AMOD-5210H: Foundations of Modelling

Jasmeet Singh Saini

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After Loading required packages and then reading the excel file.

```
library(readxl)
dataset_excel <- read_excel("ass3data.xlsx")
```

Let's performing data extraction.

```
set.seed(0758054)
index <- sample(1:nrow(dataset_excel),200)
AMOD5210 <- dataset_excel[index, ]
```

Question 1

Report the frequencies for males and females in your subsample, as well as the mean, median, standard deviation, minimum and maximum values for the variable "age".

```
table(AMOD5210$Gender)
```

```
##
## Female   Male
##    119     81
```

Hence, the *frequency* for males and females is **81** and **119** respectively.

The mean, median, standard deviation, minimum and maximum values for the variable "age" is given below,

```
#Minimum
min(AMOD5210$Age, na.rm = TRUE)
```

```
## [1] 19
```

```
#Maximum
max(AMOD5210$Age, na.rm = TRUE)
```

```
## [1] 79
```

The *minimum* and *maximum values* for the variable "age" is **19** and **79** respectively.

```r
#Standard Deviation
sd(AMOD5210$Age, na.rm = TRUE)
```

```
## [1] 14.19257
```

```r
#Mean
mean(AMOD5210$Age, na.rm = TRUE)
```

```
## [1] 46.41
```

```r
# Median
median(AMOD5210$Age, na.rm = TRUE)
```

```
## [1] 46
```

The *Standard Deviation*, *Mean* and *Median* values for the variable "age" is **14.19257**, **46.41** and **46** respectively.

```r
library(psych)
describe(AMOD5210$Age)
```

```
##    vars   n  mean    sd median trimmed   mad min max range skew kurtosis se
## X1    1 200 46.41 14.19     46   46.26 16.31  19  79    60 0.12    -0.73  1
```

Question 2

Are the continuous variables of "age", "AG", and "LTW" in your subsample normally distributed? If not, how would you describe these distributions and what could you do to make them more normal?

To check the continuous variables of "age", "AG", and "LTW" in the normally distributed, we will use Shapiro-Wilks test.

For "age"

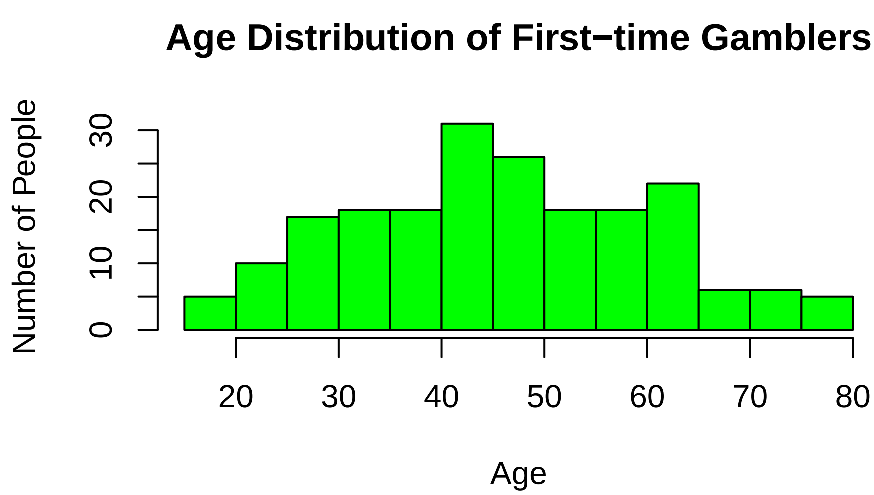
Let's test for "age"

```
shapiro.test(AMOD5210$Age)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  AMOD5210$Age
## W = 0.9844, p-value = 0.02596
```

This how a histogram looks like:

```
hist(AMOD5210$Age, xlab = "Age"
     , ylab = "Number of People"
     , main = "Age Distribution of First-time Gamblers"
     , prob = FALSE
     , col = "green")
```



By Shapiro-Wilk normality test the p-value < 0.05. Hence, it is not normally distributed.

For "AG"

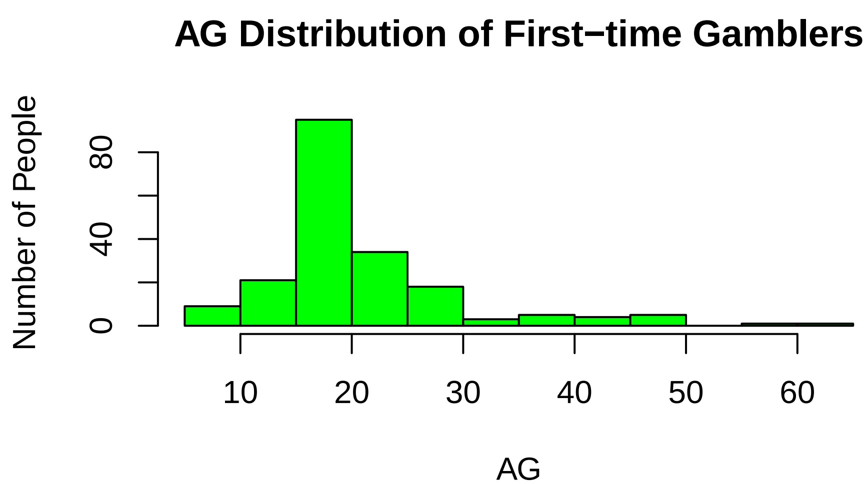
Let's test for "AG" (continuous variable for age of 1st time gambling for money).

```
shapiro.test(AMOD5210$AG)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  AMOD5210$AG
## W = 0.81998, p-value = 2.679e-14
```

This how a histogram looks like:

```
hist(AMOD5210$AG, xlab = "AG"
     , ylab = "Number of People"
     , main = "AG Distribution of First-time Gamblers"
     , prob = FALSE
     , col = "green")
```



By Shapiro-Wilk normality test the p-value < 0.05. Hence, it is not normally distributed.

For "LTW"

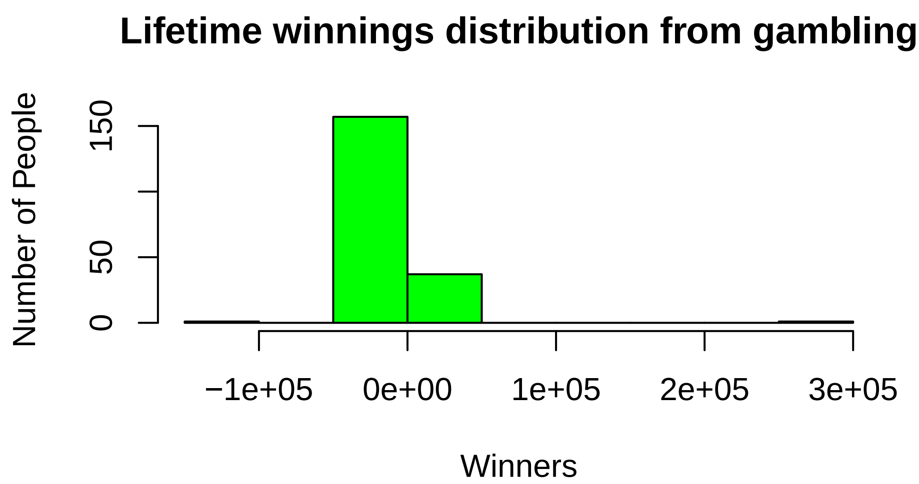
Finally, let's test for "LTW" (continuous variable for estimated lifetime winnings from gambling)

```
shapiro.test(AMOD5210$LTW)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  AMOD5210$LTW
## W = 0.21491, p-value < 2.2e-16
```

This how a histogram looks like:

```
hist(AMOD5210$LTW, xlab = "Winners"
     , ylab = "Number of People"
     , main = "Lifetime winnings distribution from gambling"
     , prob = FALSE
     , col = "green")
```



By Shapiro-Wilk normality test the p-value < 0.05. Hence, it is not normally distributed.

We can observe that these graph are not normal. We can confirm this throught Shapiro-Wilk normality test where we observed that the p-value for these graph are less than 0.05. While the first graph appears to be not normal, the second and third graph are right-skewed. **We can increase the sample size to make them more.**

Question 3

Using an appropriate inferential statistic, determine whether males and females scored significantly different on any of the variables "AG", "LTW", and "gambled". Also, evaluate and comment on whether the basic assumptions of your chosen statistic were met.

Inferential statistic for "AG" variable.

Step 1 : Hypothesis & assumptions

Let's define **Null Hypothesis** H_o and **Alternative Hypothesis** H_A to use inferential statistic.

H_o : There is no significantly difference between the score of males and females on the variable "AG" (that is, age of first time gambling).

H_A : There is significantly difference between the score of males and females on the variable "AG" (that is, age of first time gambling).

Let's organize the data by group and get some descriptive statistics:

```
library(rstatix)
```

```
##
## Attaching package: 'rstatix'

## The following object is masked from 'package:stats':
##
##     filter
```

```
group_by_gender <- group_by(AMOD5210, Gender)
get_summary_stats(group_by_gender,AG,type="mean_sd")
```

```
## # A tibble: 2 x 5
##   Gender variable     n  mean    sd
##   <chr>  <fct>    <dbl> <dbl> <dbl>
## 1 Female AG         115  23.4  9.55
## 2 Male   AG          81  19.6  8.64
```

Now, we need to test some **assumptions**. Firstly, let's check for extreme outliers.

```
identify_outliers(group_by_gender, AG)
```

```
## # A tibble: 15 x 11
##    Gender    ID   Age Income MS          AG   LTW Gambled Onset is.out~1 is.ex~2
##    <chr>  <dbl> <dbl>  <dbl> <chr>    <dbl> <dbl>   <dbl> <chr> <lgl>    <lgl>
##  1 Female  1180    61  55000 married     45  4000      50 Late  TRUE     FALSE
##  2 Female   674    52  55000 married     48 -3000      60 Late  TRUE     FALSE
##  3 Female  1816    50 175000 married     45  -500     200 Late  TRUE     FALSE
##  4 Female  2140    59  35000 married     50 -1200     200 Late  TRUE     FALSE
##  5 Female  2036    72  35000 divorced    65  -300      50 Late  TRUE     TRUE
##  6 Female  3117    77  10000 divorced    50  -100     200 Late  TRUE     FALSE
```

```
##  7 Female   842    66  55000 married     45 -2000     250 Late  TRUE     FALSE
##  8 Male    3597    67  35000 married     50     0     100 Late  TRUE     TRUE
##  9 Male     899    63  75000 married     45  -200      10 Late  TRUE     TRUE
## 10 Male    3455    41  75000 divorced     8  2500     400 Early TRUE     FALSE
## 11 Male    2321    76 135000 married     50   -10       2 Late  TRUE     TRUE
## 12 Male    3680    46  75000 married      5  2000       0 Early TRUE     FALSE
## 13 Male    2378    78  55000 married     60     0     100 Late  TRUE     TRUE
## 14 Male    1890    62  55000 married     30 -1000     500 Late  TRUE     FALSE
## 15 Male    2167    53  45000 married     27 -2300       7 Late  TRUE     FALSE
## # ... with abbreviated variable names 1: is.outlier, 2: is.extreme
```

Here, we get extreme outliers in the AG variable. But, we will perform the t-test.

Step 2 : Testing

Now, we will test for normality using **Shapiro-Wilks Test**.

```
# To test using Shapiro-Wilks
shapiro_test(group_by_gender, AG)
```

```
## # A tibble: 2 x 4
##   Gender variable statistic        p
##   <chr>  <chr>        <dbl>    <dbl>
## 1 Female AG           0.851 2.10e- 9
## 2 Male   AG           0.730 6.75e-11
```

Here, $p < 0.05$ for male as well as female. It not a normal distribution and we will use t-test, that is, Levene Test.

Now, to test for homogeneity of variance, we will use Levene Test.

```
# Test for homogeneity of variance(Levene Test)
levene_test(AMOD5210, AG ~ Gender)
```

```
## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.
```

```
## # A tibble: 1 x 4
##     df1   df2 statistic     p
##   <int> <int>     <dbl> <dbl>
## 1     1   194      1.97 0.162
```

Here, $p > 0.05$, Therefore, the variance of male and female is non-homogeneous.

Since, the condition or assumptions is not met during testing. Now, we will test using t-test to get the conclusion between the score of males and females on the variable "AG".

Now, let's run t-test for independent.

```
t_test(AG ~ Gender, data = AMOD5210, var.equal = TRUE)
```

```
## # A tibble: 1 x 8
##   .y.   group1 group2    n1    n2 statistic    df       p
## * <chr> <chr>  <chr>  <int> <int>     <dbl> <dbl>   <dbl>
## 1 AG    Female Male     115    81      2.88   194 0.00442
```

As $p < 0.05$, therefore, we have enough evidence to **reject** the **Null Hypothesis** (H_0), that is, there is a significantly difference between the score of males and females on the variable "AG".

Step 3 : Conclusion

The current study sought to determine whether or not there is a significantly difference between the score of males and females on the variable "AG". A 200 random samples were taken from a dataset of 3947 observation(81 males, 119 female).The sample contained few extreme outliers. A Shapiro-Wilks test didn't demonstrated normality. Moreover, Levene's test demonstrated non-heterogeneity of variance. The mean of "AG" for male was 19.580(SD = 8.637) and for female it was 23.417(SD = 9.550). An independent sample T-test showed that, $t(194) = 2.880084$, $p < 0.05$, concluding that the mean difference in "AG" between male and female in the sample was statistically significant.

Inferential statistic for "LTW" variable.

Step 1 : Hypothesis & assumptions

Let's define **Null Hypothesis** H_o and **Alternative Hypothesis** H_A to use inferential statistic.

H_o : There is no significantly difference between the score of males and females on the variable "LTW" (that is, lifetime winnings from gambling).

H_A : There is significantly difference between the score of males and females on the variable "LTW" (that is, lifetime winnings from gambling).

Let's organize the data by group and get some descriptive statistics:

```
library(rstatix)
get_summary_stats(group_by_gender,LTW,type="mean_sd")
```

```
## # A tibble: 2 x 5
##   Gender variable     n  mean     sd
##   <chr>  <fct>    <dbl> <dbl>  <dbl>
## 1 Female LTW        115 -975.  3913.
## 2 Male   LTW         81 -612. 33558.
```

Now, we need to test some **assumptions**. Firstly, let's check for extreme outliers.

```
identify_outliers(group_by_gender, LTW)
```

```
## # A tibble: 49 x 11
##    Gender    ID   Age Income MS         AG   LTW Gambled Onset is.out~1 is.ex~2
##    <chr>  <dbl> <dbl>  <dbl> <chr>   <dbl> <dbl>   <dbl> <chr> <lgl>    <lgl>
##  1 Female  3227    42  10000 married    27 -3000      50 Late  TRUE     FALSE
##  2 Female  1180    61  55000 married    45  4000      50 Late  TRUE     TRUE
##  3 Female  3464    34  45000 married    18 -5000      80 Early TRUE     TRUE
##  4 Female    96    49  55000 married    16  5000      60 Early TRUE     TRUE
```

```
##  5 Female  1176    63  55000 married    30  -2500       2 Late  TRUE     FALSE
##  6 Female  3682    43  65000 married    18   2000       0 Early TRUE     FALSE
##  7 Female  3252    47  75000 married    33 -10000     300 Late  TRUE     TRUE
##  8 Female  2442    55 175000 married    30  -3000     150 Late  TRUE     FALSE
##  9 Female  2436    37  25000 single     10   3000     400 Early TRUE     TRUE
## 10 Female  1522    37  55000 married    19   2000       0 Late  TRUE     FALSE
## # ... with 39 more rows, and abbreviated variable names 1: is.outlier,
## #   2: is.extreme
```

Here, we get extreme outliers in the LTW variable. But, we will perform the t-test.

Step 2 : Testing

Now, we will test for normality using **Shapiro-Wilks Test**.

```
# To test using Shapiro-Wilks
shapiro_test(group_by_gender, LTW)
```

```
## # A tibble: 2 x 4
##   Gender variable statistic        p
##   <chr>  <chr>        <dbl>    <dbl>
## 1 Female LTW          0.709 8.69e-14
## 2 Male   LTW          0.290 6.48e-18
```

Here, $p < 0.05$ for male as well as female. It a not normal distribution and we will use t-test, that is, Levene Test.

Now, to test for homogeneity of variance, we will use Levene Test.

```
# Test for homogeneity of variance(Levene Test)
levene_test(AMOD5210, LTW ~ Gender)
```

```
## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.
```

```
## # A tibble: 1 x 4
##     df1   df2 statistic      p
##   <int> <int>     <dbl>  <dbl>
## 1     1   194      4.51 0.0350
```

Here, $p < 0.05$, Therefore, the variance of male and female is non homogeneous.

Since, the condition or assumptions is not met during testing. Now, we will test using t-test to get the conclusion between the score of males and females on the variable "LTW".

Now, let's run t-test for independent.

```
t_test(LTW ~ Gender, data = AMOD5210, var.equal = TRUE)
```

```
## # A tibble: 1 x 8
##   .y.   group1 group2    n1    n2 statistic    df     p
## * <chr> <chr>  <chr>  <int> <int>     <dbl> <dbl> <dbl>
## 1 LTW   Female Male     115    81    -0.115   194 0.908
```

As $p > 0.05$, therefore, we have enough evidence to **accept** the **Null Hypothesis** (H_0), that is, there is a no significantly difference between the score of males and females on the variable "LTW".

Step 3 : Conclusion

The current study sought to determine whether or not there is a significantly difference between the score of males and females on the variable “Gambled”. A 200 random samples were taken from a dataset of 3947 observation(81 males, 119 female).The sample contained few extreme outliers. A Shapiro-Wilks test didn’t demonstrated normality. Moreover, Levene’s test demonstrated heterogeneity of variance. The mean of “Gambled” for male was -611.790(SD = 33558.163) and for female it was -975.278(SD = 3912.717). An independent sample T-test showed that, $t(194) = -0.1151715 $, $p > 0.05$, concluding that the mean difference in “Gambled” between male and female in the sample was not statistically significant.

Inferential statistic for “Gambled” variable

Step 1 : Hypothesis & assumptions

Let’s define **Null Hypothesis** H_o and **Alternative Hypothesis** H_A to use inferential statistic.

H_o : There is no significantly difference between the score of males and females on the variable “Gambled” (that is, amount of money gambled in past 12 months).

H_A : There is significantly difference between the score of males and females on the variable “Gambled” (that is, amount of money gambled in past 12 months).

Let’s organize the data by group and get some descriptive statistics:

```
library(rstatix)
get_summary_stats(group_by_gender,Gambled,type="mean_sd")
```

```
## # A tibble: 2 x 5
##   Gender variable     n  mean    sd
##   <chr>  <fct>    <dbl> <dbl> <dbl>
## 1 Female Gambled    119  68.6  110.
## 2 Male   Gambled     81  84.1  121.
```

Now, we need to test some **assumptions**. Firstly, let’s check for extreme outliers.

```
identify_outliers(group_by_gender, Gambled)
```

```
## # A tibble: 15 x 11
##    Gender    ID   Age Income MS          AG    LTW Gambled Onset is.ou~1 is.ex~2
##    <chr>  <dbl> <dbl>  <dbl> <chr>    <dbl>  <dbl>   <dbl> <chr> <lgl>   <lgl>
##  1 Female  3252    47  75000 married     33 -1   e4     300 Late  TRUE    FALSE
##  2 Female  2436    37  25000 single      10  3   e3     400 Early TRUE    TRUE
##  3 Female  2295    42  45000 divorced    16 -1   e3     250 Early TRUE    FALSE
##  4 Female  2715    47 135000 married     19 -1   e4     700 Late  TRUE    TRUE
##  5 Female   539    41  85000 married     16  6.5e3     425 Early TRUE    TRUE
##  6 Female   842    66  55000 married     45 -2   e3     250 Late  TRUE    FALSE
##  7 Female  1409    64  35000 married     20  1   e3     500 Late  TRUE    TRUE
##  8 Male    2997    56 110000 married     16  5   e3     300 Early TRUE    FALSE
##  9 Male    3455    41  75000 divorced     8  2.5e3     400 Early TRUE    TRUE
## 10 Male    1964    51  55000 married     22 -1.5e4     300 Late  TRUE    FALSE
## 11 Male    2391    40  85000 married     13 -1   e4     300 Early TRUE    FALSE
## 12 Male    1890    62  55000 married     30 -1   e3     500 Late  TRUE    TRUE
## 13 Male    2633    67  35000 married     18 -1.5e5     450 Early TRUE    TRUE
```

```
## 14 Male      17    48  80000 married     19 -1.5e4     500 Late  TRUE    TRUE
## 15 Male     426    44  85000 married     20 -3   e3     400 Late  TRUE    TRUE
## # ... with abbreviated variable names 1: is.outlier, 2: is.extreme
```

Here, we get extreme outliers in the Gambled variable. But, we will perform the t-test.

Step 2 : Testing

Now, we will test for normality using **Shapiro-Wilks Test**.

```r
# To test using Shapiro-Wilks
shapiro_test(group_by_gender, Gambled)
```

```
## # A tibble: 2 x 4
##   Gender variable statistic        p
##   <chr>  <chr>        <dbl>    <dbl>
## 1 Female Gambled      0.648 1.77e-15
## 2 Male   Gambled      0.710 2.40e-11
```

Here, $p < 0.05$ for male as well as female. It a not normal distribution and we will use t-test, that is, Levene Test.

Now, to test for homogeneity of variance, we will use Levene Test.

```r
# Test for homogeneity of variance(Levene Test)
levene_test(AMOD5210, Gambled ~ Gender)
```

```
## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.
```

```
## # A tibble: 1 x 4
##     df1   df2 statistic     p
##   <int> <int>     <dbl> <dbl>
## 1     1   198     0.833 0.363
```

Here, $p > 0.05$, Therefore, the variance of male and female is homogeneous.

Since, the condition or assumptions is not met during testing. Now, we will test using t-test to get the conclusion between the score of males and females on the variable "Gambled".

Now, let's run t-test for independent.

```r
t_test(Gambled ~ Gender, data = AMOD5210, var.equal = TRUE)
```

```
## # A tibble: 1 x 8
##   .y.     group1 group2    n1    n2 statistic    df     p
## * <chr>   <chr>  <chr>  <int> <int>     <dbl> <dbl> <dbl>
## 1 Gambled Female Male     119    81    -0.944   198 0.347
```

As $p > 0.05$, therefore, we have enough evidence to **accept** the **Null Hypothesis** (H_0), that is, there is a no significantly difference between the score of males and females on the variable "Gambled".

Step 3 : Conclusion

The current study sought to determine whether or not there is a significantly difference between the score of males and females on the variable “Gambled”. A 200 random samples were taken from a dataset of 3947 observation(81 males, 119 female).The sample contained few extreme outliers. A Shapiro-Wilks test didn’t demonstrated normality. Moreover, Levene’s test demonstrated heterogeneity of variance. The mean of “Gambled” for male was 84.123(SD = 120.928) and for female it was 68.588(SD = 109.573). An independent sample T-test showed that, $t(198) = -0.9435949$, $p > 0.05$, concluding that the mean difference in “Gambled” between male and female in the sample was not statistically significant.

Question 4

Using an appropriate inferential statistic, determine whether marital status is significantly dependent on reporting an early or late onset of gambling ("Onset")?

Step 1: Hypothesis

Let's define **Null Hypothesis** H_o and **Alternative Hypothesis** H_A to use inferential statistic.

H_o : Marital Status is NOT significantly dependent on reporting an early or late onset of gambling.

H_A : Marital Status is significantly dependent on reporting an early or late onset of gambling.

Step 2: Testing

To conduct the Test of Independence, that is, **Chi-Squared Test**, we need to build the table of frequency for Onset and MS:

```
frequency_table <- table(AMOD5210$Onset, AMOD5210$MS)
frequency_table
```

```
##
##          divorced married single
##   Early         9      64     13
##   Late         20      78     12
```

For Chi-Squared Test, we know

```
chisq.test(x = frequency_table, correct = FALSE)
```

```
##
##  Pearson's Chi-squared test
##
## data:  frequency_table
## X-squared = 2.6943, df = 2, p-value = 0.26
```

Since p > 0.05, we have enough evidence to accept **Null Hypothesis** H_o, that is, Marital status is not dependent on the Onset of gambling.

We know there is an effect, but we don't know where that effect is since we have a 2 x 3 contingency table.We need to perform a post-hoc test to know where the effect is

```
# First, let's install and load a useful package
#install.packages("chisq.posthoc.test")
library(chisq.posthoc.test)
# Now, let's run a chi-square post-hoc test
chisq.posthoc.test(frequency_table)
```

```
##   Dimension     Value  divorced    married     single
## 1     Early Residuals -1.509900  0.5457321  0.8761884
## 2     Early  p values  0.786414  1.0000000  1.0000000
## 3      Late Residuals  1.509900 -0.5457321 -0.8761884
## 4      Late  p values  0.786414  1.0000000  1.0000000
```

Step 3: Conclusion

The present research seeks to determine whether marital status is significantly dependent on reporting an early or late onset of gambling. A 200 sample of (81 Males, 119 Female) were taken and then divided based on marital status: Single ($N = 26$), Married ($N = 144$) and Divorced ($N = 30$). A Chi-square Test of Independence revealed that the marital status is independent on reporting an early or late onset of gambling, $X^2(2, N = 200) = 2.6943, p > 0.05$.

Question 5

What are the correlations (reported to 3 decimals) for the following pairs of variables: "age" and "LTW"; "age" and "gambled"; and "AG" and "LTW". Report the p-values for each correlation. For each of the relevant correlations, what is the slope and intercept when "LTW" is the Y variable (i.e., dependent variable)? One of the key assumptions when interpreting a correlation is that the x and y variables are linearly related. Do you think this assumption is met for each of the 3 correlations?

Let's check the statistics of the dataset:

```
library(psych)
describe(AMOD5210, fast = TRUE)
```

```
## Warning in FUN(newX[, i], ...): no non-missing arguments to min; returning Inf

## Warning in FUN(newX[, i], ...): no non-missing arguments to min; returning Inf

## Warning in FUN(newX[, i], ...): no non-missing arguments to min; returning Inf

## Warning in FUN(newX[, i], ...): no non-missing arguments to max; returning -Inf

## Warning in FUN(newX[, i], ...): no non-missing arguments to max; returning -Inf

## Warning in FUN(newX[, i], ...): no non-missing arguments to max; returning -Inf
```

```
##         vars   n     mean       sd     min    max  range      se
## ID         1 200  2029.27  1084.54      17   3935   3918   76.69
## Age        2 200    46.41    14.19      19     79     60    1.00
## Income     3 200 59950.00 36329.69   10000 175000 165000 2568.90
## MS         4 200      NaN       NA     Inf   -Inf   -Inf      NA
## Gender     5 200      NaN       NA     Inf   -Inf   -Inf      NA
## AG         6 196    21.83     9.35       5     65     60    0.67
## LTW        7 196  -825.06 21702.37 -150000 254000 404000 1550.17
## Gambled    8 200    74.88   114.26       0    700    700    8.08
## Onset      9 196      NaN       NA     Inf   -Inf   -Inf      NA
```

We will now check **assumption** on all variables, before performing *correlation test*.

Let's check for the outliers for all four variables, that is, "LTW", "AG", "Age", "Gambled" :

```
identify_outliers(AMOD5210, LTW)
```

```
## # A tibble: 49 x 11
##       ID   Age Income MS      Gender    AG    LTW Gambled Onset is.out~1 is.ex~2
##    <dbl> <dbl>  <dbl> <chr>   <chr>  <dbl>  <dbl>   <dbl> <chr> <lgl>    <lgl>
##  1   349    65  45000 married Male      17   5000      10 Early TRUE     FALSE
##  2  1180    61  55000 married Female    45   4000      50 Late  TRUE     FALSE
##  3  2152    60  45000 married Male      16 -10000     200 Early TRUE     TRUE
##  4  3464    34  45000 married Female    18  -5000      80 Early TRUE     FALSE
```

```
##  5  2997    56 110000 married Male      16   5000     300 Early TRUE     FALSE
##  6    96    49  55000 married Female    16   5000      60 Early TRUE     FALSE
##  7  3252    47  75000 married Female    33 -10000     300 Late  TRUE     TRUE
##  8  1377    60  85000 married Male      16  -5000     150 Early TRUE     FALSE
##  9  2436    37  25000 single  Female    10   3000     400 Early TRUE     FALSE
## 10   589    29  75000 single  Male      19   5000     200 Late  TRUE     FALSE
## # ... with 39 more rows, and abbreviated variable names 1: is.outlier,
## #   2: is.extreme
```

```
identify_outliers(AMOD5210, AG)
```

```
## # A tibble: 16 x 11
##       ID   Age Income MS       Gender    AG   LTW Gambled Onset is.out~1 is.ex~2
##    <dbl> <dbl>  <dbl> <chr>    <chr>  <dbl> <dbl>   <dbl> <chr> <lgl>    <lgl>
##  1  3597    67  35000 married  Male      50     0     100 Late  TRUE     FALSE
##  2  1180    61  55000 married  Female    45  4000      50 Late  TRUE     FALSE
##  3   899    63  75000 married  Male      45  -200      10 Late  TRUE     FALSE
##  4  2683    72  10000 divorced Female    40  -200       0 Late  TRUE     FALSE
##  5  2321    76 135000 married  Male      50   -10       2 Late  TRUE     FALSE
##  6  3454    65  35000 married  Female    40    50       0 Late  TRUE     FALSE
##  7   674    52  55000 married  Female    48 -3000      60 Late  TRUE     FALSE
##  8  1816    50 175000 married  Female    45  -500     200 Late  TRUE     FALSE
##  9  2378    78  55000 married  Male      60     0     100 Late  TRUE     TRUE
## 10  2140    59  35000 married  Female    50 -1200     200 Late  TRUE     FALSE
## 11  2118    52 110000 married  Female    39 -5000     200 Late  TRUE     FALSE
## 12  2036    72  35000 divorced Female    65  -300      50 Late  TRUE     TRUE
## 13  2310    60  10000 divorced Female    40 -2000      75 Late  TRUE     FALSE
## 14  2623    64 110000 married  Female    40  -100       0 Late  TRUE     FALSE
## 15  3117    77  10000 divorced Female    50  -100     200 Late  TRUE     FALSE
## 16   842    66  55000 married  Female    45 -2000     250 Late  TRUE     FALSE
## # ... with abbreviated variable names 1: is.outlier, 2: is.extreme
```

```
identify_outliers(AMOD5210, Age)
```

```
##  [1] ID         Age        Income     MS         Gender     AG
##  [7] LTW        Gambled    Onset      is.outlier is.extreme
## <0 rows> (or 0-length row.names)
```

```
identify_outliers(AMOD5210, Gambled)
```

```
## # A tibble: 15 x 11
##       ID   Age Income MS       Gender    AG    LTW Gambled Onset is.ou~1 is.ex~2
##    <dbl> <dbl>  <dbl> <chr>    <chr>  <dbl>  <dbl>   <dbl> <chr> <lgl>   <lgl>
##  1  2997    56 110000 married  Male      16  5   e3     300 Early TRUE    FALSE
##  2  3252    47  75000 married  Female    33 -1   e4     300 Late  TRUE    FALSE
##  3  3455    41  75000 divorced Male       8  2.5e3     400 Early TRUE    TRUE
##  4  2436    37  25000 single   Female    10  3   e3     400 Early TRUE    TRUE
##  5  1964    51  55000 married  Male      22 -1.5e4     300 Late  TRUE    FALSE
##  6  2295    42  45000 divorced Female    16 -1   e3     250 Early TRUE    FALSE
##  7  2391    40  85000 married  Male      13 -1   e4     300 Early TRUE    FALSE
##  8  1890    62  55000 married  Male      30 -1   e3     500 Late  TRUE    TRUE
##  9  2633    67  35000 married  Male      18 -1.5e5     450 Early TRUE    TRUE
```

```
## 10  2715     47 135000 married  Female    19 -1   e4      700 Late  TRUE    TRUE
## 11   539     41  85000 married  Female    16  6.5e3      425 Early TRUE    TRUE
## 12    17     48  80000 married  Male      19 -1.5e4      500 Late  TRUE    TRUE
## 13   426     44  85000 married  Male      20 -3  e3      400 Late  TRUE    TRUE
## 14   842     66  55000 married  Female    45 -2  e3      250 Late  TRUE    FALSE
## 15  1409     64  35000 married  Female    20  1  e3      500 Late  TRUE    TRUE
## # ... with abbreviated variable names 1: is.outlier, 2: is.extreme
```

All four variables have few outliers. Now, we will follow the next steps, that is, Shapiro-Wilks Test.

Now, we will test for normality using **Shapiro-Wilks Test**.

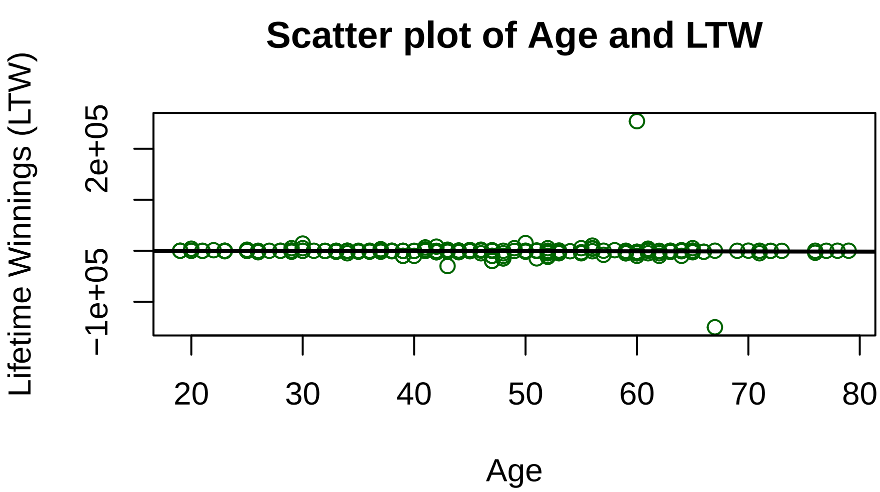
```
# To test using Shapiro-Wilks
shapiro_test(AMOD5210, vars = c("Age", "LTW","Gambled","AG"))
```

```
## # A tibble: 4 x 3
##   variable statistic        p
##   <chr>        <dbl>    <dbl>
## 1 AG           0.820 2.68e-14
## 2 Age          0.984 2.60e- 2
## 3 Gambled      0.679 2.68e-19
## 4 LTW          0.215 5.28e-28
```

All the four variables in Shapiro-Wilks test has $p < 0.05$. It seem that all the four variables are not Normal Distribution. We will now use Spearman's Rho Correlation method, that is, non-parametric correlation test.

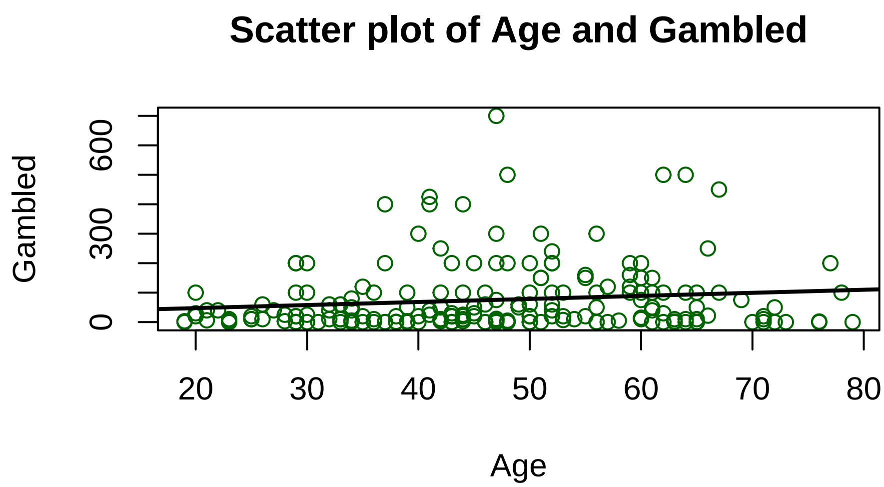
Now, let's check the linearity in all the four variables, that is, "LTW", "AG", "Age", "Gambled":

```
# For "Age" and "LTW"
plot(AMOD5210$Age, AMOD5210$LTW, col = "darkgreen",
     xlab = "Age", ylab = "Lifetime Winnings (LTW)" , main = "Scatter plot of Age and LTW")
abline(lm(AMOD5210$LTW ~ AMOD5210$Age, data = AMOD5210), col = "black", lw = 2)
```



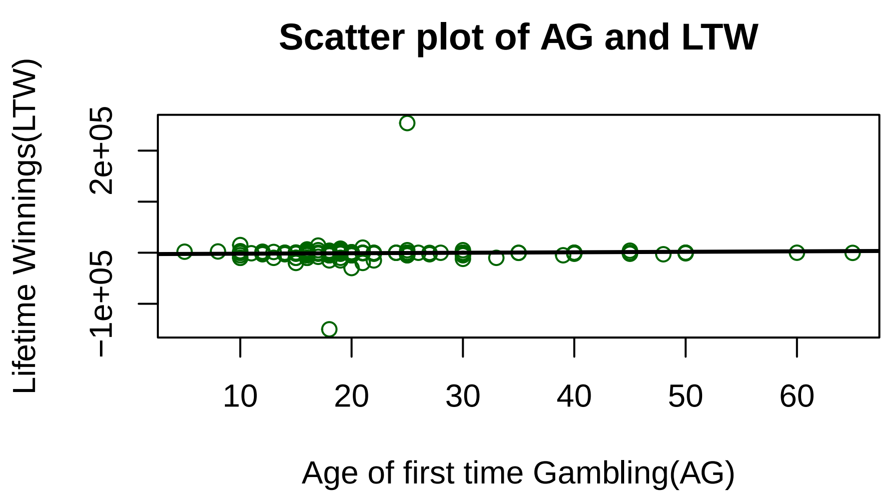
The scatter plot for "Age" and "LTW" shows that, as the persons age *increases*, the Lifetime Winnings (LTW) *does not changes* too much. Therefore, the regression line, which was seen in the above plot is almost *constant* and does not show **linearity**.

```r
# For Age and Gambled
plot(AMOD5210$Age, AMOD5210$Gambled, col = "darkgreen",
     xlab = "Age", ylab = "Gambled" , main = "Scatter plot of Age and Gambled")
abline(lm(AMOD5210$Gambled ~ AMOD5210$Age, data = AMOD5210), col = "black", lw = 2)
```



Here, the scatter plot for "Age" and "Gambled" shows that, as the persons age *increases*, the Gambled *changes* very little. Therefore, the regression line, which was seen in the above plot is almost *constant* and does not show **linearity**.

```r
# For  AG and LTW
plot(AMOD5210$AG, AMOD5210$LTW, col = "darkgreen",
     xlab = "Age of first time Gambling(AG)", ylab = "Lifetime Winnings(LTW)" , main = "Scatter plot of
abline(lm(AMOD5210$LTW ~ AMOD5210$AG, data = AMOD5210), col = "black", lw = 2)
```



Here, the scatter plot for "AG" and "LTW" shows that, as Age of first time gambling(AG) *increases*, the Lifetime Winnings(LTW) *does not changes* too much. Therefore, the regression line, which was seen in the above plot is almost *constant* and does not show **linearity**.

Hence, none of them the correlation shows the condition of Linearity.

- **"Age" and "LTW"** Now lets perform correlation test

```
correlation_age_ltw <- cor.test(AMOD5210$Age, AMOD5210$LTW, method = "spearman")
```

```
## Warning in cor.test.default(AMOD5210$Age, AMOD5210$LTW, method = "spearman"):
## Cannot compute exact p-value with ties
```

```
correlation_age_ltw
```

```
##
##  Spearman's rank correlation rho
##
## data:  AMOD5210$Age and AMOD5210$LTW
## S = 1418468, p-value = 0.0686
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##        rho
## -0.1303528
```

```
# Reporting to 3 decimals points
round(correlation_age_ltw$estimate,3)
```

```
##   rho
## -0.13
```

Therefore, the *Spearman's rank correlation rho between "Age" and "LTW"* is **-0.13**.

```
lm(AMOD5210$Age ~ AMOD5210$LTW,data = AMOD5210)
```

```
##
## Call:
## lm(formula = AMOD5210$Age ~ AMOD5210$LTW, data = AMOD5210)
##
## Coefficients:
##  (Intercept)  AMOD5210$LTW
##    4.641e+01    -1.146e-05
```

"LTW" is the dependent variable in the correlation test, therefore, Slope is $-1.146e-05$ and Y-Intercept is $4.641e+01$.

- **"Age" and "Gambled"**

```r
correlation_age_gambled <- cor.test(AMOD5210$Age, AMOD5210$Gambled, method = "spearman")
```

```
## Warning in cor.test.default(AMOD5210$Age, AMOD5210$Gambled, method =
## "spearman"): Cannot compute exact p-value with ties
```

```r
correlation_age_gambled
```

```
##
##  Spearman's rank correlation rho
##
## data:  AMOD5210$Age and AMOD5210$Gambled
## S = 1184794, p-value = 0.1164
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##       rho
## 0.1113825
```

```r
# Reporting to 3 decimals points
round(correlation_age_gambled$estimate,3)
```

```
##   rho
## 0.111
```

Therefore, the *Spearman's rank correlation rho between "Age" and "Gambled"* is **0.111**.

- **"AG" and "LTW"**

```r
correlation_ag_ltw <- cor.test(AMOD5210$AG, AMOD5210$LTW, method = "spearman")
```

```
## Warning in cor.test.default(AMOD5210$AG, AMOD5210$LTW, method = "spearman"):
## Cannot compute exact p-value with ties
```

```r
correlation_ag_ltw
```

```
##
##  Spearman's rank correlation rho
##
## data:  AMOD5210$AG and AMOD5210$LTW
## S = 1285645, p-value = 0.7331
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##         rho
## -0.02450817
```

```r
# Reporting to 3 decimals points
round(correlation_ag_ltw$estimate,3)
```

```
##    rho
## -0.025
```

Therefore, the *Spearman's rank correlation rho between "AG" and "LTW"* is **-0.025**.

```
lm(AMOD5210$AG ~ AMOD5210$LTW,data = AMOD5210)
```

```
##
## Call:
## lm(formula = AMOD5210$AG ~ AMOD5210$LTW, data = AMOD5210)
##
## Coefficients:
##  (Intercept)  AMOD5210$LTW
##    2.185e+01     1.725e-05
```

"LTW" is the dependent variable in the correlation test, therefore, Slope is $1.725e - 05$ and Y-Intercept is $2.185e + 01$.

Question 6

Using an appropriate inferential statistic, determine whether an individual's income level differs across married, single, and divorced individuals ("MS"). Also, evaluate and comment on whether the basic assumptions of your chosen statistic were met.

To test whether an individual's income level differs across married, single, and divorced individuals ("MS"), we will test using **Independent ANOVA Test**.

Step 1: Hypothesis and Assumptions

Let's define **Null Hypothesis** H_o and **Alternative Hypothesis** H_A to use inferential statistic.

H_o : An individual's income level doesn't differs across married, single, and divorced individuals ("MS").

H_A : An individual's income level differs across married, single, and divorced individuals ("MS").

Let's organize the data by group and get some descriptive statistics.

```r
# install.packages("datarium")
# install.packages("rstatix")
library(rstatix)
library(datarium)
ms_group <- group_by(AMOD5210, MS)
get_summary_stats(ms_group, Income, type = "mean_sd")
```

```
## # A tibble: 3 x 5
##   MS       variable     n   mean     sd
##   <chr>    <fct>    <dbl>  <dbl>  <dbl>
## 1 divorced Income      30 35333. 20634.
## 2 married  Income     144 68958. 35389.
## 3 single   Income      26 38462. 34257.
```

Let's test some **assumptions**.

Firstly, we will also look for extreme outlier.

```r
identify_outliers(ms_group, Income)
```

```
## # A tibble: 7 x 11
##   MS          ID   Age Income Gender    AG    LTW Gambled Onset is.out~1 is.ex~2
##   <chr>    <dbl> <dbl>  <dbl> <chr>  <dbl>  <dbl>   <dbl> <chr> <lgl>    <lgl>
## 1 divorced  3408    43  85000 Male      20 -30000      20 Late  TRUE     FALSE
## 2 divorced  3479    42  85000 Female    19   8000      10 Late  TRUE     FALSE
## 3 married   2442    55 175000 Female    30  -3000     150 Late  TRUE     FALSE
## 4 married   3068    48 175000 Female    24   -100       5 Late  TRUE     FALSE
## 5 married   1816    50 175000 Female    45   -500     200 Late  TRUE     FALSE
## 6 married   1136    71 175000 Male      20  -5000      20 Late  TRUE     FALSE
## 7 married   3183    44 175000 Female    20   -100      10 Late  TRUE     FALSE
## # ... with abbreviated variable names 1: is.outlier, 2: is.extreme
```

Since, we have two outlier. But, we are going to proceed with the normality test, using Shapiro-Wilks Test.

```
shapiro_test(ms_group, Income)
```

```
## # A tibble: 3 x 4
##   MS       variable statistic          p
##   <chr>    <chr>        <dbl>      <dbl>
## 1 divorced Income       0.890 0.00479
## 2 married  Income       0.929 0.00000141
## 3 single   Income       0.802 0.000189
```

As $p < 0.05$, the data is not normally distributed for any of the Marital status, that is, divorced, married, single.

Step 2: Testing

Finally, we need to test for homogeneity of variance.

```
levene_test(AMOD5210, Income ~ MS)
```

```
## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.
```

```
## # A tibble: 1 x 4
##     df1   df2 statistic      p
##   <int> <int>     <dbl>  <dbl>
## 1     2   197      3.22 0.0421
```

As $p < 0.05$, the distribution shows that non-homogeneity in variance across marital status and thus it is not followed.

Now, lets test two-way independent ANOVA test and view the ANOVA summary table:

```
Ind.ANOVA <- aov(Income ~ MS, ms_group)
Anova(Ind.ANOVA, type = "III")
```

```
## Anova Table (Type III tests)
##
## Response: Income
##                 Sum Sq  Df F value    Pr(>F)
## (Intercept) 3.7453e+10   1  33.419 2.872e-08 ***
## MS          4.1871e+10   2  18.680 3.726e-08 ***
## Residuals   2.2078e+11 197
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

As $p < 0.05$, there is enough evidence to **reject** *Null Hypothesis*(H_o). Thus, the income level differs across different categories of Marital Status (MS).

Also, to determine the difference in income levels across categories of MS, we will use Post-hoc test.

```r
t_test(AMOD5210, Income ~ MS, var.equal = FALSE, p.adjust.method = "bonferroni")
```

```
## # A tibble: 3 x 10
##   .y.    group1   group2     n1    n2 statistic    df          p   p.adj p.adj~1
## * <chr>  <chr>    <chr>   <int> <int>     <dbl> <dbl>      <dbl>   <dbl> <chr>
## 1 Income divorced married    30   144    -7.03   70.1    1.1 e-9 3.3 e-9 ****
## 2 Income divorced single     30    26    -0.406  39.8    6.87e-1 1   e+0 ns
## 3 Income married  single    144    26     4.16   35.3    1.95e-4 5.85e-4 ***
## # ... with abbreviated variable name 1: p.adj.signif
```

Step 3: Conclusion

The current study determines whether or not the income level differs across married, single, and divorced individuals ("MS").A 200 random samples taken from the dataset and examined(39 Divorced, 141 Married ,20 Single). The sample contained 2 outliers. A Shapiro-wilks test demonstrated that the distribution across married, single, and divorced individuals ("MS") was not normaly distributed and Levene's test shows the non-homogeneity in variance. The mean income for divorced was 35333.33(SD = 20633.64),the mean income for married was 68958.33 (SD = 35389.32), the mean income for single was 38461.54 (SD = 34256.95). An Independent test showed that the Income level differs across married, single, and divorced individuals ("MS"), $F(2, 197) = 18.680$, $p < 0.05$. Bonferroni-corrected pairwise comparisons showed that the single category had significantly higher income level than both the divorced and married categories, while the married category had significantly higher income level than the divorced category.