MAS Workshop

Department of Statistics - USJ

2024-03-28

```
# load the packages

library(readxl)    # to load the data set
library(dplyr)     # select operator
library(ggplot2)   # to create plots
library(magrittr)  # pipe operator
library(car)       # to obtain vif value
library(DescTools) # to obtain the mode
```

Multiple linear regression analysis

Example:
Suppose we aim to identify the factors affecting earnings from the product sales in the apparel industry. To examine the relationship between selected variables and earnings, we will conduct a multiple regression analysis. For this analysis, we will utilize the variables Earnings, MOH Value, and Std Hrs. The response variable is earnings whereas MOH Value and Std Hrs are the predictor variables.

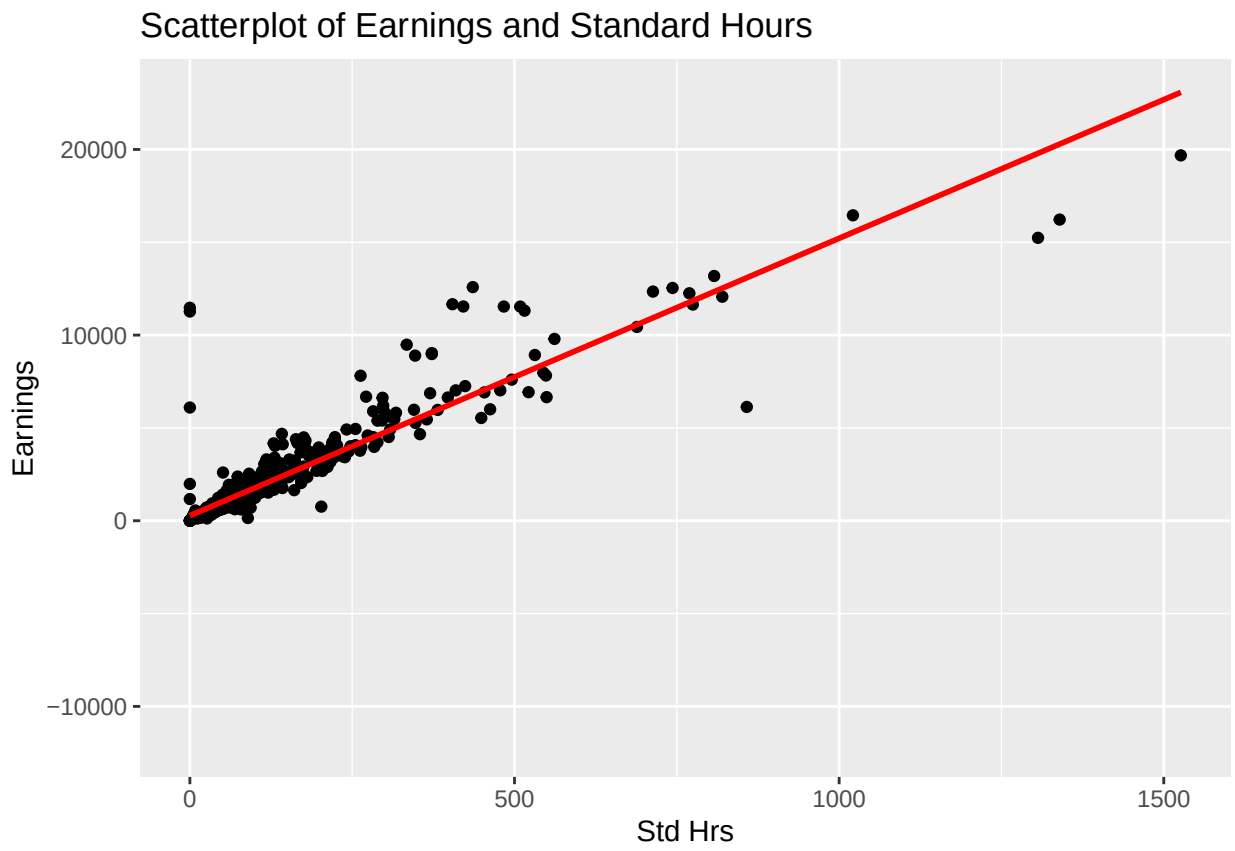
```
# load the data set
MAS_data_set <- read_excel("data set 2.xlsx")

# create a data set for regression analysis
Reg_data <- MAS_data_set %>%
  select(`MOH Value`, `Earnings`,`Std Hrs`)
```

Check the linearity assumption

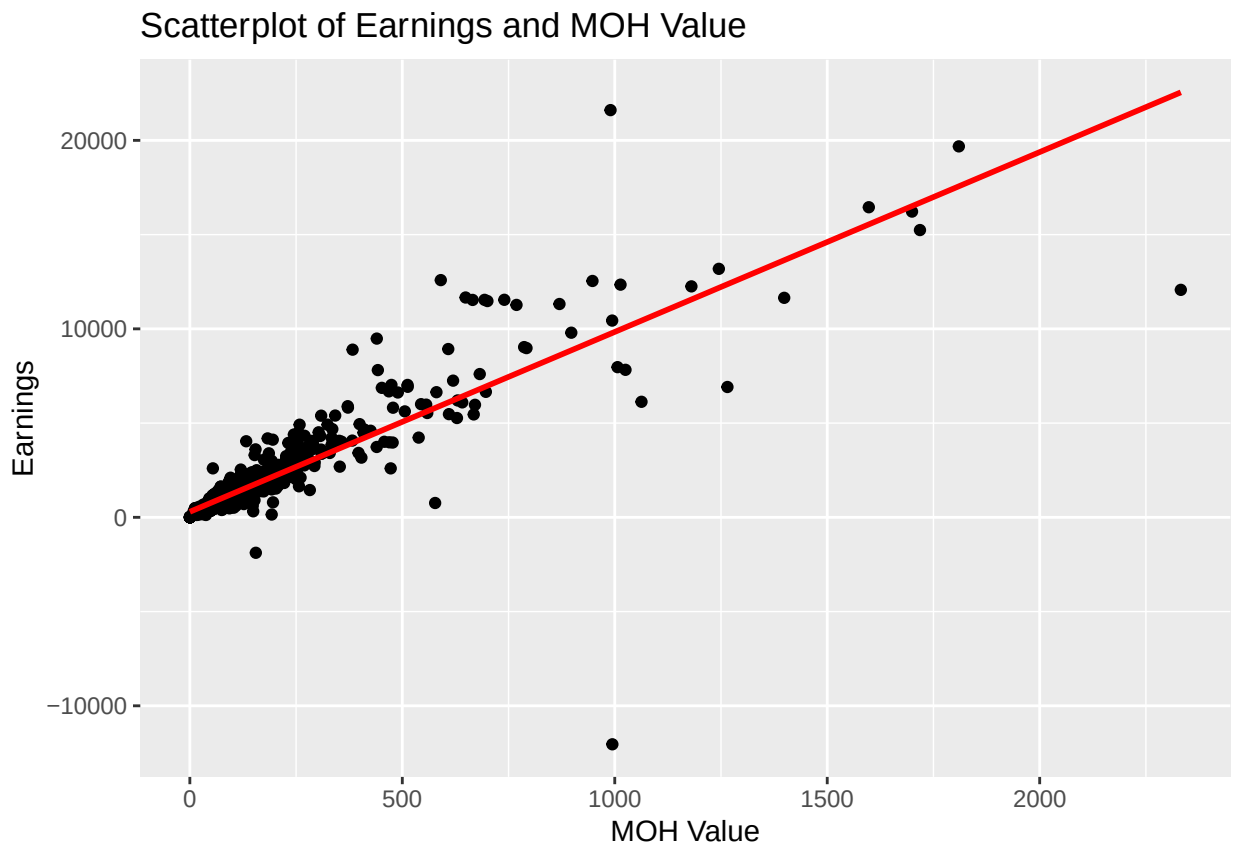
```
# scatter plot of Earnings and Standard Hours

ggplot(Reg_data, aes(x=`Std Hrs`, y= Earnings)) +
  geom_point() + geom_smooth(method = lm, se = FALSE, color = "red")+
  ggtitle("Scatterplot of Earnings and Standard Hours")
```




```
# scatter plot of Earnings and MOH Value

ggplot(Reg_data, aes(x=`MOH Value`, y= Earnings)) +
  geom_point() + geom_smooth(method = lm, se = FALSE, color = "red")+
  ggtitle("Scatterplot of Earnings and MOH Value")
```



Fit the model

```
Call:
lm(formula = Earnings ~ `Std Hrs` + `MOH Value`, data = Reg_data)

Residuals:
    Min      1Q  Median      3Q     Max
-6847.3  -248.4  -157.2    60.3  7315.7

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 225.9173    44.2228   5.109  4.3e-07 ***
`Std Hrs`     6.8198     0.6583  10.359  < 2e-16 ***
`MOH Value`   5.6160     0.4265  13.167  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 934.3 on 636 degrees of freedom
  (8 observations deleted due to missingness)
Multiple R-squared:  0.8733,    Adjusted R-squared:  0.8729
F-statistic:  2192 on 2 and 636 DF,  p-value: < 2.2e-16
```

Checking assumptions

Check the multicollinearity assumption

```
vif(model_reg)  # Since VIF values are less than 10, we can avoid the multicollinearity
```

```
  `Std Hrs` `MOH Value`
   8.174816    8.174816
```

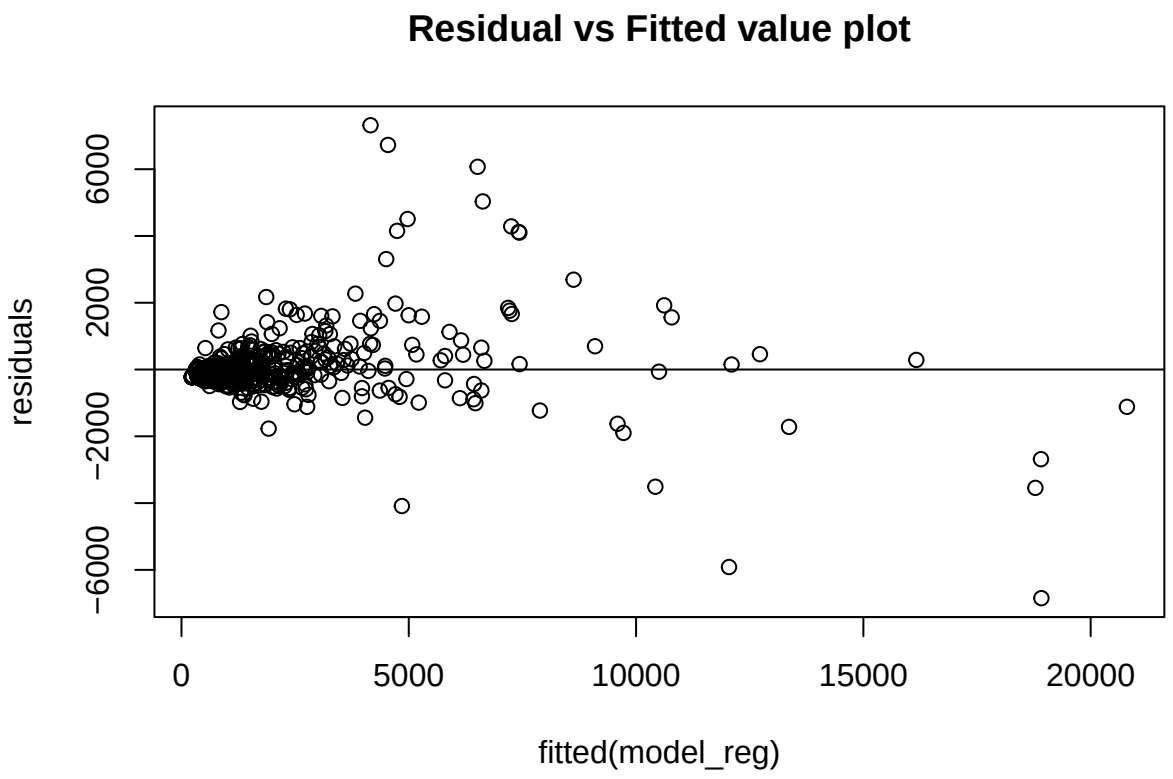
Check the constant variance assumption of residuals

```
# obtain the residuals
residuals <- resid(model_reg)

# residual vs. fitted value plot
plot(fitted(model_reg), residuals) + title("Residual vs Fitted value plot")
```

```
integer(0)
```

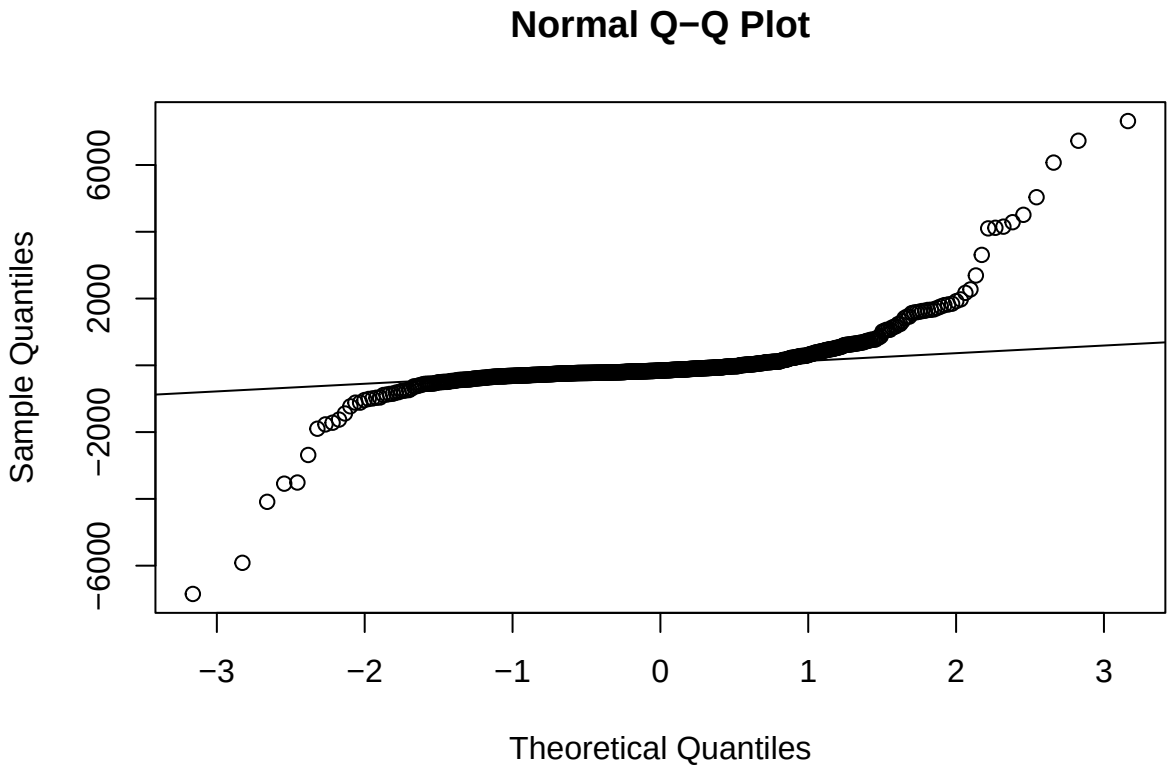
```
# add a horizontal line at 0
abline(0,0)
```



Check the normal assumption of residuals

```
# Q-Q plot for residuals
qqnorm(residuals)
```

```r
# add a straight diagonal line to the plot
qqline(residuals)
```



Hypothesis Testing

One sample test for mean - Slide no 61

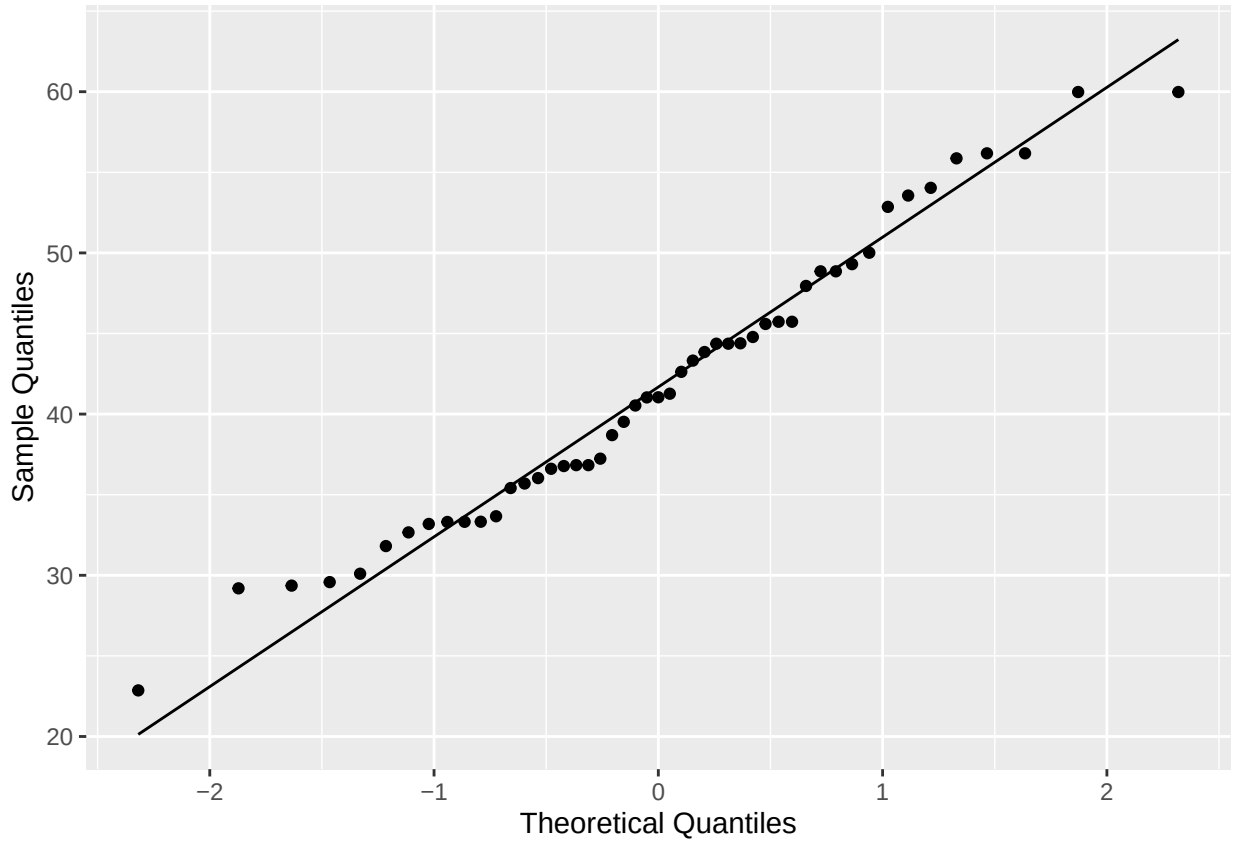
Example: Suppose we want to test whether the mean earnings per hour for Outer Known customer group is less than 50 at 5% significance level.

```
# loading dataset
Hypothesis.data <- read_excel("Hypothesis Data.xlsx")
```

Step 1: Check whether Earnings per hour values are normally distributed

Normal probability plot

```
ggplot(Hypothesis.data, aes(sample = Earnings.per.hour)) + stat_qq() +
  stat_qq_line() +
  labs(x = "Theoretical Quantiles", y = "Sample Quantiles")
```



Normality test

```
shapiro.test(Hypothesis.data$Earnings.per.hour)
```

```
    Shapiro-Wilk normality test

data:  Hypothesis.data$Earnings.per.hour
W = 0.97508, p-value = 0.3806
```

Hypothesis to be tested:

H0: Data are normally distributed.

H1: Data are not normally distributed.

According to the Shapiro-Wilk normality test p-value = 0.3806 > 0.05.

Hence, We can conclude that Earnings per hour values are normally distributed.

Step 2: Perform the t-test

```
t.test(Hypothesis.data$Earnings.per.hour, alternative = "less", mu = 50)
```

```
    One Sample t-test

data:  Hypothesis.data$Earnings.per.hour
t = -6.5365, df = 48, p-value = 1.89e-08
alternative hypothesis: true mean is less than 50
95 percent confidence interval:
     -Inf 43.84388
sample estimates:
mean of x
 41.71904
```

Since p-value = 1.89e-08 < 0.05, we reject null hypothesis.

Hence, there is sufficient evidence to suggest that the mean earnings per hour for the Outer Known customer group is less than 50.

Two sample test for comparison between means - Slide no 63

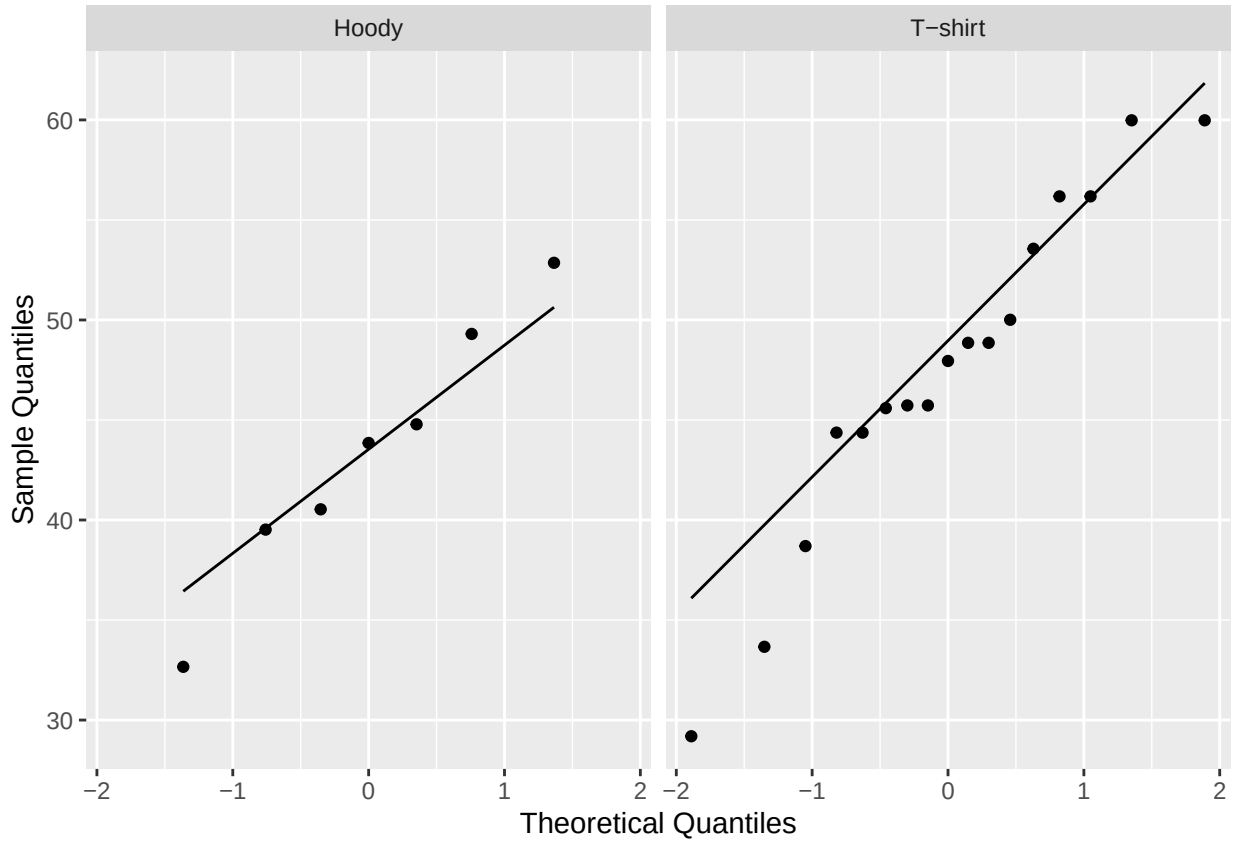
Example: Suppose we want test whether there is a significant difference in earnings per hour between Hoody products and T-shirt products of Outer Known customer group at 5% significance level.

```
# Loading relevant data
two.sample.data <- Hypothesis.data %>% filter(Product.name %in% c("Hoody", "T-shirt"))
```

Step 1: Check whether Earnings per hour values are normally distributed

Normal probability plot

```
ggplot(two.sample.data, aes(sample = Earnings.per.hour)) + stat_qq() +
  stat_qq_line() + facet_grid(.~Product.name) +
  labs(x = "Theoretical Quantiles", y = "Sample Quantiles")
```



Normality test

```
test1 <- two.sample.data %>% filter(Product.name == "Hoody")
shapiro.test(test1$Earnings.per.hour)
```

```
    Shapiro-Wilk normality test

data:  test1$Earnings.per.hour
W = 0.98413, p-value = 0.9771
```

```
test2 <- two.sample.data %>% filter(Product.name == "T-shirt")
shapiro.test(test2$Earnings.per.hour)
```

```
    Shapiro-Wilk normality test

data:  test2$Earnings.per.hour
W = 0.94884, p-value = 0.4384
```

Hypothesis to be tested:

H0: Data are normally distributed.

H1: Data are not normally distributed.

According to the Shapiro-Wilk normality test both p-values > 0.05.

Hence, We can conclude that Earnings per hour values of the two categories are normally distributed.

Step 2: Check for equality of variance

```
var.test(Earnings.per.hour ~ Product.name, data = two.sample.data,
         alternative = "two.sided")
```

```
    F test to compare two variances

data:  Earnings.per.hour by Product.name
F = 0.61833, num df = 6, denom df = 16, p-value = 0.5739
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 0.1850935 3.2424317
sample estimates:
ratio of variances
         0.6183291
```

Hypothesis to be tested:

H0: Two population variances are equal.

H1: Two population variances are not equal.

According to the F test both p-values $= 0.5739 > 0.05$.

Hence, We can conclude that Two population variances are equal.

Step 3: Perform the t-test

```
t.test(Earnings.per.hour ~ Product.name, data = two.sample.data,
       alternative = "two.sided", var.equal = TRUE)
```

```
    Two Sample t-test

data:  Earnings.per.hour by Product.name
t = -1.1755, df = 22, p-value = 0.2524
alternative hypothesis: true difference in means between group Hoody and group T-shirt is not equal to 0
95 percent confidence interval:
 -11.672730   3.227215
sample estimates:
  mean in group Hoody mean in group T-shirt
             43.35860              47.58136
```

Since p-value $= 0.2524 > 0.05$, we do not reject null hypothesis.

Hence, there is sufficient evidence to conclude that there is a significant difference in earnings per hour between the two product types.

Descriptive Statistics

Load the data

```
data_descriptive <- read_xlsx("Descriptive Statistics - Data.xlsx")
```

Glimpse on the dataset

```
glimpse(data_descriptive)
```

```
Rows: 1,111
Columns: 10
$ Date                <dttm> 2023-01-01, 2023-01-01, 2023-01-01, 2023-01-01, 2~
$ `Customer Group`    <chr> "SLICK CHICKS", "SLICK CHICKS", "SLICK CHICKS", "S~
$ Plant               <chr> "D051", "D051", "D051", "D051", "D051", "D051", "D~
$ `Product hierarchy` <chr> "Swim Bottom", "Swim Bottom", "Swim Bottom", "Swim~
$ Gender              <chr> "WOMEN", "WOMEN", "WOMEN", "WOMEN", "WOMEN", "WOME~
$ SMV                 <dbl> 4.880, 4.880, 4.734, 4.734, 4.734, 4.734, 4.880, 4~
$ `Shipping Type`     <chr> "Courier", "Courier", "Courier", "Courier", "Couri~
$ `Order Qty`         <dbl> 200, 200, 200, 200, 200, 200, 3, 197, 3, 197, 3, 1~
$ Earnings            <dbl> 509.2671800, 836.6231200, 812.6663206, 812.6663206~
$ `Std Hrs`           <dbl> 16.2666667, 16.2666667, 15.7800000, 15.7800000, 15~
```

slide number: 39

one way frequency table

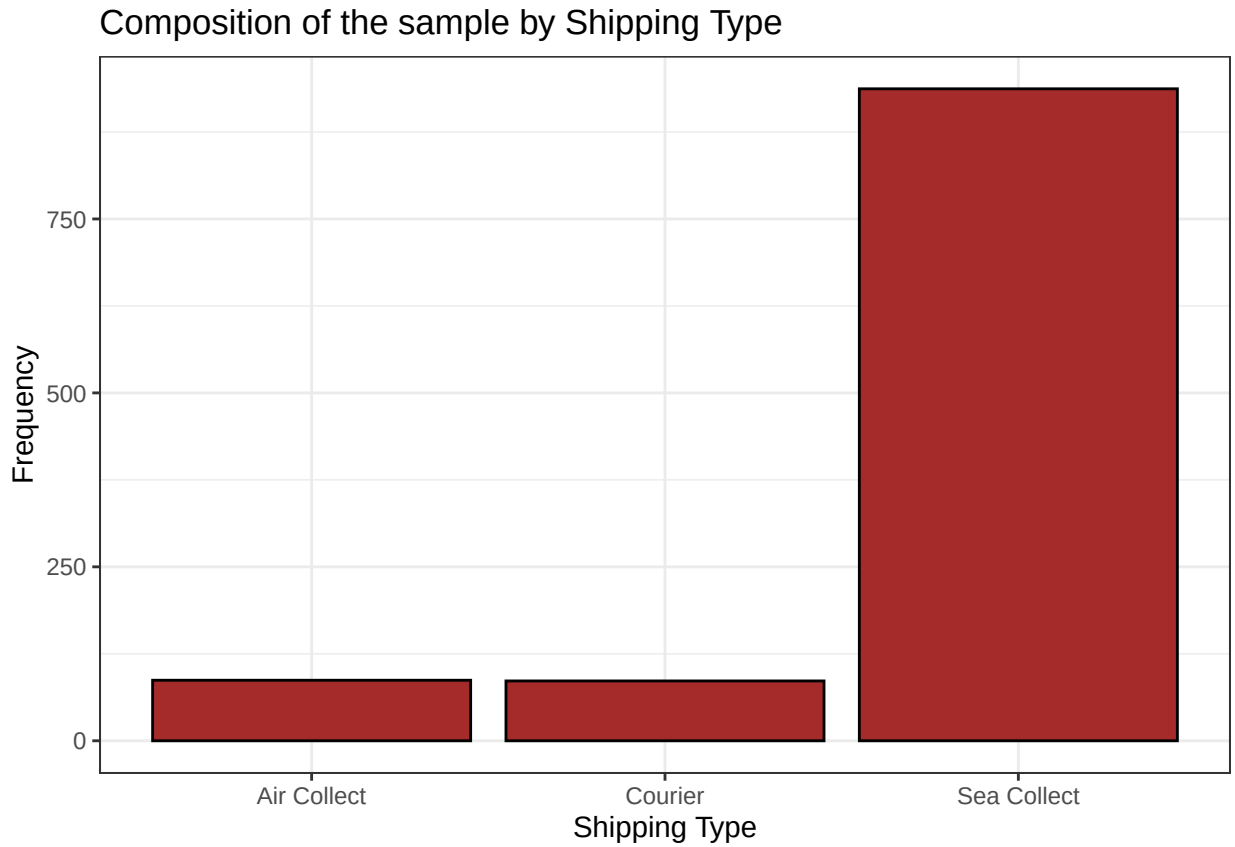
```
table(data_descriptive$`Shipping Type`)
```

```
Air Collect     Courier Sea Collect
         87          86         937
```

slide number: 40

barchart

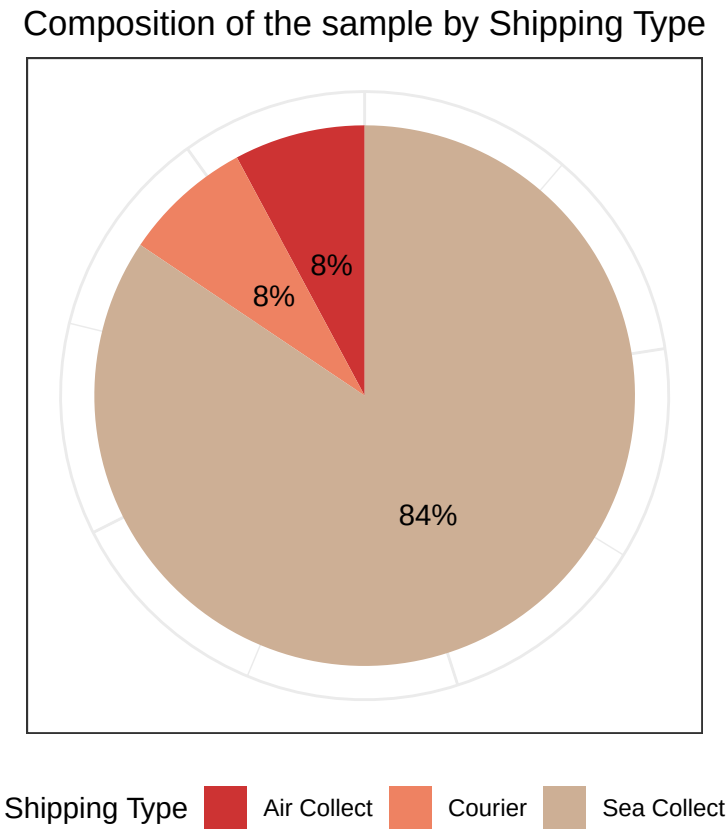
```
data_descriptive %>%
  select(`Shipping Type`) %>%
  na.omit() %>%
  ggplot(aes(x = as.factor(`Shipping Type`))) +
  geom_bar(color="black",
           fill="brown" ) +
  theme_bw() +
  labs(title = "Composition of the sample by Shipping Type",
       x = "Shipping Type",
       y = "Frequency")
```



slide number: 41

pie chart

```
data.frame(Shipping_Type = c("Air Collect", "Courier", "Sea Collect"),
           Frequency = c(87, 86, 937)) %>%
  ggplot(aes(x = "",
             y = Frequency,
             fill = Shipping_Type)) +
  geom_bar(stat="identity",
           width=1) +
  coord_polar("y",
              start=0) +
  geom_text(aes(label = paste0(
    round((Frequency/sum(Frequency))*100), "%")),
    position = position_stack(vjust = 0.5)) +
  theme_bw() +
  scale_fill_manual(values=c("brown3", "salmon2", "peachpuff3")) +
  labs(x = NULL,
       y = NULL,
       fill = "Shipping Type",
       title = "Composition of the sample by Shipping Type") +
  theme(axis.line = element_blank(),
        axis.text = element_blank(),
        axis.ticks = element_blank(),
        plot.title = element_text(hjust = 0.5)) +
  theme(legend.position = "bottom")
```


Composition of the sample by Shipping Type
8%
8%
84%
Shipping Type
Air Collect
Courier
Sea Collect

slide number: 42

summary measures

```
# mean
mean(data_descriptive$SMV,
     na.rm = TRUE)
```

```
[1] 10.39356
```

```
# median
median(data_descriptive$SMV,
       na.rm = TRUE)
```

```
[1] 9.741
```

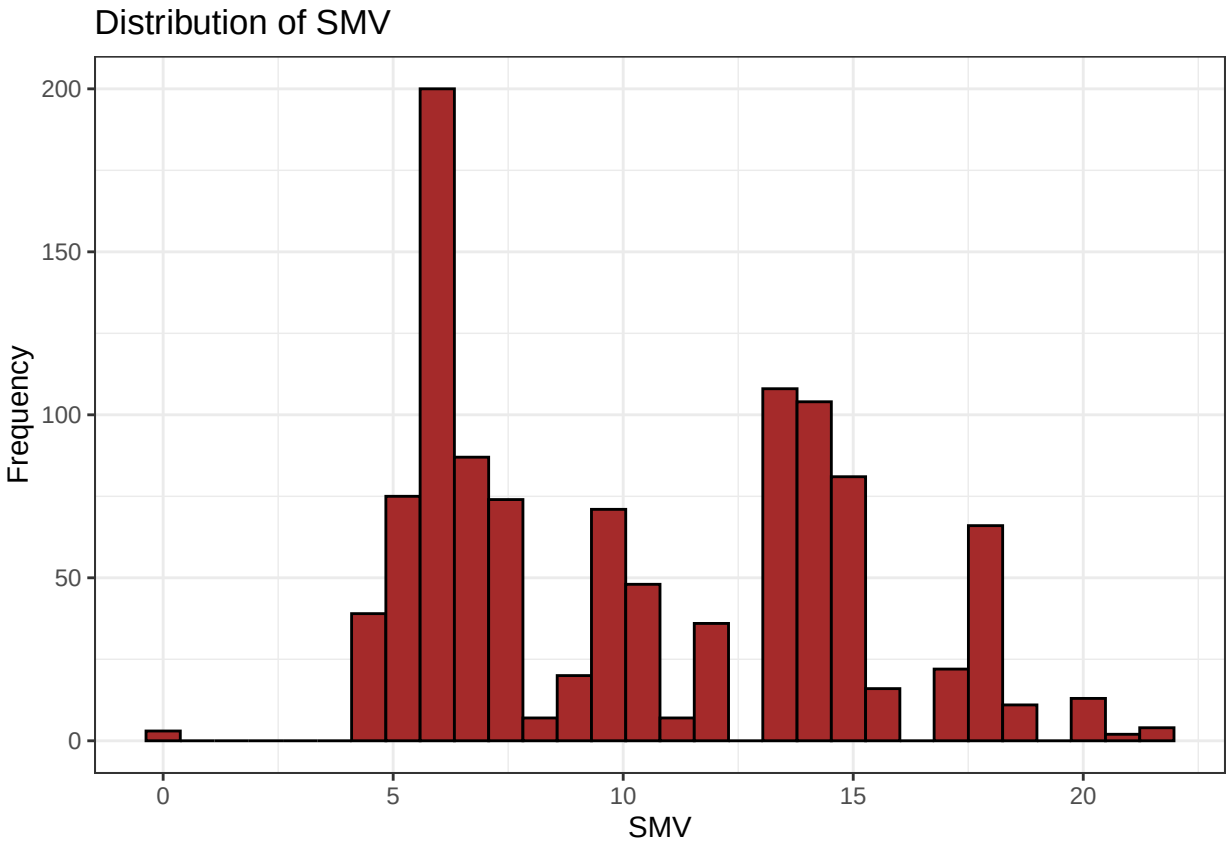
```
# mode
Mode(data_descriptive$SMV,
     na.rm = TRUE)
```

```
[1] 14.088
attr(,"freq")
[1] 71
```

slide number: 43

histogram

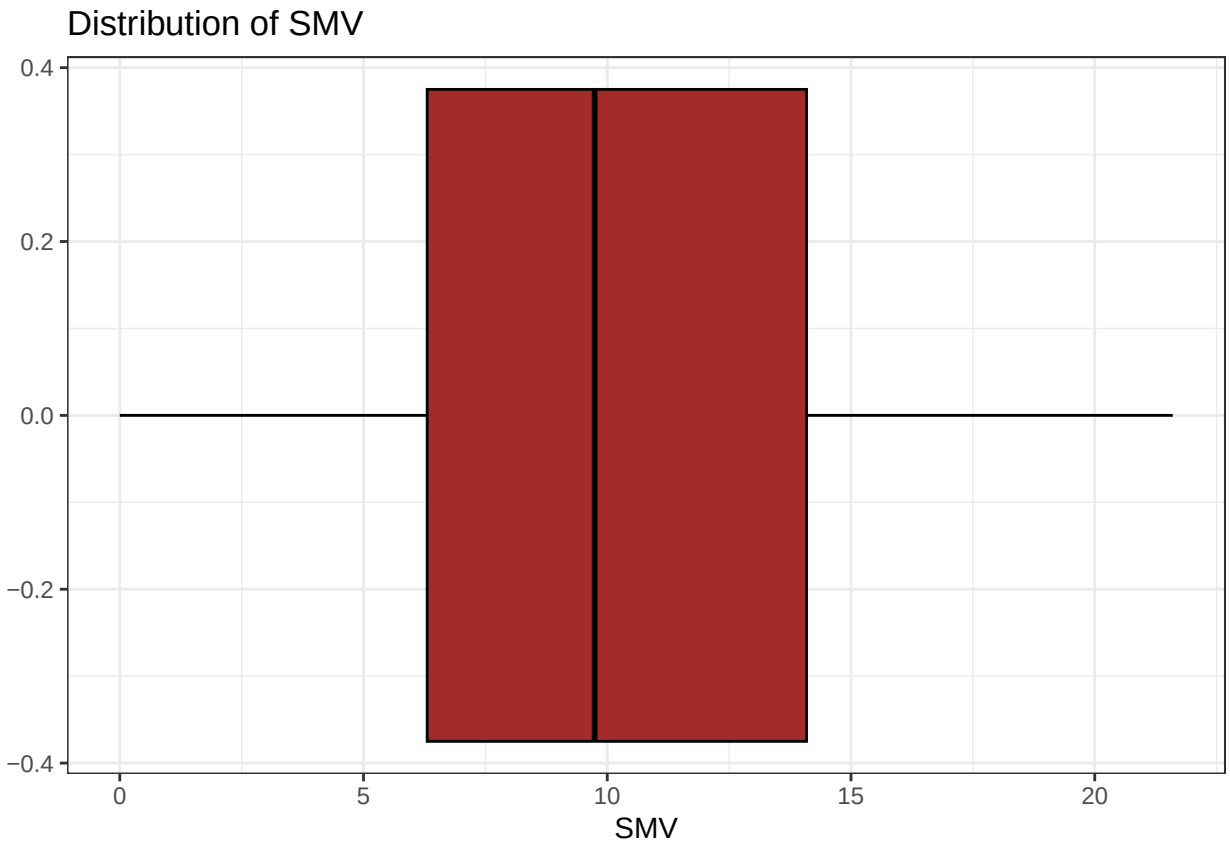
```
data_descriptive %>%
  select(SMV) %>%
  na.omit() %>%
  ggplot(aes(x = SMV)) +
  geom_histogram(color = "black",
                 fill = "brown") +
  theme_bw() +
  labs(title = "Distribution of SMV",
       x = "SMV",
       y = "Frequency")
```



slide number: 44

boxplot

```
data_descriptive %>%
  select(SMV) %>%
  na.omit() %>%
  ggplot(aes(x = SMV)) +
  geom_boxplot(color = "black",
               fill = "brown" ) +
  theme_bw() +
  labs(title = "Distribution of SMV")
```



slide number: 47

two way frequency table

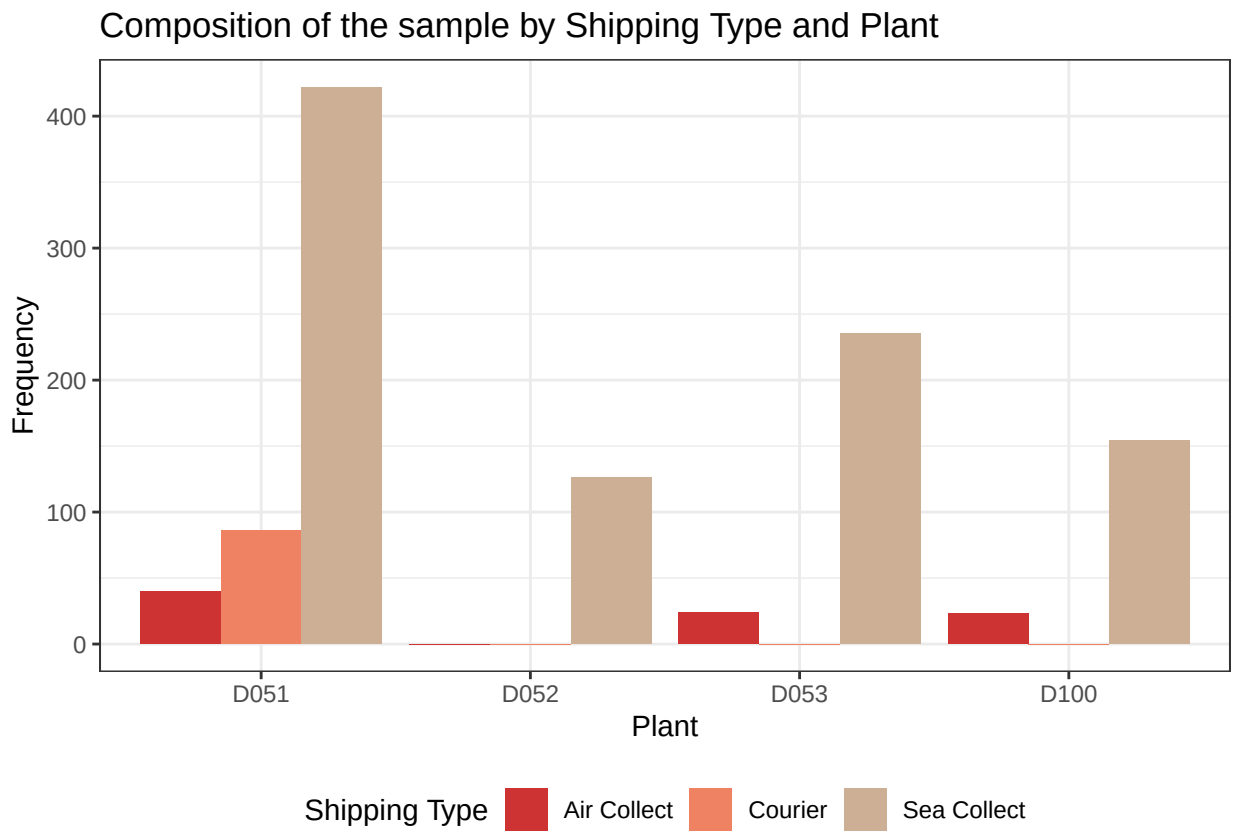
```
table(data_descriptive$`Shipping Type`,
      data_descriptive$Plant)
```

```
             D051 D052 D053 D100
  Air Collect   40    0   24   23
  Courier       86    0    0    0
  Sea Collect  422  126  235  154
```

slide number: 48

cluster bar chart

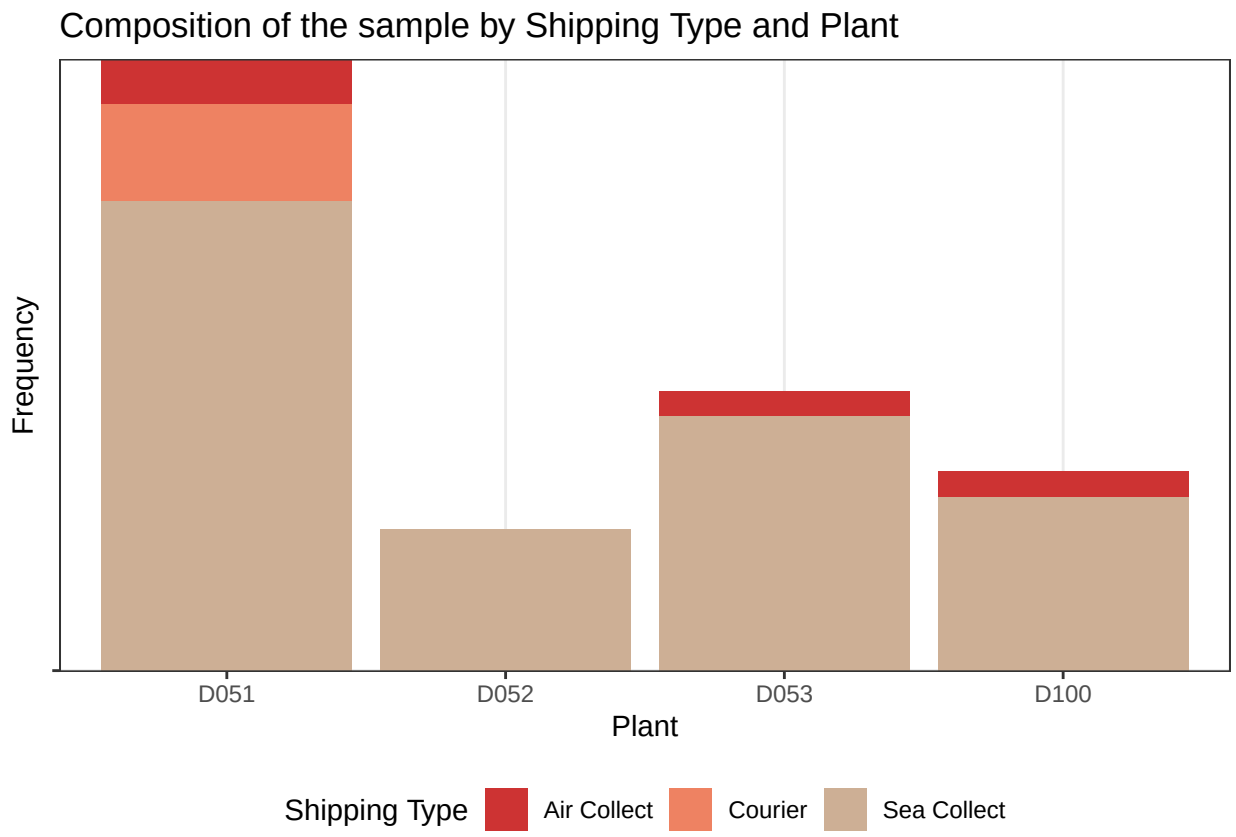
```
table(data_descriptive$`Shipping Type`,
      data_descriptive$Plant) %>%
  as.data.frame() %>%
  ggplot(aes(x = Var2, y = Freq, fill = Var1)) +
  geom_bar(stat = "identity", position = position_dodge()) +
  theme_bw() +
  scale_fill_manual(values=c("brown3", "salmon2", "peachpuff3")) +
  labs(x = "Plant",
       y = "Frequency",
       fill = "Shipping Type",
       title = "Composition of the sample by Shipping Type and Plant") +
  theme(legend.position = "bottom")
```



slide number: 49

stacked bar chart

```
data_descriptive %>%
  na.omit() %>%
  ggplot(aes(x = Plant, y = "", fill = `Shipping Type`)) +
  geom_bar(stat = "identity") +
  theme_bw() +
  scale_fill_manual(values = c("brown3", "salmon2", "peachpuff3")) +
  labs(x = "Plant",
       y = "Frequency",
       fill = "Shipping Type",
       title = "Composition of the sample by Shipping Type and Plant") +
  theme(legend.position = "bottom")
```



slide number: 50

scatterplot

```
data_descriptive %>%
  ggplot(aes(x = `Order Qty`,
             y = Earnings)) +
  geom_point(col = "brown") +
  theme_bw() +
  labs(title = "Scatterplot of Order Quantity and Earnings",
       x = "Order Quantity",
       y = "Earnings")
```

slide number: 51

boxplot with groups

```
data_descriptive %>%
  select(SMV,
         `Shipping Type`) %>%
  na.omit() %>%
  ggplot(aes(x = SMV,
             y = `Shipping Type`,
             fill = `Shipping Type`)) +
  geom_boxplot() +
  theme_bw() +
  scale_fill_manual(values=c("brown3", "salmon2", "peachpuff3")) +
  labs(x = "SMV",
       y = "Shipping Type",
       fill = "Shipping Type",
       title = "Distribution of SMV by Shipping Type") +
  theme(legend.position = "bottom")
```

Correlation Analysis

slide number: 54

```
data_descriptive %>%
  na.omit() %>%
  ggplot(aes(x = `Order Qty`,
             y = Earnings)) +
  geom_point(col = "brown") +
  theme_bw() +
  labs(title = "Scatterplot of Order Quantity and Earnings",
       x = "Order Quantity",
       y = "Earnings")
```


```
# positive linear relationship
```

```
cor(x = data_descriptive$`Order Qty`,
    y = data_descriptive$Earnings)
```

```
[1] 0.9371457
```

```
# r = 0.9371457
```