Homework #1

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```r
knitr::opts_chunk$set(echo = TRUE, fig.width = 10, warning = FALSE, message = FALSE)
library(tidyverse)
library(knitr)
library(kableExtra)
library(grid)
library(gridExtra)
library(broom)
library(ggfortify)

ozone <- read.csv("~/Downloads/ozone.csv")
```

1

> Create a table with the overall (across sites and days) mean, standard deviation, and percent missing.

```r
ozone_pivot <-
  ozone %>%
  # Pivot Day columns to Rows
  pivot_longer(starts_with("Day"), names_to = "day", values_to = "value") %>%
  mutate(
    # convert day to integer for easier processing
    day = as.integer(str_replace(day, "Day.", ""))
  )

ozone_pivot %>%
  summarise(
    mean = mean(value, na.rm = TRUE),
    sd = sd(value, na.rm = TRUE),
    perc_na = sum(is.na(value)) / n()
  ) %>% kable(
    caption = "Overall Summary Statistics"
  ) %>% kable_styling(bootstrap_options = "striped", latex_options = "hold_position")
```

Table 1: Overall Summary Statistics

mean	sd	perc_na
51.27333	17.26207	0.0432246

2

a. Compute the mean, variance, and percent missing for each of the n sites;
b. Make a histogram of each variable (all three histograms should have n observations);

c. create scatter plots of each pair of these variables (each of the three plots should have n points)

```
ozone_summary <-
  ozone_pivot %>%
  group_by(Station.ID) %>%
  summarise(
    mean = mean(value, na.rm = TRUE),
    sd = sd(value, na.rm = TRUE),
    perc_na = sum(is.na(value)) / n(),
    var = var(value, na.rm = TRUE)
  )

ozone_summary %>%
  select(-var) %>%
  # There are 1000+ stations. Limit for viewing purposes
  head(10) %>%
  kable(
    caption = "A sample of Station Observation Summaries"
  ) %>% kable_styling(bootstrap_options = "striped", latex_options = "hold_position")
```

Table 2: A sample of Station Observation Summaries

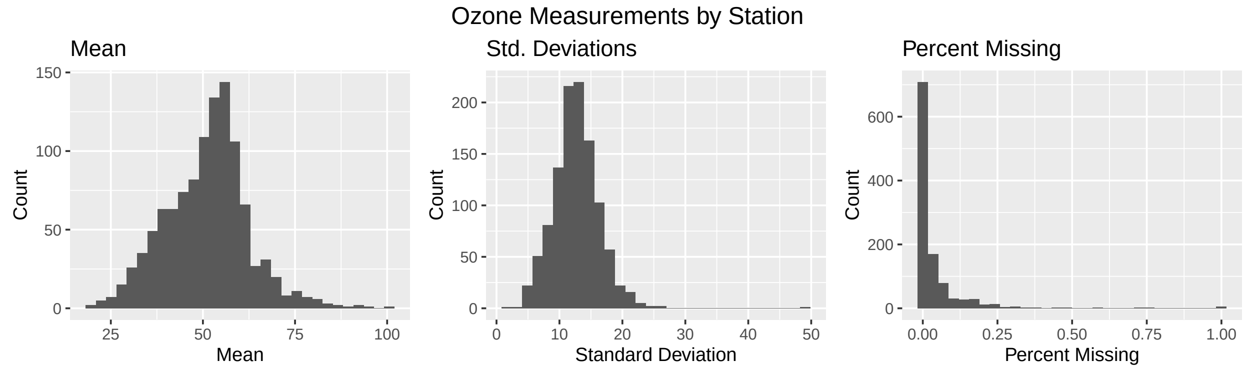
Station.ID	mean	sd	perc_na
1	39.55608	16.93143	0.1612903
2	40.67765	11.44378	0.0000000
3	44.82777	14.17176	0.0000000
4	38.78773	11.18569	0.0322581
5	41.24200	12.40991	0.0645161
6	42.80556	13.98266	0.1290323
7	41.88306	16.61801	0.0000000
8	44.81452	19.68811	0.0000000
9	41.15229	12.93453	0.0000000
10	43.51293	17.36322	0.0645161

```
plot_mean <-
  ozone_summary %>%
  ggplot(aes(x = mean)) +
    geom_histogram() +
    labs(x = "Mean", y = "Count", title = "Mean")

plot_sd <-
  ozone_summary %>%
  ggplot(aes(x = sd)) +
    geom_histogram() +
    labs(x = "Standard Deviation", y = "Count", title = "Std. Deviations")

plot_percmis <-
  ozone_summary %>%
  ggplot(aes(x = perc_na)) +
    geom_histogram() +
    labs(x = "Percent Missing", y = "Count", title = "Percent Missing")

grid.arrange(plot_mean, plot_sd, plot_percmis, ncol = 3,  top = textGrob("Ozone Measurements by Station
                            gp=gpar(fontsize=14,font=1),just=c("center")))
```

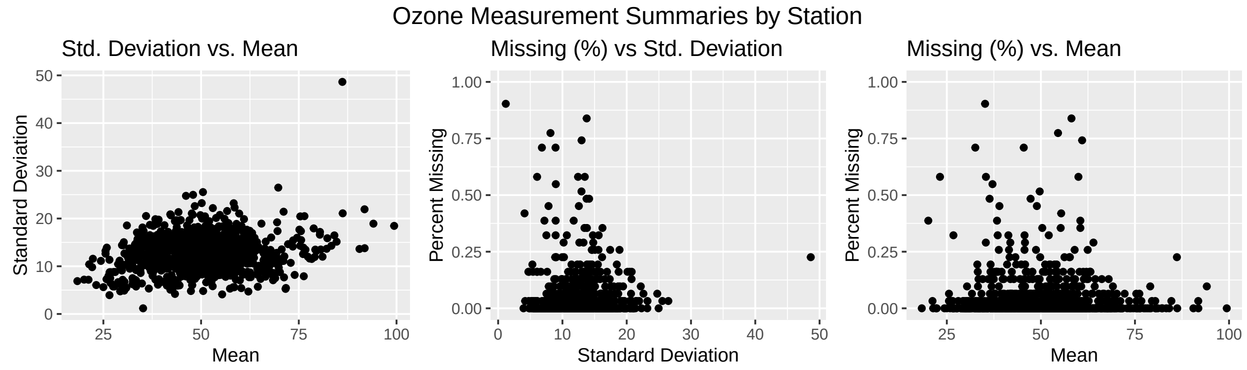


```
plot_mean <-
  ozone_summary %>%
  ggplot(aes(x = mean, y = sd)) +
    geom_point() +
    labs(x = "Mean", y = "Standard Deviation", title = "Std. Deviation vs. Mean")

plot_sd <-
  ozone_summary %>%
  ggplot(aes(x = sd, y = perc_na)) +
    geom_point() +
    labs(x = "Standard Deviation", y = "Percent Missing", title = "Missing (%) vs Std. Deviation")

plot_percmis <-
  ozone_summary %>%
  ggplot(aes(x = mean, y = perc_na)) +
    geom_point() +
    labs(y = "Percent Missing", x = "Mean", title = "Missing (%) vs. Mean")

grid.arrange(
  plot_mean,
  plot_sd,
  plot_percmis,
  ncol = 3,
  top = textGrob("Ozone Measurement Summaries by Station",
                            gp=gpar(fontsize=14,font=1),just=c("center"))
)
```



3

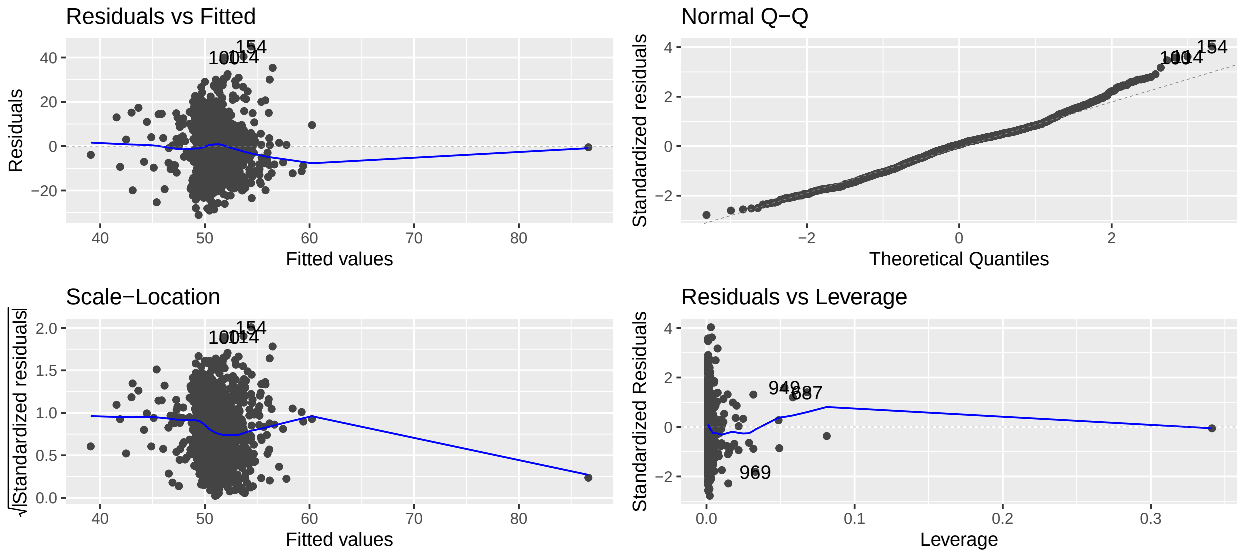
Conduct a linear regression with response equal to the site's mean and the site's variance and percent missing as covariates.

```r
model1 <- lm(mean ~ var + perc_na, data = ozone_summary)

tidy(model1) %>%
  kable() %>%
  kable_styling(bootstrap_options = "striped", latex_options = "hold_position")
```

term	estimate	std.error	statistic	p.value
(Intercept)	48.5895500	0.6328189	76.782713	0.0000000
var	0.0170994	0.0029618	5.773334	0.0000000
perc_na	-10.5407498	3.6119795	-2.918275	0.0035916

```r
autoplot(model1)
```



Residuals vs Fitted

Normal Q−Q

Scale−Location

Residuals vs Leverage

Assumptions

In order to use Linear Regression, certain assumptions must be met.

Normality

The QQ plot shows the standardized residuals lining up close to the theoretical line except for the upper tail which deviates from the line. The Shapiro-Wilk test indicates that there is convincing evidence that the data are non-normal (p-value = 6.487e-07). However, there are enough observations and the normality assumption is robust so regression can still be used.

```r
shapiro.test(model1$residuals) %>%
  tidy() %>%
  kable() %>%
  kable_styling(bootstrap_options = "striped", latex_options = "hold_position")
```

statistic	p.value	method
0.9898134	6e-07	Shapiro-Wilk normality test

Homogeneity of Variances

The distribution of residuals about Y = 0 is roughly in the same area though there are larger positive standardized residuals than negative standardized residuals which indicate that the variances may not be homogenous. A Levene's Test about Y = 0 indicates that there is not enough evidence to suggest that the variances are unequal between residuals above and below Y = 0 (p-value = 0.1537) so this assumption holds.

```r
lawstat::levene.test(model1$residuals, group = model1$residuals <= 0) %>%
  tidy() %>%
  kable() %>%
  kable_styling(bootstrap_options = "striped", latex_options = "hold_position")
```

statistic	p.value	method
2.037605	0.1537355	Modified robust Brown-Forsythe Levene-type test based on the absolute deviations from the media

Linearity

There are no obvious patterns present in the Residuals vs Fitted so the data appear to be linear.

Independence

The grain of the data is per weather station so each observation is independent as far as we know. The observations of a given station should not affect observations of another station.

Results

The model features are all statistically significant which is obvious and expected. Mean, Variance, and Percent missing are obviously correlated and thus this model doesn't provide any valuable insight to the data.