

```
## Loading required packages
```

```
library(agricolae)
```

```
library(ggplot2)
```

```
library(ggpubr)
```

```
library(dplyr)
```

```
library(tidyverse)
```

```
library(corrplot)
```

```
library(xts)
```

```
library(dplyr)
```

```
library(PerformanceAnalytics)
```

```
library(zoo)
```

```
library(Formula)
```

```
library(readr)
```

```
### Read the csv file for Analysis
```

```
# Read csv file by R by giving another dataset name that is read by R
```

```
df1=read.csv(file.choose(), header = T)
```

```
df1
```

```
## To see the structure of the R read dataset df run the following command
```

```
str(df)
```

```
names(df)
```

```
# Variable conversion is needed before going to One-way ANOVA-DMRT test_SE-SD-Mean estimation
```

```
df$Replication = as.factor(df$Replication)
```

```
df$Treatment = as.factor(df$Treatment)
```

```
attach(df)
```

```
str(df)
```

```
names(df)
```

```
### One-way ANOVA_CRD Design with 3-Replicaitons_for the Parameter: Fruit Weight
```

```
FWanova <- aov(Fruitweight.g.~Treatment)
```

```
summary(FWanova)
```

```
### One-way ANOVA_CRD Design with 3-Replicaitons_for the Parameter: Fruit Diameter
```

```
FDManova <- aov(Fruitdiameter.cm. ~ Treatment)
```

```
summary(FDManova)
```

```
### One-way ANOVA_CRD Design with 3-Replicaitons_for the Parameter: Fruit Length
```

```
FLanova <- aov(Fruitlength.cm. ~ Treatment)
```

```
summary(FLanova)
```

```
### One-way ANOVA_CRD Design with 3-Replicaitons_for the Parameter: Yield
```

```
FYanova <- aov(Yieldper.plant..g. ~ Treatment)
```

```
summary(FYanova)
```

```
### Mean separation and lettering_Fruit Weight
```

```
# DMRT mean comparison test-for the parameter of Fruit Weight
```

```
## DMRT test for Fruit_Weight parameter (dependent variable)
```

```
### For Fruit Weight:
```

```
duncan.FW = duncan.test(y = Fruitweight.g.,
```

```
trt = Treatment,
```

```
DFerror = FWanova$df.residual,  
MSerror = deviance(FWanova)/FWanova$df.residual,  
group = T,  
console = T)
```

DMRT test for Fruit_Diameter parameter (dependent variable)

For Fruit_Diameter:

```
duncan.FDM = duncan.test(y = Fruitdiameter.cm.,  
trt = Treatment,  
DFerror = FDManova$df.residual,  
MSerror = deviance(FDManova)/FDManova$df.residual,  
group = T,  
console = T)
```

DMRT test for Fruit_Length parameter (dependent variable)

For Fruit_Length:

```
duncan.FL = duncan.test(y = Fruitlength.cm.,  
trt = Treatment,  
DFerror = FLanova$df.residual,  
MSerror = deviance(FLanova)/FLanova$df.residual,  
group = T,  
console = T)
```

DMRT test for Fruit_Yield parameter (dependent variable)

For Fruit_Yield:

```
duncan.FY = duncan.test(y = Yieldper.plant..g.,  
trt = Treatment,
```

```
DFerror = FYanova$df.residual,  
MSerror = deviance(FYanova)/FYanova$df.residual,  
group = T,  
console = T)
```

To see the SE for the parameter Fruit_Weight as per the independent variables of the studied (Treatment)

```
FW_SE = df %>%  
  group_by(Treatment) %>%  
  summarise(FW.mean = mean(Fruitweight.g.),  
            std = sd(Fruitweight.g.),  
            SE = sd(Fruitweight.g.)/sqrt(n()))
```

```
FW_SE  
print(FW_SE)
```

To see the SE for the parameter Fruit_Diameter as per the independent variables of the studied (Treatment)

```
FDM_SE = df %>%  
  group_by(Treatment) %>%  
  summarise(FDM.mean = mean(Fruitdiameter.cm.),  
            std = sd(Fruitdiameter.cm.),  
            SE = sd(Fruitdiameter.cm.)/sqrt(n()))
```

```
print(FDM_SE)
```

```
### To see the SE for the parameter Fruit_Length as per the independent variables of the studied (Treatment)
```

```
FL_SE = df %>%
```

```
  group_by(Treatment) %>%
```

```
  summarise(FL.mean = mean(Fruitlength.cm.),
```

```
            std = sd(Fruitlength.cm.),
```

```
            SE = sd(Fruitlength.cm.)/sqrt(n()))
```

```
print(FL_SE)
```

```
### To see the SE for the parameter Fruit_Yield as per the independent variables of the studied (Treatment)
```

```
FY_SE = df %>%
```

```
  group_by(Treatment) %>%
```

```
  summarise(FY.mean = mean(Yieldper.plant..g.),
```

```
            std = sd(Yieldper.plant..g.),
```

```
            SE = sd(Yieldper.plant..g.)/sqrt(n()))
```

```
print(FY_SE)
```

```
#Correlation
```

```
names(df1)
```

```
#selecting only the numerical columns
```

```
numeric_vers <- df1 %>%
```

```
  select(-Treatment, -Replication) %>%
```

```
  mutate_all(as.numeric)
```

```
numeric_vers
```

```
#compute the correlation matrix
```

```
cor_matrix <- cor(numeric_vers, use = "complete.obs", method = "pearson")
```

```
print(cor_matrix)
```

```
plot_cor_matrix <- corrplot(cor_matrix, method = "square", type = "full", diag = FALSE, tl.col =  
"black", tl.srt = 45, tl.cex = .8,
```

```
title = "Correlation Matrix of Project Dataset", mar = c(1,.1,0.8,2))
```

```
#PCA
```

```
library(FactoMineR)
```

```
library(ggplot2)
```

```
library(mclust)
```

```
library(stats)
```

```
library(fpc)
```

```
library(ggforce)
```

```
library(grDevices)
```

```
library(factoextra)
```

```
library(stats)
```

```
#Now Doing PCA analysis on df
```

```
data.pca.df1 <- prcomp(df1[, -c(1:2)],
```

```
center = TRUE,
```

```
scale = TRUE)
```

```
data.pca.df1
```

```
p=data.pca.df1
```

```
summary(p)
```

```
df1$Treatment <- as.factor(df1$Treatment)
str(df1)
```

```
## To see the coordinates for the variables running res.var$coord command
res.var$coord
```

```
#### To see the contributions of the each variable to the PCs running res.var$contrib
con <- res.var$contrib
```

```
# To see the quality of the representation of the variables running res.var$cos2
res.var$cos2
```

```
## To see the correlations between variables and dimensions running res.var$cor
res.var$cor
```

```
#### Biplot Preparation using the Package: factoextra
```

```
library(factoextra)
```

```
fviz_pca_ind(p,col.ind="cos2",gradient.cols=c("#00AFBB","#E7B800","#FC4E07"),
             repel = TRUE)
```

```
fviz_pca_ind(p, col.ind="contrib",gradient.cols=c("#00AFBB","#E7B800","#FC4E07"),
             repel=TRUE)
```

```
## Variables_PCA-with Cos2 variable values_in circle shape with the variable contribution%-
cos2
```

```
fviz_pca_var(p,col.var="cos2",gradient.cols=c("#00AFBB","#E7B800","#FC4E07"),
             repel=TRUE)
```

```
#### Variables_PCA-With the variables contribution_contrib to the each PCA components:
```

```
fviz_pca_var(p, col.var="contrib",gradient.cols=c("#00AFBB","#E7B800","#FC4E07"),
             repel=TRUE)
```

```
fviz_pca_biplot(p,label="var", alpha.ind=1,col.var="blue",habillage=df$Treatment,
                repel=TRUE,addEllipses=FALSE, invisible="quali",legend.title="Treatment")+

```

```
theme_bw()
```

```
df1_filtered <- df1 # Adjust this line based on how you filtered data for PCA
```

```
# Run PCA
```

```
p <- prcomp(df1_filtered[,c(1:2)], center = TRUE, scale. = TRUE)
```

```
# Ensure the habillage factor matches the PCA dataset
```

```
df1_filtered$Treatment <- as.factor(df1_filtered$Treatment)
```

```
plot <- fviz_pca_biplot(p, axes = c(1, 2),
```

```
  label = "var",          # Labels for variables
```

```
  geom.ind = "point",     # Individuals as points
```

```
  col.var = "contrib",    # Color by contributions to the PC
```

```
  gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"), # Gradient colors for  
variables
```

```
  alpha.ind = 1,          # Transparency for individuals
```

```
  habillage = df1_filtered$Treatment, # Color individuals by Treatment
```

```
  repel = TRUE,           # Avoid text overlapping
```

```
  addEllipses = FALSE,    # No confidence ellipses
```

```
  legend.title = "Treatment", # Title for the treatment legend
```

```
  invisible = "quali",    # Hide qualitative supplementary variables
```

```
  scale = "contrib")      # Scaling by contribution
```

```
+ coord_cartesian(xlim = c(-10, 10), ylim = c(-4, 4)) # Set axis limits
```

```
+ theme(text = element_text(size = 16),
```

```
  axis.text.x = element_text(color="black", size=16),
```

```
  axis.text.y = element_text(color="black", size=16),
```

```
  legend.position = "right") # Position legend on the right side
```



```
+ labs(y = "PC2 (31.1%)", x = "PC1 (36.9%)", title = "PCA Biplot with Variable Contribution  
and Treatment Legend",
```

```
color = "Variable Contribution") # Labels for axes and color
```

```
# Print the plot
```

```
print(plot)
```

```
# Print the plot
```

```
print(plot + labs(y="PC2 (31.1%)", x = "PC1 (36.9%)"))
```

```
#dendo
```

```
install.packages("igraph")
```

```
library(igraph)
```

```
# Dendrogram
```

```
df_mean <- df2 %>%
```

```
  group_by(Treatment)%>% # Group data by Treatment
```

```
  summarise(across(everything(), mean, na.rm = TRUE))
```

```
# Changing Row names (generally row names are denoted by 1,2.... I want to denote the row as  
vegetable name so that when I will delete the 1st row of Veg name still I can see the vegetable )
```

```
df2 <- df1[,-1]
```

```
rownames(df_mean)<- c(df_mean$Treatment)
```

```
head(df_mean)
```

```
dim(df_mean)
```

```
df_mean$Treatment <- NULL
```

```
names(df_mean)
```

```
newdata <- (df[,3:23])
```

```
newdata
```

```
head(newdata)
```

```
#scale df_mean
```

```
df.scaled <- scale(df_mean)
```

```
res.dist <- dist(x = df.scaled,  
                method = "euclidean")
```

```
print(res.dist)
```

```
x <- as.matrix(res.dist)[1:11, 1:11]
```

```
x
```

```
round(x, digits = 3)
```

```
res.hc <- hclust(d = res.dist, method = "complete") # Corrected from 'data' to 'd'
```

```
# Plot the result of the hierarchical clustering
```

```
plot(x = res.hc)
```

```
### Coloring
```

```
require(factoextra)
```

```
library(factoextra)
```

```
fviz_dend(x = res.hc, cex = 0.7, lwd = .7)
```

```
fviz_dend(x = res.hc, cex = 0.4, lwd = 0.8)
```

```
require(grDevices)
```

```
library(grDevices)
```

```
colors()
```

```

require(scales)

library(scales)

palette()

show_col(palette(rainbow(6)))

require("ggsci")

library(ggsci)

show_col(pal_jco(palette = c("default"))(10))

show_col(pal_jco("default", alpha = 0.6)(10))

# fviz_dend = Use fviz function for enhanced visualization of dendrogram

# x = an object of class dendrogram, hclust, agnes, diana, hcut, hkmeans or HCPC
(FactoMineR).

# k = the number of groups for cutting the tree.

# cex = size of labels

# k_colors = a vector containing colors to be used for the groups. It should contain k number of
colors. Allowed values include also "grey" for grey color palettes; brewer palettes e.g. "RdBu",
"Blues", ...; and scientific journal palettes from ggsci R package, e.g.: "npg", "aaas", "lancet",
"jco", "ucscgb", "uchicago", "simpsons" and "rickandmorty"

library(NbClust)

fviz_nbclust(df_mean, kmeans, method= "gap_stat")


fviz_dend(x = res.hc, cex = 0.8, lwd = 0.8, k = 3,
          k_colors = c("red", "green3", "blue"))


fviz_dend(x = res.hc, cex = 0.8, lwd = 0.8, k = 3,
          k_colors = "jco")

```