Project 1: Exploratory Data Analysis

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Project 1: Exploratory Data Analysis

This project aims to explore different factors that impact marathon performance between gender and across age.

The `project1` data set contains info and results for each participant in the marathon races at Boston, New York City, Chicago, Twin Cities, and Grandmas from 1993 to 2016. It also includes weather parameters, such as dry and wet bulb temperature, relative humidity, black globe temperature and more. This results data already includes calculated variables `WBGT` (Wet Bulb Globe Temperature, calculated by the three temperature) and `Flag` (Groups for WBGT). The project also utilized the `course_record` data that included the record for each race, at each year.

To further assess the environmental impact, AQI data was obtained using provided code in class, which grabbed data from an API using the R package RAQSAPI. The resulted data set includes the average values for ozone level in parts per million, and the PM2.5 in Micrograms/cubic meter (LC).

Data Preprocessing

Missing Data

Project 1 Data: To understand the data set, I first generated a missing data plot by `vis_miss()`. The plot shows that there was a consistent 4% of missing data for the flag and weather measurement columns. This indicates that weather was not measured at these races. After some further exploration, table below shows that all data were missing at races 1 (Chicago), 2 (NYC), 3 (Twin Cities) at 2011, and race 4 (Grandma's) at 2012.

The flag for these were missing because they should have been calculated by the wet bulb globe temperature (WBGT), and the WBGT is also calculated by the other temperature variables, which were not measured and is dependent on these particular races in particular year. Therefore, the probability of the flag and WBGT being missing depends on both observed and unobserved variables, this should then be a case of **Missing Not at Random (MNAR).** For the other weather variables, they were missing because they are not measured in that particular year/race, but we do not have knowledge on the exact reason. Therefore, the probability of them being missing depends only on observed variables (year/race), they would then be a case of **Missing at Random (MAR).**

Table 1: Missing Data Summary: Project 1 Data

Race	Year	n_miss	n_tot
1	2011	126	126
2	2011	131	131
3	2011	118	118
4	2012	116	116

AQI Values Data: Based on the same missing graph plotted, the api column has 16% missing values. Upon further analysis, it was found that all data with sample duration = 1 hour has the api column missing. This is then **Missing At Random (MAR).**

Table 2: Missing Data Summary - AQI Values

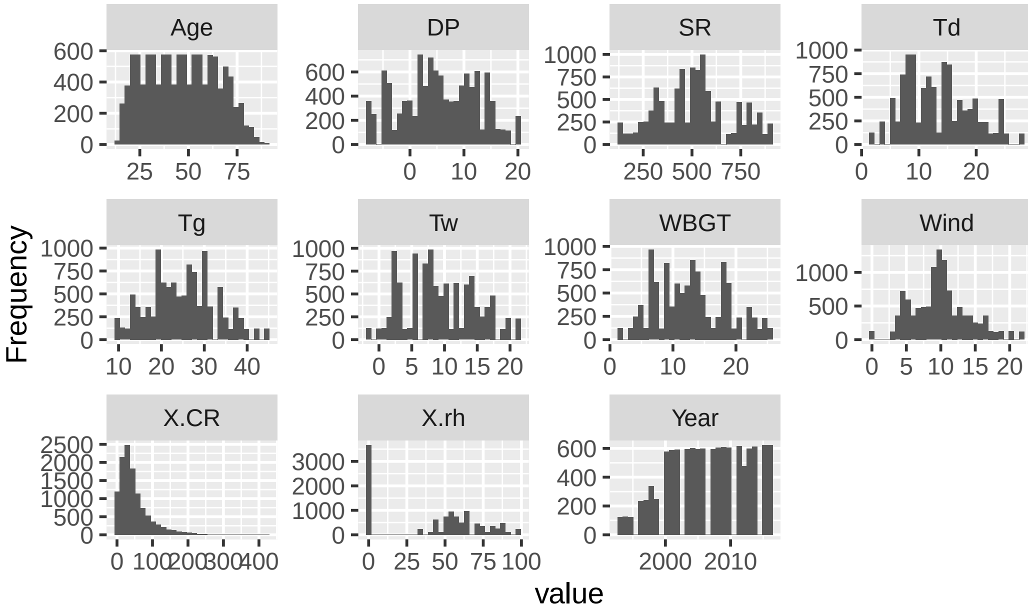
sample_duration	n_miss	n_tot
1 HOUR	1674	1674
24 HOUR	0	4034
24-HR BLK AVG	0	1335
8-HR RUN AVG BEGIN HOUR	0	3408

Course Record Data: No missingness was found in the data.

Data Quality

Project 1 Data: Using `str()`, the variable type for each columns in the data set is shown. I have first cleaned the column names so it can be easier to called out later. The race column was numeric, with values 0, 1, 2, 3, 4. Recoding them into B, C, NY, TC, D would help ease the process of understanding the data and merging with the course record data later. It is further factorized. Similar process for sex, recoding to "M" and "F". Additonally, the Sex and Flag were originally numeric and character variables, and they are also factorized to make sure future analysis treat them the way we want. For the others, they are in the correct numeric value type.

Histograms are plotted for all the numeric values in the data set. Only the %CR (percent off course record) was heavily skewed.



AQI Values Data: Upon glimpsing the data, it was observed that the entries had different coding for marathon races, and it includes the full date for each race. Therefore, recoding was done to ensure later efficiency in merging the data. The summary table below uncover the complexity of this data set, showing the breakdown of information gathered on the data.

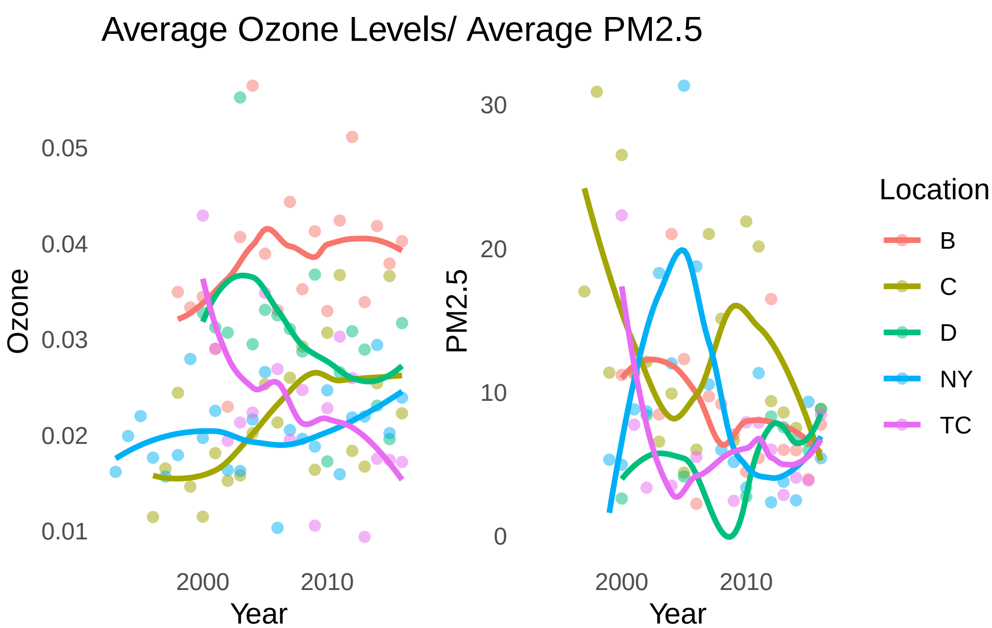
Table 3: AQI Data Summary

parameter_code	units_of_measure	sample_duration	n
44201	Parts per million	1 HOUR	1136
44201	Parts per million	8-HR RUN AVG BEGIN HOUR	3408
88101	Micrograms/cubic meter (LC)	1 HOUR	124
88101	Micrograms/cubic meter (LC)	24 HOUR	3964
88101	Micrograms/cubic meter (LC)	24-HR BLK AVG	930
88502	Micrograms/cubic meter (LC)	1 HOUR	414
88502	Micrograms/cubic meter (LC)	24 HOUR	70
88502	Micrograms/cubic meter (LC)	24-HR BLK AVG	405

According to the US Environmental Protection Agency, 88101 and 88502 are both used to report daily Air Quality Index values. The difference is that 88101 include both manually operated Federal Reference Methods (FRMs) and automated Federal Equivalent Methods (FEMs), but 88502 are “FRM-like” @EPA. Based on this information, I decide to only take the 88101 data for simplicity. PM2.5 below 12 g/m^3 is considered healthy with little to no risk from exposure, while anything above 35 g/m^3 is unhealthy @IndoorAirHygieneInstitute.

For ozone, it is measured under the parameter 44201. The quality standard is 0.08 ppm @EPA, anything above could be unhealthy. To clean the data, I created a summary by taking the average of the arithmetic mean. However, note that the summary table is not a complete data - it contains missing values for PM2.5 values from most of the early years and a few in latter years. It is possible that the PM2.5 values were not collected until later years.

The graph below on the left illustrates the change in ozone levels on race day, over the years, by marathon locations. Each color/line represents a marathon location, allowing for a comparison of trends within those areas. The points represents the average ozone measurements, and we see different fluctuations between different locations. The curve was plotted using `geom_smooth` and shows the trend. In particular, the average ozone levels at New York City was the most stable throughout years; At Twin City we see the greatest decrease; The other locations have a slight fluctuations only. Using the same method, the graph on the right shows the trend on PM2.5. There are big fluctuations for all locations.



Merging Data

The course record data is merged using a `left_join()` so we can use the record to calculate a new variable `Time` for each participant. Since course record has a `Gender` column instead of `Sex`, I have renamed that so I can left join project 1 data to course record data by `Race`, `Year`, and `Sex`. To calculate the time, I used Time (hours) $= \frac{\mathrm{CR}\times\left(1+\frac{\%CR}{100}\right)}{3600}$ so to adjust for the percent off course record and convert the final unit to hours. Afterwards, the AQI data is joined using `left_join()` as well.

Below shows a correlation plot for all the numeric columns in the final data. There are some high correlations between the weather measures. It is also obvious the course time is highly correlated with age. We will dive deeper and quantify some relations between the variables in the later sections.

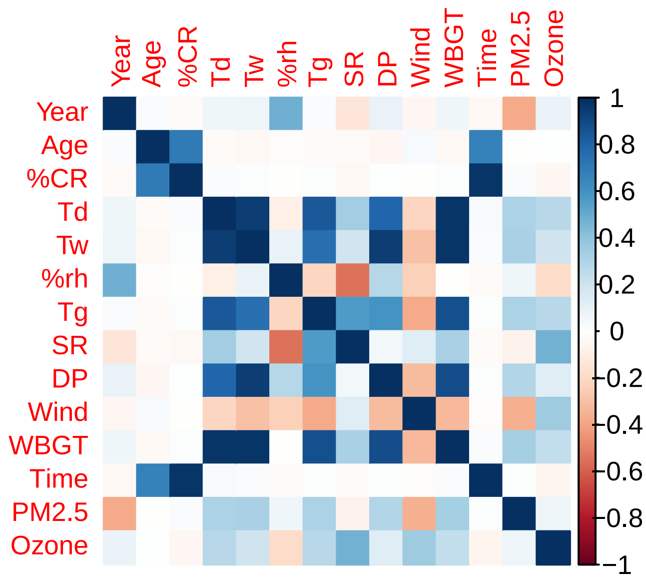
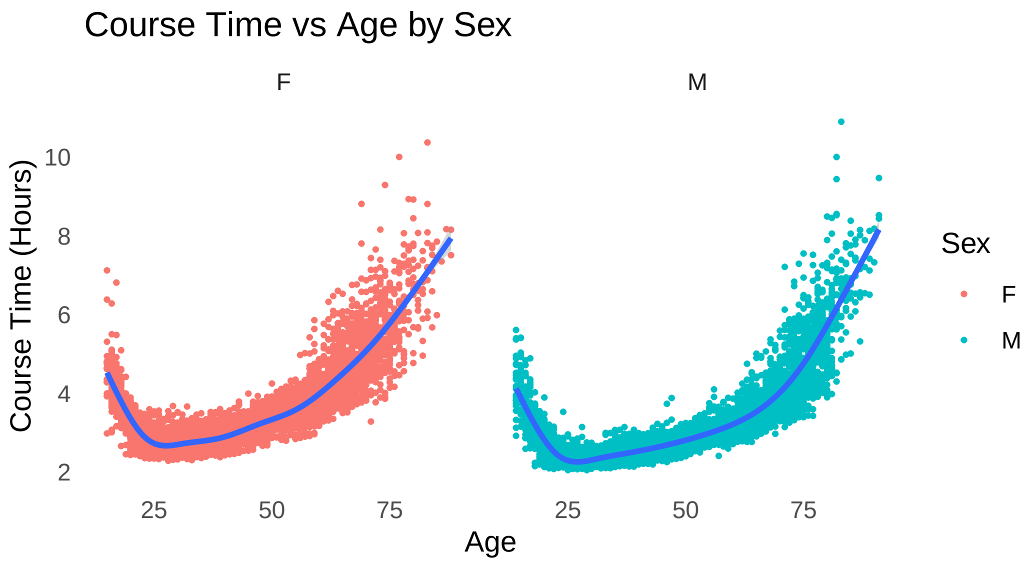


Figure 1: Correlation plot

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

Plot

The image below shows a scatter plot of time and age for men and women. The plot is divided into two panels, by sex, and the blue line represent a fitted curve performed directly by `geom_smooth()`. There seem to be a near-identical trend for men and women- both sexes gets an increasingly faster time each year they are closer to around age 25. However, as they reach the fastest time at around age 25, they gradually run slower as age increases further. We can observe a spike happening around age 60 for both sexes, but men has a steeper slope. In other words, the slower in time was more significant in the male group. On the other hand, we can see the curve for women is slightly higher than that of the men. This means that women are running slightly slower in general.



This table shows the summary statistics for age and course time for men and women. It is obvious that men (N = 6,112) had a larger sample size than women (N = 5,452). In average, the men population is also older than the female population. We again see that men have a shorter course time on average.

Characteristic	**F**, N = 5,452	**M**, N = 6,112
Age	45 (30, 59)	48 (32, 64)
Time	3.55 (2.87, 3.91)	3.17 (2.49, 3.46)

Regression

A regression model was fit to quantify the course time between sex and their ages.

$$E[\text{Time}] = \beta_0 + \beta_1 \cdot \text{Age} + \beta_2 \cdot \text{SexM}$$

Based on the results below (rounded to 3 decimal places), both Age and Sex are significantly influential on time (p-value < 0.05), with age positively associated while sex negatively associated.

Table 5: Linear Regression Model Summary

Variable	Estimate	Std. Error	t value	Significance
(Intercept)	1.793	0.019	92.341	0
Age	0.039	0.000	104.527	0
SexM	-0.491	0.013	-36.523	0

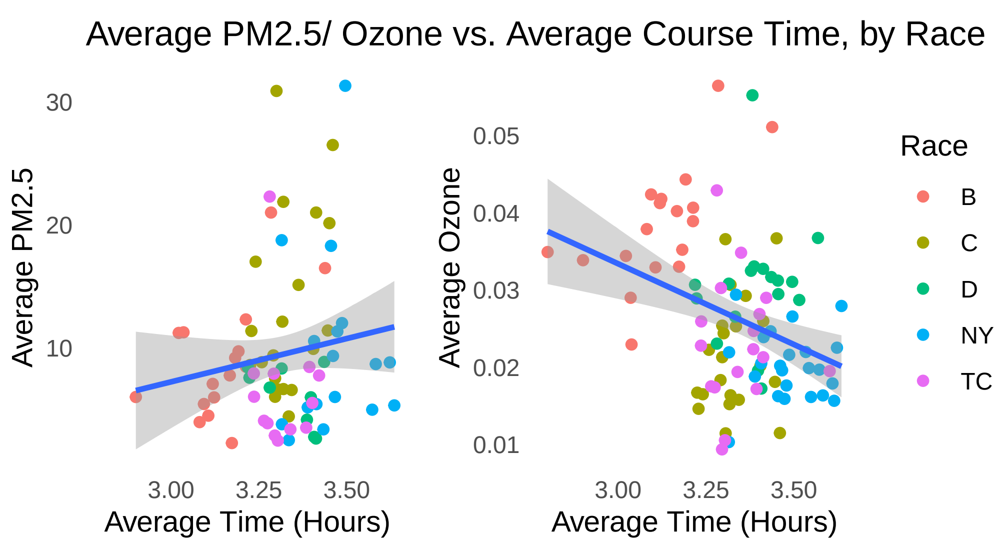
Therefore, for each unit increase in Age, the expected Time increases by $\beta_1 = 0.039$ hours, holding all other variables constant. For **Male** (SexM = 1), the expected Time decreases by $\beta_2 = -0.491$ hours compared to females, holding all other variables constant.

AIM 2: Explore the impact of environmental conditions on marathon performance, and whether the impact differs across age and gender.

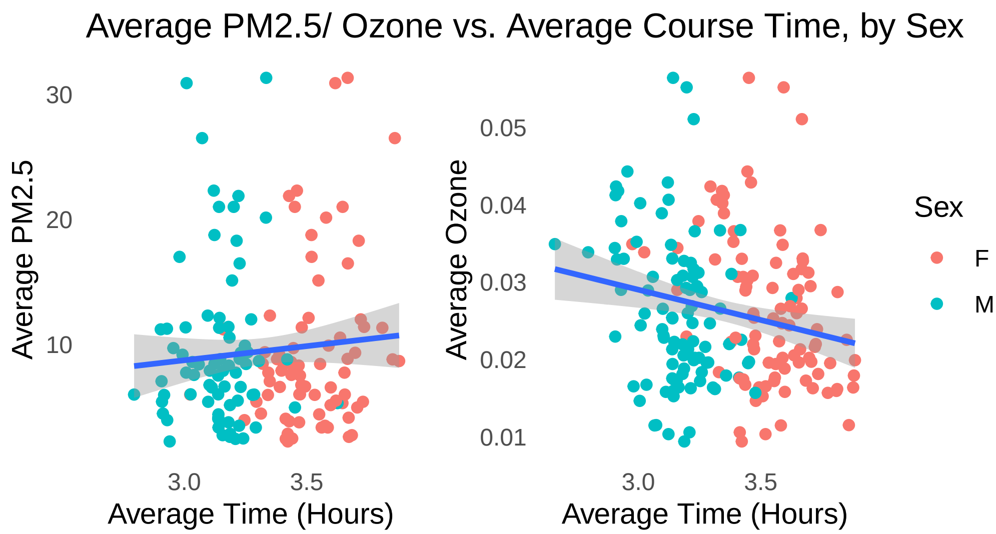
Plots

First, I looked at the aggregated data by calculating the average course time for each race/year. Most races had PM2.5 on the lower end, about under 13. Just by looking at the graph, it does not immediately appear that there is a big difference in performance comparing different PM2.5 levels. The slope drawn by `geom_smooth()` slowly increase as average time increases. This suggests that as PM2.5 level goes up, the average course time goes up. In other words, they are running slower on average.

Same process for Ozone measurements, the slope plotted with `geom_smooth` shows a decreasing trend. This is strange because it suggests that lower ozone may be associated with a longer course time. In other words, runners tends to finish the race faster when the ozone level is higher. However, it is also noticeable from both graphs that the Boston Marathon has a lower average course time among all other marathon races, and their ozone measurements seems slightly above average.



In order to see the differences between sex, I will create another aggregate that is by sex. There is a clear distinction between male and female - again, male has a shorter average time than female in overall.



Regression

To quantify the impact of environmental conditions on marathon performance, I will first focus on a regression model with only PM2.5 and Ozone: $E[\text{Time}] = \beta_0 + \beta_1 \text{PM2.5} + \beta_2 \text{Ozone}$.

Table 6: Linear Regression Model Summary

Variable	Estimate	Std. Error	t value	Significance
(Intercept)	3.433	0.033	104.121	0.000
PM2.5	0.004	0.002	2.436	0.015
Ozone	-5.630	1.090	-5.167	0.000

Since both PM2.5 and Ozone are significant, both of them were able to explain course time.

$\beta_1 = 0.004$ means that for every one unit increase in PM2.5, the course time increase by 0.004 hours (14.4 seconds), holding others constant.

$\beta_2 = -5.630$ means that for every one unit increase in Ozone, the course time decrease by -5.630 hours. Thus, by conversion, for every 0.01 unit increase in Ozone, the course time decrease by -0.0563 hours (3.378 minutes).

To find out whether the impact differs across age and gender, I added the main effects of age and gender, along with the two-way interactions of them with each environmental measure. Then, I used backward selection and the results are as follows. This method drops one variable each time and test for the significance.

The full model: $E[\text{Time}] = \beta_0 + \beta_1\text{Age} + \beta_2\text{SexM} + \beta_3\text{PM2.5} + \beta_4\text{Ozone} + \beta_5(\text{Age} \times \text{PM2.5}) + \beta_6(\text{Age} \times \text{Ozone}) + \beta_7(\text{SexM} \times \text{PM2.5}) + \beta_8(\text{SexM} \times \text{Ozone})$

Final model by backward selection: $E[\text{Time}] = \beta_0 + \beta_1\text{Age} + \beta_2\text{SexM} + \beta_3\text{PM2.5} + \beta_4\text{Ozone} + \beta_5(\text{Age} \times \text{PM2.5}) + \beta_6(\text{Age} \times \text{Ozone}) + \beta_7(\text{SexM} \times \text{PM2.5})$

Table 7: Linear Regression Model Summary

Variable	Estimate	Std. Error	t value	Significance
(Intercept)	1.7536	0.0651	26.9345	0.0000
Age	0.0409	0.0013	31.8361	0.0000
SexM	-0.4372	0.0264	-16.5871	0.0000
PM2.5	-0.0105	0.0034	-3.0985	0.0020
Ozone	4.1944	2.1464	1.9541	0.0507
Age:PM2.5	0.0004	0.0001	5.5247	0.0000
Age:Ozone	-0.2100	0.0428	-4.9104	0.0000
SexM:PM2.5	-0.0041	0.0023	-1.7602	0.0784

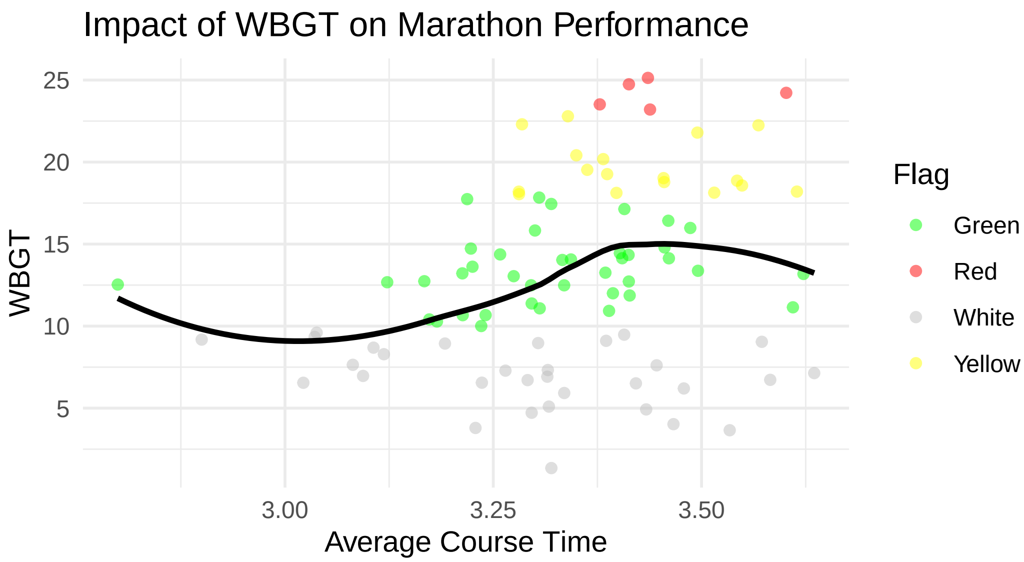
Since the interaction term for Sex * Ozone was removed, this suggests that the relationship between Ozone and Time does not differ significantly between males and females in the data set. The interaction term for Sex * PM2.5 was not removed by backward selection, but it remains insignificant ($p = 0.078$). We cannot conclude that the impact of PM2.5 on course time changes as Sex group changes.

Since the others are significant, this means that the impact of PM2.5 and ozone on course time changes as Age increases. In overall, the impact for these environmental factors are seemingly more significant to age differences, but not that much for different sexes.

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

Plots

The graph below illustrates the relationship of WBGT, flag, and the marathon performance on course time. Seems like we can almost draw vertical lines to pinpoint the appearance of new flag colors at certain time points. To elaborate, only whites and one green had an average course time <3.12, then only whites and greens had an average course time <3.28, and only whites, greens, and yellows < 3.38. This suggests that larger WBGT may be associated with a longer course time.



Regression

I started with the full model, of all the participant characteristics and weather variables in the dataset. Then, I used backward selection to find the smallest best model. Table below shows the coefficients of the final model by backward selection. The final model is as below:

$$E[\text{Time}] = \beta_0 + \beta_1 \cdot \text{Age} + \beta_2 \cdot \text{SexM} + \beta_3 \cdot \text{FlagRed} + \beta_4 \cdot \text{FlagWhite} + \beta_5 \cdot \text{FlagYellow} \\ + \beta_6 \cdot \text{Td} + \beta_7 \cdot \text{Tw} + \beta_8 \cdot \%\text{rh} + \beta_9 \cdot \text{SR} + \beta_{10} \cdot \text{DP}$$

Table 8: Linear Regression Model Summary: Backward Selection

Variable	Estimate	Std. Error	t value	Significance
(Intercept)	1.6982	0.0550	30.8900	0.0000
Age	0.0390	0.0004	102.8962	0.0000
SexM	-0.4919	0.0136	-36.1869	0.0000
FlagGreen	0.0281	0.0250	1.1243	0.2609
FlagYellow	0.1148	0.0436	2.6354	0.0084
FlagRed	0.1550	0.0620	2.5018	0.0124
Td	-0.0163	0.0092	-1.7803	0.0751
Tw	0.0589	0.0200	2.9386	0.0033
%rh	-0.0006	0.0003	-1.9177	0.0552
SR	-0.0002	0.0000	-4.2738	0.0000
DP	-0.0279	0.0090	-3.1050	0.0019

The significance for the flags verify what we have seen in the graph above. The Green Flag was not significant (p-value= 0.261), but the Yellow and Red are. This indicates that when the weather is under Green flag conditions, the runners' course time *do not* differ from those under White flag conditions. Under Yellow flag conditions, the runners have 0.115 hours (6.9 minutes) longer than those under White flag; and under Red flag conditions, the runners have 0.155 hours (9.3 minutes) longer than those under White flag.

The dry bulb temperature (Td) and humidity (%rh) were marginally significant, so their effect is still not strong enough to conclude anything.

The wet bulb temperature (Tw) is significant (p-value= 0.003), so the estimate 0.059 suggests that higher Tw lead to longer course time, which means worse performance.

Solar Ration (SR) has an extremly small p-value, so the table rounded to 4 decimal places did not show the full value. The estimate -0.0002 indicates a significant negative association with average time that higher solar radiation leads to shorter time. This effect is very significant but the effect is small because of the small estimate.

Lastly, Dew Point (DP) is significant (p-value= 0.0019), so the estimate of -0.028 indicates that higher dew points are associated with lower time, meaning better performance.

To summarize, wet bulb temperature (Tw) and Flag Conditions (especially Red) have the largest positive impacts on time (i.e., largest negative impacts on performace). This means the hotter and more humid condition are associated with worse performance.

On the other hand, Dew Point (DP) has negative impact on time (i.e., positive impact on performace), so higher dew point could be a favorable condition for better performance.

Code Appendix

```
# Load libraries
library(readr)
library(tidyverse)
set.seed(123456)
library(knitr)
library(tidyr)
library(dplyr)
library(kableExtra)
library(readr)
library(visdat)
library(naniar)
library(gtsummary)
library(patchwork)
library(DataExplorer)
library(lubridate) #To convert time
# Import data sets
aqi_values <- read_csv("aqi_values.csv")
course_record <- read_csv("course_record.csv")
marathon_dates <- read_csv("marathon_dates.csv")
project1 <- read_csv("project1.csv")

# Rename column names
colnames(project1) <- c("Race", "Year", "Sex", "Flag", "Age", "%CR", "Td",
↪  "Tw", "%rh", "Tg", "SR", "DP", "Wind", "WBGT")

###### DATA PREPROCESSING ######

## Project 1 - Missing data plot
# project1 %>% abbreviate_vars() %>% vis_miss()

## Project 1 - Missing data table
project1 %>% group_by(Race, Year) %>%
  summarize(n_miss = sum(is.na(Flag)),
            n_tot = n()) %>%
  filter(n_miss > 0) %>%
  kable(digits = 2, caption = "Missing Data Summary: Project 1 Data")

## AQI Values - Missing data plot
# vis_miss(aqi_values)
```

```r
## AQI Values - Missing data summary
aqi_values %>% select(c(sample_duration, aqi)) %>%
  group_by(sample_duration) %>%
  summarise(n_miss = sum(is.na(aqi)),
            n_tot = n()) %>%
  kable(digits = 2, caption = "Missing Data Summary - AQI Values")
## Course Record - Missing data plot
# vis_miss(course_record)
## Project 1 - Data Quality
# str(project1)

project1 <- project1 %>%
  mutate(Race = case_when(
    Race == 0 ~ "B",
    Race == 1 ~ "C",
    Race == 2 ~ "NY",
    Race == 3 ~ "TC",
    Race == 4 ~ "D",
    ),
    Sex = case_when(
    Sex == 0 ~ "F",
    Sex == 1 ~ "M"
    )
    ) %>%
  mutate(across(c(Race, Sex, Flag),
         as.factor))

# Project 1 - Plot histogram
plot_histogram(project1, nrow = 5L)
# plot_bar(project1, ncol = 5L)

# AQI - Data Quality
aqi_values %>%
  group_by(parameter_code, units_of_measure, sample_duration) %>%
  summarise(n=n()) %>%
  kable(caption = "AQI Data Summary")

# AQI - Change marathon names and add year column
aqi_values_adj <- aqi_values %>%
  mutate(
    marathon = case_when(
```

```
      marathon == "Boston" ~ "B",
      marathon == "Chicago" ~ "C",
      marathon == "NYC" ~ "NY",
      marathon == "Twin Cities" ~ "TC",
      marathon == "Grandmas" ~ "D"
      ),
    year = year(date_local)
    )

# AQI - Filter data for simplicity
aqi_values_adj <- aqi_values_adj %>%
  filter(parameter_code %in% c(88101, 44201)) %>%

   ↪  select(-c("cbsa_code","state_code","county_code","site_number","date_local"))

# AQI - Create summary by year, race
aqi_summary_by_year <- aqi_values_adj %>%
  group_by(year, marathon, units_of_measure) %>%
  summarise(avg_arithmetic_mean=mean(arithmetic_mean, na.rm = TRUE))

aqi_summary_by_year <-
  spread(aqi_summary_by_year, units_of_measure, avg_arithmetic_mean) %>%
  arrange(year)

colnames(aqi_summary_by_year) <- c("Year", "Race", "PM2.5", "Ozone")

# AQI - Change over time plots
a <- ggplot(aqi_summary_by_year, aes(x = Year, y = Ozone, color = Race)) +
  geom_point(alpha=0.5) +
  geom_smooth(se = FALSE) +
  # facet_wrap(~ Race) +
  labs(title = "Average Ozone Levels/ Average PM2.5",
       x = "Year") +
  theme_minimal() +
  scale_color_discrete(name = "Location") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank()) +
  guides(color="none")
b <- ggplot(aqi_summary_by_year, aes(x = Year, y = `PM2.5`, color = Race)) +
  geom_point(alpha=0.5) +
  geom_smooth(se = FALSE) +
  # facet_wrap(~ Race) +
```

```
  labs(x = "Year") +
  theme_minimal() +
  scale_color_discrete(name = "Location") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank())
a+b

# Course Record - Data Quality
course_record <- course_record %>% rename("Sex" = "Gender")

# Merge project 1 with course record
project1_CR <- project1 %>%
  left_join(course_record, by = c("Race", "Year", "Sex"))

# Calculate time
project1_CR$Time <- (project1_CR$CR * (1+project1_CR$`%CR`/100))/3600 %>%
  as.numeric()

# Merge project 1 + course record with AQI data
project1_CR_aqi <- project1_CR %>%
  left_join(aqi_summary_by_year, by = c("Race", "Year"))
# Correlation of full numeric data
library(corrplot)

project1_CR_aqi$Time <- project1_CR_aqi$Time %>% as.numeric()
data <- select_if(project1_CR_aqi,is.numeric) %>% na.omit() %>%
 ↪  abbreviate_vars()
M = cor(data)
corrplot(M, method = 'color', tl.cex = 0.8)

###### AIM 1 ######

# Age vs Time plot
ggplot(project1_CR_aqi, aes(x = Age, y = Time)) +
  geom_point(aes(color=Sex), size = 0.5) +
  geom_smooth() +
  facet_wrap(~ Sex) +
  labs(title = "Course Time vs Age by Sex",
       x = "Age",
       y = "Course Time (Hours)") +
  theme_minimal() +
  theme(panel.grid.major = element_blank(),
```

```
        panel.grid.minor = element_blank())
# Age & Time Summary by Sex
project1_CR_aqi %>% dplyr::select(Age, Sex, Time)%>%
  tbl_summary(by = Sex,
              type = list(where(is.numeric) ~ "continuous"),
              statistic = list(all_continuous() ~ "{mean} ({p25}, {p75})"))
               ↪  %>%
  bold_labels() #%>%
  #add_p()

# Regression model - Time effects on Sex and Age
model <- lm(as.numeric(Time) ~ Age + Sex, data = project1_CR_aqi)

# Print results
summary <- summary(model)
coefficients <- as.data.frame(summary$coefficients)
kable(coefficients, digits = 3,
      caption = "Linear Regression Model Summary",
      col.names = c("Variable", "Estimate", "Std. Error", "t value",
       ↪  "Significance"))

###### AIM 2 ######

# Create summary data by race & year
new_data <- project1_CR_aqi %>% group_by(Race, Year, PM2.5, Ozone) %>%
 ↪  summarize(Avg_Time = mean(as.numeric(Time)))

# AQI data vs Average Time plots
a <- ggplot(new_data, aes(x = Avg_Time, y = PM2.5)) +
  geom_point(aes(color = Race)) +
  geom_smooth(method = "lm") +
  labs(title = "Average PM2.5/ Ozone vs. Average Course Time, by Race",
       x = "Average Time (Hours)",
       y = "Average PM2.5") +
  theme_minimal() +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank()) +
  guides(color="none")
b <- ggplot(new_data, aes(x = Avg_Time, y = Ozone)) +
  geom_point(aes(color = Race)) +
  geom_smooth(method = "lm") +
  labs(x = "Average Time (Hours)",
```

```
       y = "Average Ozone") +
  theme_minimal() +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank())

a + b

# Create summary table further by sex
new_data <- project1_CR_aqi %>% group_by(Race, Year, Sex, PM2.5, Ozone) %>%
 ↪  summarize(Avg_Time = mean(as.numeric(Time)))

# AQI data vs Average Time plots BY SEX
a <- ggplot(new_data, aes(x = Avg_Time, y = PM2.5)) +
  geom_point(aes(color = Sex)) +
  geom_smooth(method = "lm") +
  labs(title = "Average PM2.5/ Ozone vs. Average Course Time, by Sex",
       x = "Average Time (Hours)",
       y = "Average PM2.5") +
  theme_minimal() +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank()) +
  guides(color="none")

b <- ggplot(new_data, aes(x = Avg_Time, y = Ozone)) +
  geom_point(aes(color = Sex)) +
  geom_smooth(method = "lm") +
  labs(x = "Average Time (Hours)",
       y = "Average Ozone") +
  theme_minimal() +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank())

a + b

# Regression model, Time to AQI data
model <- lm(Time ~ PM2.5 + Ozone, data = project1_CR_aqi)

# Print results
summary <- summary(model)
coefficients <- as.data.frame(summary$coefficients)
kable(coefficients, digits = 3,
      caption = "Linear Regression Model Summary",
```

```
      col.names = c("Variable", "Estimate", "Std. Error", "t value",
       ↪  "Significance"))
# Regression model, Time to AQI data + Age & Sex
full_model <- lm(Time ~ Age + Sex + PM2.5 + Ozone
                 + Age * PM2.5 + Age * Ozone
                 + Sex * PM2.5 + Sex * Ozone,
                 data = project1_CR_aqi)

# summary(full_model)

# Backward selection
backward_model <- step(full_model, direction = "backward")
summary <- summary(backward_model)

# Print results
coefficients <- as.data.frame(summary$coefficients)
kable(coefficients, digits = 4,
      caption = "Linear Regression Model Summary",
      col.names = c("Variable", "Estimate", "Std. Error", "t value",
       ↪  "Significance"))

###### AIM 3 ######

# Create summary table by race, year, WBGT, flag
new_data <- project1_CR_aqi %>% group_by(Race, Year, WBGT, Flag) %>%
 ↪  summarize(Avg_Time = mean(as.numeric(Time))) %>% na.omit()

# Plot average time by WBGT/Flag
ggplot(new_data, aes(x = Avg_Time, y = WBGT)) +
  geom_point(aes(color = Flag), alpha = 0.5) +
  geom_smooth(method = "loess", se = FALSE, color = "black") +
  labs(title = "Impact of WBGT on Marathon Performance",
       x = "Average Course Time",
       y = "WBGT",
       color = "Flag") +
  scale_color_manual(values = c("Green" = "green",
                                "Red" = "red",
                                "White" = "grey",
                                "Yellow" = "yellow"
                              )) +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank()) +
```

```r
  theme_minimal()
# Regression model - Course Time & Weather
project1_CR_aqi$Flag <- factor(project1_CR_aqi$Flag, levels = c("White",
↪  "Green", "Yellow", "Red")) #Set white flag as reference

model <- lm(as.numeric(Time) ~ Age + Sex + Flag + Td + Tw + `%rh` + Tg + SR +
↪  DP + Wind + WBGT, data = project1_CR_aqi)
# summary(model)

# Backward selection model
final_model <- step(model, direction = "backward")
summary <- summary(final_model)

# Print results
coefficients <- as.data.frame(summary$coefficients)
kable(coefficients, digits = 4,
      caption = "Linear Regression Model Summary: Backward Selection",
      col.names = c("Variable", "Estimate", "Std. Error", "t value",
       ↪  "Significance"))
```