

# Worksheet10

STAT414

2024-11-27

Module10 deals with a wellknown topic, but more in depth than you may have studied in your previous stat course (like Stat 350 or 351 or 355). The worksheet will require you to use the `tTestPower` function of `EnvStats`. Read the help file in the `EnvStats` carefully—will help you in completing the workseet.

```
library(EnvStats)
```

```
##
```

```
## Attaching package: 'EnvStats'
```

```
## The following objects are masked from 'package:stats':
```

```
##
```

```
##      predict, predict.lm
```

```
# 1. we use the two-sample t-test to compare sulfate concentrations (EPA.09.Ex.16.1.sulfate.df)  
# at a background and downgradient well. The resulting t-statistic is 5.66 with  
# 12 degrees of freedom.
```

```
data <- EPA.09.Ex.16.1.sulfate.df
```

```
data
```

##	Month	Year	Well.type	Sulfate.ppm
## 1	Jan	1995	Background	560
## 2	Apr	1995	Background	530
## 3	Jul	1995	Background	570
## 4	Oct	1995	Background	490
## 5	Jan	1996	Background	510
## 6	Apr	1996	Background	550
## 7	Jul	1996	Background	550
## 8	Oct	1996	Background	530
## 9	Jan	1995	Downgradient	NA
## 10	Apr	1995	Downgradient	NA
## 11	Jul	1995	Downgradient	600
## 12	Oct	1995	Downgradient	590
## 13	Jan	1996	Downgradient	590
## 14	Apr	1996	Downgradient	630
## 15	Jul	1996	Downgradient	610
## 16	Oct	1996	Downgradient	630

```

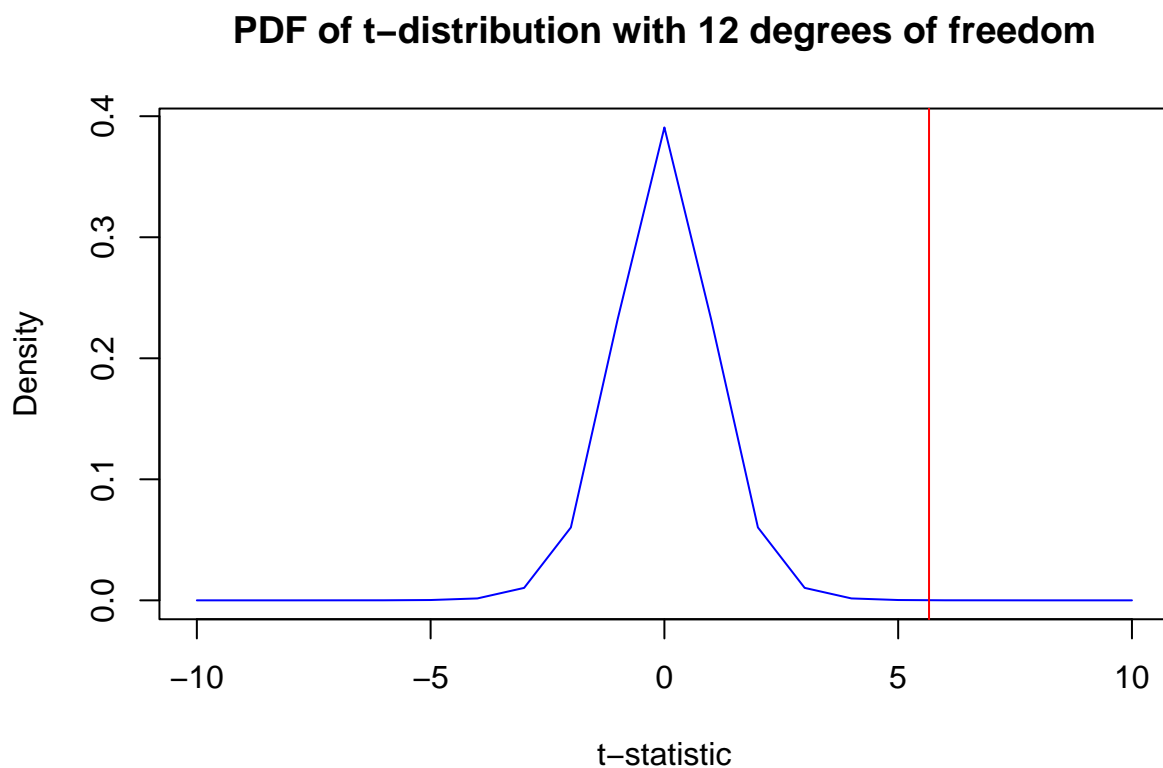
t_statistic <- 5.66
dof <- 12

# (a) Plot the pdf of a t-distribution with 12 degrees of freedom and add a
#vertical line at x = 5.66.

#Generate some set of values x to plot the pdf
x <- seq(-10, 10, by=1)
#dt(x, degrees_of_freedom) is the density of t-distribution
plot(x, dt(x,dof), type = "l", col="blue", xlab = "t-statistic", ylab = "Density",
     main = "PDF of t-distribution with 12 degrees of freedom")

#Superimpose line at x=5.66, v is the x-values for vertical lines
abline(v = t_statistic, col = "red")

```



```

# (b) Explain what part of this plot represents the p-value for the test of the
# null hypothesis that the average sulfate concentrations at the two wells are the
# same against the alternative hypothesis that the average concentration of sulfate
# at the downgradient well is larger than the average concentration at the back-ground
# well.

cat(" mu1 = average concentration of sulfate at downgradient well, mu2 = background well
    H0: mu1 = mu2
    HA: mu1 > mu2")

```

```
## mu1 = average concentration of sulfate at downgradient well, mu2 = background well
## H0: mu1 = mu2
## HA: mu1 > mu2
```

```
cat("The p-value in the plot is the area under the curve, since p-value can be
represented by the area under the curve of the PDF. Therefore for the given
t-statistic and x-line 5.66, we can analyze the p-value (area under the curve)
above x=5.66 to determine a result for the hypothesis test. We use the upper-tail
test P(T>5.66) which is to the right of x=5.66, because the t-statistic is
calculated by (mu1 - mu2 / SE) and our alternative hypothesis is HA: mu1 > mu2.")
```

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## represented by the area under the curve of the PDF. Therefore for the given
## t-statistic and x-line 5.66, we can analyze the p-value (area under the curve)
## above x=5.66 to determine a result for the hypothesis test. We use the upper-tail
## test P(T>5.66) which is to the right of x=5.66, because the t-statistic is
## calculated by (mu1 - mu2 / SE) and our alternative hypothesis is HA: mu1 > mu2.
```

```
p1 <- pt(t_statistic, df=12, lower.tail=FALSE)
p1
```

```
## [1] 5.279756e-05
```

```
cat("The p-value of the upper-tail test is extremeley small and less than .05,
therefore we reject H0 in support of HA.")
```

```
## The p-value of the upper-tail test is extremeley small and less than .05,
## therefore we reject H0 in support of HA.
```

```
# 2. Consider the copper concentrations stored in the data frame EPA.09.Ex.16.4.copper.df
# in EnvStats package. Use the t-test and Wilcoxon rank sum test to compare the data
# from the two background wells.
```

```
data_downgradient <- data[data$Well.type == "Downgradient",]
data_background <- data[data$Well.type == "Background",]
```

```
cat("It turns out that, in estimating the variance of the difference of two
means, the assumption of equality of variances of the population is
crucial. This assumption is popularly known as homoscedasticity.
If we can assume that the variances of the two population are equal, in
other words the two populations are homoscedastic, then a more efficient
estimator of the variance of the two means can be obtained.
Therefore use var.equal = FALSE in t.test because we are testing the means
of the 2 independent and unpaired samples. ")
```

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## means, the assumption of equality of variances of the population is
## crucial. This assumption is popularly known as homoscedasticity.
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## other words the two populations are homoscedastic, then a more efficient
```

```
## estimator of the variance of the two means can be obtained.
## Therefore use var.equal = FALSE in t.test because we are testing the means
## of the 2 independent and unpaired samples.
```

```
t.test(data_downgradient$Sulfate.ppm, data_background$Sulfate.ppm,
       paired=FALSE, var.equal=FALSE)
```

```
##
## Welch Two Sample t-test
##
## data: data_downgradient$Sulfate.ppm and data_background$Sulfate.ppm
## t = 5.9826, df = 11.955, p-value = 6.485e-05
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## 45.82035 98.34631
## sample estimates:
## mean of x mean of y
## 608.3333 536.2500
```

```
cat("The wilcoxon rank-sum test is the non-parametric equivalent of the independent
t-test. Used to test differences between two conditions in which different
participants have been used. Samples must have equal variance; homoscedasticity.")
```

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## t-test. Used to test differences between two conditions in which different
## participants have been used. Samples must have equal variance; homoscedasticity.
```

```
wilcox.test(data_downgradient$Sulfate.ppm, data_background$Sulfate.ppm,
            paired=FALSE, var.equal=TRUE)
```

```
## Warning in wilcox.test.default(data_downgradient$Sulfate.ppm,
## data_background$Sulfate.ppm, : cannot compute exact p-value with ties
```

```
##
## Wilcoxon rank sum test with continuity correction
##
## data: data_downgradient$Sulfate.ppm and data_background$Sulfate.ppm
## W = 48, p-value = 0.002309
## alternative hypothesis: true location shift is not equal to 0
```

```
cat("Both p-values for the wilcoxon rank sum test and independent t-test are
less than .05, meaning that there is significant statistical support for the
alternative hypothesis, which is that the average sulfate concentrations for
background wells and downgradient wells differ in value.")
```

```
## Both p-values for the wilcoxon rank sum test and independent t-test are
## less than .05, meaning that there is significant statistical support for the
## alternative hypothesis, which is that the average sulfate concentrations for
## background wells and downgradient wells differ in value.
```

```
# 3. The following data shows age at diagnosis of Type II diabetes among young adults.
# Is the age at diagnosis different for males and females.
# Males 19, 22,16,29,24
# Females 20,11,17,12
```

```
males <- c(19,22,16,29,24)
females <- c(20,11,17,12)
```

```
# (a) What test procedures are applicable to this data structure? Write down the
# assumptions of for each of the candidate procedure.
```

```
cat("1. Independent t-test: Independent samples, follow normal distribution, equal variances
    2. Wilcoxon rank sum test: Independent samples, data is ordinal (can be ranked),
    distributions are similar in shape
    3. Welch's t-test: independent samples, follow normal distribution, does not
    need equal variances.
    Note: Wilxocon's signed-rank test is used for paired data, this is not paired
    ")
```

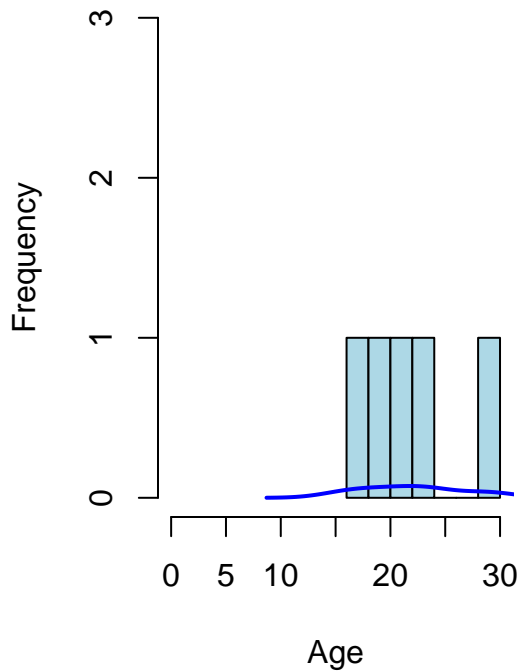
```
## 1. Independent t-test: Independent samples, follow normal distribution, equal variances
##      2. Wilcoxon rank sum test: Independent samples, data is ordinal (can be ranked),
##      distributions are similar in shape
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##      need equal variances.
##      Note: Wilxocon's signed-rank test is used for paired data, this is not paired
##
```

```
# (b) Which procedure would you recommend and why?
```

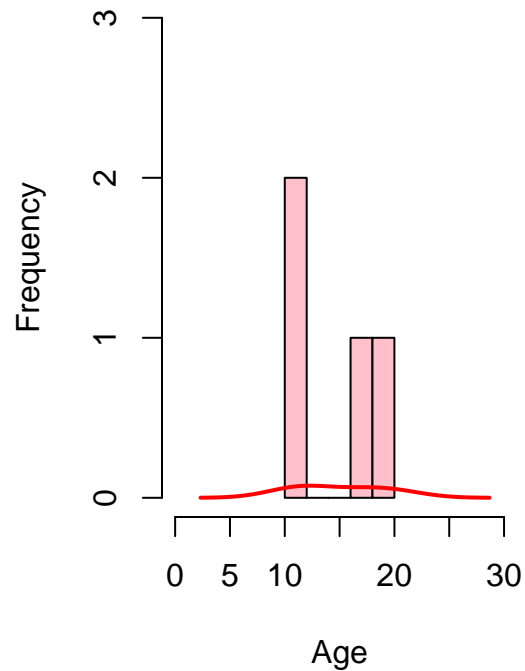
```
par(mfrow = c(1, 2), mar = c(5, 5, 4, 2))
# Histogram for males
hist(males, breaks = 5, col = "lightblue", main = "Histogram of Males",
     xlab = "Age", ylab = "Frequency", xlim=c(0,30), ylim=c(0,3))
lines(density(males), col = "blue", lwd = 2)

# Histogram for females
hist(females, breaks = 5, col = "pink", main = "Histogram of Females",
     xlab = "Age", ylab = "Frequency", xlim=c(0,30), ylim=c(0,3))
lines(density(females), col = "red", lwd = 2)
```

### Histogram of Males



### Histogram of Females



```
var(ages)
```

```
## [1] 24.5
```

```
var(females)
```

```
## [1] 18
```

```
cat("The distributions are too small and not curved to follow normality. The  
variances between males and females are not equal: 24.5 vs 18, therefore  
the best choice is the nonparametric approach of Wilcoxon rank sum test. The  
distribution are also somewhat similar in shape.")
```

```
## The distributions are too small and not curved to follow normality. The  
## variances between males and females are not equal: 24.5 vs 18, therefore  
## the best choice is the nonparametric approach of Wilcoxon rank sum test. The  
## distribution are also somewhat similar in shape.
```

```
# (c) Regardless of your recommendation above, apply both the parametric and  
# nonparametric methods to this example and compare the results.
```

```
# 1. Independent t-test, equal variances  
t.test(ages, females, var.equal = TRUE)
```

```
##
## Two Sample t-test
##
## data: males and females
## t = 2.2393, df = 7, p-value = 0.06014
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.3916462 14.3916462
## sample estimates:
## mean of x mean of y
##      22      15
```

```
# 2. Wilcoxon rank sum test, nonparametric
wilcox.test(males, females)
```

```
##
## Wilcoxon rank sum exact test
##
## data: males and females
## W = 17, p-value = 0.1111
## alternative hypothesis: true location shift is not equal to 0
```

```
# 3. Welch's t-test, unequal variances
t.test(males, females, var.equal = FALSE)
```

```
##
## Welch Two Sample t-test
##
## data: males and females
## t = 2.2831, df = 6.9288, p-value = 0.05675
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.2649222 14.2649222
## sample estimates:
## mean of x mean of y
##      22      15
```

```
cat("Indepdent t-test:      p-value = 0.06014
    Wilcoxon rank sum test: p-value = 0.1111
    Welch's t-test:       p-value = 0.05675")
```

```
All 3 tests fail to reject the null hypothesis at alpha = .05. Thus we conclude
that there is not enough evidence to support the hypothesis that there is a
statistically significant difference in the age of diagnosis for diabetes
between males and females.")
```

```
## Indepdent t-test:      p-value = 0.06014
##   Wilcoxon rank sum test: p-value = 0.1111
##   Welch's t-test:       p-value = 0.05675
##
## All 3 tests fail to reject the null hypothesis at alpha = .05. Thus we conclude
## that there is not enough evidence to support the hypothesis that there is a
## statistically significant difference in the age of diagnosis for diabetes
## between males and females.
```