HW1 Dan Schumacher

installs and imports

```
library(tidyverse)
```

##

Exercise 1: Descriptive Statistics

##

Set up

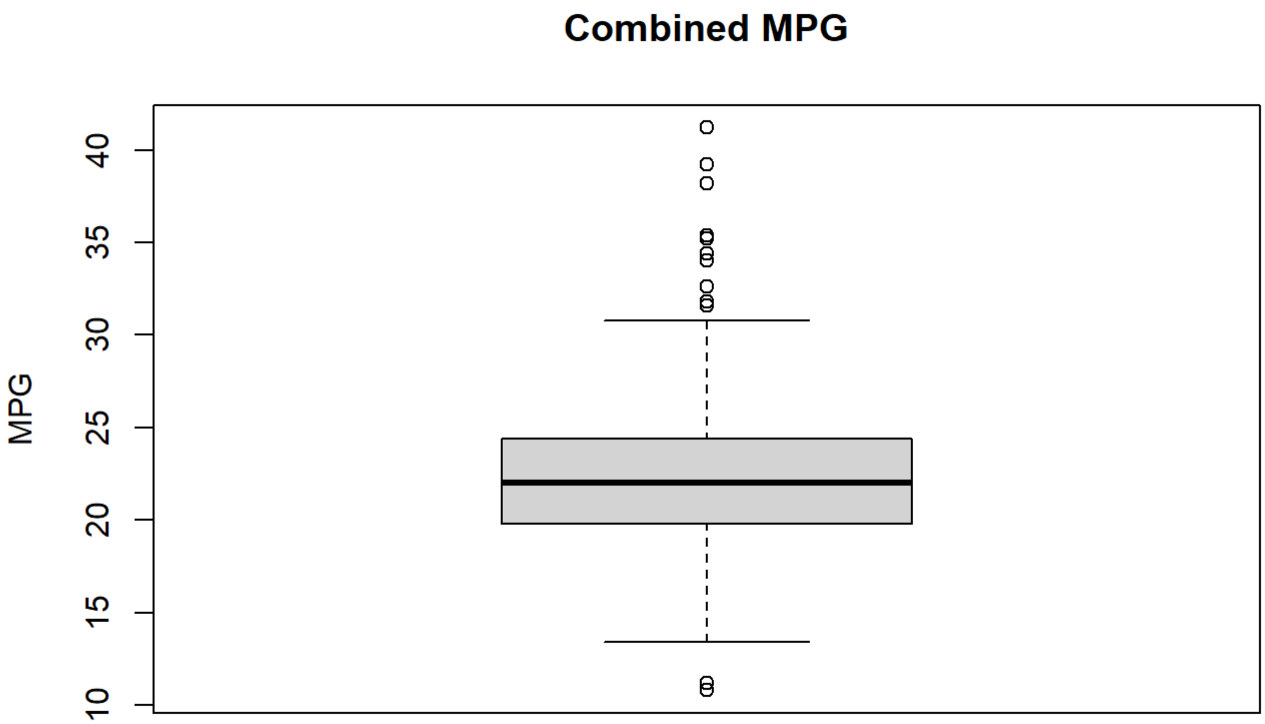
a.1) Create a combined mpg variable called MPG_Combo which combines 60% of the MPG_City and 40% of the MPG_Highway.

```
#load data
cars=read.csv("Cars.csv", header = TRUE)  # read dataset
# Create a combined mpg variable
MPG_Combo <- 0.6*cars$MPG_City+0.4*cars$MPG_Highway
#Turn into database
cars=data.frame(cars,MPG_Combo)
```

a.2) Obtain a box plot for MPG_Combo and comment on what the plot tells us about fuel efficiency.

1. This plot looks normally distributed but *has a large number of outliers*. The median mpg_combo miles per gallon is around 22.5 mpg. Q1 is roughly 20; Q3 is roughly 25. Min at 15, max at 30.

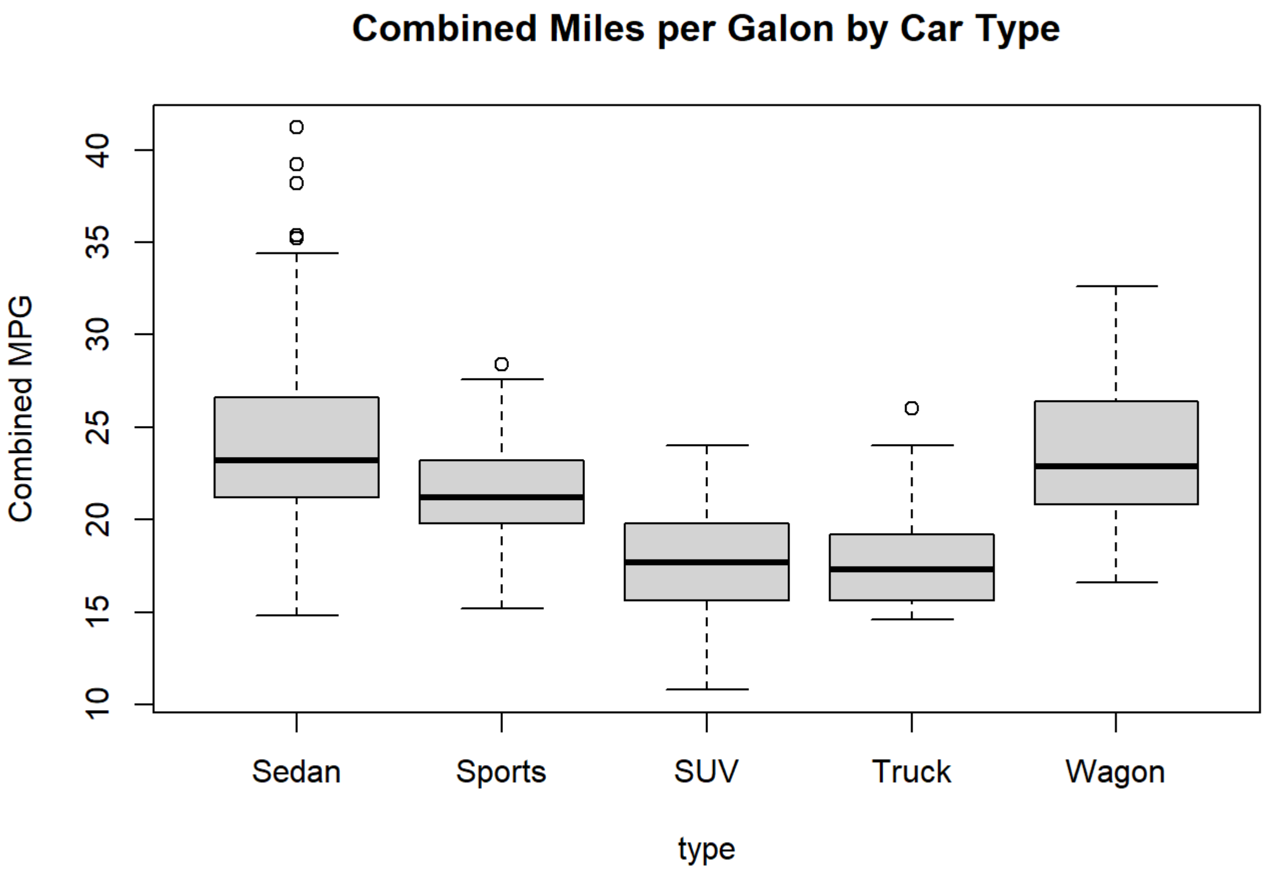
```
boxplot(cars$MPG_Combo,
        main = 'Combined MPG',
        ylab = 'MPG')
```



B.) Obtain box plots for MPG_Combo by Type and comment on any differences you notice between the different vehicle types combined fuel efficiency.

These boxplots show that SUV and Truck have the lowest combined mpg performance. Sedan and Wagon have the highest mpg performance. Sedan is also responsible for most of the outliers. Sedan (minus outliers), Sports, and SUV all *look* normally distributed. Trucks clearly are Right Skewed. Wagon seems slightly right skewed.

```
boxplot(MPG_Combo ~ Type,
        data = cars,
        main = 'Combined Miles per Galon by Car Type',
        xlab = 'type',
        ylab = 'Combined MPG')
```



C.) Obtain basic descriptive statistics for Horsepower for all vehicles. Comment on any general features and statistics of the data. Use visual and quantitative methods to comment on whether an assumption of Normality would be reasonable for Horsepower variable.

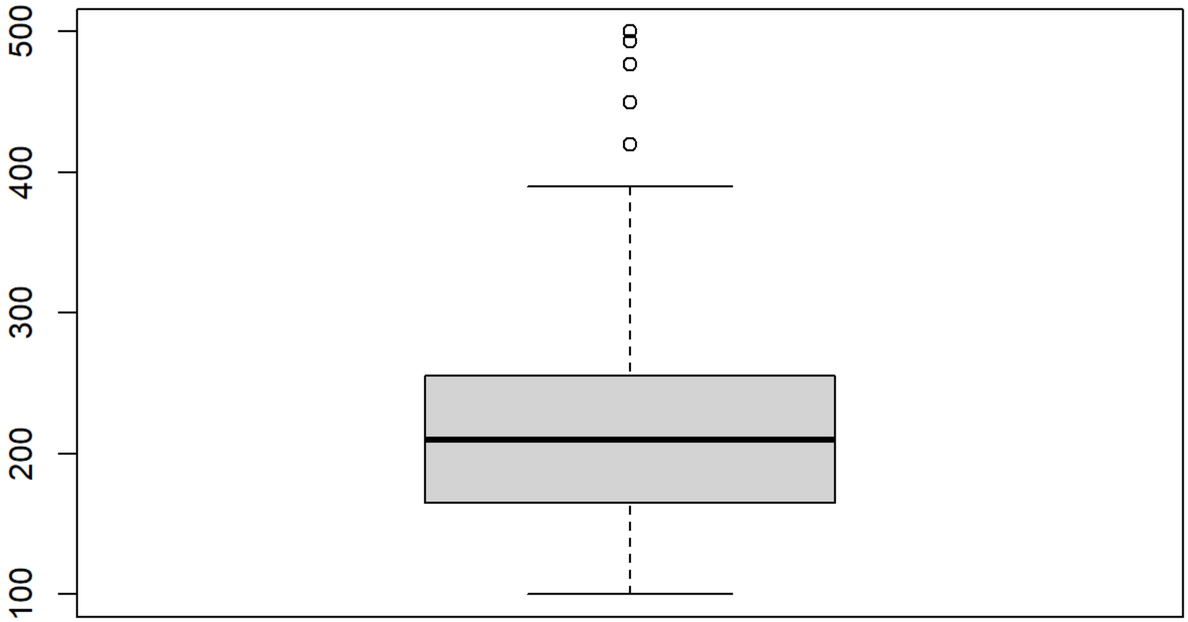
Here we see that the mean is slightly larger than the median meaning that the data collectively could potentially be right skewed (positively skewed) however with only a difference of 6.8 it is hard to tell without further tests.

```
summary(cars$Horsepower)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  100.0   165.0   210.0   216.8   255.0   500.0 
```

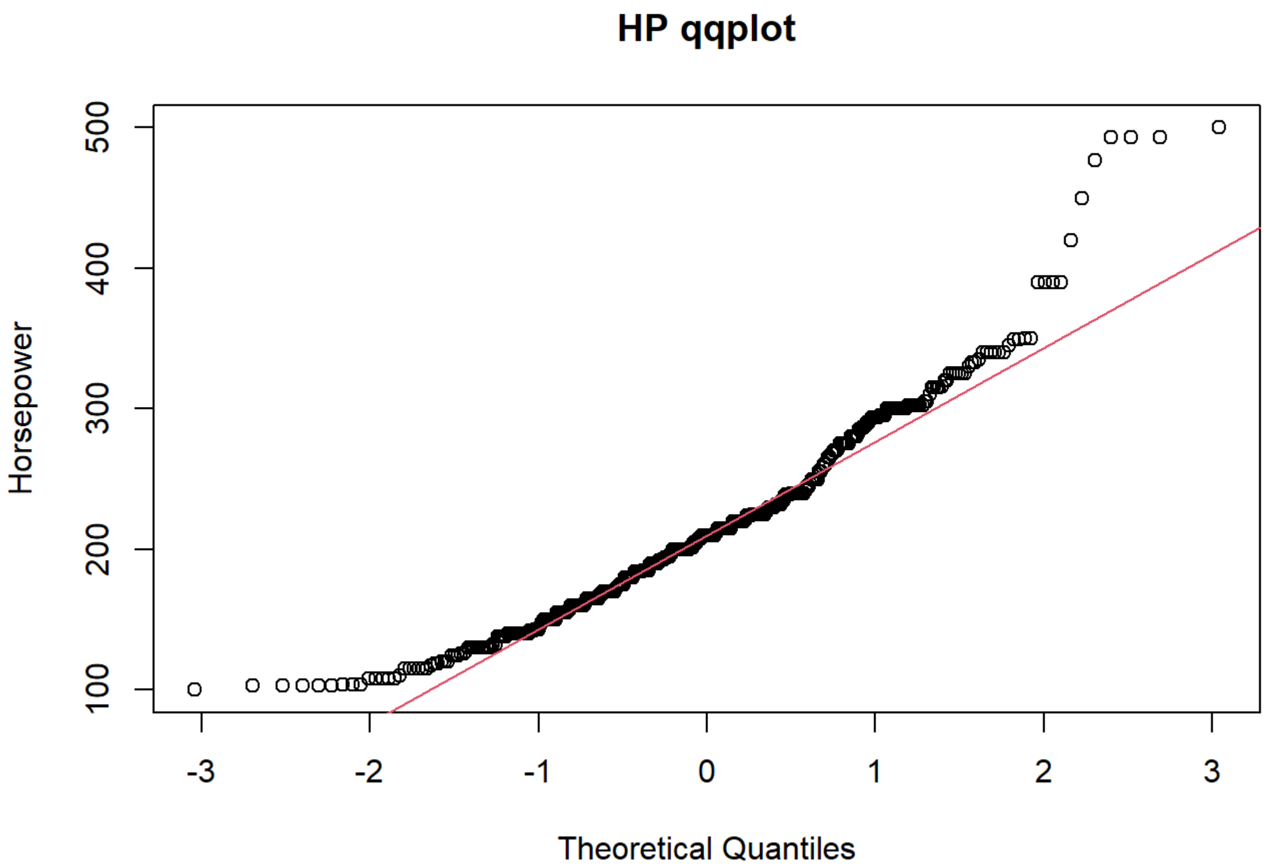
The box-plot is evidence towards Horsepower being right skewed.

```
boxplot(cars$Horsepower)
```



This follows the theoretical curve pretty well until about +1 quantile.

```
qqnorm(cars$Horsepower, main = 'HP qqplot', ylab='Horsepower'); qqline(cars$Horsepower,col =2)
```



To be thorough, we will run a Shapiro-Wilk test.

H0: data is norm dist

Halt: data is not norm dist

Below we see a very small p-value. With a great deal of certainty we can reject the null hypothesis. Horsepower is not normally distributed.

```
shapiro.test(cars$Horsepower)
```

```

    Shapiro-Wilk normality test

data:  cars$Horsepower
W = 0.94573, p-value = 2.32e-11
```

D.) Use visual and quantitative methods to comment on whether an assumption of normality would be reasonable for Horsepower variable by Type, especially for Sports, SUV , and Truck (i.e., check normality of Horsepower from Type of i) Sports, ii) SUV, and iii) Truck.

1. Visual:

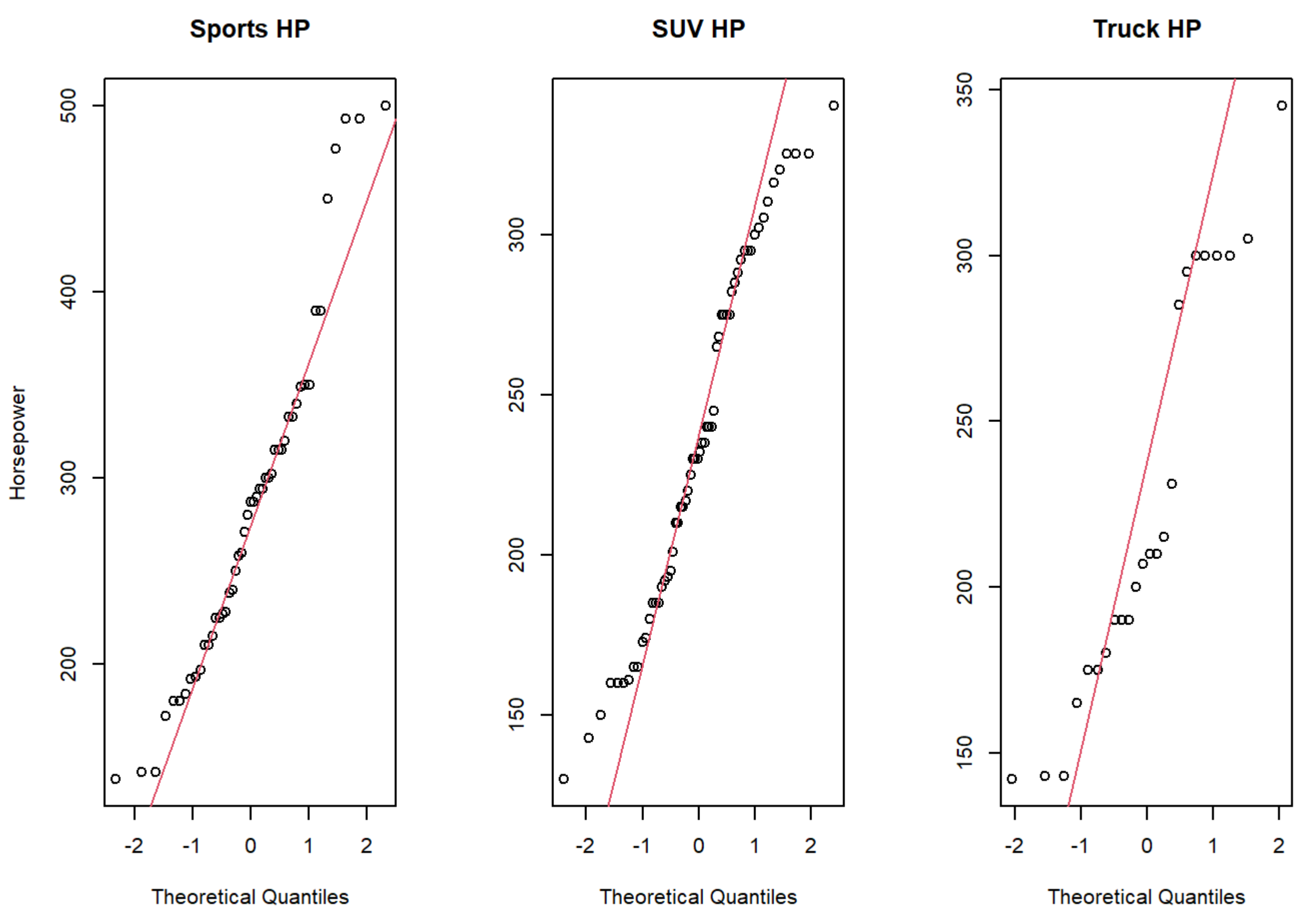
1. Sport and SUV follow the ideal line pretty well. Truck, not so much. These charts support Sports and SUV being Normally distributed, and Truck having a non-normal distribution.

```
par(mfrow = c(1,3))
Sports = filter(cars, Type == 'Sports')
SUV = filter(cars, Type == 'SUV')
Truck = filter(cars, Type == 'Truck')

## Visual
qqnorm(Sports$Horsepower, main = 'Sports HP', ylab='Horsepower');
qqline(Sports$Horsepower,col =2)

qqnorm(SUV$Horsepower, main = 'SUV HP', ylab='');
qqline(SUV$Horsepower, col =2)

qqnorm(Truck$Horsepower, main = 'Truck HP', ylab='');
qqline(Truck$Horsepower, col =2)
```



2. Quantitative

We will use the Shapiro-Wilk test. Here we see that all 3 categories have a low enough p value to reject the Shapiro-Wilk H0. We can continue assuming that all three variables are *not* normally distributed.

```r
shapiro.test(Sports$Horsepower)
```

```
    Shapiro-Wilk normality test

data:  Sports$Horsepower
W = 0.94276, p-value = 0.01898
```

```r
shapiro.test(SUV$Horsepower)
```

```
    Shapiro-Wilk normality test

data:  SUV$Horsepower
W = 0.95945, p-value = 0.04423
```

```r
shapiro.test(Truck$Horsepower)
```

```
    Shapiro-Wilk normality test

data:  Truck$Horsepower
W = 0.8951, p-value = 0.01697
```

##

Exercise 2: HYPOTHESIS TESTING

Perform a hypothesis test of whether **SUV** has different Horsepower than **Truck**, and state your conclusions.

##

a.) Which test should we perform, and why? Justify your answer based on findings on Exercise 1

1. The data has 2 populations (SUV and Truck)

2. We need to know if our data is normally distributed. We will use the Shapiro-Wilk Normality Test.

   H0: Normally distributed

   Halt: Not Normally distributed

   Below we see that both of our data sets have a p-value of less than .05. Therefore, we can continue under the assumption that both populations are *not* normally distributed.

```r
shapiro.test(SUV$Horsepower)
```

```
	Shapiro-Wilk normality test

data:  SUV$Horsepower
W = 0.95945, p-value = 0.04423
```

```r
shapiro.test(Truck$Horsepower)
```

```
	Shapiro-Wilk normality test

data:  Truck$Horsepower
W = 0.8951, p-value = 0.01697
```

3. To review, our data :

   1. has 2 populations

   2. is not normally distributed

   Therefore we will perform the *Wilcoxen Rank Test*.

b.) Specify null and alternative hypotheses.

1. H0: the 2 populations are from the same distribution

   Halt: the 2 populations are ***not*** from the same distribution.

c.) State the conclusion based on the test result.

1. With a p value = .3942, we cannot reject the null hypothesis. These two populations (Truck and SUV) are from the same population.

```r
#teacher syntax
# we need our data to only contain the variables we are testing
suvTruck = cars %>%
  filter(
    Type %in% c('SUV','Truck')
  )

wilcox.test(Horsepower ~ Type, data=suvTruck, exact=F, alternative = 'two.sided')
```

```
	Wilcoxon rank sum test with continuity correction

data:  Horsepower by Type
```

```
W = 806.5, p-value = 0.3942
alternative hypothesis: true location shift is not equal to 0
```

```
#my original syntax
wilcox.test(SUV$Horsepower,
            Truck$Horsepower,
            alternative = 'two.sided')
```

```

    Wilcoxon rank sum test with continuity correction

data:  SUV$Horsepower and Truck$Horsepower
W = 806.5, p-value = 0.3942
alternative hypothesis: true location shift is not equal to 0
```

##

Exercise 3: HYPOTHESIS TESTING (AGAIN)

Perform a hypothesis test -whether Wind in July has a different speed (mph) than Wind in August

##

Set up

```
July = filter(airquality, Month == '7')
August = filter(airquality, Month == '8')
```

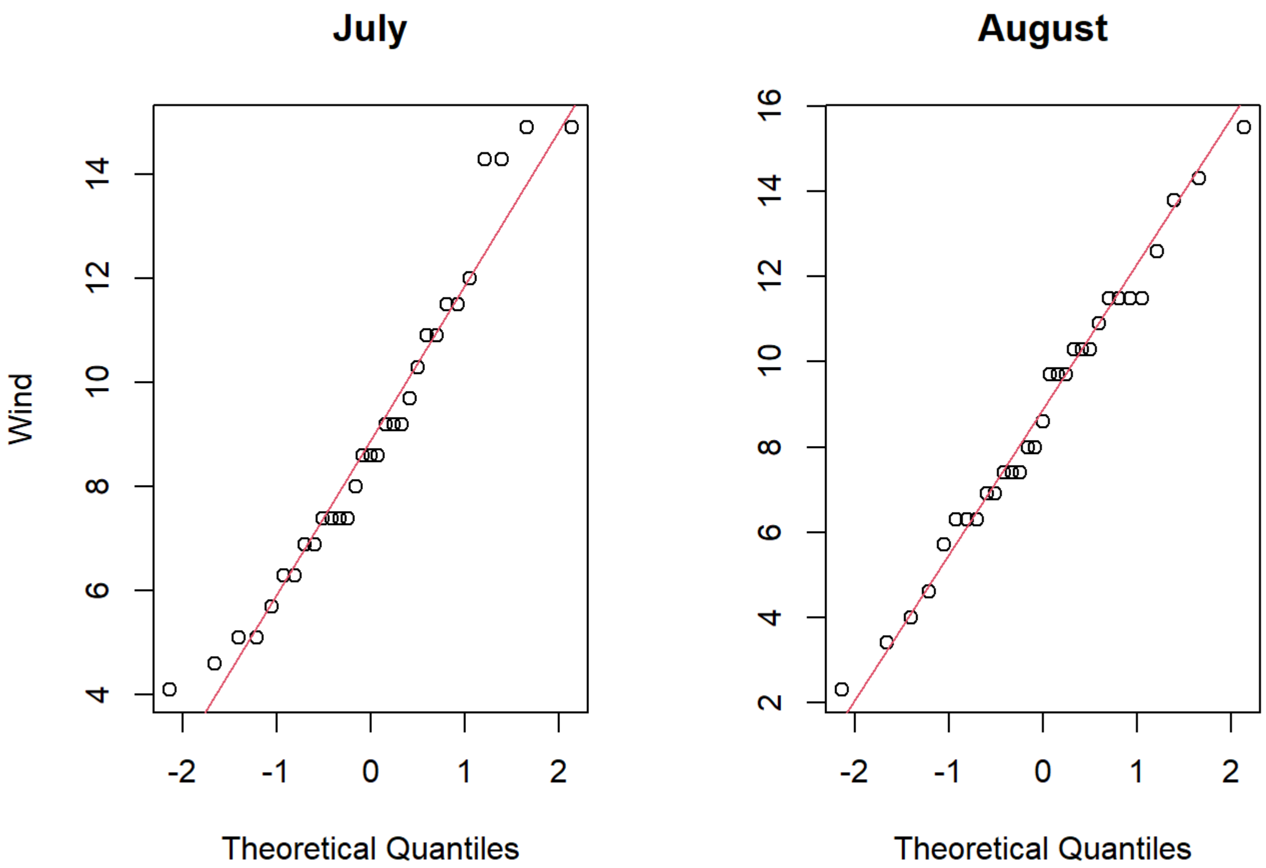
a.) Which test should we perform, and why? See QQ-plot and perform the Shapiro-Wilk test for normality check.

The data looks like it follows the ideal red line extremely well! Let's verify with our Shapiro-Wilk Normality Test.

```
par(mfrow = c(1,2))

## Visual
qqnorm(July$Wind, main = 'July', ylab='Wind');
qqline(July$Wind,col =2)

qqnorm(August$Wind, main = 'August', ylab='');
qqline(August$Wind, col =2)
```



1. According to the results below (High p-values, therefor cannot reject null), we can continue assuming that both groups are normally distributed.

```
# Remember:
#     H0:   Normally distributed
#     Halt: NOT Normally Distributed
```

```
head(airquality)
```

```
  Ozone Solar.R Wind Temp Month Day
1    41     190  7.4   67     5   1
2    36     118  8.0   72     5   2
3    12     149 12.6   74     5   3
4    18     313 11.5   62     5   4
5    NA      NA 14.3   56     5   5
6    28      NA 14.9   66     5   6
```

```
#teacher syntax
shapiro.test(airquality$Wind[airquality$Month == 7])
```

```
    Shapiro-Wilk normality test
```

```
data:  airquality$Wind[airquality$Month == 7]
W = 0.95003, p-value = 0.1564
```

```
shapiro.test(airquality$Wind[airquality$Month == 8])
```

```
    Shapiro-Wilk normality test

data:  airquality$Wind[airquality$Month == 8]
W = 0.98533, p-value = 0.937
```

```
#my original syntax
shapiro.test(July$Wind)
```

```
    Shapiro-Wilk normality test

data:  July$Wind
W = 0.95003, p-value = 0.1564
```

```
shapiro.test(August$Wind)
```

```
    Shapiro-Wilk normality test

data:  August$Wind
W = 0.98533, p-value = 0.937
```

Again, we have 2 populations (July & August). However, this time around we *can* assume that both groups are normally distributed. There is one more step before we continue. Do the groups have the same (pooled t-test) or different (Satterthwaite t-test) variances?

To find out whether the two populations share variance, we must perform an F-Test

1. H0: var1 = var2

   Halt: var1 != var2

2. In the following code, we see a high p-value! We cannot reject H0. Therefor we will assume that the variance is the same between our populations.

```
#teacher notation
#make dataset of only July + Aug
julAug = airquality %>%
  filter(
    Month %in% c(7,8)
  )
var.test(Wind ~ Month, julAug, alternative = 'two.sided')
```

```
	F test to compare two variances

data:  Wind by Month
F = 0.8857, num df = 30, denom df = 30, p-value = 0.7418
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 0.4270624 1.8368992
sample estimates:
ratio of variances
         0.8857035
```

```
#my original notation. Both give the same result!
var.test(July$Wind, August$Wind, alternative = "two.sided")
```

```
	F test to compare two variances

data:  July$Wind and August$Wind
F = 0.8857, num df = 30, denom df = 30, p-value = 0.7418
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 0.4270624 1.8368992
sample estimates:
ratio of variances
         0.8857035
```

1. To review, we will use a ***pooled t-test*** because:

    1. 2 populations
    2. Both Normally distributed
    3. same variance between populations

b.) Specify null and alternative hypotheses

1. H0: $\mu_1 = \mu_2$ (mean jul = mean aug)

   Halt: $\mu_1 \neq \mu_2$ (mean jul != mean aug)

c.) State the conclusion based on the test result

With a p value of .85 we cannot reject the null hypothesis. We conclude that on average wind speed is the same in July and August.

```
#teacher notation
t.test(Wind ~ Month, julAug, var.equl = T, altenattive = 'two.sided')
```

```
	Welch Two Sample t-test
```

```
data:  Wind by Month
t = 0.1865, df = 59.78, p-value = 0.8527
alternative hypothesis: true difference in means between group 7 and group 8 is not equal to 0
95 percent confidence interval:
 -1.443229  1.740003
sample estimates:
mean in group 7 mean in group 8 
       8.941935        8.793548 
```

```
#my original notation. Gives same result.
t.test(July$Wind, August$Wind, var.equal=T, alternative = 'two.sided')
```

```

	Two Sample t-test

data:  July$Wind and August$Wind
t = 0.1865, df = 60, p-value = 0.8527
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -1.443108  1.739883
sample estimates:
mean of x mean of y 
 8.941935  8.793548 
```