performance by Flag Conditions Stratified by Age Ranges",
    x = "Age Ranges",
    y = "Marathon Performance (Runtimes)",
    fill = "Flag Color"  # Title for the legend
  ) +
  theme(
    (legend.position = "right"),
    plot.title = element_text(hjust = 0.5, size = 12))

flag_age_ranges









# Select only numeric columns from the data frame for correlation plot
airquality<- course_record_project1%>%
  select(Runtimes, `Dry bulb Temp C` , `Percent Relative Humidity` , `Black Globe Temp C` ,
       `Wind Speed` , `Dew Point in C` ,`Solar Radiation` , `Age (yr)` ,`Wet Bulb Globe Temp` , Year,
       avg_ppm)


#Compute the correlation matrix
cor_matrix2 <- cor(airquality, use = "complete.obs")  # Use complete.obs to ignore NAs
```

```r
# Melt the correlation matrix for ggplot2
library(reshape2)
cor_data2<- melt(cor_matrix2)


# Visualize the Correlation Plot of the the Weather Parameters
ggplot(data=cor_data2, aes(x= Var1, y= Var2, fill=value))+
  geom_tile(color= "white")+
  geom_text(aes(label = round(value, 2)), color = "black", size = 4) +
  scale_fill_gradient2(low= "hotpink", high="royalblue", mid = "white",
  midpoint=0,
  limit=c(-1,1),
  space="Lab",
  name="Correlation")+
  labs(title="Weather Parameters with the Largest Impact on Marathon Performance Correlation Plot")+
  theme_minimal(base_family="Times")+
  theme(axis.text.x= element_text(angle =45, vjust= 1, hjust = 1),
    plot.title = element_text(hjust = 0.5, size = 12))  # Center and set title size to 20



# Summarize data by Flag to calculate the median, IQR, Q1 (25th percentile), and Q3 (75th percentile) f
flag_summary <- course_record_project1 %>%
  group_by(Flag,age_ranges) %>%
  summarise(
    Median_Runtime = median(Runtimes, na.rm = TRUE),       # Median of Runtimes
    IQR_Runtime = IQR(Runtimes, na.rm = TRUE),             # IQR of Runtimes
    Q1_Runtime = quantile(Runtimes, 0.25, na.rm = TRUE),   # Lower quartile (25th percentile)
    Q3_Runtime = quantile(Runtimes, 0.75, na.rm = TRUE)    # Upper quartile (75th percentile)
  )
```