PDA Project 1

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Introduction

Studies have shown that weather conditions such as temperature cause decreased performance in endurance events^1. These effects become more prominent in events such as the marathon, where distances and durations are longer^2. Gender differences in thermoregulation^5 and endurance performance^4 have been previously shown in studies. Additionally, older people also do not thermoregulate as efficiently as younger people^3, which may make the effect of adverse weather conditions worse. Therefore, the main questions are whether hot weather conditions decrease marathon performance, if there is a difference between men and women, and if weather conditions affect different age groups differently. Based on the existing literature, the hypothesis for this study is that older runners would be more affected by hot weather conditions than younger runners, and that the effects would be similar between men and women.

EDA

In this dataset, the best performances for each individual age are recorded for females and males at 5 US marathons spanning 1993-2016. The 5 races are the Chicago, New York City, Twin Cities, and Grandma's marathons. The Twin Cities and Grandma's marathons have data starting in 2000, Chicago has data starting in 1996, Boston has data starting in 1998, and New York City has data starting in 1993. All races have data up to the year 2016. The youngest runner across all races and years was 14 and the oldest was 91. Finishing times are provided as the percent off the course record to make the data comparable across races. For example, a percent course record of 40% means that person had a finishing time 1.4 times higher than the course record for that race.

Additionally, weather data was collected for each race from Air Force sources. Weather variables included dry bulb temperature (TD), wet bulb temperature (TW), percent relative humidity (RH), black globe temperature (TG), solar radiation (SR), dew point (DP), and wind speed. Temperatures are measured in Celsius, with wet bulb accounting for humidity, and black globe accounting for solar radiation. Two summary variables are also included: wet bulb globe temperature (WBGT) and flag. WBGT is a weighted average of dry, wet, and black globe temperatures, the flag variable bins the WBGT into levels ranging from `White` indicating the coolest conditions (WBGT<10C), to `Black` where conditions are bad enough that races are canceled (WBGT>28C).

An important step before further analysis is to investigate missing values in the data. When looking at the proportion of missingness in each column, we find that only the weather variables have missingness, and they each have the same 4.25% missingness. This suggests that some races may be missing weather data, which is confirmed when seeing that the missingness is exclusive to the Chicago, NYC, and Twin Cities marathons in 2011, and Grandma's marathon in 2012. We have a large data set of 11564 observations with less than 5% missingness, and the missingness is restricted to races with fully missing weather data, analysis is unlikely to be significantly biased. Therefore, complete case analysis is appropriate and no imputation techniques are necessary for these data.

Table 1 summarizes the available variables from the data set. In addition to original time measure of percent course record, the finishing times for each observation were converted to minutes using the available course record data for each race and year. This allows for a more natural finishing time that is easier to interpret.

Chicago and New York have more observations than the other marathons, but recall these are the races with

Table 1: Data Characteristics by Race

Characteristic	**Boston** N = 2088	**Chicago** N = 2553	**Grandma's** N = 2000	**New York City** N = 2930	**Twin Cities** N = 1993
Sex					
F	984 (47%)	1,210 (47%)	934 (47%)	1,402 (48%)	922 (46%)
M	1,104 (53%)	1,343 (53%)	1,066 (53%)	1,528 (52%)	1,071 (54%)
Flag					
Green	810 (39%)	1,459 (60%)	702 (37%)	901 (32%)	834 (44%)
Red	123 (5.9%)	116 (4.8%)	237 (13%)	0 (0%)	116 (6.2%)
White	1,040 (50%)	732 (30%)	0 (0%)	1,394 (50%)	587 (31%)
Yellow	115 (5.5%)	120 (4.9%)	945 (50%)	504 (18%)	338 (18%)
Age	47 (17)	46 (18)	44 (18)	50 (19)	45 (17)
Percent_CR	41 (34)	52 (47)	48 (40)	55 (56)	46 (37)
TD	11.6 (5.9)	12.4 (6.1)	18.9 (3.3)	11.7 (4.7)	13.1 (5.5)
TW	7.6 (3.8)	8.5 (5.7)	14.9 (2.5)	7.6 (5.0)	9.9 (5.4)
RH	60 (20)	60 (10)	68 (16)	51 (18)	64 (16)
TG	24 (8)	25 (6)	32 (8)	21 (6)	25 (7)
SR	650 (187)	460 (95)	677 (191)	401 (131)	436 (139)
DP	3 (4)	5 (7)	12 (3)	3 (7)	6 (7)
Wind	12.0 (4.5)	8.2 (3.2)	9.2 (2.9)	11.2 (4.6)	8.8 (3.2)
WBGT	11.3 (4.5)	12.1 (5.8)	18.6 (3.2)	10.7 (4.9)	13.2 (5.4)
Time	188 (46)	200 (63)	204 (56)	209 (76)	201 (51)

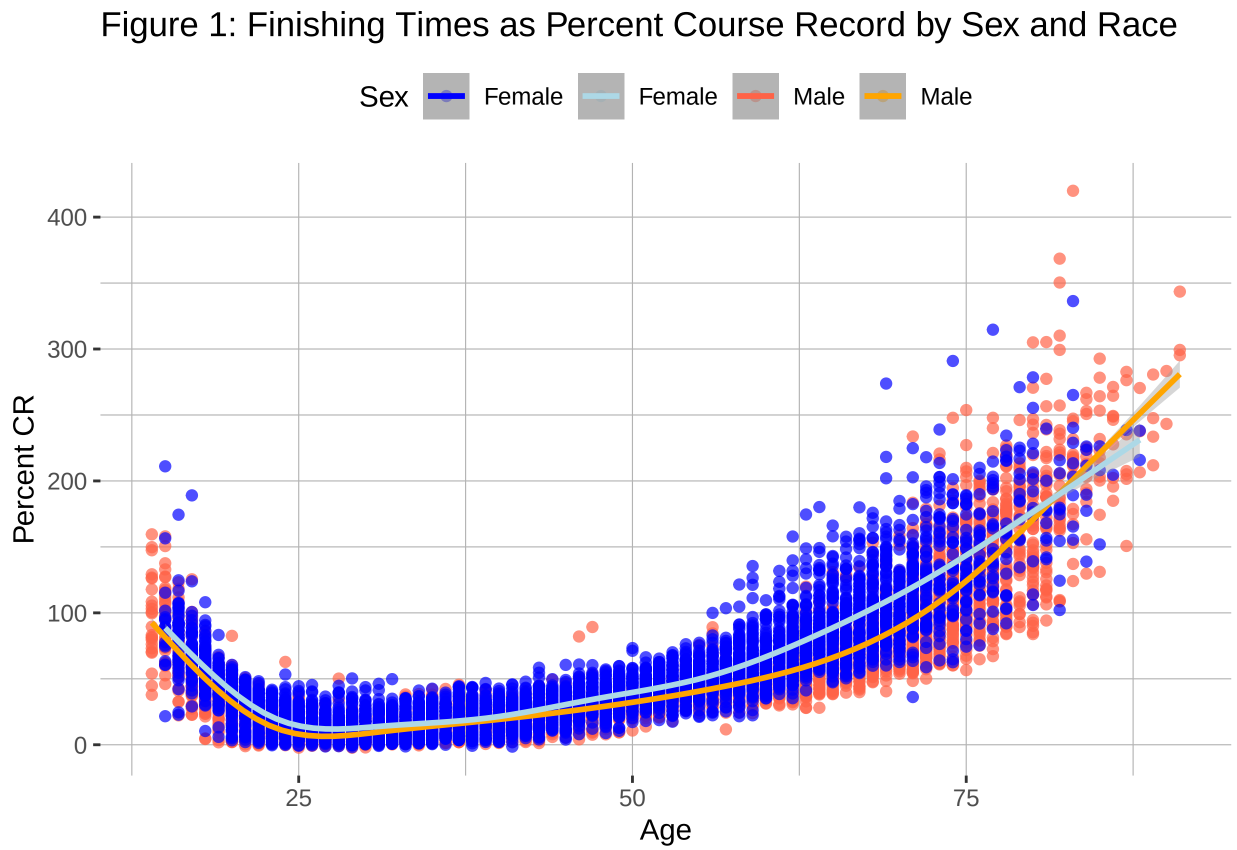
[1] n (%); Mean (SD)

data from 1996 and 1993, respectively. We can see that there are slightly more male observations than female races, with the proportion remaining similar across races. Average ages and standard deviations are similar across races, with NYC having the oldest average of 50 years. Boston is the fastest race, with the average finishing time 12-21 minutes faster than than the others, which is also reflected in the lowest average percent course record of 41%.

Excluding wind, the weather measurements for the Boston, Chicago, NYC, and Twin Cities races are similar with moderate values and primarily white and green flags. In contrast, Grandma's race has 50% yellow flag rate with no white flag observations and an average WBGT measure 5.4C higher than the next highest average. This is not unexpected when considering that Grandma's is the only race run in the summer. Boston runs in April, Chicago and Twin Cities run in October, NYC runs in November, but Grandma's runs in the middle of June (http://www.usamarathonlist.com/). We would expect more temperate conditions in the spring and fall compared to the summer.

Aim 1

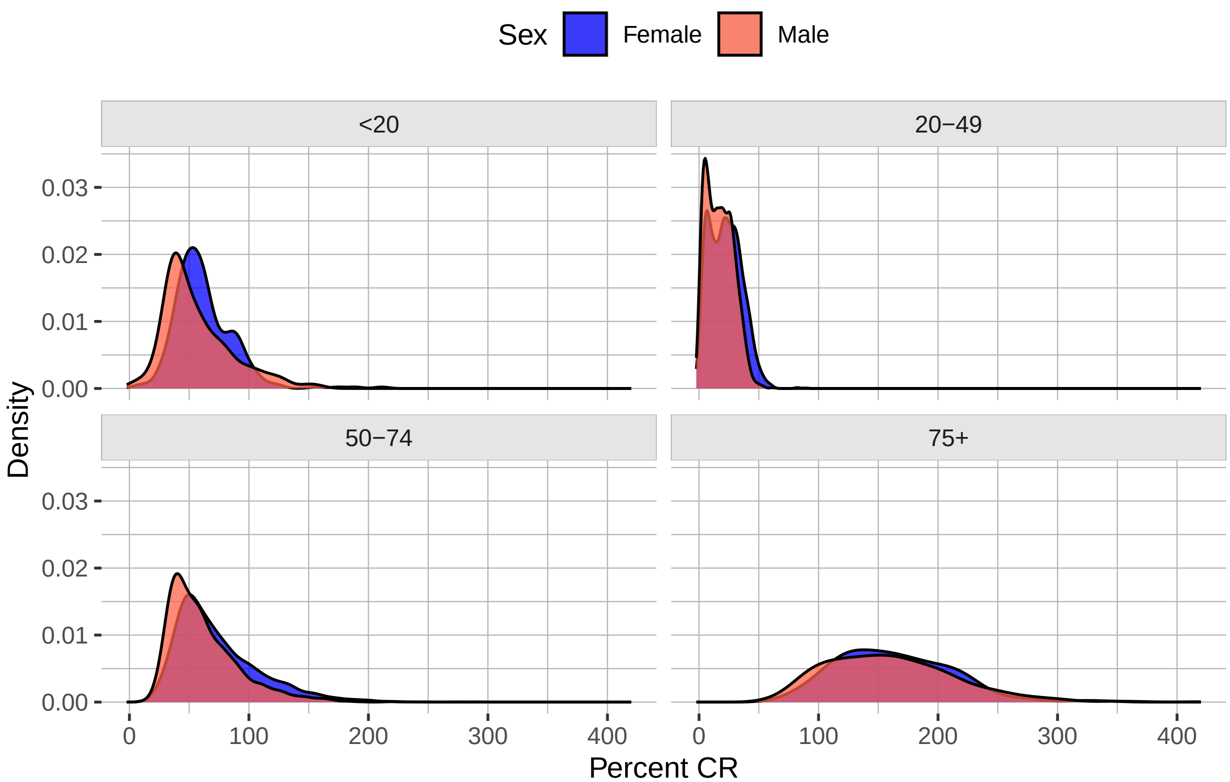
The first aim of this project is to assess the effect of age on performance for both men and women. Figure 1 plots percent course record against age with smoothed lines, separating by sex. In this aim, we are interested at looking at the differences in effect age has on both genders and not the raw differences between genders. Therefore, it makes more sense to use percent course record instead of time in minutes, as each observation will be compared to the best ever performance for that gender.



We can see that the data forms a U-shape, indicating a non-linear relationship between marathon performance and age. Peak performance for both sexes occurs just after age 25, as indicated by the lowest points on the smoothed lines. The smoothed lines are relatively flat between ages 25 and 50, indicating age does not have much effect in this age range, whereas the curves slope more for runners under 25 and above 50. Runners under 25 improve dramatically for each year older, and runners above 50 slow down increasingly quickly for each additionally year older. Overall, men have a slight performance advantage in terms of percent course record over women at most ages as expected, however at ages greater than approximately 80, women actually outperform men on average.

Based on the shape of the curve in Figure 1, we can select natural bins for age by performance. Grouping age to under 20, 20-49, 50-74, and 75+ will allow us to better look at the performance distributions at different ages. Figure 2 shows these distributions for both sexes.

Figure 2: Distribution of Finishing Times by Sex and Age Category



For all of the age groups, there is considerable overlap between the distributions for males and females, with the male distributions shifted slightly faster. The <20 age group has the least overlap, meaning that at ages under 20, males have more of a performance advantage over women compared to the other age groups.

We see that the distributions for the under 20 and 50-74 age groups are quite similar, peaking near 50% course record and almost all of the density falling between 0% and 150% course record. The 20-48 age group clearly has the best performance, with almost the entire density falling under 50% course record. The over 75 age group has a much flatter distribution than the other age groups due to the broader range of finishing times. The variance in finishing times is the smallest in the 20-49 group, largest in the 75+ age group, and somewhere in between for the <20 and 50-74 age groups.

Based on Figures 1 and 2, we can see age does affect marathon performance, but the effect is different based on age group. For runners under 25, increasing age improves marathon performance, whereas after 25, increasing age reduces performance. The amount of performance reduction is small between aged 25 and 50, but becomes increasingly larger for ages 50+. The peak performance years for both sexes is around 25-30 years old, and the corresponding 20-49 age group has the lowest variation in finishing times. The 75+ age group has the slowest finishing times as we would expect, but also the highest variability in performance. In general, the effect of age does not greatly differ between males and females.

Aim 2

The second aim of this project is to investigate if and how weather conditions affect marathon performance, and if these effects differ by sex and age. Recall one of the summary weather variables was the flag status of each race. We can look at a summary of the data grouped by these flags to see if there are any differences between the groups. Table 2 shows these characteristics, excluding the raw weather measurements, as they are used to calculate flag status.

As we previously noted, Grandma's marathon is the only one running in the summer, and it is therefore unsurprising to see that it accounts for 47% and 40% of the yellow and red flags, respectively. The number of

Table 2: Data Characteristics by Flag

Characteristic	**Green** N = 4706	**Red** N = 592	**White** N = 3753	**Yellow** N = 2022	**p-value**
Race					<0.001
Boston	810 (17%)	123 (21%)	1,040 (28%)	115 (5.7%)	
Chicago	1,459 (31%)	116 (20%)	732 (20%)	120 (5.9%)	
Grandma's	702 (15%)	237 (40%)	0 (0%)	945 (47%)	
New York City	901 (19%)	0 (0%)	1,394 (37%)	504 (25%)	
Twin Cities	834 (18%)	116 (20%)	587 (16%)	338 (17%)	
Sex					>0.9
F	2,222 (47%)	279 (47%)	1,769 (47%)	948 (47%)	
M	2,484 (53%)	313 (53%)	1,984 (53%)	1,074 (53%)	
Age	46 (18)	45 (18)	47 (18)	46 (18)	0.002
Percent_CR	48 (44)	53 (41)	48 (46)	51 (44)	<0.001
Time	200 (60)	207 (56)	198 (62)	206 (61)	<0.001

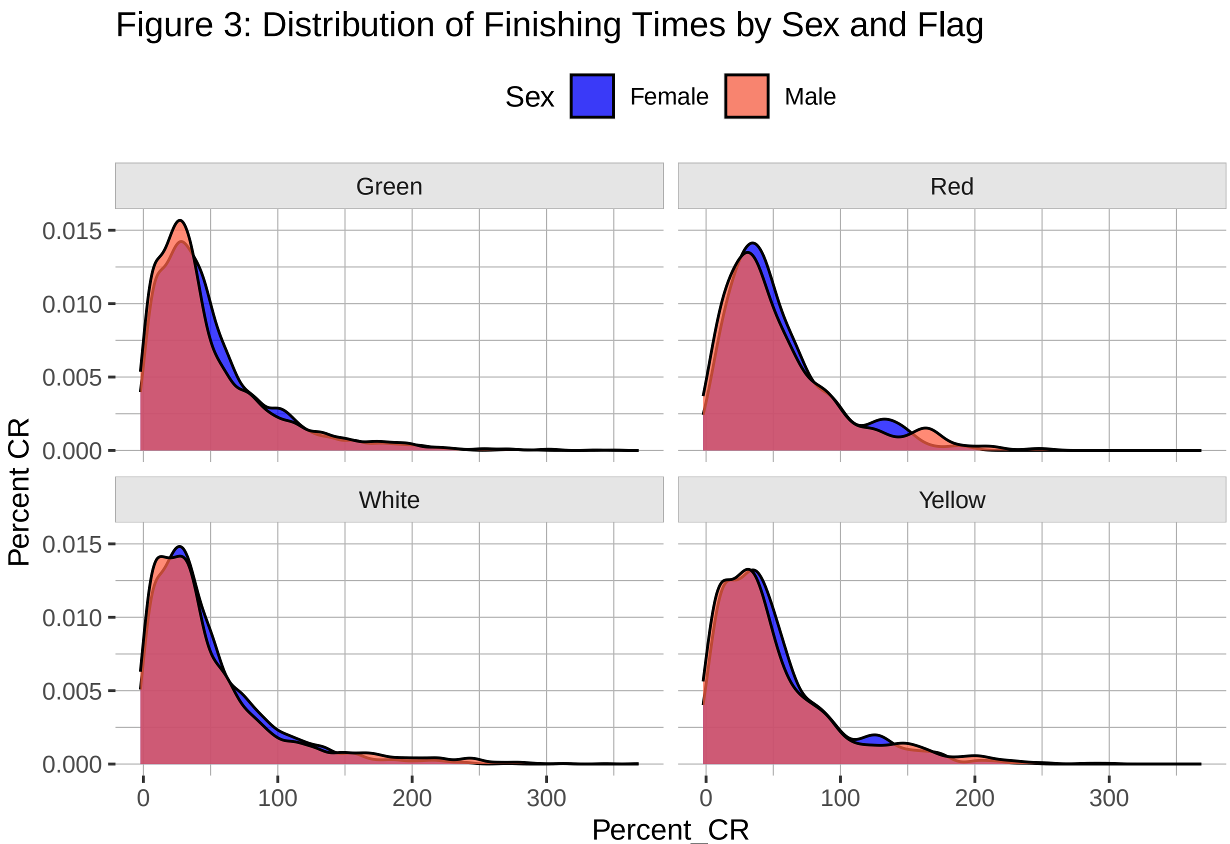
[1] n (%); Mean (SD)

[2] Pearson's Chi-squared test; Kruskal-Wallis rank sum test

observations under a red flag is much smaller than all other flags, which is to be expected, as adverse weather conditions leads to fewer participants and finishers. There is no difference in gender of finishers across the different flags, with the proportions of male and female observations remaining exactly the same.

Age and finishing time, as both percent course record and time in minutes, both show significant differences across the flag types. The average age of 45 is the lowest in red flag finishers, and the highest is 47 under white flag conditions, which are the coolest conditions. Similarly, the slowest average finishing times occur under red flag conditions. Average finishing times under white and green flag conditions are the fastest, echoing the results of average ages under the best conditions. Based on these tables, there weather conditions do significantly affect marathon performance.

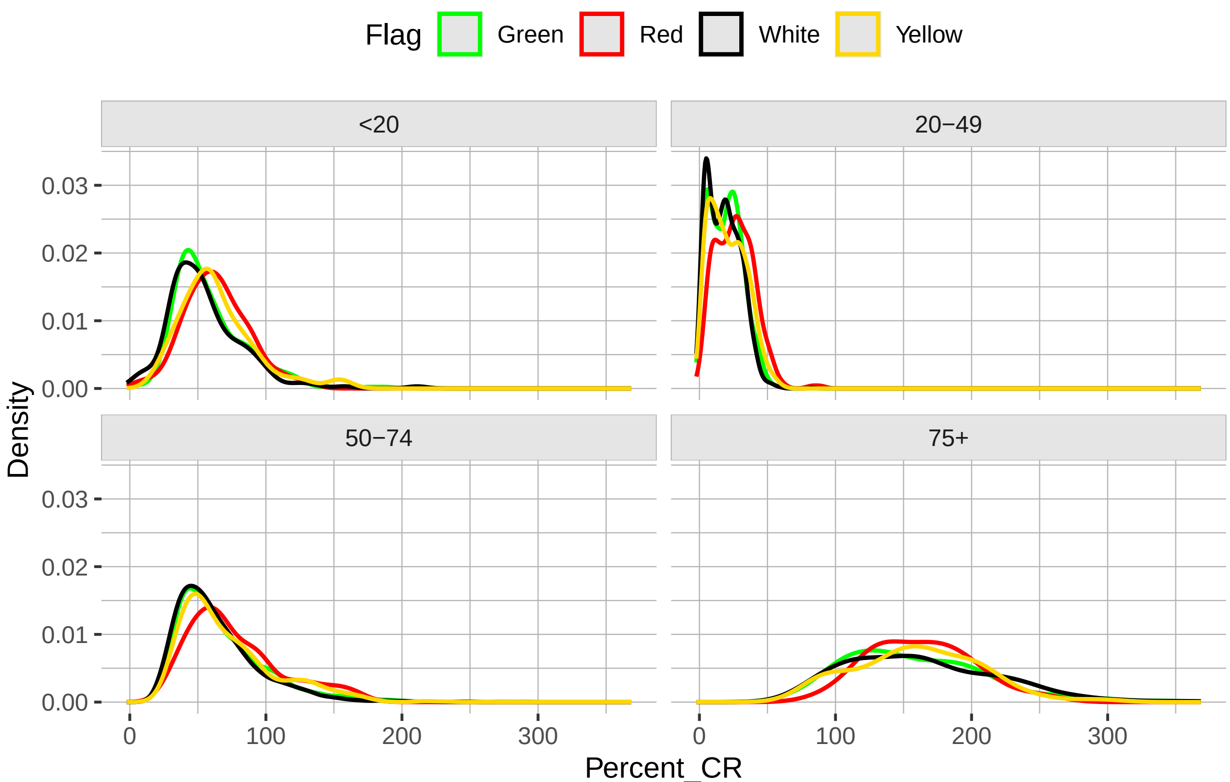
In Figure 3, we visualize the distribution of finishing times by sex and flag.



There are some differences in these distributions, but they appear small. The peaks of the red flag distributions are slightly further right than the under the other flags, indicating slower times. Conversely, the distributions under white flag conditions are slightly further left, indicating faster times. The red flag red and yellow flag distributions also have slightly wider peaks, indicating higher variance of finishing times. However, these differences are again very small. The overlap of the male and female distributions are similar across flag conditions. This means there does not appear to be much difference in the effect of weather conditions on finishing time between sexes.

We can also look at the how weather conditions affect age groups differently by using the same age categories as before. Figure 4 shows the distributions of percent course record for each flag type, separated into age bins.

Figure 4: Distribution of Finishing Times by Age and Flag



Like Figure 3, there are some visible differences in Figure 4, but they are slight. In the under 20 age group, we can see a clear difference in peak location for white and green flags compared to red and yellow flags. The peaks of the red and yellow distributions are clearly to the right of the white and green flag distributions, indicating slower times under the hotter conditions. In the 50-74 age group, the distribution of finishing times under yellow flag conditions is more similar to white and green flag conditions, and the distribution for red flag conditions is slightly off to the right. Similarly in the 20-49 age group, there is not much difference between the yellow flag distribution compared to the white and green flag conditions. Again, the red flag conditions distribution is slower than the other flags, but there is still considerable overlap. Finally, the 75+ age group distributions have high variance, resulting in flatter peaks, which makes comparison less clear. However, red and yellow flag condition distributions do appear further right, indicating slower finishing times.

Overall, there is not much visual difference between the distributions of finishing times for the different flag conditions. In all age groups, the red flag conditions resulted in slower finishing time. Under yellow flag conditions, only the under 20 and over 75 age groups show finishing time distributions further right, suggesting that the 20-49 and 50-74 age groups are not as affected by yellow flag conditions.

In both Figures 3 and 4, we saw some differences in finishing times as weather conditions worsened, but the differences were small. Furthermore, conditions did not seem to affect genders differently, but there was some difference in effect across age groups. These results agree with the findings in Table 2, but we can use one more measure to determine the extent of these differences. We will fit a linear regression model to finishing time with interaction terms between WBGT and age, and WBGT and sex. In this case, we will use finishing time in minutes, because that has a more natural interpretation than percent course record in this setting. The results of this simple linear regression are found in Table 3. Because we recognize that the 20-49 age group is the highest performing, we will set it as the baseline level.

In Table 3, we see that age, sex, and weather conditions as summarized by WBGT all have significant effects on finishing time in minutes, with p-values all less than 0.001. Using the under 20-49 age group as the baseline, being under 20 results in a 47 minute slower in finishing time on average, being 50-74 results in a 59 minute slower finishing time on average, and being 75+ results in a 197 minute drop off in finishing

Table 3: Linear Regression of Time (m) with WBGT Interactions

Characteristic	**Beta**	**95% CI**	**p-value**
Age_cat			
20-49	—	—	
<20	47	39, 55	<0.001
50-74	59	55, 62	<0.001
75+	197	190, 205	<0.001
WBGT	0.59	0.39, 0.80	<0.001
Sex			
F	—	—	
M	-32	-35, -29	<0.001
Age_cat * WBGT			
<20 * WBGT	0.51	0.00, 1.0	0.050
50-74 * WBGT	0.51	0.25, 0.76	<0.001
75+ * WBGT	-0.77	-1.3, -0.23	0.006
WBGT * Sex			
WBGT * M	-0.09	-0.33, 0.15	0.5

[1] CI = Confidence Interval

time on average. For every unit increase in WBGT, finishing time increases by 0.59 minutes on average for the baseline group. We also see that males have a finishing time 32 minutes faster than women on average. These interpretations hold all other variables constant.

When looking at the interaction terms, we see some of the results are significant. As we expected from our figures, the effect of WBGT does not significantly differ by sex, given that the p-value for the `WBGT*Sex` interaction is 0.5. The interaction terms for the categorical age and WBGT interaction are significant, as we thought based on Table 2 and Figure 4. The p-value for the under 20 group is just barely significant, whereas for the 50-74 and 75+ groups, the p-values are less than 0.006, indicating highly significant differences. Both under 20 and 50-74 age groups show a greater slowing of finishing time compared to baseline due to their positive interaction coefficient. The interaction coefficient for the 75+ group is surprisingly negative, indicating a lesser effect on finishing time.

Based on the tables and figures, we find that weather conditions do have a negative impact on marathon performance in general. The effect does not vary significantly between genders, but does between age. Compared to the baseline 20-49 age group, WBGT results in more slowing for age groups <20 and 50-74, but less slowing for ages 75+.

Aim 3

The final aim of this project is to determine which weather conditions have the largest impact on race performance. To determine this, we will again fit a simple linear regression model to assess the significance and magnitude of associations between weather conditions and finishing time. As before, we will use finishing time in minutes for better interpretation. Because WBGT is calculated from dry bulb, wet bulb, and black globe temperature, we will exclude those underlying measures and only include WBGT to prevent multicollinearity.

Based on the results in Table 4, we see that the significant weather variables are relative humidity (RH) and solar radiation (SR), and WBGT. Dew point and wind are not significantly associated with finishing time. For every unit increase in WBGT, we expect finishing time to increase by 0.81 minutes on average, controlling for the other variables. Surprisingly, RH and SR have negative coefficients, indicating each unit increase of these variables improves finishing time.

Table 4: Linear Regression of Time (m) and Weather Conditions

Characteristic	Beta	95% CI	p-value
RH	-0.27	-0.38, -0.15	<0.001
SR	-0.03	-0.03, -0.02	<0.001
DP	0.08	-0.58, 0.74	0.8
Wind	0.16	-0.14, 0.46	0.3
WBGT	0.81	0.04, 1.6	0.039

[1] CI = Confidence Interval

Limitations

Overall, some of the results were expected, but some were also surprising. For example, we would not expect WBGT to improve performance among 75+ runners or humidity and solar radiation to improve performance times. However, It is important to note that we used simple linear regression models and did not do any model selection or diagnostics. As we saw in Figure 1, the relationship between finishing time and age was not linear, which suggests other non-linear relationships as well. This means that our unexpected results may be the result of ill-fitting models, and the true effects are closer to what we would expect.

Another limitation of our data is that it contains only the top finisher for every age in each race. This may cause selection bias towards high performers. As we saw in Figure 4, weather conditions may not affect the elite athletes as much as the average athlete, so selecting only the best performers from each age may underestimate the effect of weather conditions. Because there are fewer observations for the very young and very old ages, we may not have adequate sample size to assess associations.

In terms of the weather data, the measurements are averages across the entire day, which may not accurately reflect the weather conditions of each runner. For example, if a runner started later, it may have gotten hotter, or if a slow runner spends longer on course, they may have experienced a longer period of hotter conditions. The weather data is not granular to the individual level, which also may affect the associations between weather conditions.

References

1. Ely, B. R., Cheuvront, S. N., Kenefick, R. W., & Sawka, M. N. (2010). Aerobic performance is degraded, despite modest hyperthermia, in hot environments. Med Sci Sports Exerc, 42(1), 135-41.
2. Ely, M. R., Cheuvront, S. N., Roberts, W. O., & Montain, S. J. (2007). Impact of weather on marathon-running performance. Medicine and science in sports and exercise, 39(3), 487-493.
3. Kenney, W. L., & Munce, T. A. (2003). Invited review: aging and human temperature regulation. Journal of applied physiology, 95(6), 2598-2603.
4. Besson, T., Macchi, R., Rossi, J., Morio, C. Y., Kunimasa, Y., Nicol, C., … & Millet, G. Y. (2022). Sex differences in endurance running. Sports medicine, 52(6), 1235-1257.
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Code Appendix

```
knitr::opts_chunk$set(echo = FALSE)
knitr::opts_chunk$set(message = FALSE)
library(knitr)
library(tidyverse)
library(lubridate)
library(gtsummary)
library(kableExtra)
library(gt)
# read course record data
cr_dat<-read.csv("course_record.csv")
# expand race names
cr_dat$Race<-case_when(cr_dat$Race=="B"~"Boston",
                       cr_dat$Race=="C"~"Chicago",
                       cr_dat$Race=="D"~"Grandma's",
                       cr_dat$Race=="NY"~"New York City",
                       TRUE~"Twin Cities")

# read data
dat<-read.csv("project1.csv")
# rename columns
names(dat)<-c("Race", "Year", "Sex", "Flag", "Age", "Percent_CR", "TD", "TW",
              "RH", "TG", "SR", "DP", "Wind", "WBGT")
dat$Sex<-ifelse(dat$Sex==1, "M", "F")
# label races by location
dat$Race<-case_when(dat$Race==0~"Boston",
                    dat$Race==1~"Chicago",
                    dat$Race==2~"New York City",
                    dat$Race==3~"Twin Cities",
                    TRUE~"Grandma's")



# join course record data by race, year, and gender
full_dat<-left_join(dat, cr_dat, by=c("Race", "Year", "Sex"="Gender"))

# convert CR to minutes
in_minutes<-function(times){
  #' takes a vector of times in the format "hours:minutes:seconds" and returns the number of minutes
  #' @param times a character vector containing the times to convert
  #' @return a numeric vector of the same length as times containing the times in minutes
  #'

  # convert to hours minutes and seconds
  convert<-hms(times)

  # calculate minutes
  mins<-hour(convert)*60+minute(convert)+second(convert)/60
  return(mins)
}

#convert percent_cr to times
full_dat<-full_dat%>%mutate(cr.time=in_minutes(CR),
```

```
                            Time=cr.time*(1+Percent_CR/100))



# fix irregularity of decimal relative humidities by converting to percent
full_dat<-full_dat%>%mutate(RH=ifelse(RH<1, RH*100, RH))

# blank flag values are black missing
full_dat$Flag<-ifelse(full_dat$Flag=="", NA, full_dat$Flag)

## numbers for summary in text
get_years<-function(data, race){
  #' this function finds the range of years for a given race in the data
  #' @param data, the dataframe containing at least the race and year columns
  #' @param race, character name of race
  #' @return vector containing the start and endpoints of the range of years for the given race
  #'
  data%>%filter(Race==race)%>%select(Year)%>%unique()%>%range()
}

# boston race years
get_years(full_dat, "Boston")
# NYC race years
get_years(full_dat, "New York City")
# TC race years
get_years(full_dat, "Twin Cities")
# Gma's race years
get_years(full_dat, "Grandma's")
# Chi race years
get_years(full_dat, "Chicago")
num_missing<-function(data){
  #' Returns the number of missing values in the given data
  #' @param data, data vector or data frame of any type
  #' @return the number of NA values in the data

  return(length(which(is.na(data))))
}

# table of missingness proportion
kable(apply(full_dat, 2, num_missing)/nrow(dat))

# look at races with missingness, choosing arbitrary age present in all races
# and first weather measurement
full_dat%>%filter(is.na(TD))%>%group_by(Race)%>%filter(Age==25)
## create table 1
tbl_summary(select(full_dat, -c(Year, CR, cr.time)), by=Race, missing="no",
            statistic = list(all_continuous()~ "{mean} ({sd})",
                             all_categorical()~ "{n} ({p}%)"))%>%
  modify_header(all_stat_cols() ~ "**{level}**  \nN = {n}")%>%
  modify_caption("Data Characteristics by Race")%>%
  as_kable_extra(booktabs=TRUE)
#### plot percent course record with smoothed line, by sex and race
g<-ggplot(full_dat, aes(x=Age, y=Percent_CR, color=Sex))+
```

```
  geom_point(alpha=.7)+
  geom_smooth(aes(x=Age, y=Percent_CR, color="orange"), dat=full_dat[full_dat$Sex=="M",])+
  geom_smooth(aes(x=Age, y=Percent_CR, color="lightblue"), dat=full_dat[full_dat$Sex=="F",])+
  #facet_wrap(~Race, )+
  scale_color_manual(values=c("blue","lightblue", "tomato", "orange"), labels=c("Female", "Female", "Ma
  labs(x="Age", y="Percent CR", title=
         "Figure 1: Finishing Times as Percent Course Record by Sex and Race")+
  theme(legend.position = "top",
        panel.background = element_rect(fill="white"),
        strip.background =element_rect(fill="grey90", linewidth = .2,
                                       colour = "grey70"),
        panel.grid.major = element_line(color="grey70", linewidth=.2),
        panel.grid.minor = element_line(color="grey70", linewidth=.2),
        legend.key = element_rect(fill = "grey90")
        )

g
# create bins for age
full_dat<-full_dat%>%mutate(Age_cat=case_when(Age<20~"<20",
                                              Age<50~"20-49",
                                              Age<75~"50-74",
                                              TRUE~"75+"))

### plot times by race and sex
ggplot(full_dat, aes(x=Percent_CR, fill=Sex))+
  geom_density(alpha=.75)+
  facet_wrap(~Age_cat)+
  scale_fill_manual(values=c("blue","tomato"), labels=c("Female", "Male"))+
  labs(x="Percent CR", y="Density", title="Figure 2: Distribution of Finishing Times by Sex and Age Cat
  theme(legend.position = "top",
        panel.background = element_rect(fill="white"),
        strip.background =element_rect(fill="grey90", linewidth = .2,
                                       colour = "grey70"),
        panel.grid.major = element_line(color="grey70", linewidth=.2),
        panel.grid.minor = element_line(color="grey70", linewidth=.2),
        legend.key = element_rect(fill = "grey90")
        )
## table of data characteristics by flag
tbl_summary(select(full_dat, c(Race, Sex, Age, Percent_CR,Time, Flag)), by=Flag,
            missing="no",
            statistic = list(all_continuous()~ "{mean} ({sd})",
                             all_categorical()~ "{n} ({p}%)"))%>%
  add_p()%>%
  modify_header(all_stat_cols() ~ "**{level}**  \nN = {n}")%>%
  modify_caption("Data Characteristics by Flag")%>%
  as_kable_extra(booktabs=TRUE)
ggplot(full_dat[!is.na(full_dat$Flag),], aes(x=Age, y=Percent_CR, color=Sex))+
  geom_smooth(aes(x=Age, y=Percent_CR))+
  facet_wrap(~Flag)+
  scale_color_manual(values=c("blue", "tomato"), labels=c("Female", "Male"))+
  labs(x="Age", y="Percent CR", title=
         "Figure 3: Finishing Times as Percent Course Record by Sex and Flag")+
  theme(legend.position = "top",
```

```
        panel.background = element_rect(fill="white"),
        strip.background =element_rect(fill="grey90", linewidth = .2,
                                        colour = "grey70"),
        panel.grid.major = element_line(color="grey70", linewidth=.2),
        panel.grid.minor = element_line(color="grey70", linewidth=.2),
        legend.key = element_rect(fill = "grey90")
        )
ggplot(full_dat[!is.na(full_dat$Flag),], aes(x=Percent_CR, fill=Sex))+
  geom_density(alpha=.75)+
  facet_wrap(~Flag)+
  scale_fill_manual(values=c("blue", "tomato"), labels=c("Female", "Male"))+
  labs(x="Percent_CR", y="Percent CR", title=
         "Figure 3: Distribution of Finishing Times by Sex and Flag")+
  theme(legend.position = "top",
        panel.background = element_rect(fill="white"),
        strip.background =element_rect(fill="grey90", linewidth = .2,
                                        colour = "grey70"),
        panel.grid.major = element_line(color="grey70", linewidth=.2),
        panel.grid.minor = element_line(color="grey70", linewidth=.2),
        legend.key = element_rect(fill = "grey90")
        )

full_dat<-full_dat%>%mutate(color=case_when(Flag=="White"~"white",
                                                  Flag=="Green"~"green",
                                                  Flag=="Yellow"~"yellow",
                                                  Flag=="Red"~"red",
                                                  TRUE~NA
                                        ))

ggplot(full_dat[!is.na(full_dat$Flag),], aes(x=Percent_CR, color=Flag))+
  geom_density(alpha=.75, linewidth=.75)+
  facet_wrap(~Age_cat)+
  scale_color_manual(values=c("green", "red","black", "gold"),
                  labels=c("Green", "Red", "White", "Yellow"))+
  labs(x="Percent_CR", y="Density", title=
         "Figure 4: Distribution of Finishing Times by Age and Flag")+
  theme(legend.position = "top",
        panel.background = element_rect(fill="white"),
        strip.background =element_rect(fill="grey90", linewidth = .2,
                                        colour = "grey70"),
        panel.grid.major = element_line(color="grey70", linewidth=.2),
        panel.grid.minor = element_line(color="grey70", linewidth=.2),
        legend.key = element_rect(fill = "grey90")
        )

# linear regression of time with WBGT interactions
# set baseline age group to 20-49
full_dat$Age_cat<-factor(full_dat$Age_cat, ordered = FALSE)
full_dat$Age_cat<-relevel(full_dat$Age_cat, ref="20-49")

l<-lm(Time~Age_cat*WBGT+Sex*WBGT, data=full_dat)

# summary table of regression coefficients
```

```r
tbl_regression(l)%>%
  modify_caption("Linear Regression of Time (m) with WBGT Interactions")%>%
  as_kable_extra(booktabs=TRUE)

# fit linear model for weather conditions
weather_fit<-lm(Time~RH+SR+DP+Wind+WBGT, data=full_dat)

# summary table of regression coefficients
tbl_regression(weather_fit)%>%
  modify_caption("Linear Regression of Time (m) and Weather Conditions")%>%
  as_kable_extra(booktabs=TRUE)
```