

# I do it for fun

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# Theme

“bootstrap”, “cerulean”, “cosmo”, “darkly”, “flatly”, “journal”, “lumen”, “paper”, “readable”, “sandstone”, “simplex”, “spacelab”, “united”, “yeti”

## Data Types

Data types are used to represent different types of data in R. R has several built-in data types, such as numeric, character, integer, complex, and logical. Data types are used to store different types of data, such as numbers, text, and logical values.

```
x <- "Hello Charles, I hope you're working hard to become who you are destined to be by God's purpose?"  
x
```

```
## [1] "Hello Charles, I hope you're working hard to become who you are destined to be by God's purpose"
```

```
class(x) # checking the class of variable x
```

```
## [1] "character"
```

```
y <- pi^2 # calculating the square of pi  
y
```

```
## [1] 9.869604
```

```
class(y) # checking the class of variable y
```

```
## [1] "numeric"
```

```
z <- 15L # assigning 15 to variable z  
z
```

```
## [1] 15
```

```
class(z) # checking the class of variable z
```

```
## [1] "integer"
```

```
a <- (5 + 2i)^2 # calculating the square of (5 + 2i)  
a
```

```
## [1] 21+20i
```

```
class(a) # checking the class of variable a
```

```
## [1] "complex"
```

```
l <- TRUE # assigning TRUE to variable l
class(l) # checking the class of variable l
```

```
## [1] "logical"
```

```
x <- list(age = c(10,21,22), weight = c(30,33,32)) # creating a list x
x
```

```
## $age
## [1] 10 21 22
##
## $weight
## [1] 30 33 32
```

```
names(x) # Calling the names of the list x
```

```
## [1] "age"      "weight"
```

```
length(x) # checking the length of the list x
```

```
## [1] 2
```

```
kx <- data.frame(age = c(11,14,22), weight = c(30,33,32)) # creating a dataframe xk
kx
```

```
##   age weight
## 1  11     30
## 2  14     33
## 3  22     32
```

```
d <- c("Charles Kwame Appiah is my name") # creating a vector
d
```

```
## [1] "Charles Kwame Appiah is my name"
```

```
class(d) # checking the class of variable d
```

```
## [1] "character"
```

```
length(d) # checking the length of variable d
```

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

```
nchar(d) # checking the number of characters in variable d
```

```
## [1] 31
```

```
f<- c(1,3,4,6,7) # creating a vector
f
```

```
## [1] 1 3 4 6 7
```

```
class(f)# checking the class of variable f
```

```
## [1] "numeric"
```

## Integers

Integers in R are stored as numeric data type. To create an integer in R, you can use the L suffix or the `as.integer()` function.

```
2 + 3
```

```
## 5
```

```
import pandas as pd
```

```
df = pd.read_csv("C:/Users/HP/Desktop/Data Science/Machine learning/kyphosis.csv")
```

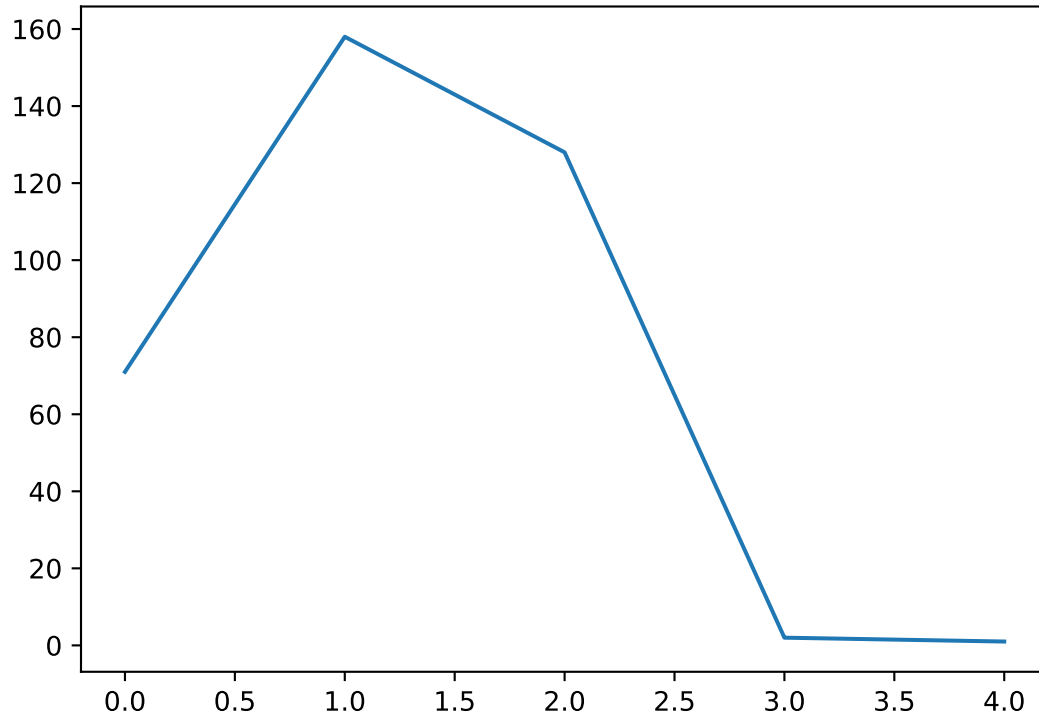
```
df.info
```

```
## <bound method DataFrame.info of      Kyphosis  Age  Number  Start
## 0    absent    71      3      5
## 1    absent   158      3     14
## 2    present   128      4      5
## 3    absent     2      5      1
## 4    absent     1      4     15
## ..      ...    ...    ...    ...
## 76    present   157      3     13
## 77    absent    26      7     13
## 78    absent   120      2     13
## 79    present    42      7      6
## 80    absent    36      4     13
##
## [81 rows x 4 columns]>
```

```
df.describe()
```

```
##           Age      Number      Start
## count    81.000000  81.000000  81.000000
## mean     83.654321   4.049383  11.493827
## std      58.104251   1.619423   4.883962
## min       1.000000   2.000000   1.000000
## 25%      26.000000   3.000000   9.000000
## 50%      87.000000   4.000000  13.000000
## 75%     130.000000   5.000000  16.000000
## max     206.000000  10.000000  18.000000
```

```
df["Age"].head().plot()
```



```
fo<- c(1L,3L,4L,6L,7L) # creating a vector  
fo
```

```
## [1] 1 3 4 6 7
```

```
class(fo) # checking the class of variable fo
```

```
## [1] "integer"
```

## Vectors

Vectors can be created with the `c()` function. The `c()` function can take multiple arguments and combine them into a single vector. The `c()` function can also be used to combine multiple vectors into a single vector.

```
# Initialization  
x <- vector(mode = "logical", length = 5) # creating a vector with 5 logical elements  
x
```

```
## [1] FALSE FALSE FALSE FALSE FALSE
```

```
class(x) # checking the class of variable x
```

```
## [1] "logical"
```

```
x[1:3] <- TRUE # indexing the first to third element with TRUE  
x
```

```
## [1] TRUE TRUE TRUE FALSE FALSE
```

## Logical

Logical vectors are created with the `c()` function. Logical vectors can be used to store TRUE or FALSE values. Logical vectors are used in R to represent binary data. Binary data is data that can take on one of two values, such as TRUE or FALSE.

```
s <- c(TRUE, FALSE, TRUE, 1) # creating a vector  
s
```

```
## [1] 1 0 1 1
```

```
as.logical(s) # converting the vector to logical
```

```
## [1] TRUE FALSE TRUE TRUE
```

## List

List is a collection of multiple objects. The objects can be of different classes. Lists are created with the `list()` function

```
q <- list("Hello World", 2015L, TRUE, 32.1) # creating a list  
q
```

```
## [[1]]  
## [1] "Hello World"  
##  
## [[2]]  
## [1] 2015  
##  
## [[3]]  
## [1] TRUE  
##  
## [[4]]  
## [1] 32.1
```

```
class(q[[2]]) # Checking the class of list 2
```

```
## [1] "integer"
```

```
class(q[[4]]) # Checking the class of list 4
```

```
## [1] "numeric"
```

```
class(q[[1]]) # Checking the class of list 1
```

```
## [1] "character"
```

## Matrix

Matrix is a two-dimensional array. It is created with the `matrix()` function. The `matrix()` function takes a vector as input and reshapes it into a matrix. The `nrow` argument specifies the number of rows in the matrix, and the `ncol` argument specifies the number of columns in the matrix.

```
mat <- c(2,4,5,7) # creating a vector
dim(mat) <- c(2,2) # creating a matrix with 2 rows and 2 columns
mat
```

```
##      [,1] [,2]
## [1,]    2    5
## [2,]    4    7
```

```
mar = c(2,4,5,7,8,9) # creating a vector
dim(mar) <- c(3,2) # creating a matrix with 3 rows and 2 columns
mar
```

```
##      [,1] [,2]
## [1,]    2    7
## [2,]    4    8
## [3,]    5    9
```

```
temp <- c(3,4,5,5.6,6,7) # creating a vector
mati <- matrix(temp, nrow = 2, ncol = 3, byrow = TRUE) # creating a matrix with 2 rows and 3 columns
mati
```

```
##      [,1] [,2] [,3]
## [1,]  3.0    4    5
## [2,]  5.6    6    7
```

```
temp <- c(3,4,5,5.6,6,7, 8, 9, 10) # creating a vector
mato <- matrix(temp, nrow = 3, ncol = 3, byrow = TRUE) # creating a matrix with 3 rows and 3 columns
mato
```

```
##      [,1] [,2] [,3]
## [1,]  3.0    4    5
## [2,]  5.6    6    7
## [3,]  8.0    9   10
```

```
# Default byrow = FALSE
temp <- c(3,4,5,5.6,6,7) # creating a vector
mati <- matrix(temp, nrow = 2, ncol = 3, byrow = FALSE) # creating a matrix with 2 rows and 3 columns
mati
```

```
##      [,1] [,2] [,3]
## [1,]    3  5.0    6
## [2,]    4  5.6    7
```

```
t1 <- c(23, 55) # creating a vector
t2 <- c(34, 45) # creating a vector
```

```
# By rows
rbind(t1,t2) # binding them by their rows
```

```
##      [,1] [,2]
## t1    23   55
## t2    34   45
```

```
t3 <- c(32, 50)
t4 <- c(43, 54)
```

```
# By columns
cbind(t3,t4) # binding them by their columns
```

```
##      t3 t4
## [1,] 32 43
## [2,] 50 54
```

## Factors and Nominal Data

Factors are used to represent categorical data in R. Factors are created with the `factor()` function. The `factor()` function takes a vector as input and converts it into a factor. Factors are used to represent nominal data, which is data that has no inherent order.

```
factor <- c("Yes","No","No","Yes") # creating a vector
factor # use to encode vectors as factors
```

```
## [1] "Yes" "No"  "No"  "Yes"
```

```
f <- factor(c("Yes","No","No","Yes"), levels = c("Yes","No"), ordered = TRUE) # creating a factor
f
```

```
## [1] Yes No  No  Yes
## Levels: Yes < No
```



## Missing Values

Missing values are represented by the NA value in R. The `is.na()` function can be used to check if a value is missing. The `is.na()` function returns **TRUE** if the value is missing and **FALSE** otherwise.

```
x <- NA # Missing number
x
```

```
## [1] NA
```

```
is.na(x) # checking if it is a missing number
```

```
## [1] TRUE
```

```
u <- 0/0 # Missing number
u
```

```
## [1] NaN
```

```
class(u) # checking for the class of variable u
```

```
## [1] "numeric"
```

## Dataframe

Data frames are used to store tabular data in R. Data frames are created with the `data.frame()` function. The `data.frame()` function takes vectors as input and combines them into a data frame. Data frames are used to store data in a structured format.

```
a <- c("Charles","Richmond","Nicholas") # creating a vector
b <- c(12, 23, 45) # creating a vector
c <- c(FALSE,TRUE,TRUE) # creating a vector

dfr <- data.frame(Username = a, Age = b, Adult = c) # creating a dataframe
dfr
```

```
##   Username Age Adult
## 1  Charles  12 FALSE
## 2 Richmond  23  TRUE
## 3 Nicholas  45  TRUE
```

```
# First Row
dfr[1,] # accessing row 1 of the dataframe
```

```
##   Username Age Adult
## 1  Charles  12 FALSE
```

```
# First Column
dfr[,1] # accessing column 1 [Username] of the dataframe
```

```
## [1] "Charles" "Richmond" "Nicholas"
```

```
# Selecting only Age Column
dfr$Age
```

```
## [1] 12 23 45
```

```
# Selecting only Username Column
dfr$Username
```

```
## [1] "Charles" "Richmond" "Nicholas"
```

```
# Selecting only Adult Column
dfr$Adult
```

```
## [1] FALSE TRUE TRUE
```

## Reading Data From File

Reading data from a file is a common task in data analysis. R provides functions to read data from various file formats, such as CSV, Excel, and text files. The `read.csv()` function is used to read data from a CSV file. The `read.csv()` function takes the path to the CSV file as input and returns a data frame. Sample data is provided in the Training `r.csv` file.

```
### Importing Datasets
```

```
library(readxl) # Importing the readxl package
```

```
dat <- read.csv("C:/Users/HP/Desktop/Data Science/Machine learning/Training r.csv") # reading the dataset
#print(dat, na.rm = TRUE)
head(dat) # displaying the first few rows of the dataset
```

```
##   itching skin_rash nodal_skin_eruptions continuous_sneezing shivering chills
## 1      1         1             1                0            0        0
## 2      0         1             1                0            0        0
## 3      1         0             1                0            0        0
## 4      1         1             0                0            0        0
## 5      1         1             1                0            0        0
## 6      0         1             1                0            0        0
##   joint_pain stomach_pain acidity ulcers_on_tongue muscle_wasting vomiting
## 1          0           0        0                0                0        0
## 2          0           0        0                0                0        0
## 3          0           0        0                0                0        0
## 4          0           0        0                0                0        0
## 5          0           0        0                0                0        0
## 6          0           0        0                0                0        0
##   burning_micturition spotting_urination fatigue weight_gain anxiety
## 1                   0                0        0                0        0
```

## 2	0	0	0	0	0	
## 3	0	0	0	0	0	
## 4	0	0	0	0	0	
## 5	0	0	0	0	0	
## 6	0	0	0	0	0	
##	cold_hands_and_feets	mood_swings	weight_loss	restlessness	lethargy	
## 1	0	0	0	0	0	
## 2	0	0	0	0	0	
## 3	0	0	0	0	0	
## 4	0	0	0	0	0	
## 5	0	0	0	0	0	
## 6	0	0	0	0	0	
##	patches_in_throat	irregular_sugar_level	cough	high_fever	sunken_eyes	
## 1	0	0	0	0	0	
## 2	0	0	0	0	0	
## 3	0	0	0	0	0	
## 4	0	0	0	0	0	
## 5	0	0	0	0	0	
## 6	0	0	0	0	0	
##	breathlessness	sweating	dehydration	indigestion	headache	yellowish_skin
## 1	0	0	0	0	0	0
## 2	0	0	0	0	0	0
## 3	0	0	0	0	0	0
## 4	0	0	0	0	0	0
## 5	0	0	0	0	0	0
## 6	0	0	0	0	0	0
##	dark_urine	nausea	loss_of_appetite	pain_behind_the_eyes	back_pain	
## 1	0	0	0	0	0	
## 2	0	0	0	0	0	
## 3	0	0	0	0	0	
## 4	0	0	0	0	0	
## 5	0	0	0	0	0	
## 6	0	0	0	0	0	
##	constipation	abdominal_pain	diarrhoea	mild_fever	yellow_urine	
## 1	0	0	0	0	0	
## 2	0	0	0	0	0	
## 3	0	0	0	0	0	
## 4	0	0	0	0	0	
## 5	0	0	0	0	0	
## 6	0	0	0	0	0	
##	yellowing_of_eyes	acute_liver_failure	fluid_overload	swelling_of_stomach		
## 1	0	0	0	0	0	
## 2	0	0	0	0	0	
## 3	0	0	0	0	0	
## 4	0	0	0	0	0	
## 5	0	0	0	0	0	
## 6	0	0	0	0	0	
##	swelled_lymph_nodes	malaise	blurred_and_distorted_vision	phlegm		
## 1	0	0	0	0	0	
## 2	0	0	0	0	0	
## 3	0	0	0	0	0	
## 4	0	0	0	0	0	
## 5	0	0	0	0	0	
## 6	0	0	0	0	0	

##	throat_irritation	redness_of_eyes	sinus_pressure	runny_nose	congestion
## 1	0	0	0	0	0
## 2	0	0	0	0	0
## 3	0	0	0	0	0
## 4	0	0	0	0	0
## 5	0	0	0	0	0
## 6	0	0	0	0	0
##	chest_pain	weakness_in_limbs	fast_heart_rate	pain_during_bowel_movements	
## 1	0	0	0		0
## 2	0	0	0		0
## 3	0	0	0		0
## 4	0	0	0		0
## 5	0	0	0		0
## 6	0	0	0		0
##	pain_in_anal_region	bloody_stool	irritation_in_anus	neck_pain	dizziness
## 1	0	0		0	0
## 2	0	0		0	0
## 3	0	0		0	0
## 4	0	0		0	0
## 5	0	0		0	0
## 6	0	0		0	0
##	cramps	bruising	obesity	swollen_legs	swollen_blood_vessels
## 1	0	0	0	0	0
## 2	0	0	0	0	0
## 3	0	0	0	0	0
## 4	0	0	0	0	0
## 5	0	0	0	0	0
## 6	0	0	0	0	0
##	puffy_face_and_eyes	enlarged_thyroid	brittle_nails	swollen_extremeties	
## 1	0	0	0		0
## 2	0	0	0		0
## 3	0	0	0		0
## 4	0	0	0		0
## 5	0	0	0		0
## 6	0	0	0		0
##	excessive_hunger	extra_marital_contacts	drying_and_tingling_lips		
## 1	0		0		0
## 2	0		0		0
## 3	0		0		0
## 4	0		0		0
## 5	0		0		0
## 6	0		0		0
##	slurred_speech	knee_pain	hip_joint_pain	muscle_weakness	stiff_neck
## 1	0	0	0	0	0
## 2	0	0	0	0	0
## 3	0	0	0	0	0
## 4	0	0	0	0	0
## 5	0	0	0	0	0
## 6	0	0	0	0	0
##	swelling_joints	movement_stiffness	spinning_movements	loss_of_balance	
## 1	0	0	0	0	0
## 2	0	0	0	0	0
## 3	0	0	0	0	0
## 4	0	0	0	0	0

## 5	0	0	0	0
## 6	0	0	0	0
##	unsteadiness	weakness_of_one_body_side	loss_of_smell	bladder_discomfort
## 1	0	0	0	0
## 2	0	0	0	0
## 3	0	0	0	0
## 4	0	0	0	0
## 5	0	0	0	0
## 6	0	0	0	0
##	foul_smell_of_urine	continuous_feel_of_urine	passage_of_gases	
## 1	0	0	0	
## 2	0	0	0	
## 3	0	0	0	
## 4	0	0	0	
## 5	0	0	0	
## 6	0	0	0	
##	internal_itching	toxic_look_typhos.	depression	irritability
## 1	0	0	0	0
## 2	0	0	0	0
## 3	0	0	0	0
## 4	0	0	0	0
## 5	0	0	0	0
## 6	0	0	0	0
##	altered_sensorium	red_spots_over_body	belly_pain	abnormal_menstruation
## 1	0	0	0	0
## 2	0	0	0	0
## 3	0	0	0	0
## 4	0	0	0	0
## 5	0	0	0	0
## 6	0	0	0	0
##	dischromic_patches	watering_from_eyes	increased_appetite	polyuria
## 1	1	0	0	0
## 2	1	0	0	0
## 3	1	0	0	0
## 4	1	0	0	0
## 5	0	0	0	0
## 6	1	0	0	0
##	family_history	mucoid_sputum	rusty_sputum	lack_of_concentration
## 1	0	0	0	0
## 2	0	0	0	0
## 3	0	0	0	0
## 4	0	0	0	0
## 5	0	0	0	0
## 6	0	0	0	0
##	visual_disturbances	receiving_blood_transfusion		
## 1	0	0		
## 2	0	0		
## 3	0	0		
## 4	0	0		
## 5	0	0		
## 6	0	0		
##	receiving_unsterile_injections	coma	stomach_bleeding	distention_of_abdomen
## 1		0	0	0
## 2		0	0	0

```

## 3          0      0          0          0
## 4          0      0          0          0
## 5          0      0          0          0
## 6          0      0          0          0
## history_of_alcohol_consumption fluid_overload.1 blood_in_sputum
## 1          0          0          0
## 2          0          0          0
## 3          0          0          0
## 4          0          0          0
## 5          0          0          0
## 6          0          0          0
## prominent_veins_on_calf palpitations painful_walking pus_filled_pimples
## 1          0          0          0          0
## 2          0          0          0          0
## 3          0          0          0          0
## 4          0          0          0          0
## 5          0          0          0          0
## 6          0          0          0          0
## blackheads scurring skin_peeling silver_like_dusting small_dents_in_nails
## 1          0          0          0          0          0
## 2          0          0          0          0          0
## 3          0          0          0          0          0
## 4          0          0          0          0          0
## 5          0          0          0          0          0
## 6          0          0          0          0          0
## inflammatory_nails blister red_sore_around_nose yellow_crust_ooze
## 1          0          0          0          0
## 2          0          0          0          0
## 3          0          0          0          0
## 4          0          0          0          0
## 5          0          0          0          0
## 6          0          0          0          0
## prognosis X
## 1 Fungal infection NA
## 2 Fungal infection NA
## 3 Fungal infection NA
## 4 Fungal infection NA
## 5 Fungal infection NA
## 6 Fungal infection NA

```

```

data <- read_xlsx("C:/Users/HP/Desktop/Data Science/Pandas/Copy of V1- UN Data on Refugees (AiCE __ Data
head(data) # displaying the first few rows of the dataset

```

```

## # A tibble: 6 x 8
## Country or territory of asylum or r~1 Country or territory~2 Year 'Refugees*'
## <chr> <chr> <dbl> <dbl>
## 1 Afghanistan Iran (Islamic Rep. of) 2021 38
## 2 Afghanistan Pakistan 2021 72188
## 3 Albania China 2021 14
## 4 Albania Egypt 2021 5
## 5 Albania Iraq 2021 5
## 6 Albania Serbia and Kosovo: S/~ 2021 57
## # i abbreviated names: 1: 'Country or territory of asylum or residence',
## # 2: 'Country or territory of origin'

```

```
## # i 4 more variables: 'Refugees assisted by UNHCR' <dbl>,
## #   'Total refugees and people in refugee-like situations**' <dbl>,
## #   'Total refugees and people in refugee-like situations assisted by UNHCR' <dbl>,
## #   'Total Administrative Cost for Host Country' <dbl>
```

## Sequence Creation

Sequence is a collection of numbers in a specific order. Sequences can be created in R using the `:` operator, the `seq()` function, and the `rep()` function. The `:` operator is used to create a sequence of numbers from a starting value to an ending value. The `seq()` function is used to create a sequence of numbers with a specified start, end, and step size. The `rep()` function is used to repeat a sequence of numbers a specified number of times.

```
v <- (10:20) # creating a sequence
v # start from 10 and end at 20
```

```
## [1] 10 11 12 13 14 15 16 17 18 19 20
```

```
w <- (-5:9)
w # start from -5 and end at 9
```

```
## [1] -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9
```

```
qw <- seq(2,34,2) # creating a sequence
qw # start from 2 and end at 34 with a moving step of 2
```

```
## [1] 2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34
```

```
iqw <- seq(2,34,length = 6) # creating a sequence
iqw # start from 2 and end at 34 with a length of 6
```

```
## [1] 2.0 8.4 14.8 21.2 27.6 34.0
```

```
repe <- rep(1:4,4) # creating a sequence
repe # repeat from 1 to 4, 4 times
```

```
## [1] 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4
```

```
eq <- rep("Hello Ann", 5) # creating a sequence
eq # repeat from Hello Ann, 5 times
```

```
## [1] "Hello Ann" "Hello Ann" "Hello Ann" "Hello Ann" "Hello Ann"
```

```
we <- seq(1,15, 2) # creating a sequence
we # start from 1 and end at 15 with a step of 2
```

```
## [1] 1 3 5 7 9 11 13 15
```

```
we[1:5] # slicing from index 1 to 5
```

```
## [1] 1 3 5 7 9
```

```
class(we) # checking the class of we
```

```
## [1] "numeric"
```

```
fo <- list("Hello","Hi","Hey") # creating a list
```

```
unlist(fo)
```

```
## [1] "Hello" "Hi"      "Hey"
```

```
fo[c(1,2)] # for several elements
```

```
## [[1]]  
## [1] "Hello"  
##  
## [[2]]  
## [1] "Hi"
```

```
fo[c(1,2,3)] # for several elements
```

```
## [[1]]  
## [1] "Hello"  
##  
## [[2]]  
## [1] "Hi"  
##  
## [[3]]  
## [1] "Hey"
```

```
fo[[2]] # for only one element
```

```
## [1] "Hi"
```

```
class(fo[[3]]) # checking the class of the third element
```

```
## [1] "character"
```

```
wi <- list(age = c(12,23,45), height = c(12.3,45.4, 34.5)) # creating a list
```

```
wi
```

```
## $age  
## [1] 12 23 45  
##  
## $height  
## [1] 12.3 45.4 34.5
```



```
class(wi) # checking the class of wi
```

```
## [1] "list"
```

```
# creating a dataframe
```

```
woo <- data.frame(age = c(12,23,45), height = c(12.3,45.4, 34.5))
```

```
woo
```

```
##   age height
```

```
## 1  12   12.3
```

```
## 2  23   45.4
```

```
## 3  45   34.5
```

```
class(woo) # checking the class of woo
```

```
## [1] "data.frame"
```

```
woo$age # selecting only the age list
```

```
## [1] 12 23 45
```

```
woo$height # selecting only the height list
```

```
## [1] 12.3 45.4 34.5
```

```
woo[["age"]] # selecting only the age list
```

```
## [1] 12 23 45
```

```
woo[["h",exact = FALSE]] # partial matching
```

```
## [1] 12.3 45.4 34.5
```

```
class(woo$age) # checking the class of age list
```

```
## [1] "numeric"
```

```
class(woo$height) # checking the class of height list
```

```
## [1] "numeric"
```

```
# creating a matrix with 3 rows and 3 columns
```

```
wr <- matrix(1:9, nrow = 3, ncol = 3, by = TRUE)
```

```
wr # creating a matrix with 3 rows and 3 columns
```

```
##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    4    5    6
## [3,]    7    8    9
```

```
class(wr) # checking the class of wr
```

```
## [1] "matrix" "array"
```

```
class(wr[1,1]) # checking the class of row 1 column 1
```

```
## [1] "integer"
```

```
class(wr[1,1, drop = FALSE]) # checking the class of row 1 column 1
```

```
## [1] "matrix" "array"
```

```
ch <- c(1:9,NA,NA,NA) # creating a vector
```

```
print(ch)
```

```
## [1]  1  2  3  4  5  6  7  8  9 NA NA NA
```

```
i<- is.na(ch) # checking for missing numbers
```

```
i
```

```
## [1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE  TRUE  TRUE
```

```
ch[!i] # removing missing numbers
```

```
## [1] 1 2 3 4 5 6 7 8 9
```

## Vectorization

Vectorization is a technique used in R to perform operations on vectors without using loops. Vectorization allows you to perform operations on vectors more efficiently than using loops. Vectorization is a key concept in R programming and is used to write efficient and concise code.

```
ew <- rnorm(1000) # creating a vector
```

```
er <- rnorm(1000) # creating a vector
```

```
cv <- vector(mode = "numeric", length = 1000) # creating a vector
```

```
# Iteration
```

```
start <- proc.time() # starting the timer
```

```
for (i in 1:1000){
```

```
  cv[i] <- ew[i] + er[i] # adding the two vectors
```

```
}
```

```
proc.time()-start # initiating the timer
```

```
##      user  system elapsed
##      0.01    0.00    0.04
```

```
# Vectorization
start <- proc.time() # starting the timer
cv <- ew + er # adding the two vectors
proc.time()-start # initiating the timer
```

```
##      user  system elapsed
##          0         0         0
```

## Control Structures

Control structures are used to control the flow of a program. Control structures allow you to execute different code blocks based on conditions. Control structures include if-else statements, for loops, while loops, and repeat loops.

```
x <- 20 # assigning 20 to x

if (x < 0) {
  print("Negative!") # checking if x is negative
}else if (x < 10) {
  print("Positive, less than 10!") # checking if x is less than 10
}else {
  print("Number greater than 10!") # checking if x is greater than 10
}
```

```
## [1] "Number greater than 10!"
```

```
x <- -20
if (x < 0) {
  print("Negative!") # checking if x is negative
}else if (x < 10) {
  print("Positive, less than 10!") # checking if x is less than 10
}else {
  print("Number greater than 10!") # checking if x is greater than 10
}
```

```
## [1] "Negative!"
```

```
x <- 6 # assigning 6 to x
if (x < 0) {
  print("Negative!") # checking if x is negative
}else if (x < 10) {
  print("Positive, less than 10!") # checking if x is less than 10
}else {
  print("Number greater than 10!") # checking if x is greater than 10
}
```

```
## [1] "Positive, less than 10!"
```

## For Loop

For loop is used to execute a block of code for a specified number of times. For loops are used when you know the number of iterations in advance. For loops are used to iterate over a sequence of values.

```
for (i in 1:100){  
  cat(i)  
  cat(" ") # inserting spaces between the numbers  
}
```

```
## 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99 100
```

```
letters # lower case
```

```
## [1] "a" "b" "c" "d" "e" "f" "g" "h" "i" "j" "k" "l" "m" "n" "o" "p" "q" "r" "s"  
## [20] "t" "u" "v" "w" "x" "y" "z"
```

```
LETTERS # upper case
```

```
## [1] "A" "B" "C" "D" "E" "F" "G" "H" "I" "J" "K" "L" "M" "N" "O" "P" "Q" "R" "S"  
## [20] "T" "U" "V" "W" "X" "Y" "Z"
```

```
class(letters) #
```

```
## [1] "character"
```

```
for (x in letters){  
  cat(x)  
  cat(" ") # inserting spaces between the letters  
}
```

```
## a b c d e f g h i j k l m n o p q r s t u v w x y z
```

## While loop

While loops are used to execute a block of code as long as a condition is true. While loops are used when you do not know the number of iterations in advance.

```
x <- -1 # assigning -1 to x  
while (x < 5){  
  print(x) #  
  x <- x + 1  
}
```

```
## [1] -1  
## [1] 0  
## [1] 1  
## [1] 2  
## [1] 3  
## [1] 4
```

```
x<- 1
repeat{
print(x)
if (x > 7){
break
}
x <- x + 1
}
```

```
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
```

```
for (i in 1:100){
# Over ride the first 80 iterations
if (i <= 80){
next
}
print(i)
}
```

```
## [1] 81
## [1] 82
## [1] 83
## [1] 84
## [1] 85
## [1] 86
## [1] 87
## [1] 88
## [1] 89
## [1] 90
## [1] 91
## [1] 92
## [1] 93
## [1] 94
## [1] 95
## [1] 96
## [1] 97
## [1] 98
## [1] 99
## [1] 100
```

## Functions

Functions

```
myPrinter <- function(x){
  for (i in seq(x)){
    print("Hello, Charles")
  }
}
myPrinter(3)
```

```
## [1] "Hello, Charles"
## [1] "Hello, Charles"
## [1] "Hello, Charles"
```

```
volume <- function(x=3, y=3, z=3){
  print(x*y*z)
}
volume(y=3,z=5,x=11)
```

```
## [1] 165
```

```
volume()
```

```
## [1] 27
```

```
myPrinter <- function(..., mes){
  print(sum(...))
  print(mes)
}
myPrinter (3, 5, 11, mes= "Hi! Richmond")
```

```
## [1] 19
## [1] "Hi! Richmond"
```

```
#ls() # displaying objects stored in R currently
```

## Iterated Functions

Iterated function systems (IFS) are a method of constructing fractals; the resulting fractals are often self-similar. IFS fractals are more related to set theory than fractal geometry. They were introduced in 1988 by Michael Barnsley using the concept of affine transformations.

## lapply

`lapply` is used to apply a function to each element of a list. `lapply` returns a list of the same length as the input list, where each element is the result of applying the function to the corresponding element of the input list.

```
str(lapply) # checking the structure of lapply
```

```
## function (X, FUN, ...)
```

```
x <- list(a = rnorm(10), b = rnorm(20), c = rnorm(30))
```

```
lapply(x, mean) # checking the mean of x
```

```
## $a
## [1] -0.4574003
##
## $b
## [1] -0.1116678
##
## $c
## [1] -0.01046405
```

```
lapply(x, var) # checking the variance of x
```

```
## $a
## [1] 0.9401963
##
## $b
## [1] 0.6072367
##
## $c
## [1] 0.7275282
```

```
lapply(x, sd) # checking the standard deviation of x
```

```
## $a
## [1] 0.9696372
##
## $b
## [1] 0.7792539
##
## $c
## [1] 0.8529526
```

## sapply

sapply is used to apply a function to each element of a list and simplify the result. sapply returns a vector or matrix instead of a list.

```
str(sapply) # checking the structure of sapply
```

```
## function (X, FUN, ..., simplify = TRUE, USE.NAMES = TRUE)
```

```
xi <- list(a = rnorm(10), b = rnorm(20), c = rnorm(30))
```

```
sapply(xi, mean) # checking the mean of xi
```

```
##           a           b           c
## -0.08244251 -0.29385749  0.08847233
```

```
sapply(xi, var) # checking the variance of xi
```

```
##           a           b           c
## 0.375878 1.131216 0.850656
```

```
sapply(xi, sd) # checking the standard deviation of xi
```

```
##           a           b           c
## 0.6130889 1.0635864 0.9223101
```

## Split

split is used to split a data frame or vector into groups. split returns a list of vectors, where each vector contains the elements of the input data frame or vector that belong to a particular group.

```
dat <- data.frame(subject = 1:6, age = c(15, 17, 16, 20, 21, 23),
  adult = c(FALSE, FALSE, FALSE, TRUE, TRUE, TRUE))

s <- split(dat, dat$adult) # splitting based on the adult column

s # split them according to True and False
```

```
## $'FALSE'
##   subject age adult
## 1         1  15 FALSE
## 2         2  17 FALSE
## 3         3  16 FALSE
##
## $'TRUE'
##   subject age adult
## 4         4  20  TRUE
## 5         5  21  TRUE
## 6         6  23  TRUE
```

```
sapply(s, function(x){
  mean(x[["age"]])
})
```

```
##      FALSE      TRUE
## 16.00000 21.33333
```

```
sapply(s, function(x){
  var(x[["age"]])
})
```

```
##      FALSE      TRUE
## 1.000000 2.333333
```



```
sapply(s, function(x){
sd(x[["age"]])
})
```

```
##      FALSE      TRUE
## 1.000000 1.527525
```

## tapply

tapply is used to apply a function to each group of a vector. tapply returns a vector or matrix, where each element is the result of applying the function to the corresponding group of the input vector.

```
str(tapply)
```

```
## function (X, INDEX, FUN = NULL, ..., default = NA, simplify = TRUE)
```

```
x <- c(rnorm(10),rnorm(10),rnorm(10),rnorm(10))
```

```
f <- gl(4, 10)
```

```
f
```

```
## [1] 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 3 3 3 3 3 3 3 3 4 4 4 4 4 4 4
## [39] 4 4
## Levels: 1 2 3 4
```

```
tapply(x, f, mean)
```

```
##           1           2           3           4
## -0.081708982 -0.006995191  0.523500221 -0.141153999
```

```
tapply(x, f, var)
```

```
##           1           2           3           4
## 0.4216030 0.4889995 0.8129353 1.3410572
```

```
tapply(x, f, sd)
```

```
##           1           2           3           4
## 0.6493096 0.6992850 0.9016292 1.1580402
```

```
### Help
#?c
#?vector
#?sapply
#?lapply
#?tapply
```

## Types, Quality and Data preprocessing

Types, quality and data preprocessing are important steps in data analysis. **Types** refer to the data types of the variables in the dataset. **Quality** refers to the quality of the data, such as missing values and outliers. **Data preprocessing** refers to the steps taken to clean and prepare the data for analysis.

```
wi
```

```
## $age
## [1] 12 23 45
##
## $height
## [1] 12.3 45.4 34.5
```

```
# finding each column maximum
m <- sapply(wi,max)
m
```

```
##      age height
##    45.0    45.4
```

```
# finding each column minimum
n <- sapply(wi,min)
n
```

```
##      age height
##    12.0    12.3
```

## Regularization

Regularization is a technique used to prevent overfitting in machine learning models. Regularization adds a penalty term to the loss function to prevent the model from fitting the training data too closely. Regularization is used to improve the generalization of the model.

```
# Regularization ith range [0,1]
wi$age <- ((wi$age - n[1])/(m[1] - n[1]))*(1 - 0) + 0

wi$height <- ((wi$height - n[2])/(m[2] - n[2]))*(1 - 0)

wi
```

```
## $age
## [1] 0.0000000 0.3333333 1.0000000
##
## $height
## [1] 0.0000000 1.0000000 0.6706949
```

## Dplyr and Tidyr Packages

Dplyr is a package for data manipulation in R. Dplyr provides a set of functions for manipulating data frames, such as selecting columns, filtering rows, and summarizing data. Tidyr is a package for data tidying in R. Tidyr provides functions for reshaping data frames, such as gathering columns into rows and spreading rows into columns.

```
library(dplyr) # Importing the dplyr package

data(airquality) # loading the airquality dataset

class(airquality) # checking the class of airquality
```

```
## [1] "data.frame"
```

```
airquality <- as_tibble(airquality) # converting airquality to a tibble

class(airquality) # checking the class of airquality
```

```
## [1] "tbl_df"      "tbl"        "data.frame"
```

```
airquality # displaying the airquality dataset
```

```
## # A tibble: 153 x 6
##   Ozone Solar.R Wind Temp Month Day
##   <int>   <int> <dbl> <int> <int> <int>
## 1    41    190   7.4    67     5    1
## 2    36    118    8     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
## 7    23    299   8.6    65     5    7
## 8    19     99  13.8    59     5    8
## 9     8     19  20.1    61     5    9
## 10   NA    194   8.6    69     5   10
## # i 143 more rows
```

```
select(airquality, (Ozone), Solar.R, Day) # selecting the Ozone, Solar.R and Day columns
```

```
## # A tibble: 153 x 3
##   Ozone Solar.R Day
##   <int>   <int> <int>
## 1    41    190    1
## 2    36    118    2
## 3    12    149    3
## 4    18    313    4
## 5    NA     NA    5
## 6    28     NA    6
## 7    23    299    7
## 8    19     99    8
```

```
## 9      8      19      9
## 10     NA     194     10
## # i 143 more rows
```

```
select(airquality, -(Wind:Month)) # offsetting Wind and Month from the airquality dataset
```

```
## # A tibble: 153 x 3
##   Ozone Solar.R Day
##   <int>   <int> <int>
## 1    41    190     1
## 2    36    118     2
## 3    12    149     3
## 4    18    313     4
## 5     NA     NA     5
## 6    28     NA     6
## 7    23    299     7
## 8    19     99     8
## 9     8     19     9
## 10   NA    194    10
## # i 143 more rows
```

```
filter(airquality, Month > 5 | Month < 9, Day < 3) # filter values in Month greater than 5 and less than 9
```

```
## # A tibble: 10 x 6
##   Ozone Solar.R Wind Temp Month Day
##   <int>   <int> <dbl> <int> <int> <int>
## 1    41    190  7.4    67     5     1
## 2    36    118   8     72     5     2
## 3     NA    286  8.6    78     6     1
## 4     NA    287  9.7    74     6     2
## 5   135    269  4.1    84     7     1
## 6    49    248  9.2    85     7     2
## 7    39     83  6.9    81     8     1
## 8     9     24 13.8    81     8     2
## 9    96    167  6.9    91     9     1
## 10   78    197  5.1    92     9     2
```

```
filter(airquality, Day == 1 | Day == 2) # filter values of Day = 1 or 2
```

```
## # A tibble: 10 x 6
##   Ozone Solar.R Wind Temp Month Day
##   <int>   <int> <dbl> <int> <int> <int>
## 1    41    190  7.4    67     5     1
## 2    36    118   8     72     5     2
## 3     NA    286  8.6    78     6     1
## 4     NA    287  9.7    74     6     2
## 5   135    269  4.1    84     7     1
## 6    49    248  9.2    85     7     2
## 7    39     83  6.9    81     8     1
## 8     9     24 13.8    81     8     2
## 9    96    167  6.9    91     9     1
## 10   78    197  5.1    92     9     2
```

```
arrange(airquality,Ozone) # arrange based on Ozone
```

```
## # A tibble: 153 x 6
##   Ozone Solar.R Wind Temp Month Day
##   <int>   <int> <dbl> <int> <int> <int>
## 1     1       8  9.7    59     5  21
## 2     4      25  9.7    61     5  23
## 3     6      78 18.4    57     5  18
## 4     7      NA  6.9    74     5  11
## 5     7      48 14.3    80     7  15
## 6     7      49 10.3    69     9  24
## 7     8      19 20.1    61     5   9
## 8     9      24 13.8    81     8   2
## 9     9      36 14.3    72     8  22
## 10    9      24 10.9    71     9  14
## # i 143 more rows
```

```
arrange(airquality, Solar.R) # arrange based on Solar.R
```

```
## # A tibble: 153 x 6
##   Ozone Solar.R Wind Temp Month Day
##   <int>   <int> <dbl> <int> <int> <int>
## 1    16       7  6.9    74     7  21
## 2     1       8  9.7    59     5  21
## 3    23      13 12     67     5  28
## 4    23      14  9.2    71     9  22
## 5     8      19 20.1    61     5   9
## 6    14      20 16.6    63     9  25
## 7     9      24 13.8    81     8   2
## 8     9      24 10.9    71     9  14
## 9     4      25  9.7    61     5  23
## 10   13      27 10.3    76     9  18
## # i 143 more rows
```

```
mutate(airquality, Temp.C = round((Temp - 32) * 5/9)) # creating a new column for Temp.C
```

```
## # A tibble: 153 x 7
##   Ozone Solar.R Wind Temp Month Day Temp.C
##   <int>   <int> <dbl> <int> <int> <int> <dbl>
## 1    41     190  7.4    67     5   1    19
## 2    36     118   8     72     5   2    22
## 3    12     149 12.6    74     5   3    23
## 4    18     313 11.5    62     5   4    17
## 5    NA      NA 14.3    56     5   5    13
## 6    28      NA 14.9    66     5   6    19
## 7    23     299  8.6    65     5   7    18
## 8    19      99 13.8    59     5   8    15
## 9     8      19 20.1    61     5   9    16
## 10   NA     194  8.6    69     5  10    21
## # i 143 more rows
```

```
# Removing rows with missing values on the Ozone and Solar.R features
airquality <- filter(airquality, !is.na(Ozone), !is.na(Solar.R))
airquality
```

```
## # A tibble: 111 x 6
##   Ozone Solar.R Wind Temp Month Day
##   <int>   <int> <dbl> <int> <int> <int>
## 1    41    190  7.4    67     5     1
## 2    36    118   8     72     5     2
## 3    12    149 12.6    74     5     3
## 4    18    313 11.5    62     5     4
## 5    23    299  8.6    65     5     7
## 6    19     99 13.8    59     5     8
## 7     8     19 20.1    61     5     9
## 8    16    256  9.7    69     5    12
## 9    11    290  9.2    66     5    13
## 10   14    274 10.9    68     5    14
## # i 101 more rows
```

```
### print(airquality, n=143)
```

```
# grouping by month
by_month <- group_by (airquality, Month)
by_month
```

```
## # A tibble: 111 x 6
## # Groups:   Month [5]
##   Ozone Solar.R Wind Temp Month Day
##   <int>   <int> <dbl> <int> <int> <int>
## 1    41    190  7.4    67     5     1
## 2    36    118   8     72     5     2
## 3    12    149 12.6    74     5     3
## 4    18    313 11.5    62     5     4
## 5    23    299  8.6    65     5     7
## 6    19     99 13.8    59     5     8
## 7     8     19 20.1    61     5     9
## 8    16    256  9.7    69     5    12
## 9    11    290  9.2    66     5    13
## 10   14    274 10.9    68     5    14
## # i 101 more rows
```

```
# Finding the minimum, mean and maximum value per Month
summarize (by_month, min(Ozone), mean(Ozone), max(Ozone))
```

```
## # A tibble: 5 x 4
##   Month 'min(Ozone)' 'mean(Ozone)' 'max(Ozone)'
##   <int>         <int>         <dbl>         <int>
## 1     5             1         24.1           115
## 2     6            12         29.4            71
## 3     7             7         59.1           135
## 4     8             9          60            168
## 5     9             7         31.4            96
```

```
# Finding the minimum, mean and maximum value per Month
summarize (by_month, min(Day), mean(Day), max(Day))
```

```
## # A tibble: 5 x 4
##   Month 'min(Day)' 'mean(Day)' 'max(Day)'
##   <int>      <int>      <dbl>      <int>
## 1     5          1       16.1         31
## 2     6          7       14.3         20
## 3     7          1       16.2         31
## 4     8          1       17.2         31
## 5     9          1       15.1         30
```

```
# Finding the minimum, mean and maximum value per Month
summarize (by_month, min(Wind), mean(Wind), max(Wind))
```

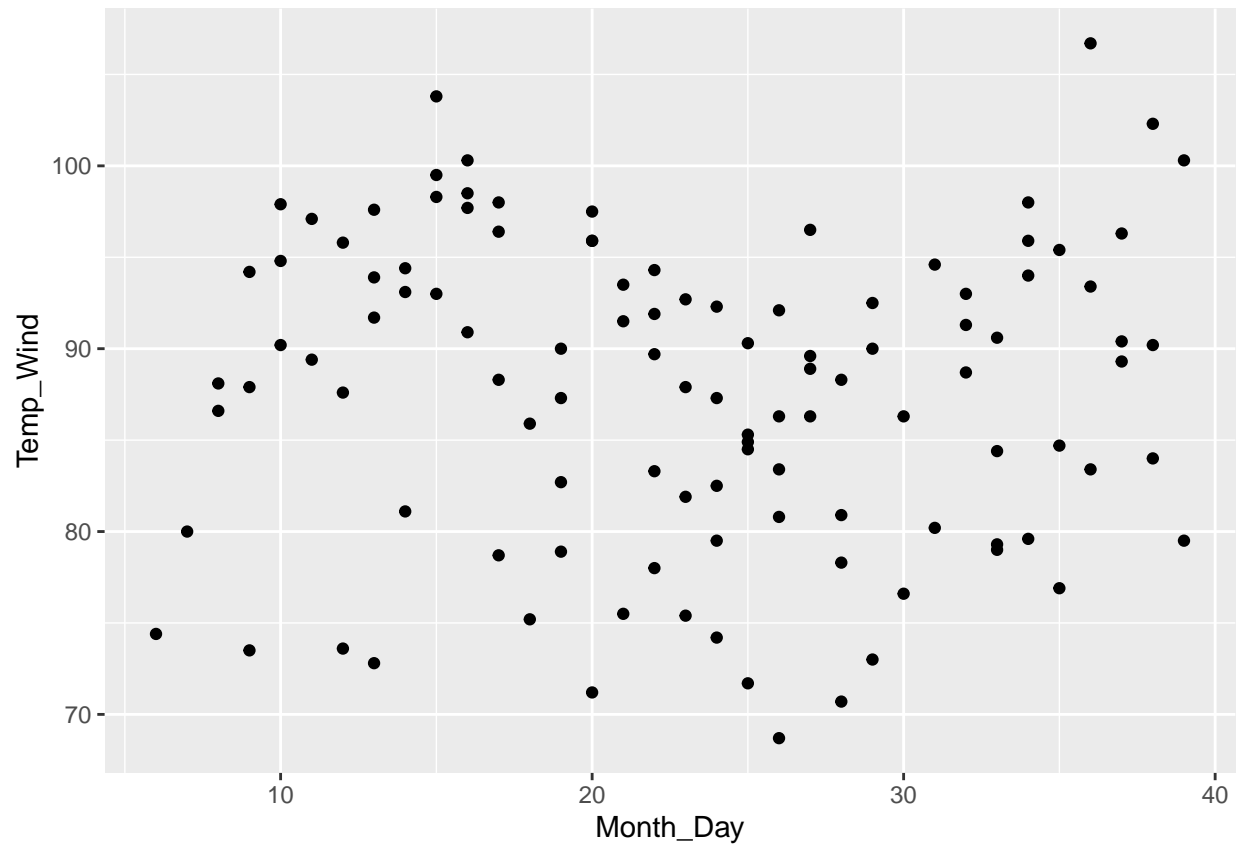
```
## # A tibble: 5 x 4
##   Month 'min(Wind)' 'mean(Wind)' 'max(Wind)'
##   <int>      <dbl>      <dbl>      <dbl>
## 1     5         5.7       11.5       20.1
## 2     6         8        12.2       20.7
## 3     7         4.1        8.52       14.9
## 4     8         2.3        8.86       15.5
## 5     9         2.8       10.1       16.6
```

```
library(tidyr)
library(ggplot2)
```

```
airquality %>% mutate(Month_Day = Month + Day, Temp_Wind = Temp + Wind)
```

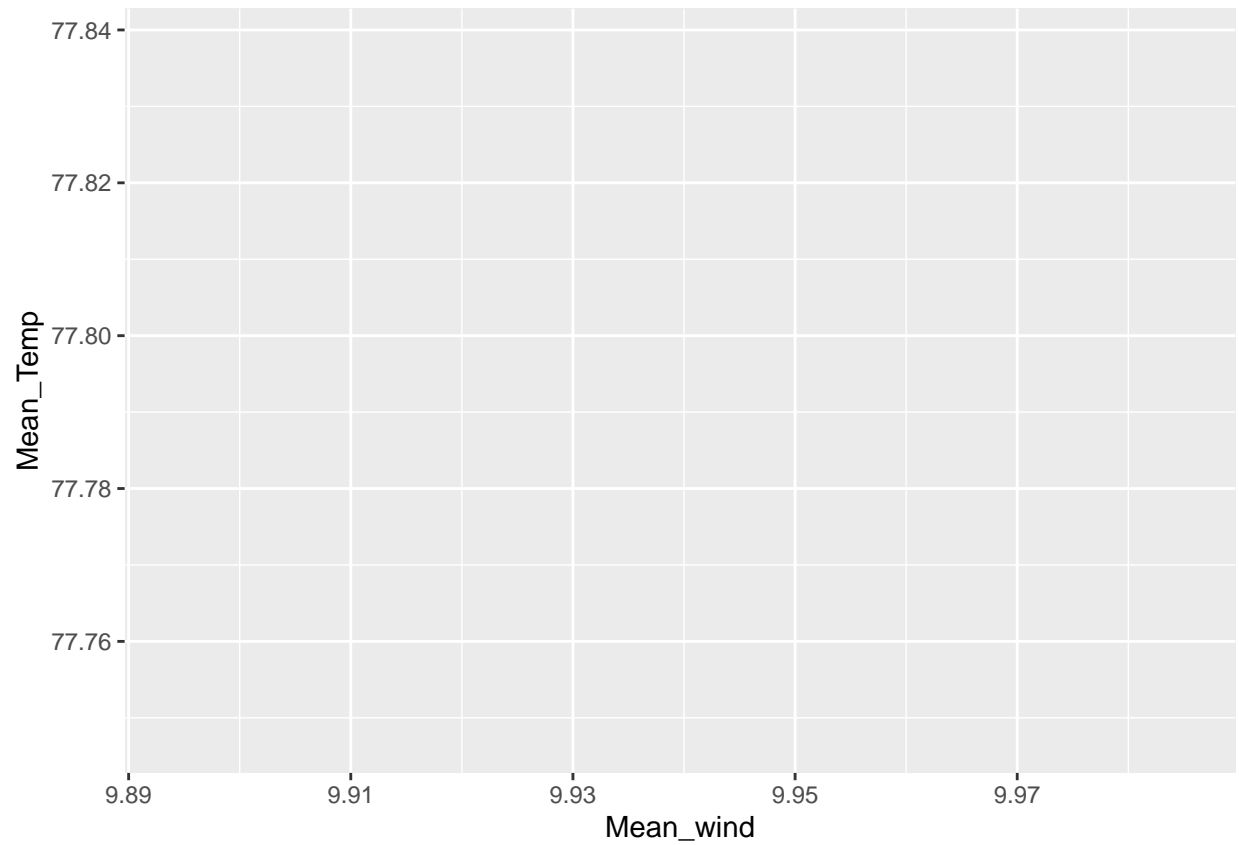
```
## # A tibble: 111 x 8
##   Ozone Solar.R Wind Temp Month Day Month_Day Temp_Wind
##   <int>   <int> <dbl> <int> <int> <int>      <int>      <dbl>
## 1    41    190  7.4   67    5    1         6       74.4
## 2    36    118  8     72    5    2         7       80
## 3    12    149 12.6   74    5    3         8      86.6
## 4    18    313 11.5   62    5    4         9      73.5
## 5    23    299  8.6   65    5    7        12      73.6
## 6    19     99 13.8   59    5    8        13      72.8
## 7     8     19 20.1   61    5    9        14      81.1
## 8    16    256  9.7   69    5   12        17      78.7
## 9    11    290  9.2   66    5   13        18      75.2
## 10   14    274 10.9   68    5   14        19      78.9
## # i 101 more rows
```

```
airquality %>% transmute(Month_Day = Month + Day, Temp_Wind = Temp + Wind) %>% ggplot() + geom_point(aes(
```

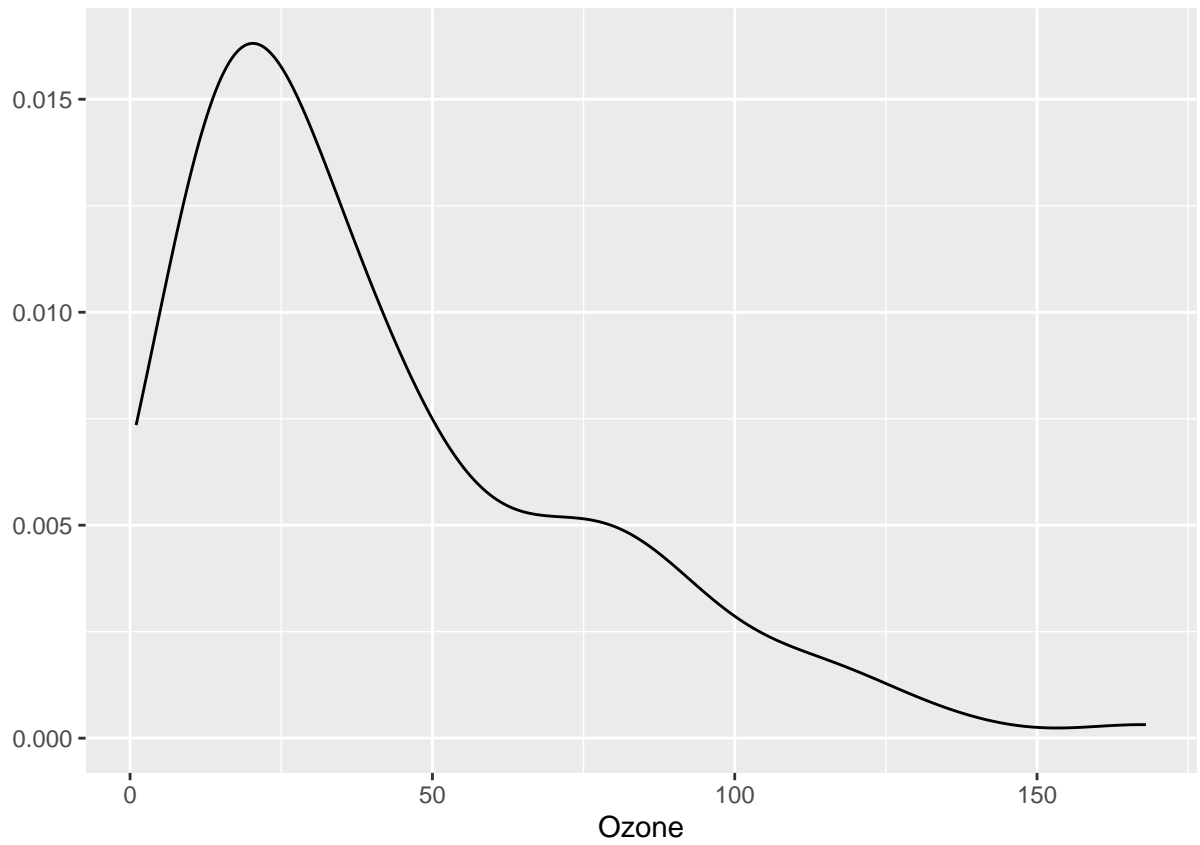


```
airquality %>% transmute(Mean_wind = mean(Wind), Mean_Temp = mean(Temp)) %>% ggplot(aes(x = Mean_wind, y = Mean_Temp))
```

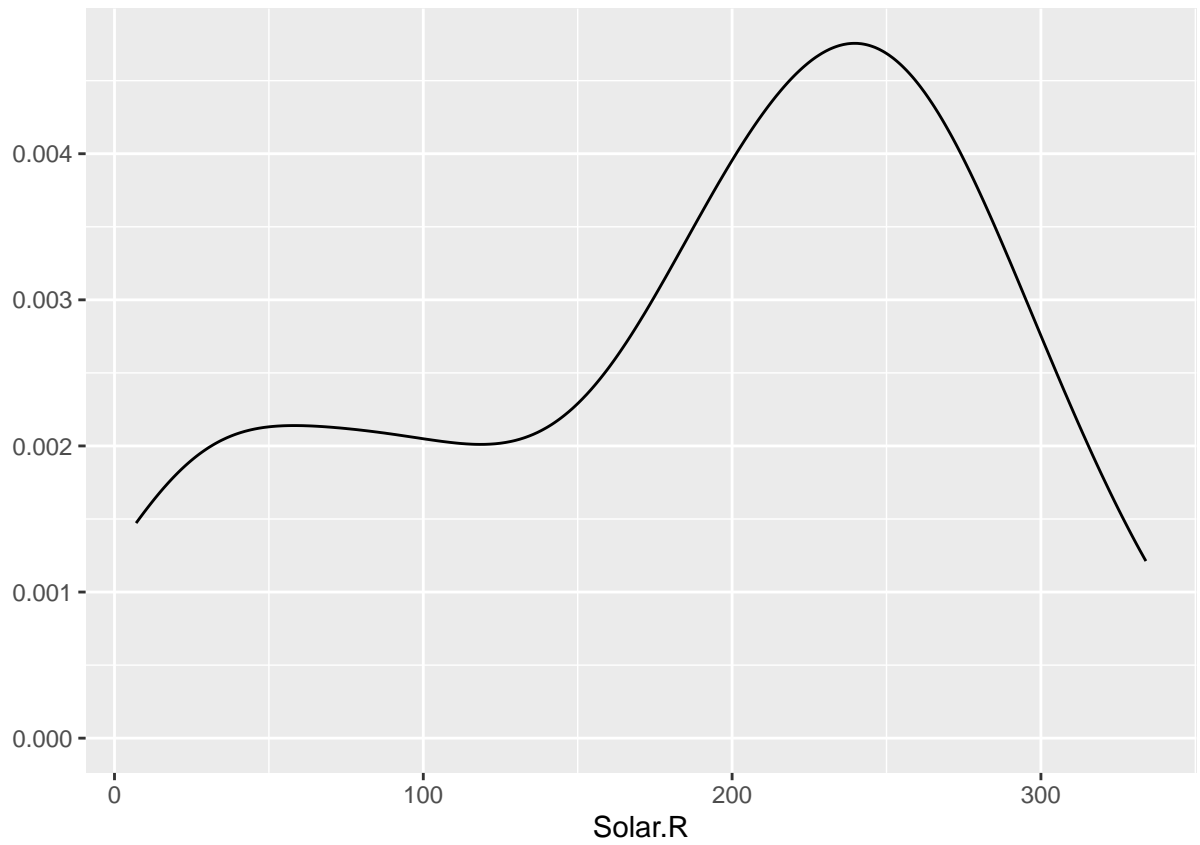




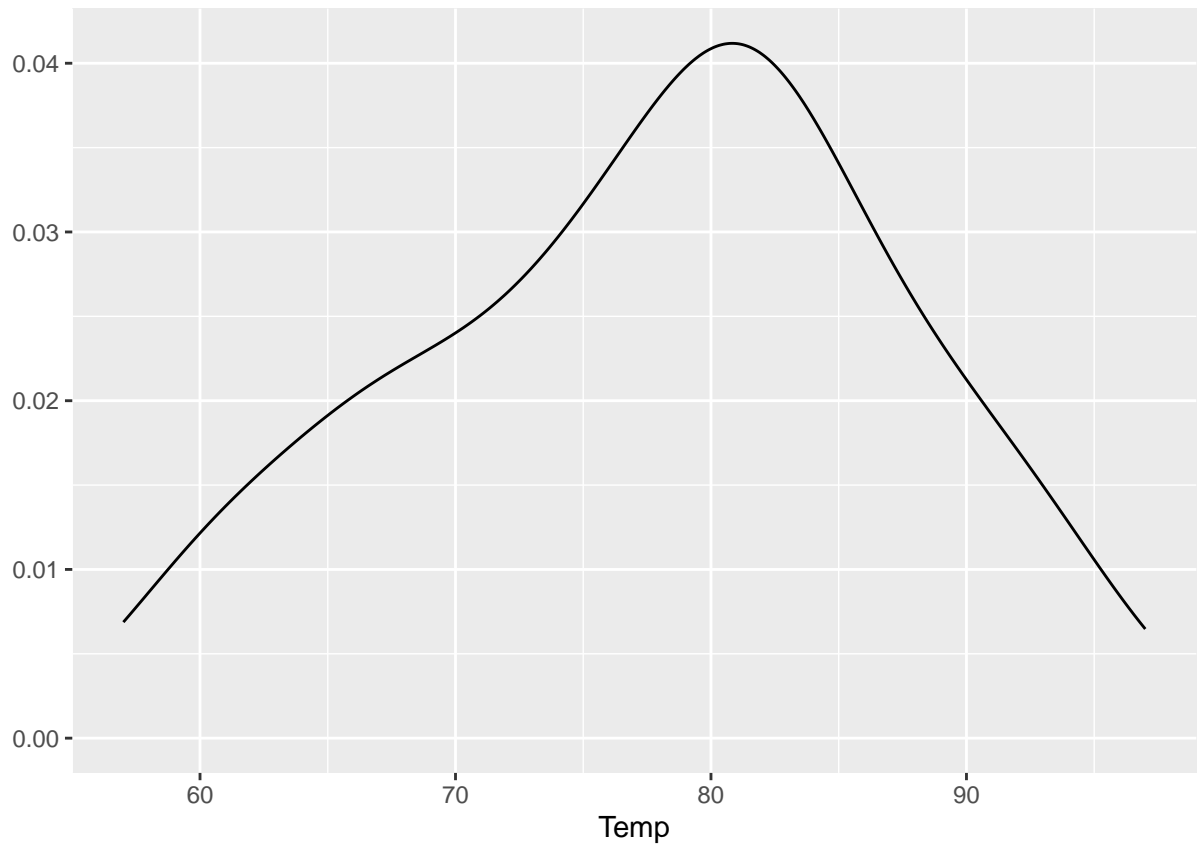
```
airquality %>% qplot (Ozone, data = ., geom = "density")
```



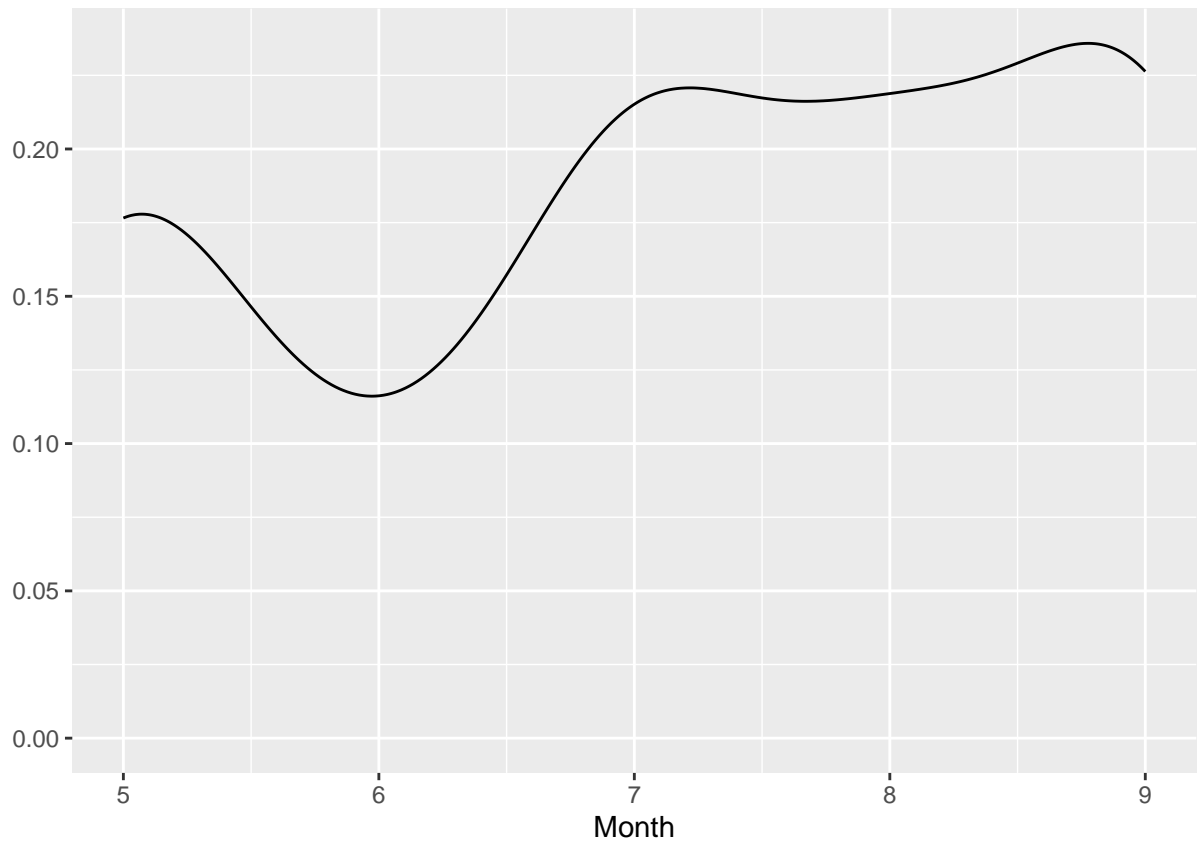
```
airquality %>% qplot (Solar.R, data = ., geom = "density")
```



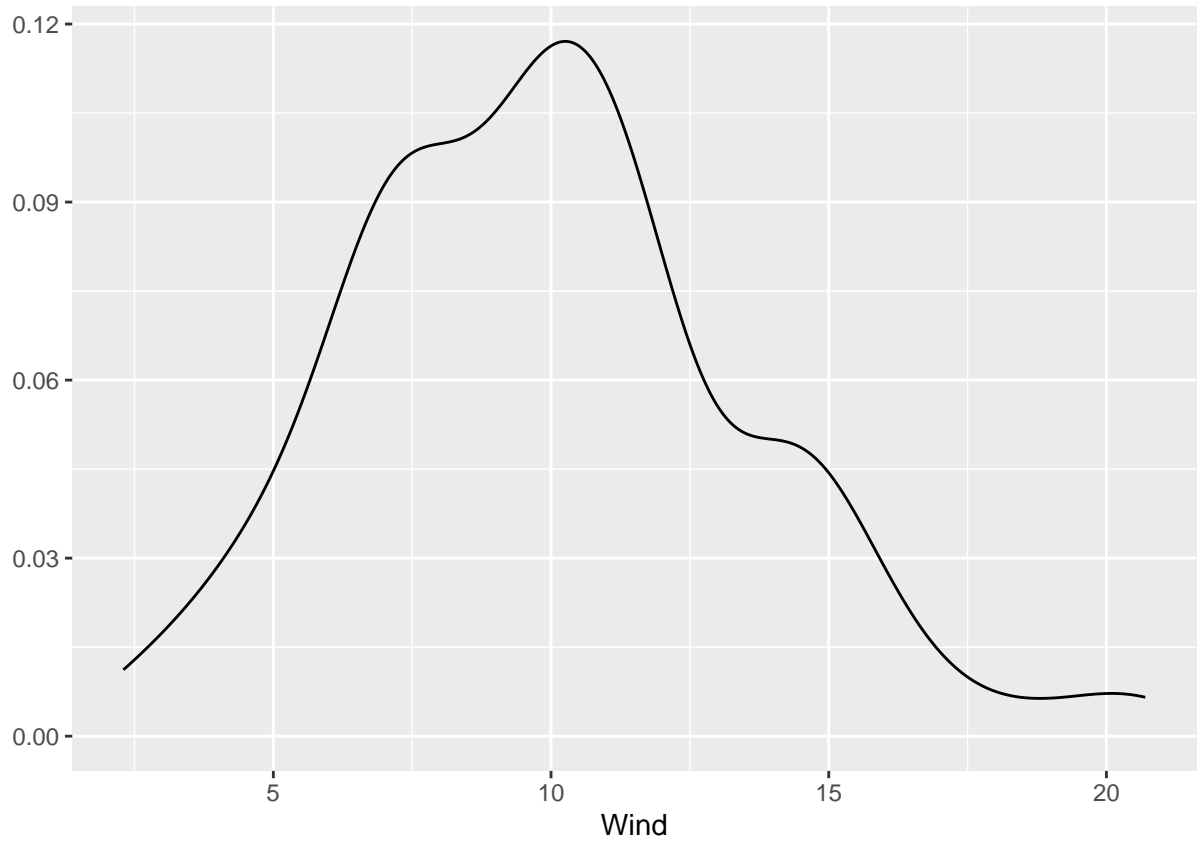
```
airquality %>% qplot (Temp, data = ., geom = "density")
```



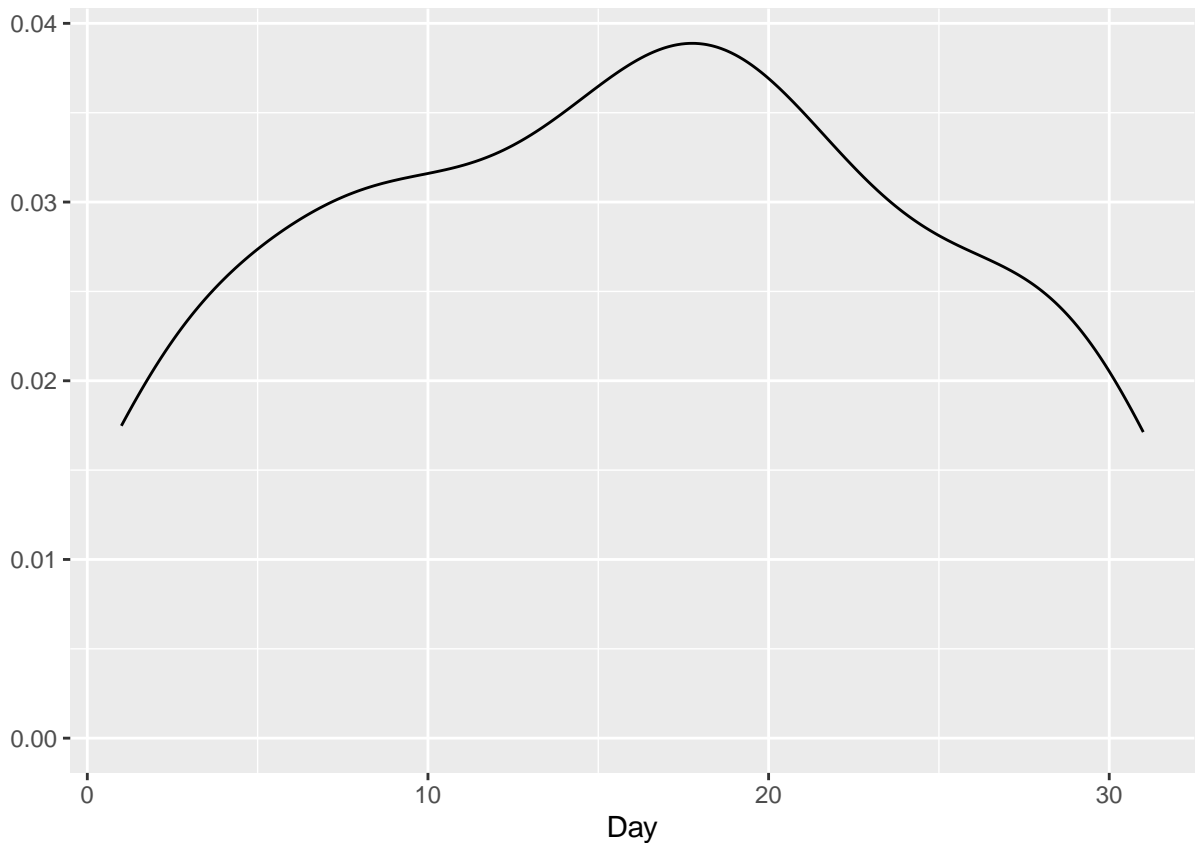
```
airquality %>% qplot (Temp, data = ., geom = "density")
```



```
airquality %>% qplot (Wind, data = ., geom = "density")
```



```
airquality %>% qplot (Day, data = ., geom = "density")
```



## Statistical Summary and Visualization

Statistical summary and visualization are important steps in data analysis. Statistical summary provides a summary of the data, such as the mean, median, and standard deviation. Visualization provides a visual representation of the data, such as bar charts and histograms.

```
internet_usage = c(22,0, 7,12,5, 33, 14, 8, 0, 9)
```

```
#internet_usage
```

```
mean(internet_usage) # finding the mean of internet_usage
```

```
## [1] 11
```

```
net_usage = c(22,0,7,12,5,NA,33,14,8,NA,0,9)
```

```
# net_usage
```

```
mean(na.omit(net_usage)) # finding the mean of net_usage with missing numbers
```

```
## [1] 11
```

```
median(net_usage, na.rm = TRUE)
```

```
## [1] 8.5
```

```

# Minimum, Maximum and Range
A = c(49,33,63,48,54,62,52,64,71,68)

min(A)

## [1] 33

max(A)

## [1] 71

which.min(A)

## [1] 2

which.max(A)

## [1] 9

print(max(A) - min(A))

## [1] 38

range(A)

## [1] 33 71

print(range(A)[2] - range(A)[1])

## [1] 38

summary(A)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   33.00   49.75   58.00   56.40   63.75   71.00

```

## Percentile Values

Percentile values are used to divide a dataset into equal parts. The `quantile()` function is used to calculate percentile values in R. The `quantile()` function takes a vector as input and returns the percentile value for the specified quantile.

```

X = c(3,4,5,6,7,8,10,10,11,12,14,14,14,15,16,17,21,25,27,32)

quantile(X,0.80)

## 80%
## 17.8

```



```
quantile(X,0.50,type = 7)
```

```
## 50%  
## 13
```

```
quantile(X,0.25,type = 7)
```

```
## 25%  
## 7.75
```

```
quantile(X,0.75,type = 7)
```

```
## 75%  
## 16.25
```

```
median(X)
```

```
## [1] 13
```

```
summary(X)
```

```
##      Min. 1st Qu.  Median      Mean 3rd Qu.      Max.  
##      3.00   7.75   13.00   13.55   16.25   32.00
```

```
sd(X)
```

```
## [1] 7.843703
```

```
# cv(X)
```

## Interquartile Range

The interquartile range (IQR) is a measure of statistical dispersion, or how spread out the values in a dataset are. The IQR is calculated as the difference between the 75th percentile (Q3) and the 25th percentile (Q1) of the dataset. The IQR is used to identify outliers in a dataset.

```
# Interquartile Range  
irq = function(X) (quantile(X,0.75) - quantile(X,0.25))  
irq(X)
```

```
## 75%  
## 8.5
```

## Variance and Standard Deviation

Variance and standard deviation are measures of statistical dispersion. Variance is the average of the squared differences between each value in the dataset and the mean of the dataset. Standard deviation is the square root of the variance. Variance and standard deviation are used to measure the spread of the values in a dataset.

```

# Variance and Standard Deviation
course = c(6, 2, 1, 9, 17, 4, 3, 2, 1, 5, 11, 4, 3, 1, 2, 2, 5, 4, 3, 6)

# 1 / course

cf = c(course, 0, course)

cf

## [1] 6 2 1 9 17 4 3 2 1 5 11 4 3 1 2 2 5 4 3 6
## [26] 17 4 3 2 1 5 11 4 3 1 2 2 5 4 3 6

vw <- 2 * course + cf + 1
vw

## [1] 19 7 4 28 52 13 10 7 4 16 34 13 10 4 7 7 16 13 10 19 13 11 5 20 44
## [26] 26 11 8 5 12 28 20 11 6 6 7 13 14 11 16 19

var(course)

## [1] 15.41842

sum((course - mean(course)) ^ 2 / (length(course) - 1))

## [1] 15.41842

sd(course)

## [1] 3.92663

sqrt(var(course))

## [1] 3.92663

std = function(x) sqrt(var(x))

std(course)

## [1] 3.92663

sqrt(course)

## [1] 2.449490 1.414214 1.000000 3.000000 4.123106 2.000000 1.732051 1.414214
## [9] 1.000000 2.236068 3.316625 2.000000 1.732051 1.000000 1.414214 1.414214
## [17] 2.236068 2.000000 1.732051 2.449490

```

```
sum(course)
```

```
## [1] 91
```

```
prod(course)
```

```
## [1] 41878425600
```

```
sort(course)
```

```
## [1] 1 1 1 2 2 2 2 3 3 3 4 4 4 5 5 6 6 9 11 17
```

```
order(course)
```

```
## [1] 3 9 14 2 8 15 16 7 13 19 6 12 18 10 17 1 20 4 11 5
```

```
sqrt(-14 + 9i)
```

```
## [1] 1.149634+3.914289i
```

## Coefficient of Variation

Coefficient of variation (CV) is a measure of relative variability. The CV is calculated as the standard deviation divided by the mean of the dataset. The CV is used to compare the variability of datasets with different units of measurement.

```
cv = function(x) ( sd(x) / mean(x) )  
cv(course)
```

```
## [1] 0.8629955
```

## Visualization of Qualitative Data

Visualization of qualitative data is an important step in data analysis. Qualitative data is data that is categorical or non-numeric. Visualization of qualitative data can help identify patterns and trends in the data. Bar charts, pie charts, and contingency matrices are commonly used to visualize qualitative data.

```
mo = c("car", "car", "bus", "metro", "metro", "car", "metro", "metro", "foot", "car", "foot", "bus", "bus", "metro")  
mo
```

```
## [1] "car" "car" "bus" "metro" "metro" "car" "metro" "metro" "foot"  
## [10] "car" "foot" "bus" "bus" "metro" "metro" "car" "car" "car"  
## [19] "metro" "car"
```

```
table(mo) # creating a table of mo
```

```
## mo  
## bus car foot metro  
## 3 8 2 7
```

```
prop.table(table(mo)) # creating a table of mo
```

```
## mo
##   bus   car  foot metro
## 0.15 0.40 0.10 0.35
```

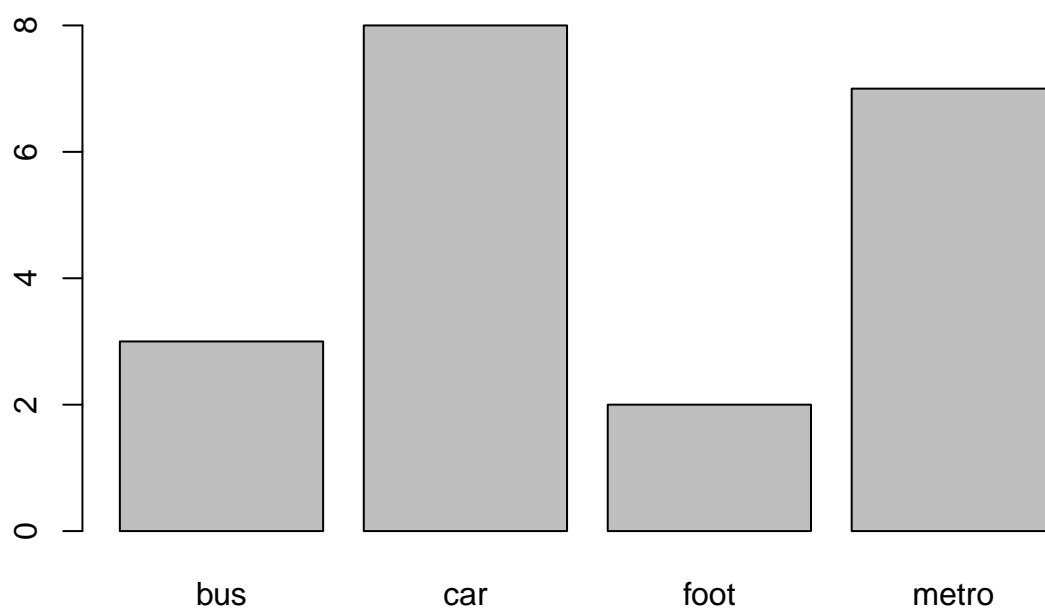
```
data.frame(mo) # creating a dataframe of mo
```

```
##      mo
## 1    car
## 2    car
## 3    bus
## 4  metro
## 5  metro
## 6    car
## 7  metro
## 8  metro
## 9   foot
## 10   car
## 11  foot
## 12   bus
## 13   bus
## 14  metro
## 15  metro
## 16   car
## 17   car
## 18   car
## 19  metro
## 20   car
```

## Bar Charts

Bar charts are used to visualize the frequency of categorical data. Bar charts are used to compare the frequency of different categories in a dataset. Bar charts are used to visualize the distribution of categorical data.

```
barplot(table(mo)) # creating a bar chart of mo
```



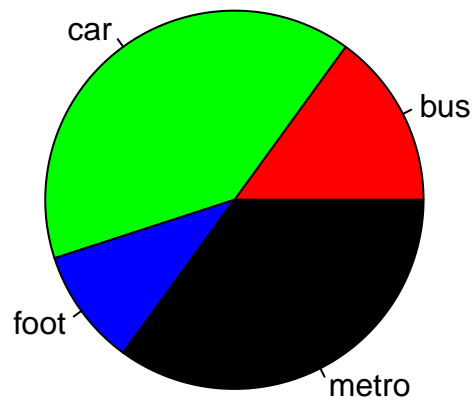
```
barplot(prop.table(table(mo))) # creating a bar chart of mo
```



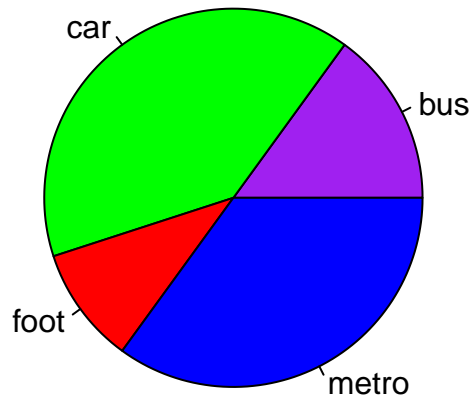
### Pie Chart

Pie charts are used to visualize the proportion of different categories in a dataset. Pie charts are used to compare the proportion of different categories in a dataset. Pie charts are used to visualize the distribution of categorical data.

```
pie(table(mo), col = c ("red", "green", "blue", "black")) # creating a pie chart of mo
```



```
pie(prop.table(table(mo)), col = c("purple", "green", "red", "blue")) # creating a pie chart of mo
```



## Contingency Matrix

A **contingency matrix** is used to visualize the relationship between two categorical variables. A contingency matrix is a two-dimensional table that shows the frequency of each combination of categories in the two variables. A contingency matrix is used to visualize the relationship between two categorical variables.

```
g = c(rep("Male",8), rep("Female",12)) # creating a vector
g
```

```
## [1] "Male" "Male" "Male" "Male" "Male" "Male" "Male" "Male"
## [9] "Female" "Female" "Female" "Female" "Female" "Female" "Female" "Female"
## [17] "Female" "Female" "Female" "Female"
```

```
mg = table(mo,g) # creating a contingency matrix of mo and g
mg
```

```
##      g
## mo   Female Male
## bus      2     1
## car      5     3
## foot     2     0
## metro    3     4
```



```
gm = data.frame(mo,g) # creating a dataframe of mo and g
gm
```

```
##      mo      g
## 1    car    Male
## 2    car    Male
## 3    bus    Male
## 4  metro    Male
## 5  metro    Male
## 6    car    Male
## 7  metro    Male
## 8  metro    Male
## 9   foot Female
## 10   car Female
## 11   foot Female
## 12   bus Female
## 13   bus Female
## 14  metro Female
## 15  metro Female
## 16   car Female
## 17   car Female
## 18   car Female
## 19  metro Female
## 20   car Female
```

```
margin.table(mg, 1) # creating a margin table of mg
```

```
## mo
##   bus   car  foot metro
##     3     8     2     7
```

```
margin.table(mg,2) # creating a margin table of mg
```

```
## g
## Female   Male
##     12     8
```

```
prop.table(mg)      # creating a table of mg
```

```
##      g
## mo    Female Male
##   bus    0.10 0.05
##   car    0.25 0.15
##   foot    0.10 0.00
##   metro    0.15 0.20
```

```
prop.table(mg,1)    # creating a table of mg
```

```
##      g
## mo    Female   Male
```

```
## bus 0.6666667 0.3333333
## car 0.6250000 0.3750000
## foot 1.0000000 0.0000000
## metro 0.4285714 0.5714286
```

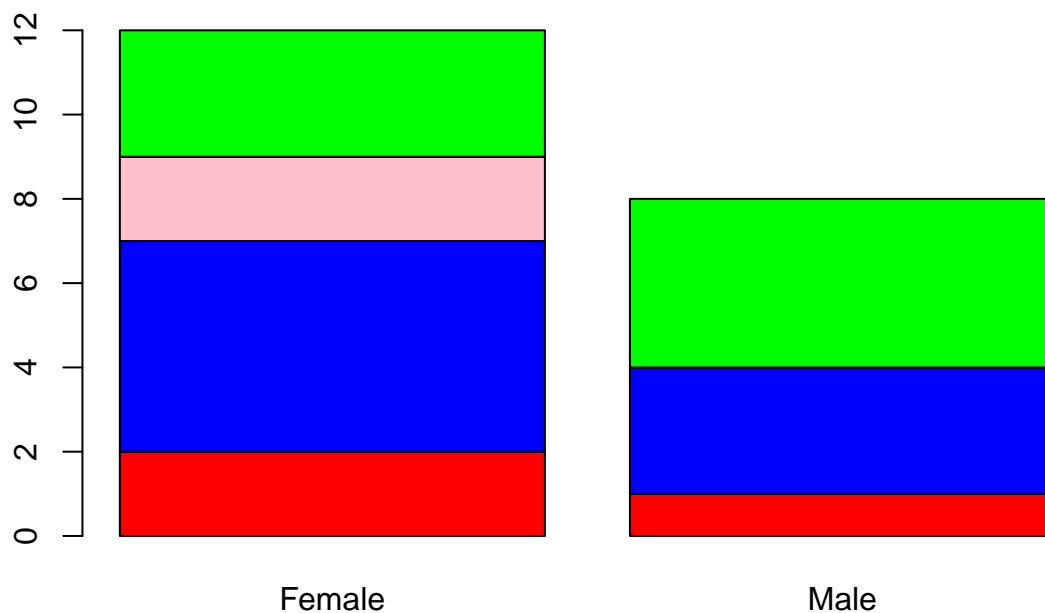
```
prop.table(mg,2) # creating a table of mg
```

```
##      g
## mo   Female   Male
## bus  0.1666667 0.1250000
## car  0.4166667 0.3750000
## foot 0.1666667 0.0000000
## metro 0.2500000 0.5000000
```

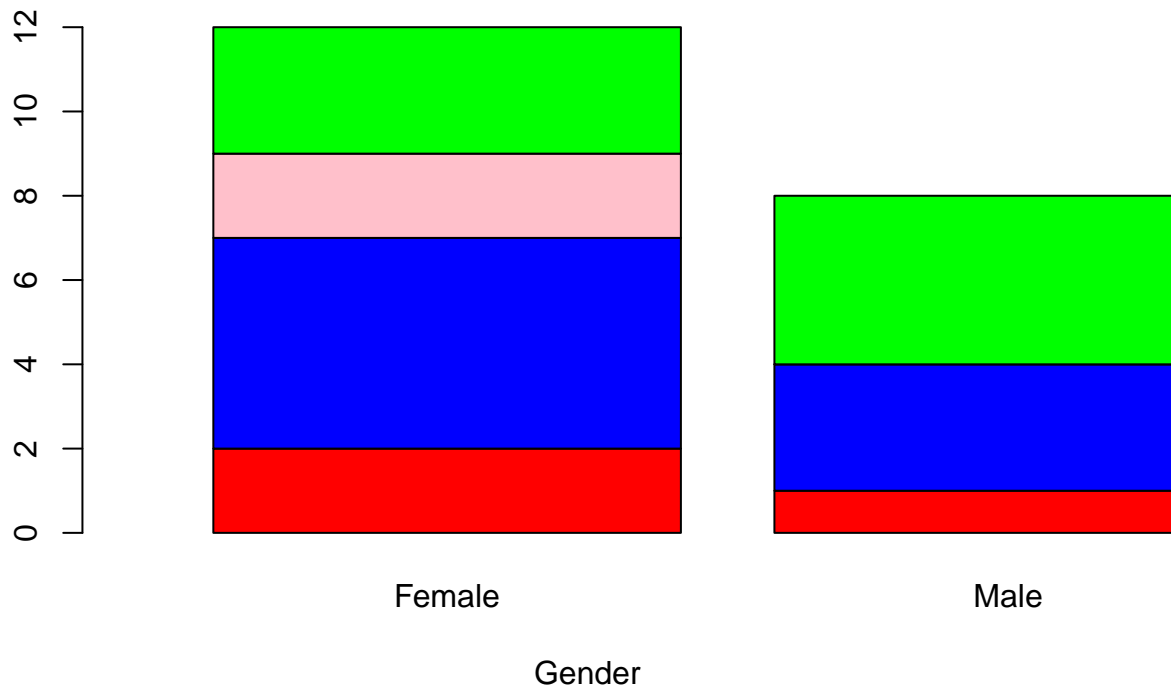
## Stacked Bar Charts and Grouped Bar Charts

Stacked bar charts are used to visualize the relationship between two categorical variables. Stacked bar charts are used to compare the frequency of different categories in one variable for each category in another variable. Stacked bar charts are used to visualize the relationship between two categorical variables.

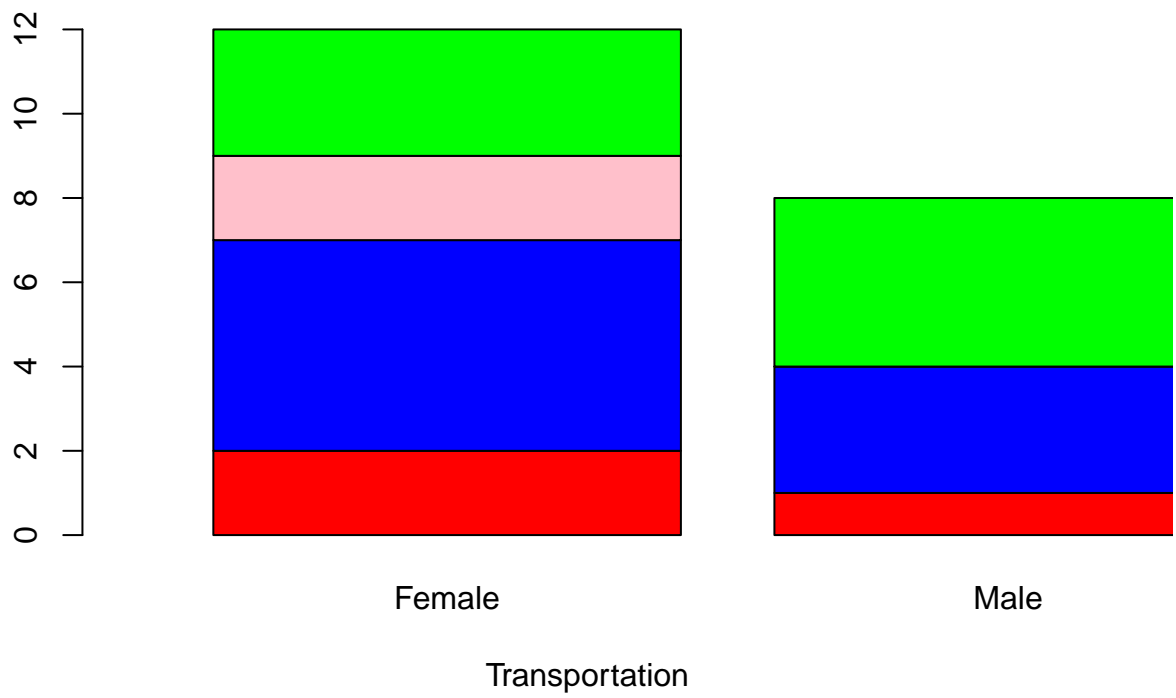
```
barplot(mg, col = c("red", "blue", "pink", "green")) # creating a bar chart of mg
```



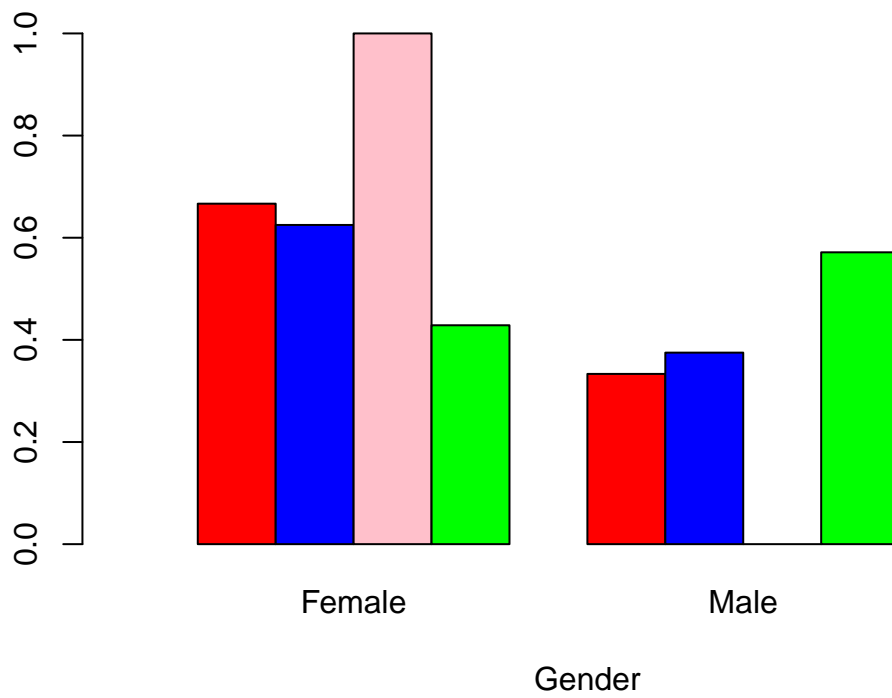
```
barplot(mg,xlim=c(0,2), xlab="Gender", length=length(levels(mo)), col = c("red","blue", "pink","green")) # crea
```



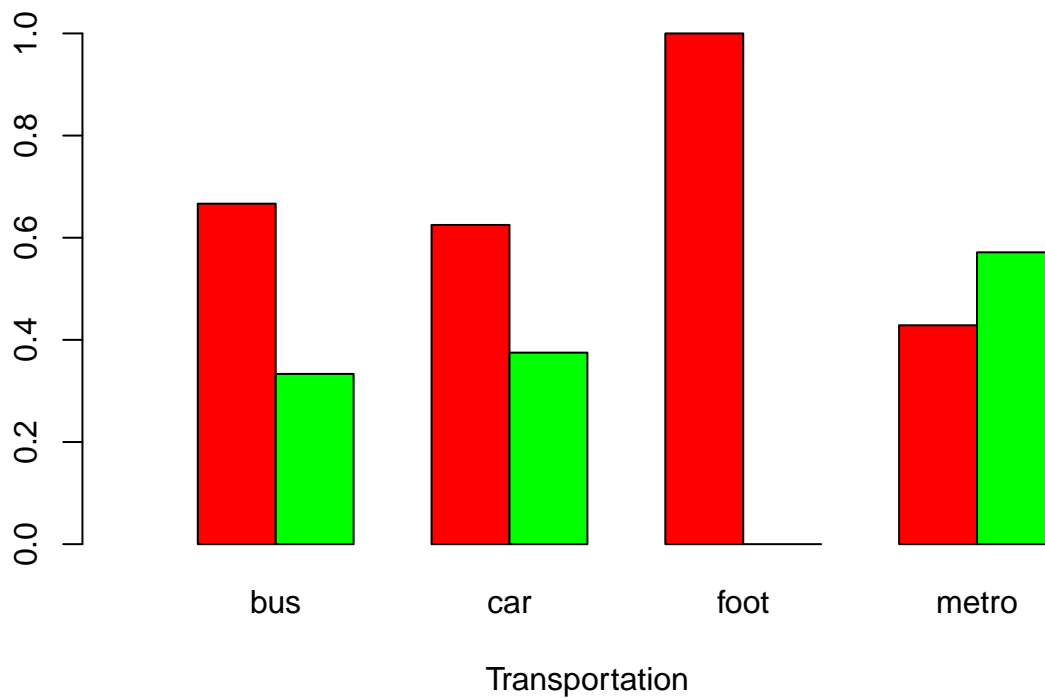
```
barplot(mg,xlim=c(0,2), xlab="Transportation", length=length(levels(g)), col = c("red","blue", "pink","green"))
```



```
barplot(prop.table(mg,1), width=0.25, xlim=c(0,3), ylim=c(0,1), xlab="Gender", legend=levels(mo), beside=TRUE)
```



```
mg = table(g,mo) # creating a contingency matrix of g and mo  
barplot(prop.table(mg,2), width=0.25, xlim=c(0,3), ylim=c(0,1), xlab="Transportation", legend=levels(g))
```



## Histograms

Histograms are used to visualize the distribution of numerical data. Histograms are used to show the frequency of different values in a dataset. Histograms are used to visualize the distribution of numerical data.

```
xo = c(10, 10, 5, 9, 7, 6,8,6,5,8, 10, 7, 7,8, 5, 6,4,7,9,7, 4,8, 10,10, 7,4,9,5,8,9) # creating a vector
table(xo) # creating a table of xo
```

```
## xo
##  4  5  6  7  8  9 10
##  3  4  3  6  5  4  5
```

```
data.frame(xo) # creating a dataframe of xo
```

```
##   xo
## 1  10
## 2  10
## 3   5
## 4   9
## 5   7
## 6   6
## 7   8
```

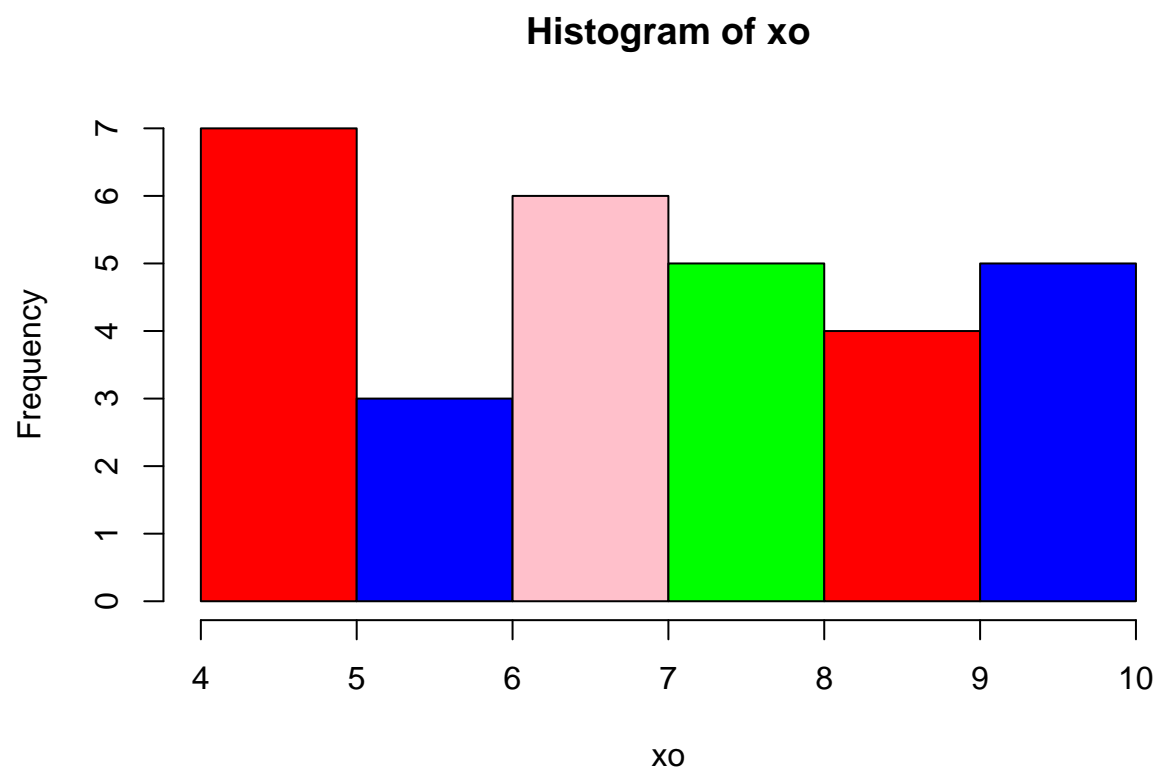
```
## 8 6
## 9 5
## 10 8
## 11 10
## 12 7
## 13 7
## 14 8
## 15 5
## 16 6
## 17 4
## 18 7
## 19 9
## 20 7
## 21 4
## 22 8
## 23 10
## 24 10
## 25 7
## 26 4
## 27 9
## 28 5
## 29 8
## 30 9
```

```
prop.table(table(xo)) # creating a table of xo
```

```
## xo
##      4      5      6      7      8      9     10
## 0.1000000 0.1333333 0.1000000 0.2000000 0.1666667 0.1333333 0.1666667
```

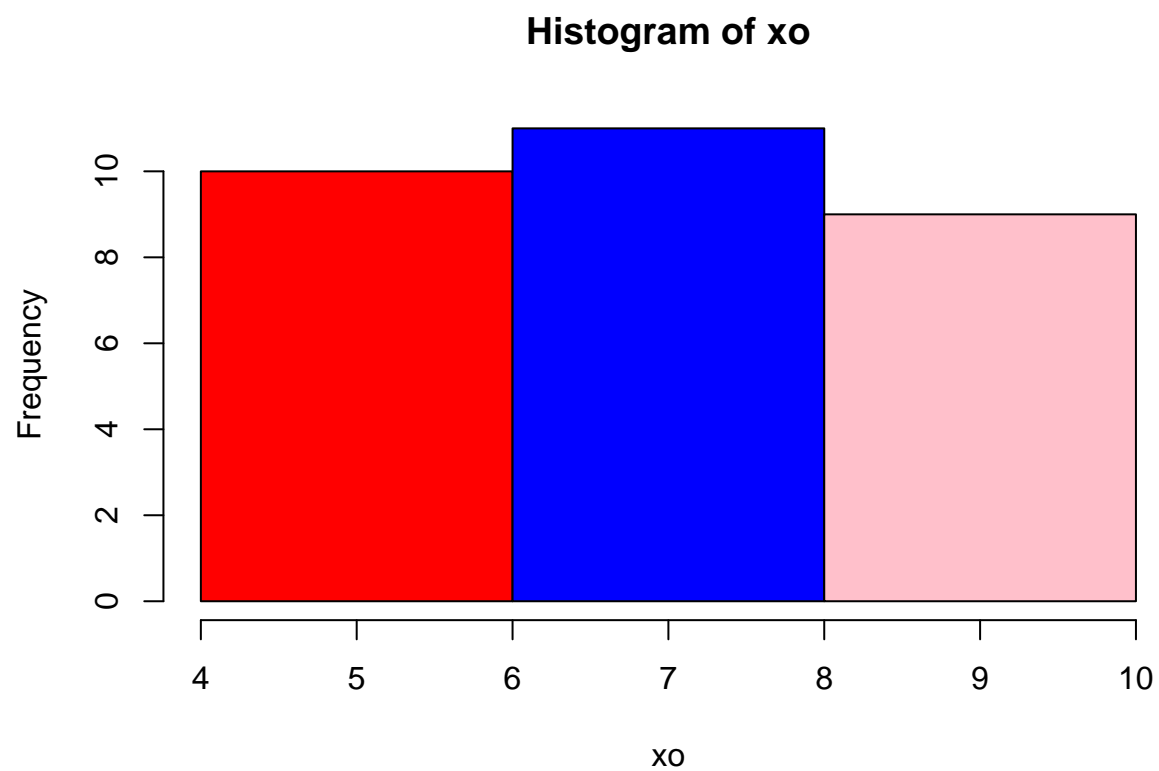
```
##?prop.table
```

```
hist(xo, col = c("red", "blue", "pink", "green")) # creating a histogram of xo
```

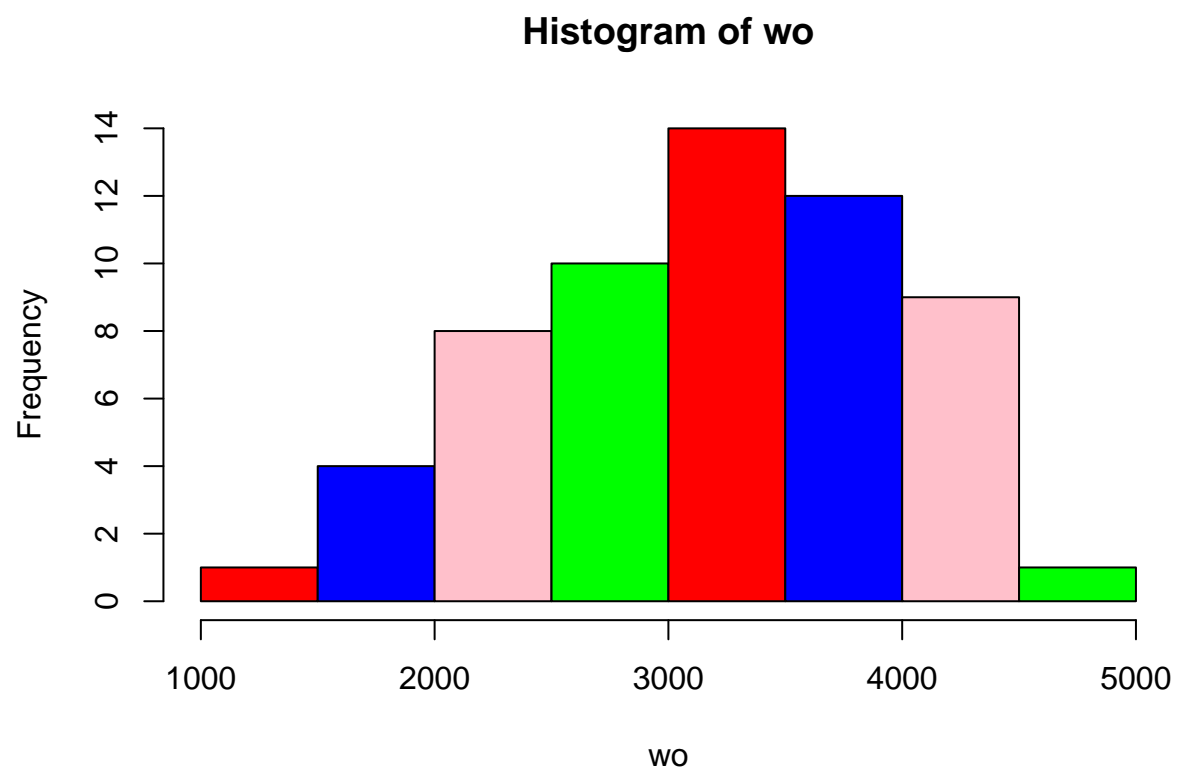


```
hist(xo, nclass = 3, col = c("red", "blue", "pink", "green")) # creating a histogram of xo
```

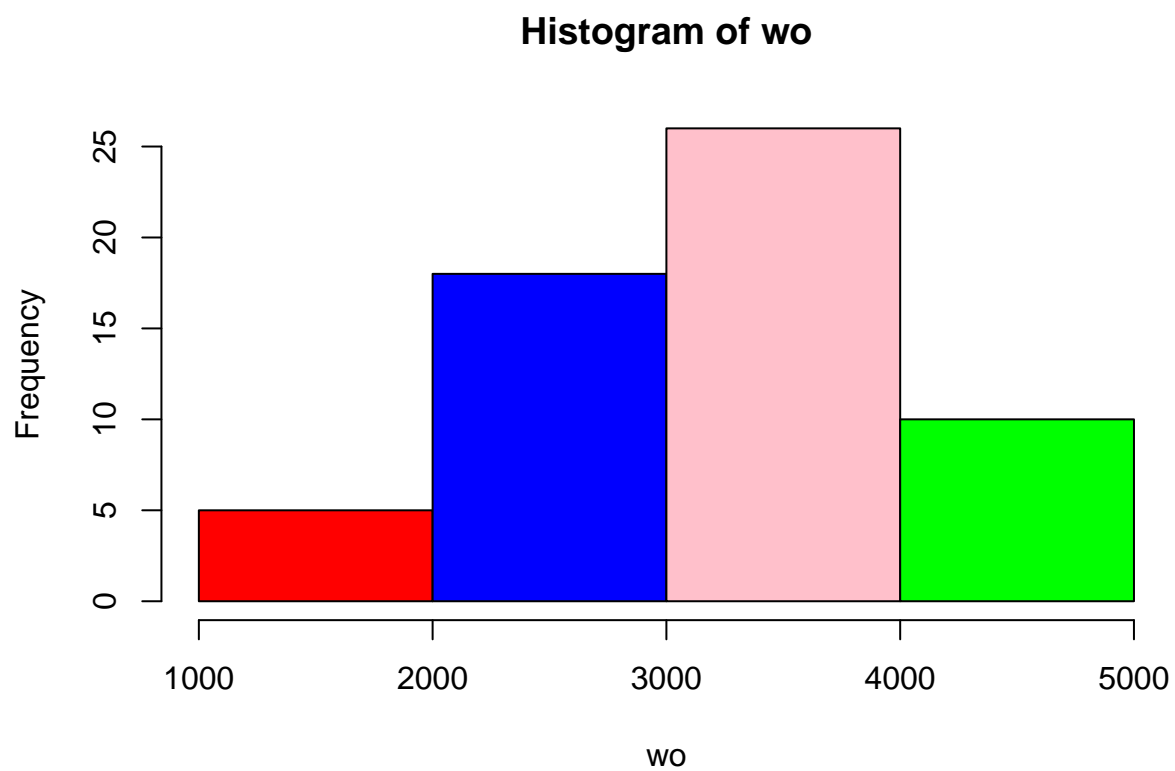




```
wo = c (1950, 2090, 2700, 3350, 4200, 3720, 4400, 2980, 3850, 4550, 3050, 2350, 1850, 2820, 3670, 2950,  
hist(wo, col = c("red","blue", "pink","green")) # creating a histogram of wo
```

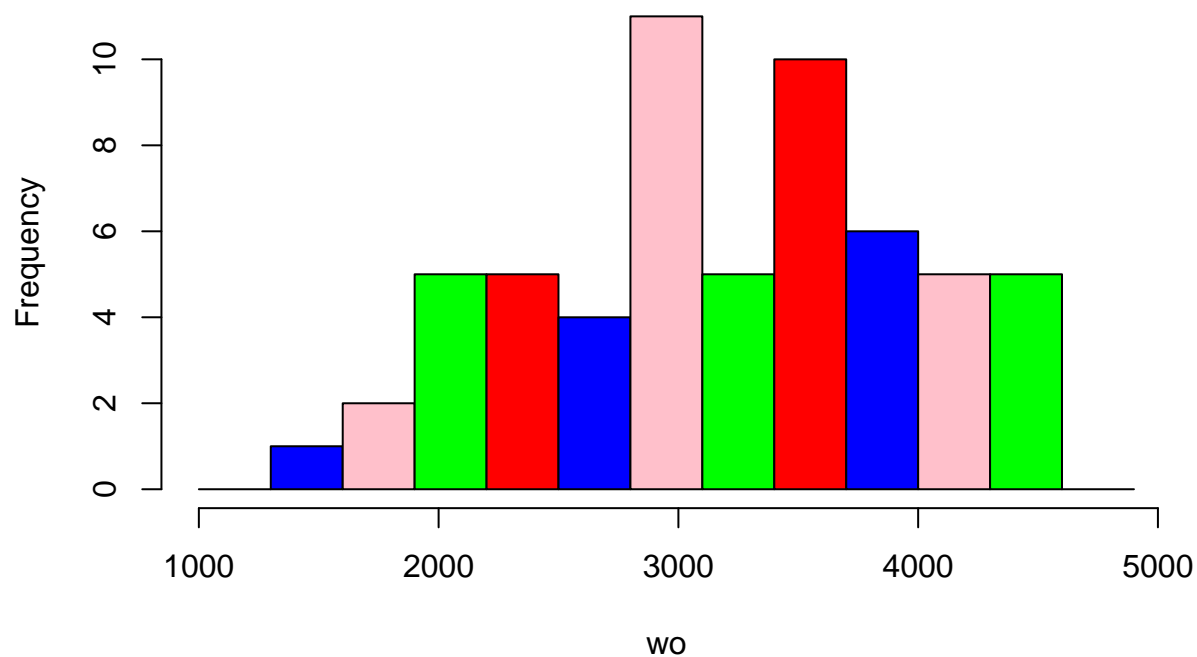


```
hist(wo, nclass=4, col = c("red","blue", "pink","green")) # creating a histogram of wo
```

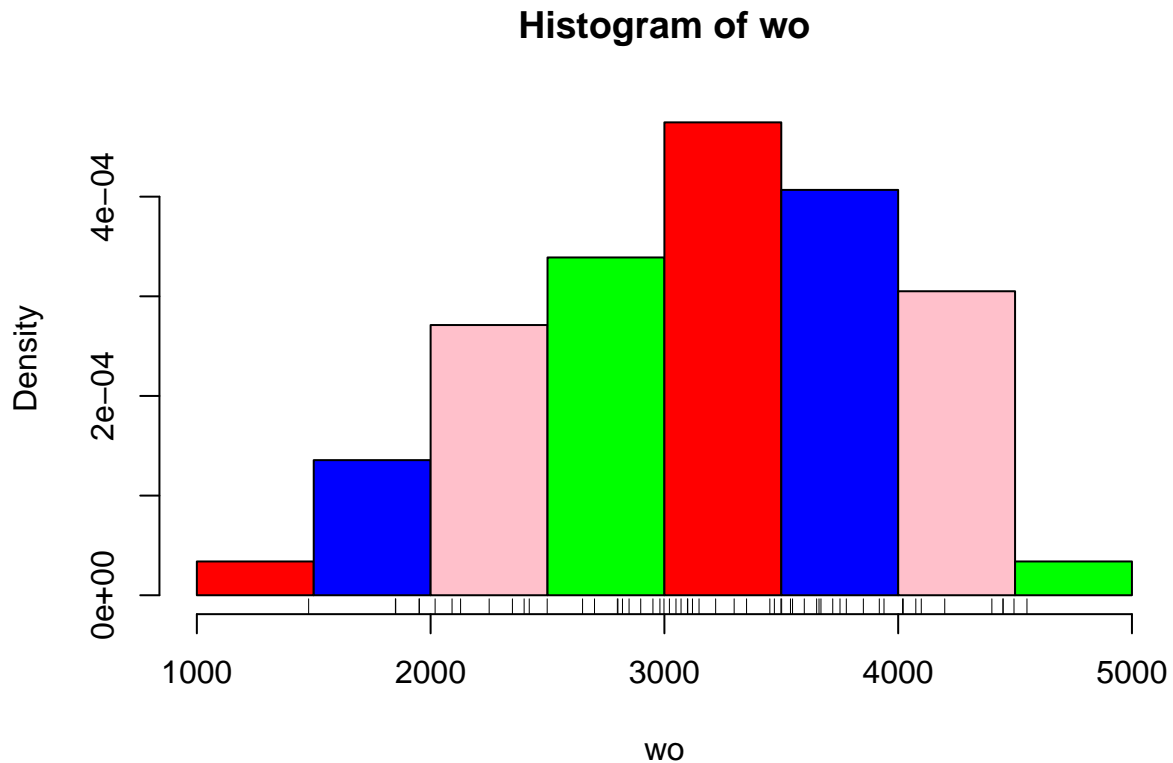


```
hist(wo, breaks= seq(from = 1000, to=5000, by=300), col = c("red","blue", "pink","green")) # creating a
```

Histogram of wo



```
hist(wo, probability=T, col = c("red","blue", "pink","green")) # creating a histogram of wo
rug(jitter(wo)) # creating a histogram of wo
```



### Frequency Polygon

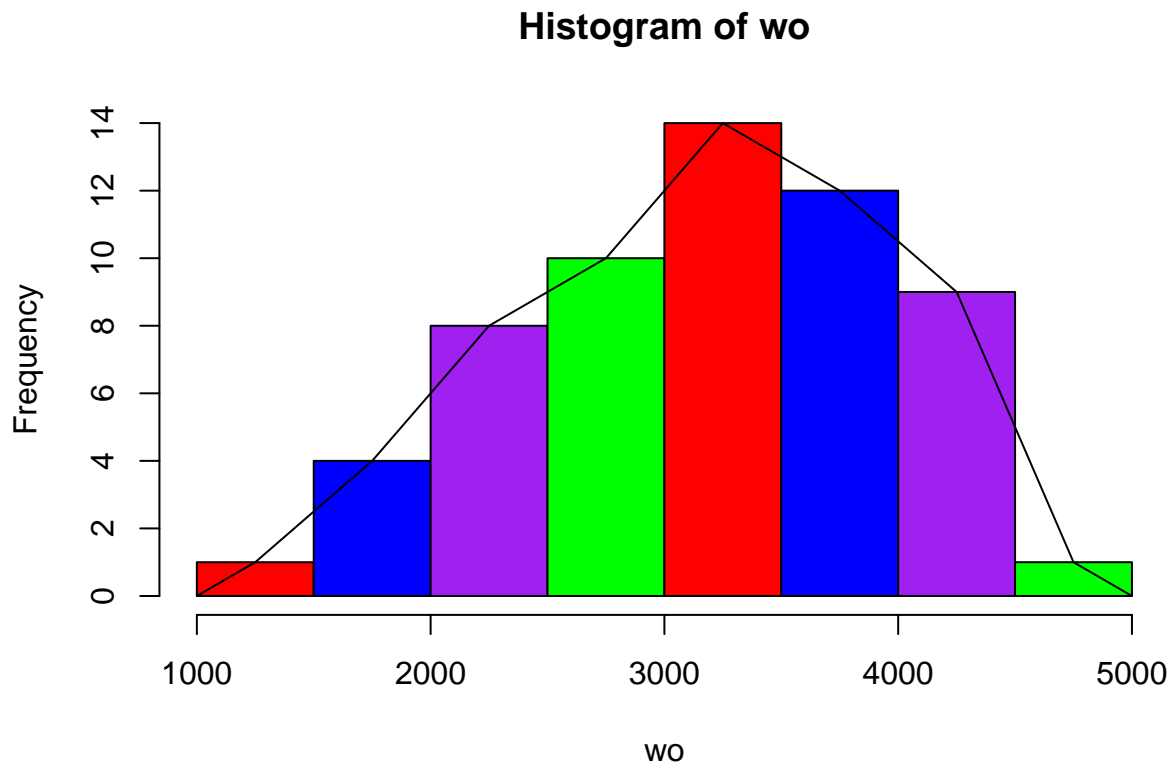
Frequency polygons are used to visualize the distribution of numerical data. Frequency polygons are used to show the frequency of different values in a dataset. Frequency polygons are used to visualize the distribution of numerical data.

```
temp = hist(wo, col = c("red", "blue", "purple", "green")) # creating a histogram of wo
temp
```

```
## $breaks
## [1] 1000 1500 2000 2500 3000 3500 4000 4500 5000
##
## $counts
## [1] 1 4 8 10 14 12 9 1
##
## $density
## [1] 3.389831e-05 1.355932e-04 2.711864e-04 3.389831e-04 4.745763e-04
## [6] 4.067797e-04 3.050847e-04 3.389831e-05
##
## $mids
## [1] 1250 1750 2250 2750 3250 3750 4250 4750
##
## $xname
## [1] "wo"
##
```

```
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
```

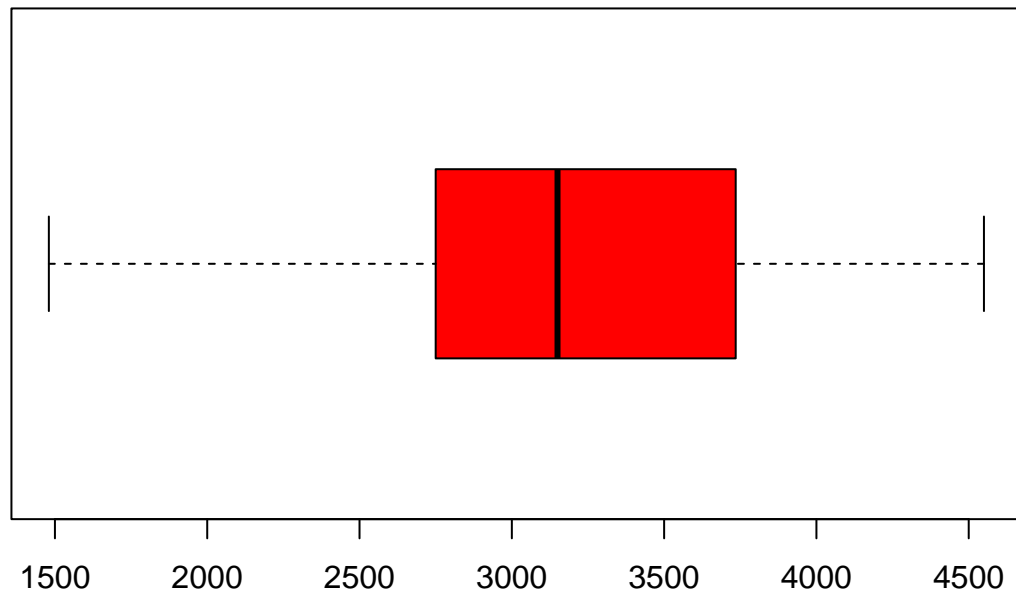
```
lines(c(min(temp$breaks), (temp$mids),max(temp$breaks)), c(0,temp$counts,0),type="l") # creating a freq
```



## Boxplot

Boxplots are used to visualize the distribution of numerical data. Boxplots are used to show the median, quartiles, and outliers in a dataset. Boxplots are used to visualize the distribution of numerical data.

```
boxplot(wo, horizontal = T, col = c("red")) # creating a boxplot of wo
```

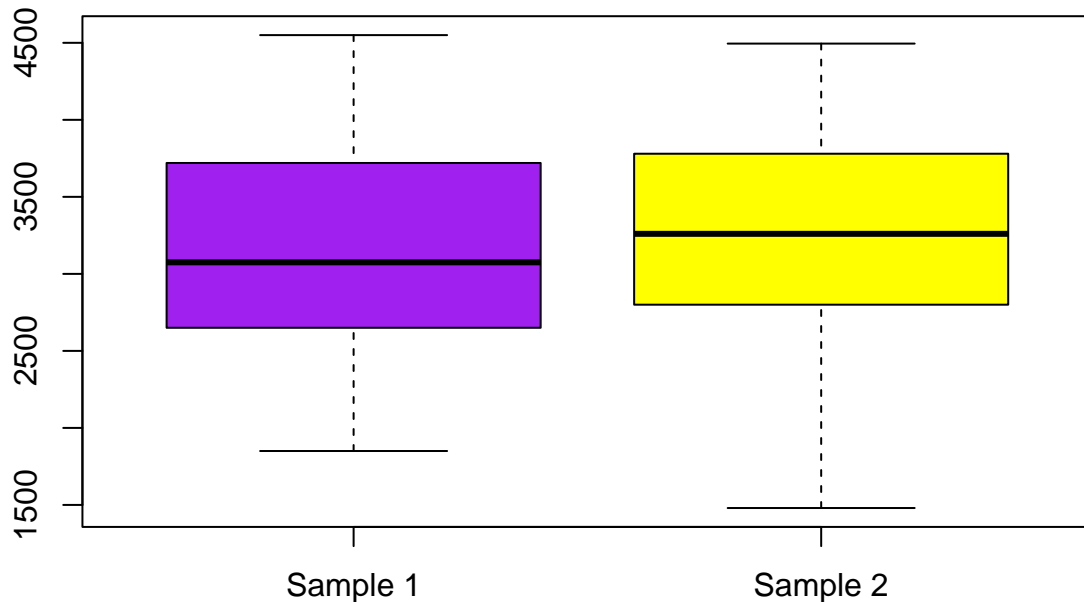


```
boxplot(wo, vertical = T, col = c("red")) # creating a boxplot of wo
```





```
boxplot(w1, w2, names = c("Sample 1", "Sample 2"), col = c("purple", "yellow" )) # creating a boxplot of
```



## Classification and Prediction

Classification and prediction are important tasks in data analysis. Classification is the process of categorizing data into different classes. Prediction is the process of predicting the value of a target variable based on the values of other variables. Classification and prediction are used to make decisions based on data.

```
computeCost <- function(X, y, th){
  m <- length(y)
  return(1/(2*m) * sum((X%*%th - y)^2))
}

computeCost(5,6,7) # computing the cost of 5,6,7
```

```
## [1] 420.5
```

```
grad_desc <- function(X, y, theta,alpha, lambda, num_iters){
  m <- length(y)
  F_history <- c(rep(0, num_iters)) # creating a vector of zeros

  for (iter in c(1:num_iters)){
```

```

temp <- vector()
temp <- theta * (1 - ((alpha*lambda)/m)) - alpha*(1/m) * (t(X) %*% (X %*% theta - y))
theta <- temp
F_history[iter] <- computeCost(X, y, theta)
}
print(F_history[num_iters])
return(list("theta" = theta, "F_history" = F_history))
}

grad_desc(2,3,5,0.1,7.5,2) # computing the output

```

```

## [1] 1.540012

## $theta
##      [,1]
## [1,] 0.6225
##
## $F_history
## [1] 5.445000 1.540012

```

## Clustering

Clustering is a technique used to group similar data points together. Clustering is used to identify patterns and relationships in data. Clustering is used to group data points into clusters based on their similarity. Clustering is used to analyze and explore data.

kmeans is a popular clustering algorithm that is used to group data points into k clusters. kmeans is an unsupervised learning algorithm that is used to identify patterns and relationships in data. kmeans is used to group data points into clusters based on their similarity.

```

iris_new <- iris # assigning iris to iris_new
### iris_new

iris_new$Species <- NULL # assigning the species class to null

kc <- kmeans(iris_new, 3) # creating a kmeans of iris_new

table(iris$Species, kc$cluster) # creating a table of iris and kc

```

```

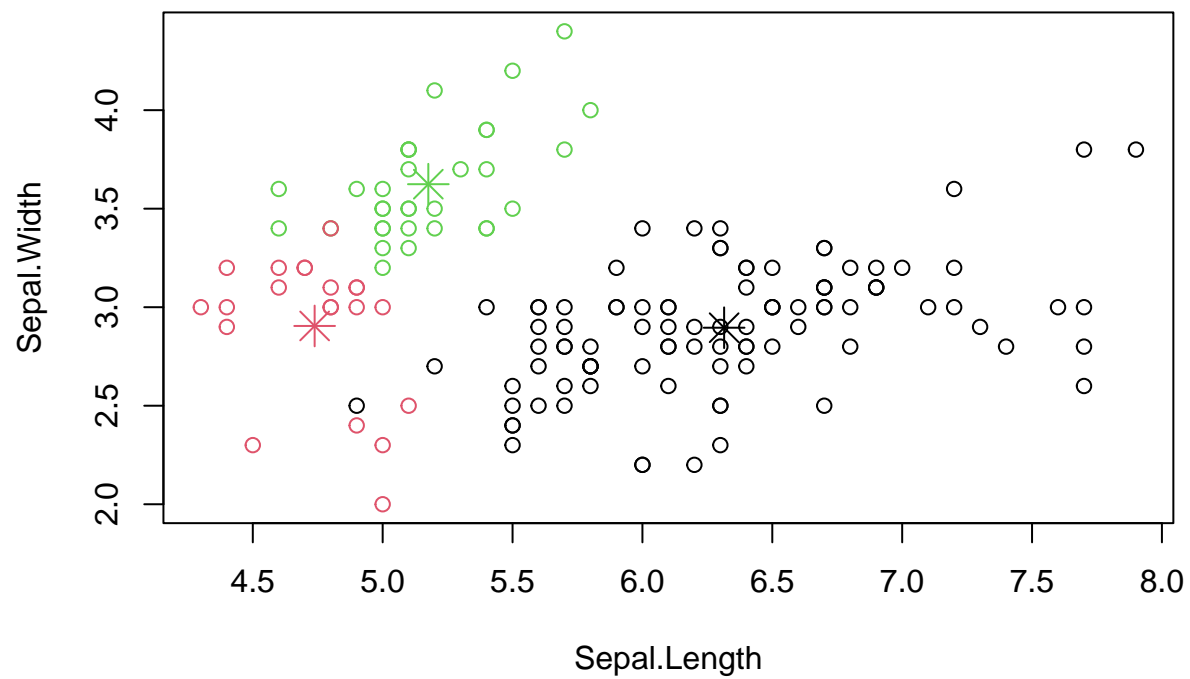
##
##      1  2  3
## setosa   0 17 33
## versicolor 46  4  0
## virginica 50  0  0

```

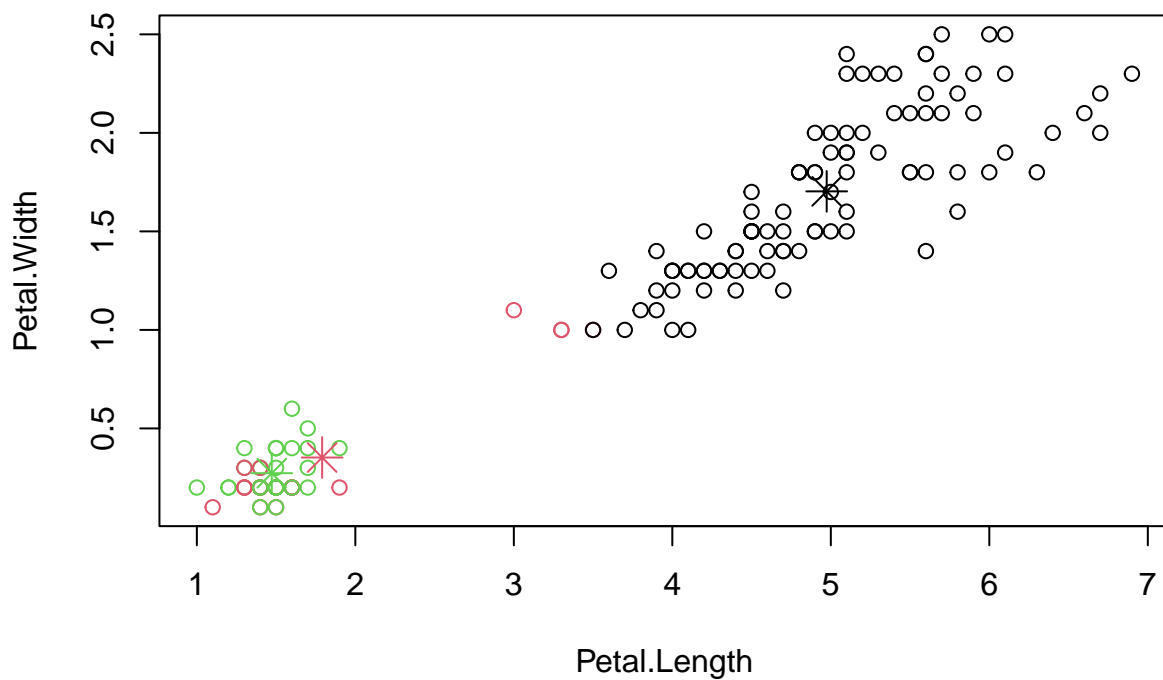
```

plot(iris_new[,c("Sepal.Length", "Sepal.Width")], col = kc$cluster) # visualizing the iris datasets
points(kc$centers[,c("Sepal.Length", "Sepal.Width")], col = 1:3, pch = 8, cex = 2)

```

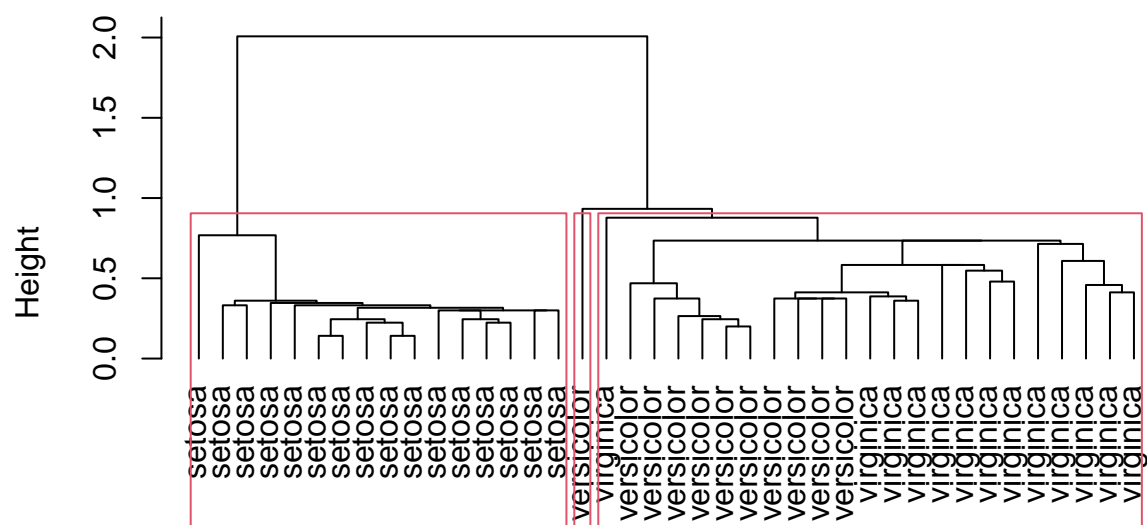


```
plot(iris_new[c("Petal.Length", "Petal.Width")], col = kc$cluster) # visualizing the iris dataset
points(kc$centers[,c("Petal.Length", "Petal.Width")], col = 1:3, pch = 8, cex = 2)
```



```
data(iris) # importing the iris dataset
set.seed(500) # setting the seed to 500 to avoid randomness
idx <- sample(1:dim(iris)[1], 40) # sampling the iris dataset
iris_Sample <- iris[idx,] # assigning the sampled iris dataset to iris_Sample
iris_Sample$Species <- NULL # assigning the species class to null
hc <- hclust(dist(iris_Sample), method = "single") # creating a hclust of iris_Sample
plot(hc, hang = -1, labels = iris$Species[idx], xlab = "Clusters") # visualizing the iris dataset
rect.hclust(hc, 3) # creating a rect.hclust of 3
```

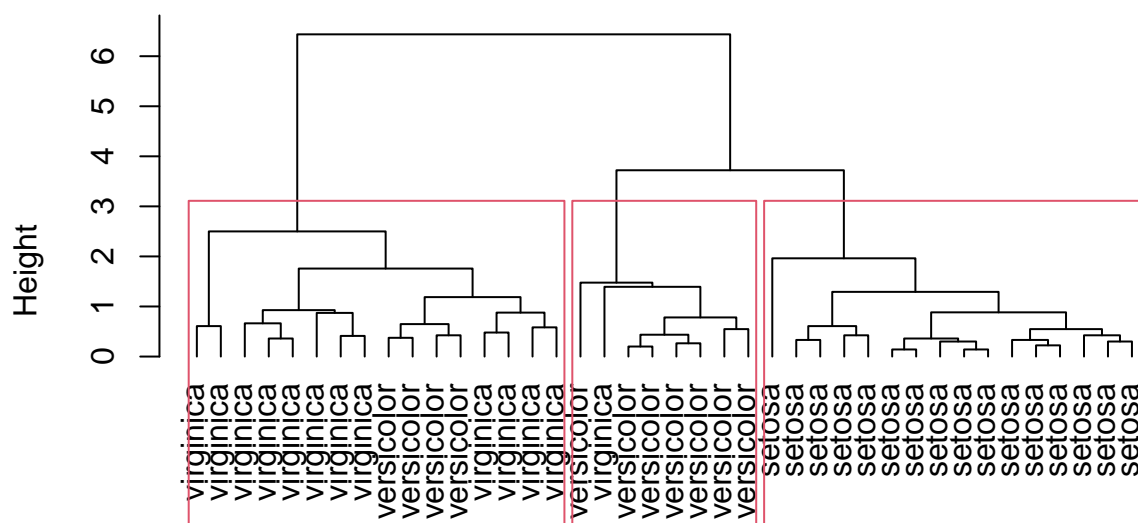
## Cluster Dendrogram



Clusters  
hclust (\*, "single")

```
hc <- hclust(dist(iris_Sample),method = "complete") # creating a hclust of iris_Sample
plot(hc, hang = -1, labels = iris$Species[idx], xlab = "Clusters") # visualizing the iris dataset
rect.hclust(hc, 3) # creating a rect.hclust of 3
```

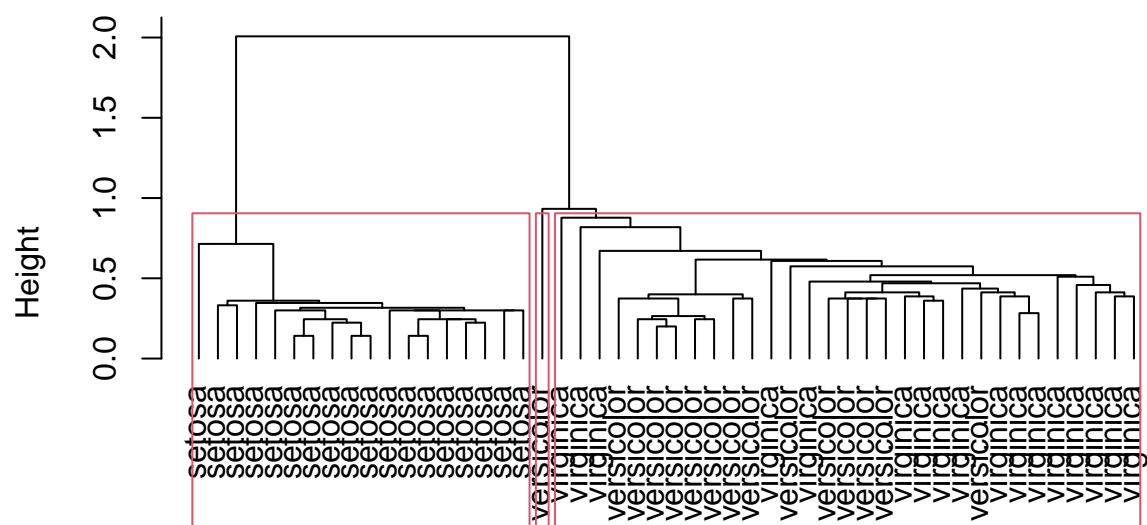
## Cluster Dendrogram



Clusters  
hclust (\*, "complete")

```
data(iris) # initiating iris dataset
set.seed(500) # setting seed to 500
idx <- sample(1:dim(iris)[1], 50) # sampling the dataset
iris_Sample <- iris[idx,] # assigning the sampled iris dataset to iris_Sample
iris_Sample$Species <- NULL # setting the species column to null
hc <- hclust(dist(iris_Sample), method = "single") # creating a hclust of iris_Sample
plot(hc, hang = -1, labels = iris$Species[idx], xlab = "Clusters") # visualizing the iris dataset
rect.hclust(hc, 3) # creating a rect.hclust of 3
```

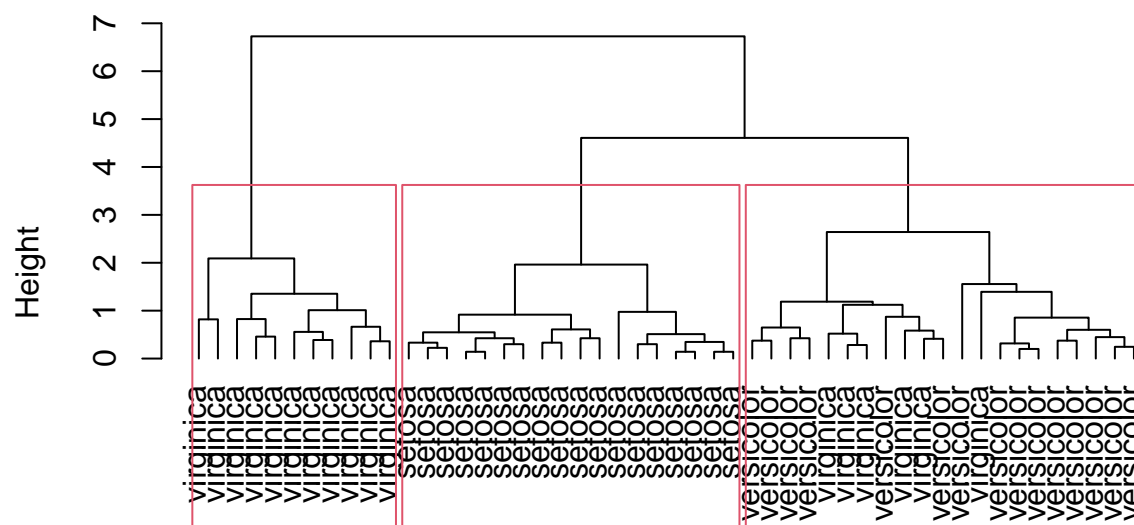
## Cluster Dendrogram



Clusters  
hclust (\*, "single")

```
hc <- hclust(dist(iris_Sample),method = "complete") # creating a hclust of iris_Sample
plot(hc, hang = -1, labels = iris$Species[idx], xlab = "Clusters") # visualizing the iris dataset
rect.hclust(hc, 3) # creating a rect.hclust of 3
```

## Cluster Dendrogram



Clusters  
hclust (\*, "complete")

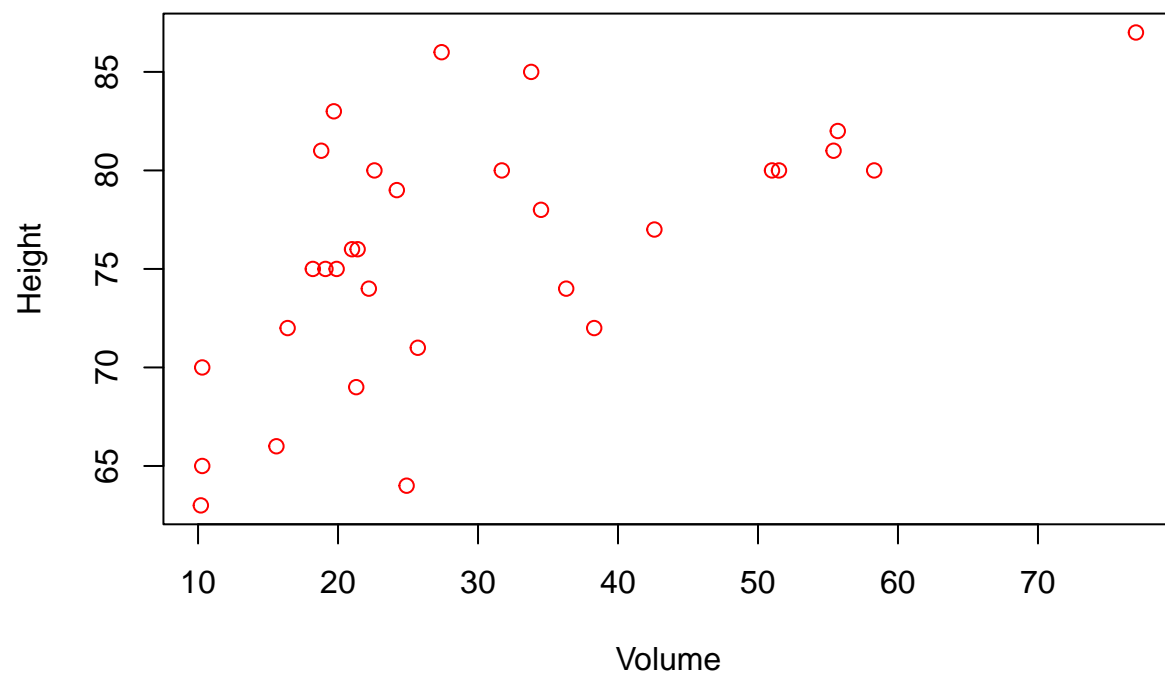
```
tr = trees # assigning trees to tr
as.data.frame(tr) # converting tr to a dataframe
```

##	Girth	Height	Volume
## 1	8.3	70	10.3
## 2	8.6	65	10.3
## 3	8.8	63	10.2
## 4	10.5	72	16.4
## 5	10.7	81	18.8
## 6	10.8	83	19.7
## 7	11.0	66	15.6
## 8	11.0	75	18.2
## 9	11.1	80	22.6
## 10	11.2	75	19.9
## 11	11.3	79	24.2
## 12	11.4	76	21.0
## 13	11.4	76	21.4
## 14	11.7	69	21.3
## 15	12.0	75	19.1
## 16	12.9	74	22.2
## 17	12.9	85	33.8
## 18	13.3	86	27.4
## 19	13.7	71	25.7
## 20	13.8	64	24.9
## 21	14.0	78	34.5

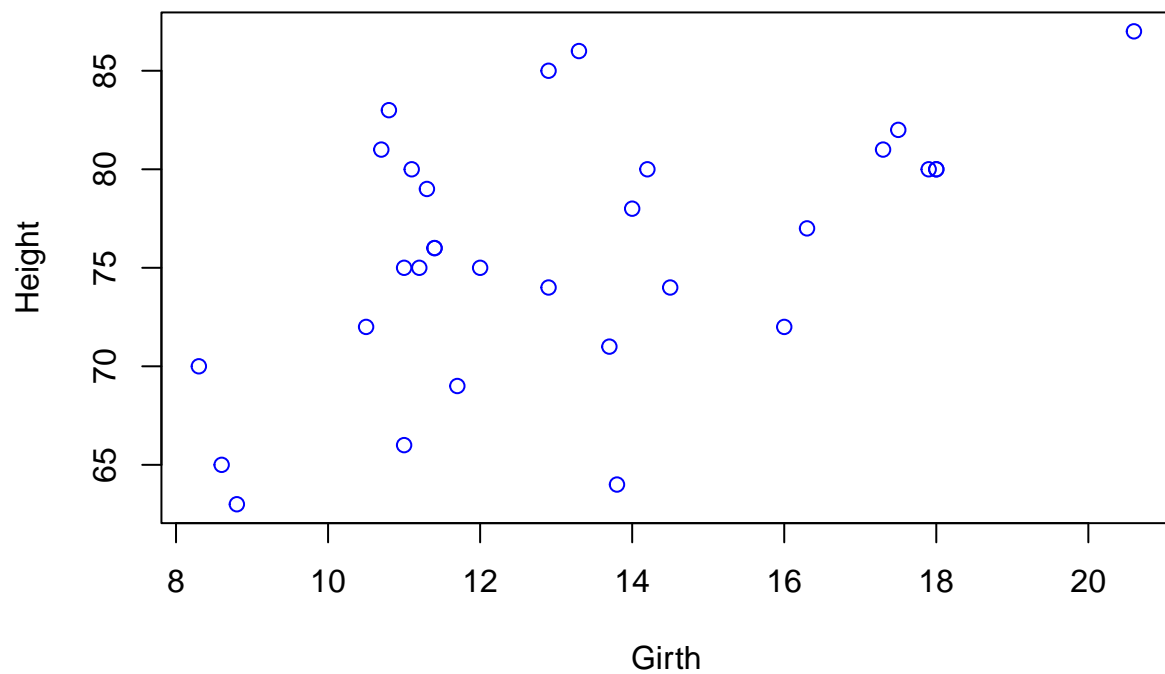


```
## 22 14.2    80  31.7
## 23 14.5    74  36.3
## 24 16.0    72  38.3
## 25 16.3    77  42.6
## 26 17.3    81  55.4
## 27 17.5    82  55.7
## 28 17.9    80  58.3
## 29 18.0    80  51.5
## 30 18.0    80  51.0
## 31 20.6    87  77.0
```

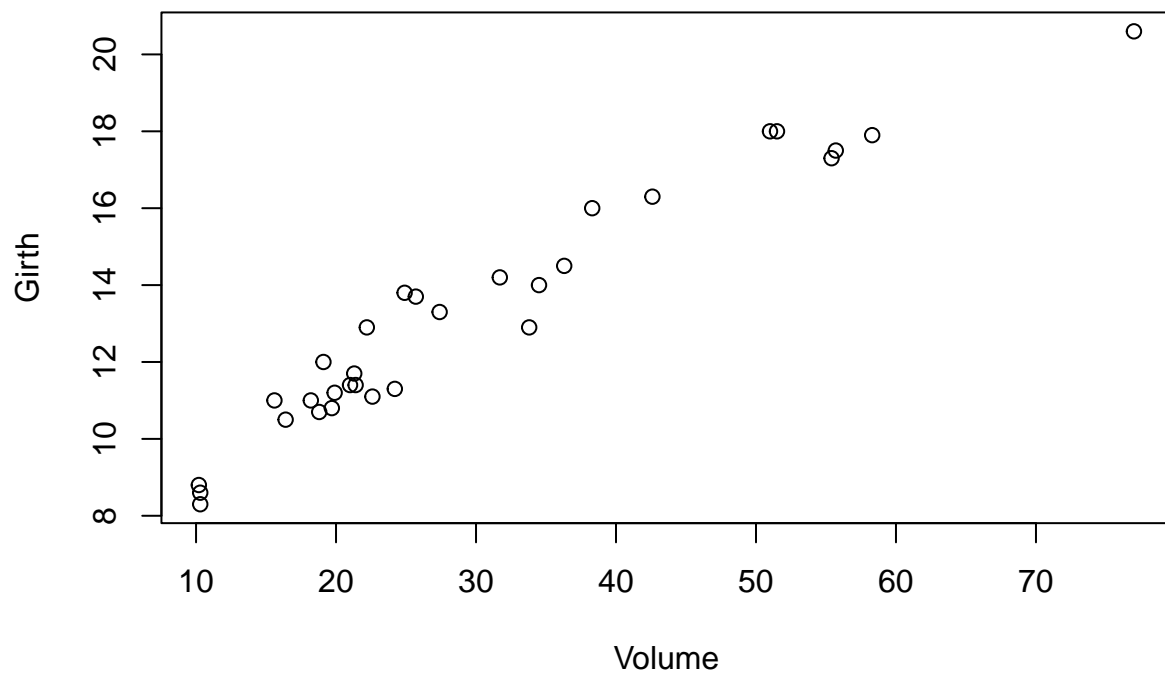
```
plot(tr[c("Volume","Height")], col = "red") # visualizing the trees dataset
```



```
plot(tr[c("Girth","Height")], col = "blue" ) # visualizing the trees dataset
```



```
plot(tr[c("Volume","Girth")], col = "black" ) # visualizing the trees dataset
```

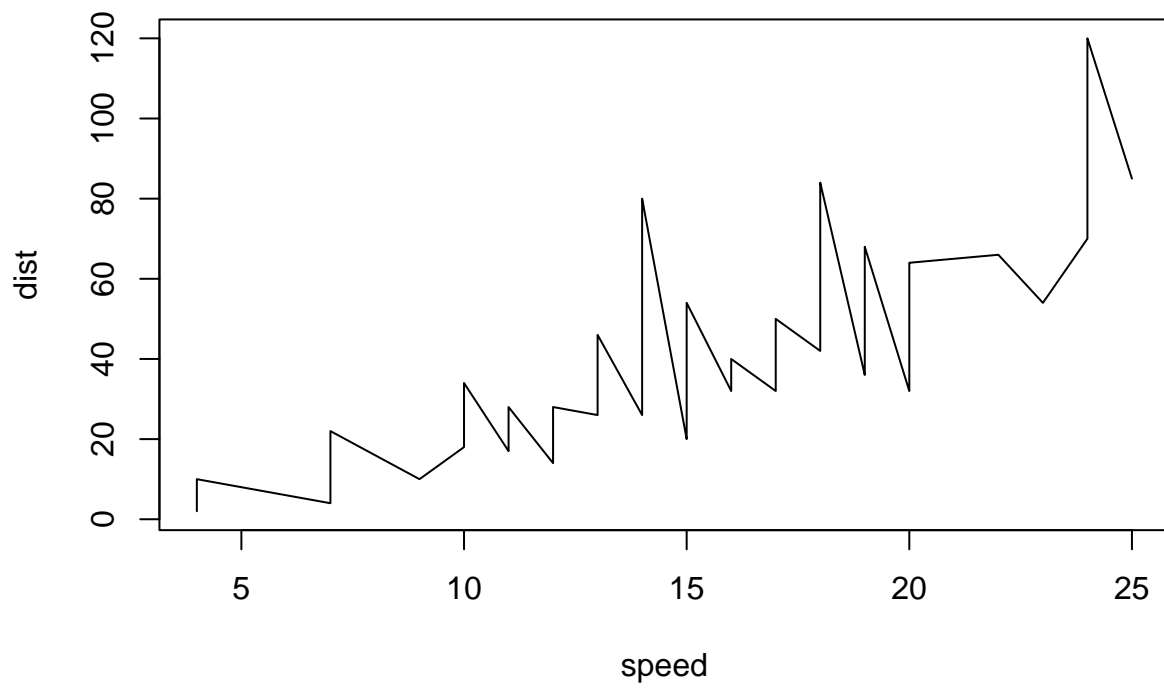


```
ca = cars # assigning cars to ca
as.data.frame(ca) # converting ca to a dataframe
```

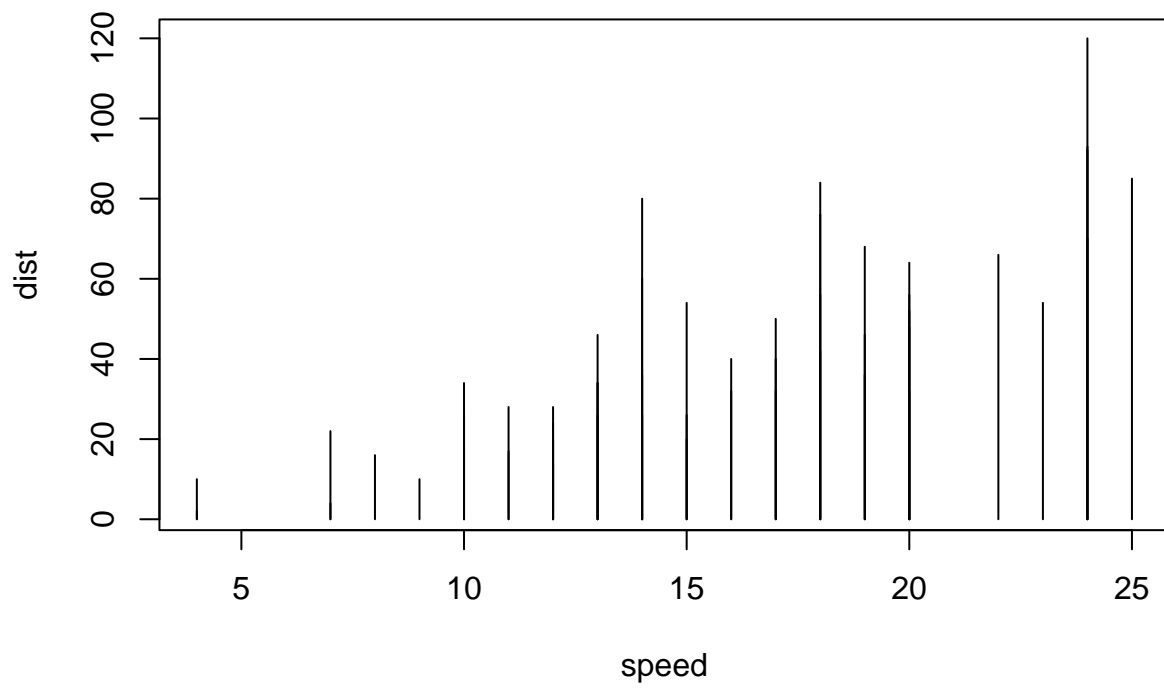
```
##      speed dist
## 1         4    2
## 2         4   10
## 3         7    4
## 4         7   22
## 5         8   16
## 6         9   10
## 7        10   18
## 8        10   26
## 9        10   34
## 10       11   17
## 11       11   28
## 12       12   14
## 13       12   20
## 14       12   24
## 15       12   28
## 16       13   26
## 17       13   34
## 18       13   34
## 19       13   46
## 20       14   26
## 21       14   36
```

```
## 22    14    60
## 23    14    80
## 24    15    20
## 25    15    26
## 26    15    54
## 27    16    32
## 28    16    40
## 29    17    32
## 30    17    40
## 31    17    50
## 32    18    42
## 33    18    56
## 34    18    76
## 35    18    84
## 36    19    36
## 37    19    46
## 38    19    68
## 39    20    32
## 40    20    48
## 41    20    52
## 42    20    56
## 43    20    64
## 44    22    66
## 45    23    54
## 46    24    70
## 47    24    92
## 48    24    93
## 49    24   120
## 50    25    85
```

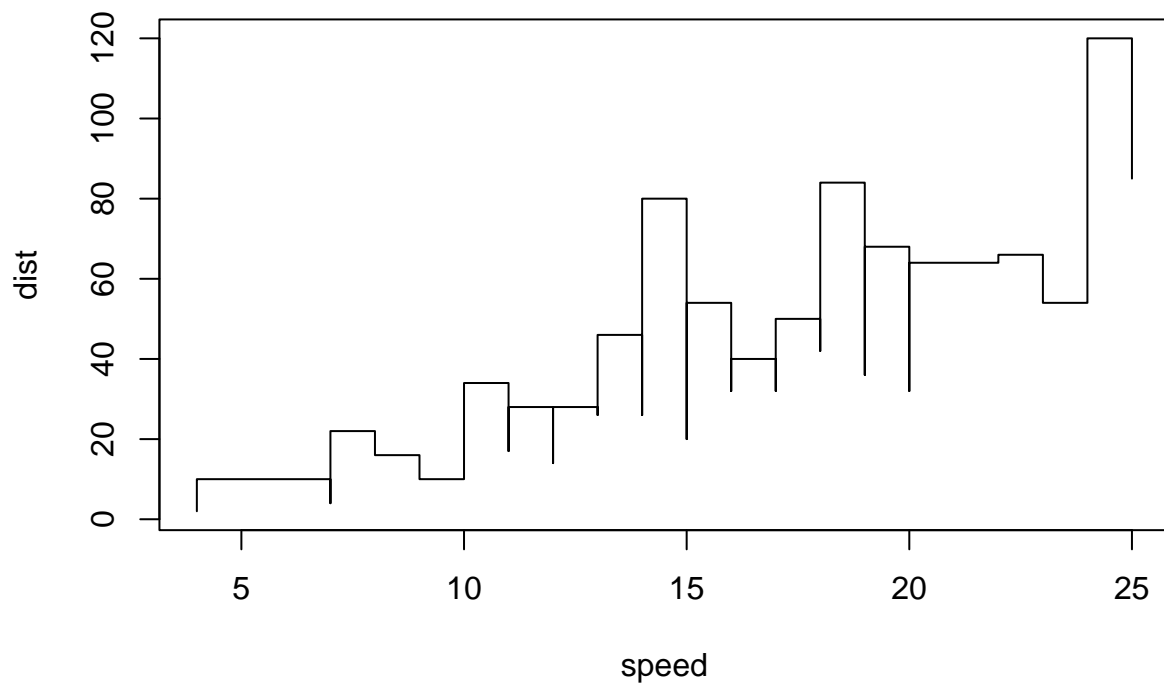
```
plot(ca[c("speed","dist")], type = "l") # visualizing the cars dataset
```



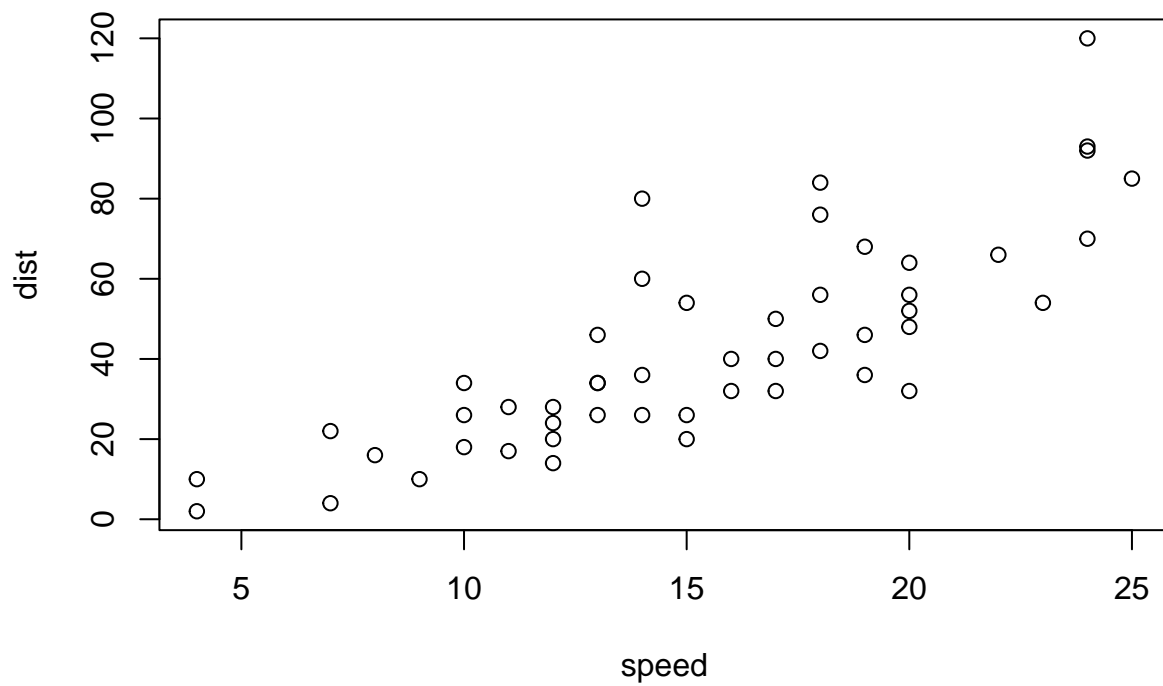
```
plot(ca[c("speed","dist")], type = "h") # visualizing the cars dataset
```



```
plot(ca[c("speed","dist")], type = "s") # visualizing the cars dataset
```



```
plot(ca[c("speed","dist")], type = "p") # visualizing the cars dataset
```

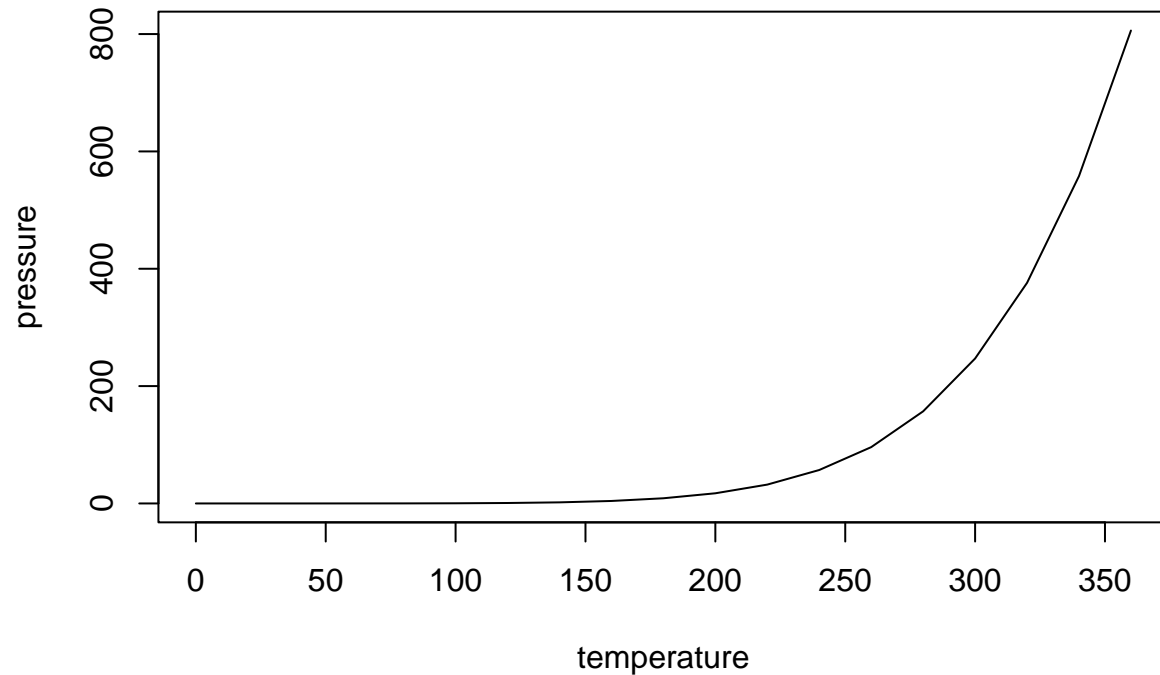


```
pre = pressure # assigning pressure to pre
as.data.frame(pre) # converting pre to a dataframe
```

```
##      temperature pressure
## 1           0    0.0002
## 2          20    0.0012
## 3          40    0.0060
## 4          60    0.0300
## 5          80    0.0900
## 6         100    0.2700
## 7         120    0.7500
## 8         140    1.8500
## 9         160    4.2000
## 10        180    8.8000
## 11        200   17.3000
## 12        220   32.1000
## 13        240   57.0000
## 14        260   96.0000
## 15        280  157.0000
## 16        300  247.0000
## 17        320  376.0000
## 18        340  558.0000
## 19        360  806.0000
```



```
plot(pre[c("temperature","pressure")], type="l") # visualizing the pressure dataset
```



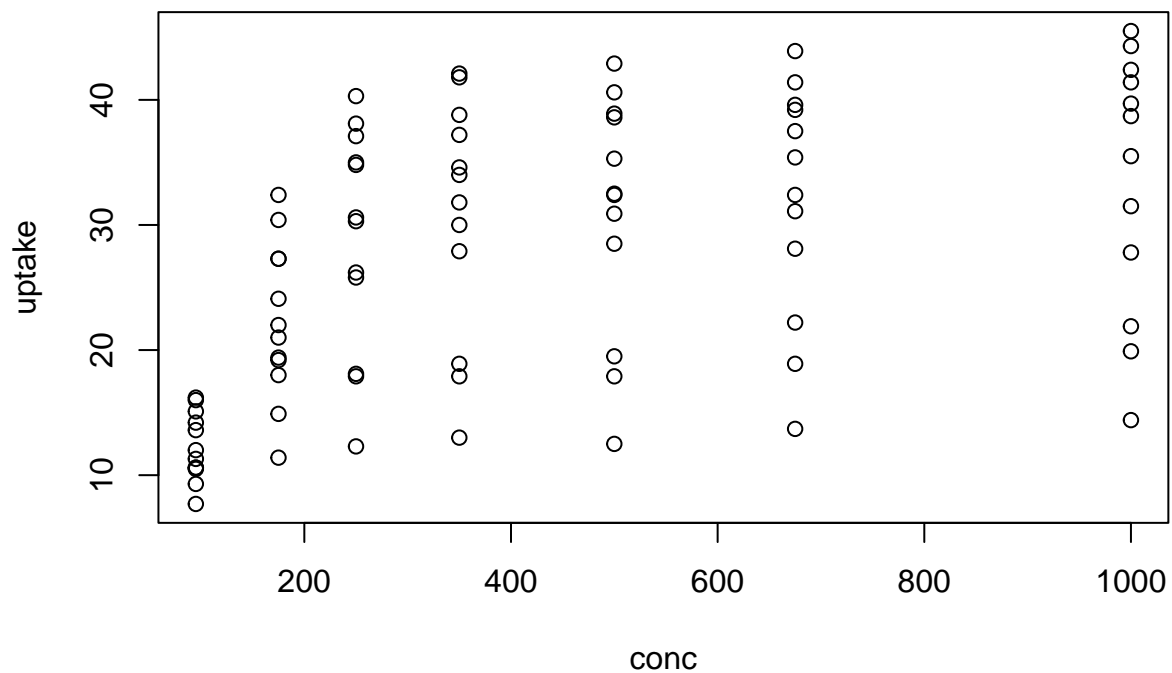
```
cab = CO2 # assigning CO2 to cab
as.data.frame(cab) # converting cab to a dataframe
```

##	Plant	Type	Treatment	conc	uptake
## 1	Qn1	Quebec	nonchilled	95	16.0
## 2	Qn1	Quebec	nonchilled	175	30.4
## 3	Qn1	Quebec	nonchilled	250	34.8
## 4	Qn1	Quebec	nonchilled	350	37.2
## 5	Qn1	Quebec	nonchilled	500	35.3
## 6	Qn1	Quebec	nonchilled	675	39.2
## 7	Qn1	Quebec	nonchilled	1000	39.7
## 8	Qn2	Quebec	nonchilled	95	13.6
## 9	Qn2	Quebec	nonchilled	175	27.3
## 10	Qn2	Quebec	nonchilled	250	37.1
## 11	Qn2	Quebec	nonchilled	350	41.8
## 12	Qn2	Quebec	nonchilled	500	40.6
## 13	Qn2	Quebec	nonchilled	675	41.4
## 14	Qn2	Quebec	nonchilled	1000	44.3
## 15	Qn3	Quebec	nonchilled	95	16.2
## 16	Qn3	Quebec	nonchilled	175	32.4
## 17	Qn3	Quebec	nonchilled	250	40.3
## 18	Qn3	Quebec	nonchilled	350	42.1

## 19	Qn3	Quebec	nonchilled	500	42.9
## 20	Qn3	Quebec	nonchilled	675	43.9
## 21	Qn3	Quebec	nonchilled	1000	45.5
## 22	Qc1	Quebec	chilled	95	14.2
## 23	Qc1	Quebec	chilled	175	24.1
## 24	Qc1	Quebec	chilled	250	30.3
## 25	Qc1	Quebec	chilled	350	34.6
## 26	Qc1	Quebec	chilled	500	32.5
## 27	Qc1	Quebec	chilled	675	35.4
## 28	Qc1	Quebec	chilled	1000	38.7
## 29	Qc2	Quebec	chilled	95	9.3
## 30	Qc2	Quebec	chilled	175	27.3
## 31	Qc2	Quebec	chilled	250	35.0
## 32	Qc2	Quebec	chilled	350	38.8
## 33	Qc2	Quebec	chilled	500	38.6
## 34	Qc2	Quebec	chilled	675	37.5
## 35	Qc2	Quebec	chilled	1000	42.4
## 36	Qc3	Quebec	chilled	95	15.1
## 37	Qc3	Quebec	chilled	175	21.0
## 38	Qc3	Quebec	chilled	250	38.1
## 39	Qc3	Quebec	chilled	350	34.0
## 40	Qc3	Quebec	chilled	500	38.9
## 41	Qc3	Quebec	chilled	675	39.6
## 42	Qc3	Quebec	chilled	1000	41.4
## 43	Mn1	Mississippi	nonchilled	95	10.6
## 44	Mn1	Mississippi	nonchilled	175	19.2
## 45	Mn1	Mississippi	nonchilled	250	26.2
## 46	Mn1	Mississippi	nonchilled	350	30.0
## 47	Mn1	Mississippi	nonchilled	500	30.9
## 48	Mn1	Mississippi	nonchilled	675	32.4
## 49	Mn1	Mississippi	nonchilled	1000	35.5
## 50	Mn2	Mississippi	nonchilled	95	12.0
## 51	Mn2	Mississippi	nonchilled	175	22.0
## 52	Mn2	Mississippi	nonchilled	250	30.6
## 53	Mn2	Mississippi	nonchilled	350	31.8
## 54	Mn2	Mississippi	nonchilled	500	32.4
## 55	Mn2	Mississippi	nonchilled	675	31.1
## 56	Mn2	Mississippi	nonchilled	1000	31.5
## 57	Mn3	Mississippi	nonchilled	95	11.3
## 58	Mn3	Mississippi	nonchilled	175	19.4
## 59	Mn3	Mississippi	nonchilled	250	25.8
## 60	Mn3	Mississippi	nonchilled	350	27.9
## 61	Mn3	Mississippi	nonchilled	500	28.5
## 62	Mn3	Mississippi	nonchilled	675	28.1
## 63	Mn3	Mississippi	nonchilled	1000	27.8
## 64	Mc1	Mississippi	chilled	95	10.5
## 65	Mc1	Mississippi	chilled	175	14.9
## 66	Mc1	Mississippi	chilled	250	18.1
## 67	Mc1	Mississippi	chilled	350	18.9
## 68	Mc1	Mississippi	chilled	500	19.5
## 69	Mc1	Mississippi	chilled	675	22.2
## 70	Mc1	Mississippi	chilled	1000	21.9
## 71	Mc2	Mississippi	chilled	95	7.7
## 72	Mc2	Mississippi	chilled	175	11.4

```
## 73  Mc2 Mississippi chilled 250 12.3
## 74  Mc2 Mississippi chilled 350 13.0
## 75  Mc2 Mississippi chilled 500 12.5
## 76  Mc2 Mississippi chilled 675 13.7
## 77  Mc2 Mississippi chilled 1000 14.4
## 78  Mc3 Mississippi chilled 95 10.6
## 79  Mc3 Mississippi chilled 175 18.0
## 80  Mc3 Mississippi chilled 250 17.9
## 81  Mc3 Mississippi chilled 350 17.9
## 82  Mc3 Mississippi chilled 500 17.9
## 83  Mc3 Mississippi chilled 675 18.9
## 84  Mc3 Mississippi chilled 1000 19.9
```

```
plot(cab[c("conc", "uptake")]) # visualizing the CO2 dataset
```



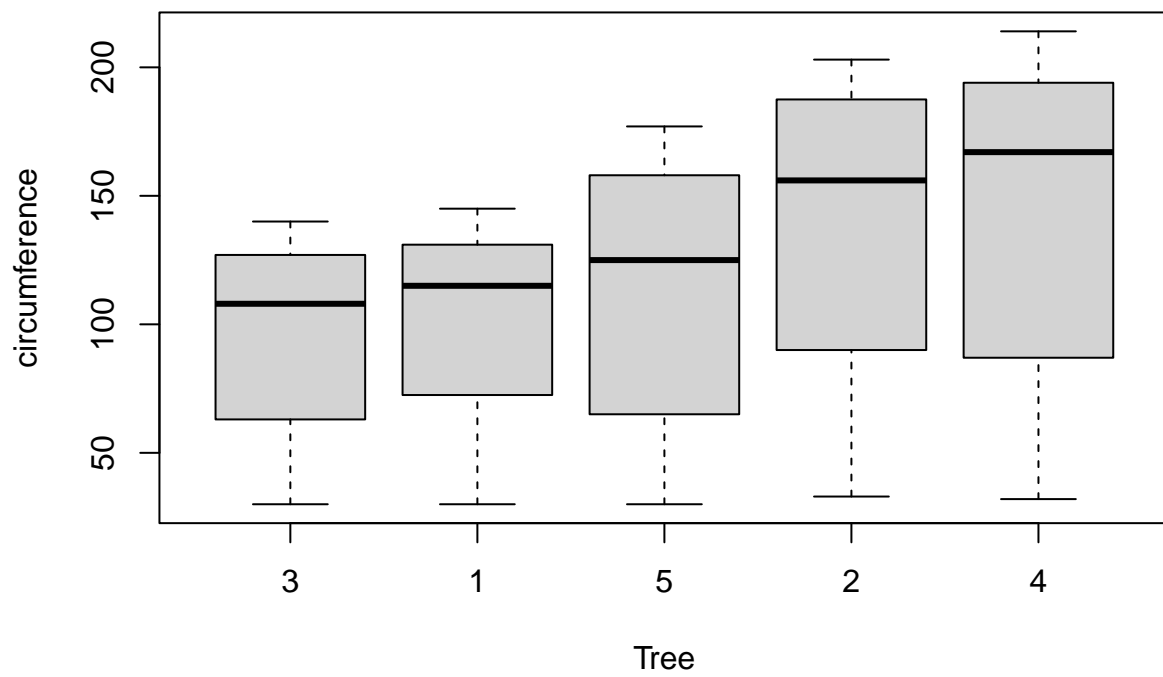
```
oran = Orange # assigning Orange to oran
```

```
as.data.frame(oran) # converting oran to a dataframe
```

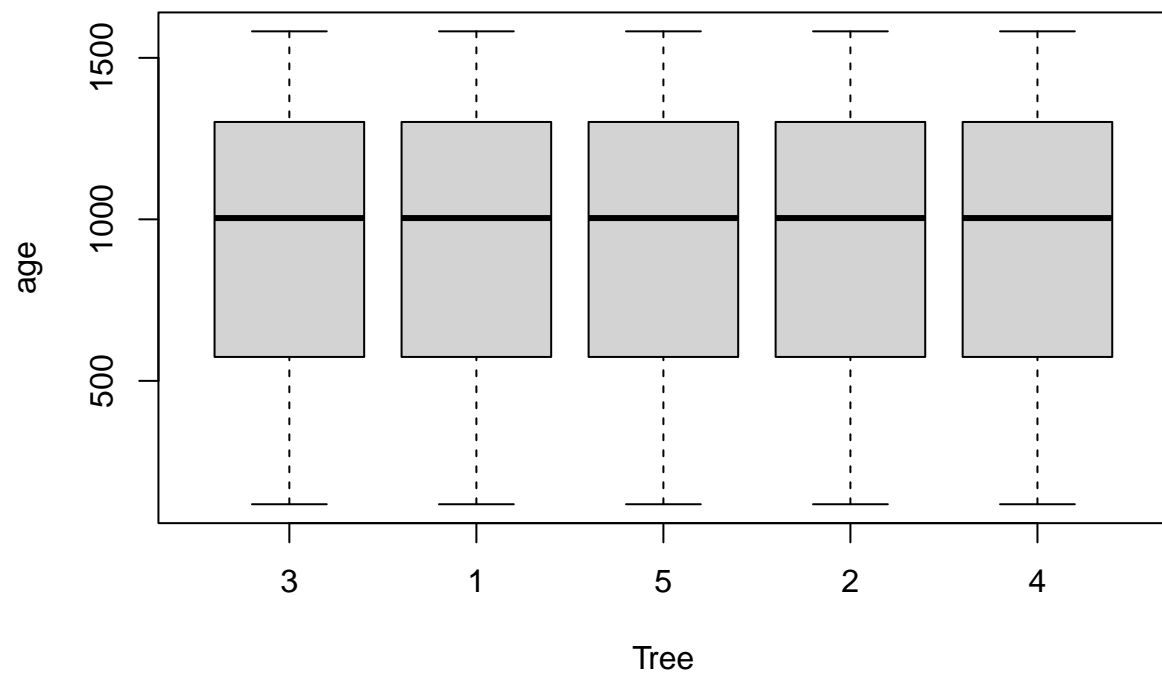
```
##      Tree  age circumference
## 1      1  118             30
## 2      1  484             58
## 3      1  664             87
## 4      1 1004            115
## 5      1 1231            120
```

## 6	1	1372	142
## 7	1	1582	145
## 8	2	118	33
## 9	2	484	69
## 10	2	664	111
## 11	2	1004	156
## 12	2	1231	172
## 13	2	1372	203
## 14	2	1582	203
## 15	3	118	30
## 16	3	484	51
## 17	3	664	75
## 18	3	1004	108
## 19	3	1231	115
## 20	3	1372	139
## 21	3	1582	140
## 22	4	118	32
## 23	4	484	62
## 24	4	664	112
## 25	4	1004	167
## 26	4	1231	179
## 27	4	1372	209
## 28	4	1582	214
## 29	5	118	30
## 30	5	484	49
## 31	5	664	81
## 32	5	1004	125
## 33	5	1231	142
## 34	5	1372	174
## 35	5	1582	177

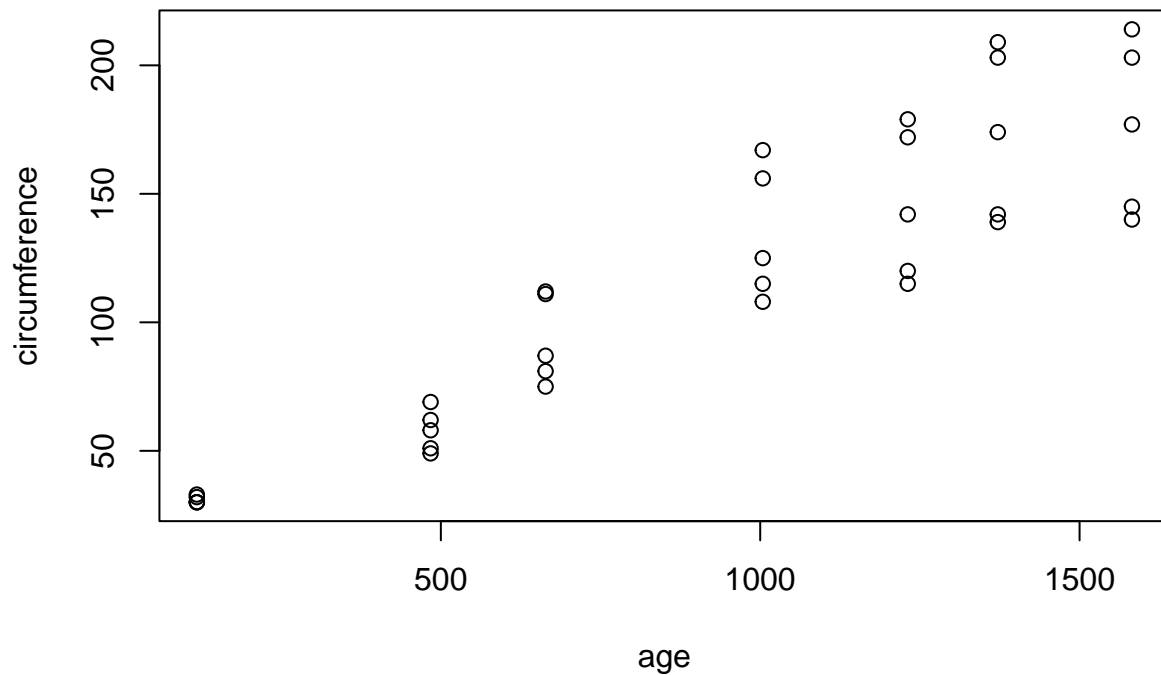
```
plot(oran[c("Tree","circumference")]) # visualizing the Orange dataset
```



```
plot(oran[c("Tree","age")]) # visualizing the Orange dataset
```



```
plot(oran[c("age","circumference")]) # visualizing the Orange dataset
```



## Mining of frequent itemsets and Association Rules

Mining of frequent itemsets and association rules is an important task in data analysis. Frequent itemsets are sets of items that occur together frequently in a dataset. Association rules are rules that describe the relationships between items in a dataset. Mining of frequent itemsets and association rules is used to identify patterns and relationships in data.

```
library(arules) # importing the arules package

db <- list(c("A", "B", "D", "E"), c("B", "C", "E"), c("A", "B", "D", "E"), c("A", "B", "C", "E"), c("A", "B", "D", "E"))

frequent <- apriori(db, parameter = list(supp = 0.5, conf = 1, target="frequent itemsets")) # creating frequent itemsets

## Apriori
##
## Parameter specification:
## confidence minval smax arem aval originalSupport maxtime support minlen
##          NA    0.1    1 none FALSE                TRUE     5     0.5     1
## maxlen          target  ext
##      10 frequent itemsets TRUE
##
## Algorithmic control:
## filter tree heap memopt load sort verbose
##    0.1 TRUE TRUE  FALSE TRUE    2    TRUE
```

```
##
## Absolute minimum support count: 3
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[5 item(s), 6 transaction(s)] done [0.00s].
## sorting and recoding items ... [5 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 done [0.00s].
## sorting transactions ... done [0.00s].
## writing ... [19 set(s)] done [0.00s].
## creating S4 object ... done [0.00s].
```

```
inspect(frequent) # inspecting the frequent itemset
```

```
##      items      support  count
## [1] {C}      0.6666667  4
## [2] {D}      0.6666667  4
## [3] {A}      0.6666667  4
## [4] {E}      0.8333333  5
## [5] {B}      1.0000000  6
## [6] {C, E}   0.5000000  3
## [7] {B, C}   0.6666667  4
## [8] {A, D}   0.5000000  3
## [9] {D, E}   0.5000000  3
## [10] {B, D}  0.6666667  4
## [11] {A, E}  0.6666667  4
## [12] {A, B}  0.6666667  4
## [13] {B, E}  0.8333333  5
## [14] {B, C, E} 0.5000000  3
## [15] {A, D, E} 0.5000000  3
## [16] {A, B, D} 0.5000000  3
## [17] {B, D, E} 0.5000000  3
## [18] {A, B, E} 0.6666667  4
## [19] {A, B, D, E} 0.5000000  3
```

```
cl <- apriori(db, parameter = list(supp = 0.5, conf = 1, target = "closed")) # creating a closed itemset
```

```
## Apriori
##
## Parameter specification:
## confidence minval smax arem aval originalSupport maxtime support minlen
##          NA      0.1    1 none FALSE              TRUE        5      0.5      1
## maxlen                target  ext
##      10 closed frequent itemsets TRUE
##
## Algorithmic control:
## filter tree heap memopt load sort verbose
##      0.1 TRUE TRUE  FALSE TRUE      2      TRUE
##
## Absolute minimum support count: 3
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[5 item(s), 6 transaction(s)] done [0.00s].
```



```
## sorting and recoding items ... [5 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 done [0.00s].
## filtering closed item sets ... done [0.00s].
## sorting transactions ... done [0.00s].
## writing ... [7 set(s)] done [0.00s].
## creating S4 object ... done [0.00s].
```

```
inspect(cl) # inspecting the closed itemset
```

```
##      items      support  count
## [1] {B}          1.0000000  6
## [2] {B, C}       0.6666667  4
## [3] {B, D}       0.6666667  4
## [4] {B, E}       0.8333333  5
## [5] {B, C, E}    0.5000000  3
## [6] {A, B, E}    0.6666667  4
## [7] {A, B, D, E} 0.5000000  3
```

```
mx <- apriori(db, parameter=list(supp=0.5, conf=1, target="maximal"))
```

```
## Apriori
##
## Parameter specification:
## confidence minval smax arem aval originalSupport maxtime support minlen
##          NA    0.1    1 none FALSE          TRUE      5     0.5     1
## maxlen                target ext
##    10 maximally frequent itemsets TRUE
##
## Algorithmic control:
## filter tree heap memopt load sort verbose
##    0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 3
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[5 item(s), 6 transaction(s)] done [0.00s].
## sorting and recoding items ... [5 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 done [0.00s].
## filtering maximal item sets ... done [0.00s].
## sorting transactions ... done [0.00s].
## writing ... [2 set(s)] done [0.00s].
## creating S4 object ... done [0.00s].
```

```
# creating a maximal itemset of db
```

```
inspect(mx) # inspecting the maximal itemset
```

```
##      items      support  count
## [1] {B, C, E}    0.5      3
## [2] {A, B, D, E} 0.5      3
```

```
rules <- apriori(db, parameter=list(supp=0.5, conf=1, target="rules")) # creating a rule of db
```

```
## Apriori
##
## Parameter specification:
## confidence minval smax arem aval originalSupport maxtime support minlen
##          1    0.1    1 none FALSE          TRUE      5    0.5    1
## maxlen target  ext
##       10 rules TRUE
##
## Algorithmic control:
## filter tree heap memopt load sort verbose
##    0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 3
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[5 item(s), 6 transaction(s)] done [0.00s].
## sorting and recoding items ... [5 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 done [0.00s].
## writing ... [16 rule(s)] done [0.00s].
## creating S4 object ... done [0.00s].
```

```
inspect(rules) # inspecting the rule
```

```
##      lhs      rhs support  confidence coverage  lift count
## [1] {}      => {B} 1.0000000 1          1.0000000 1.0 6
## [2] {C}      => {B} 0.6666667 1          0.6666667 1.0 4
## [3] {D}      => {B} 0.6666667 1          0.6666667 1.0 4
## [4] {A}      => {E} 0.6666667 1          0.6666667 1.2 4
## [5] {A}      => {B} 0.6666667 1          0.6666667 1.0 4
## [6] {E}      => {B} 0.8333333 1          0.8333333 1.0 5
## [7] {C, E}   => {B} 0.5000000 1          0.5000000 1.0 3
## [8] {A, D}   => {E} 0.5000000 1          0.5000000 1.2 3
## [9] {D, E}   => {A} 0.5000000 1          0.5000000 1.5 3
## [10] {A, D}  => {B} 0.5000000 1          0.5000000 1.0 3
## [11] {D, E}  => {B} 0.5000000 1          0.5000000 1.0 3
## [12] {A, E}  => {B} 0.6666667 1          0.6666667 1.0 4
## [13] {A, B}  => {E} 0.6666667 1          0.6666667 1.2 4
## [14] {A, D, E} => {B} 0.5000000 1          0.5000000 1.0 3
## [15] {A, B, D} => {E} 0.5000000 1          0.5000000 1.2 3
## [16] {B, D, E} => {A} 0.5000000 1          0.5000000 1.5 3
```

```
data(Adult) # importing the Adult dataset
```

```
dim(Adult) # checking the dimensions of Adult
```

```
## [1] 48842 115
```

```
inspect(apriori(Adult, parameter=list(supp = 0.75))) # inspecting the Adult dataset
```

```
## Apriori
##
## Parameter specification:
## confidence minval smax arem aval originalSupport maxtime support minlen
##          0.8    0.1    1 none FALSE              TRUE        5    0.75    1
## maxlen target  ext
##       10  rules TRUE
##
## Algorithmic control:
## filter tree heap memopt load sort verbose
##    0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 36631
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[115 item(s), 48842 transaction(s)] done [0.06s].
## sorting and recoding items ... [4 item(s)] done [0.00s].
## creating transaction tree ... done [0.01s].
## checking subsets of size 1 2 3 done [0.00s].
## writing ... [19 rule(s)] done [0.00s].
## creating S4 object ... done [0.00s].
##      lhs                                rhs          support confidence coverage
## [1] {}                                => {race=White}          0.8550428  0.8550428 1.0000000
## [2] {}                                => {native-country=United-States} 0.8974243  0.8974243 1.0000000
## [3] {}                                => {capital-gain=None}      0.9173867  0.9173867 1.0000000
## [4] {}                                => {capital-loss=None}     0.9532779  0.9532779 1.0000000
## [5] {race=White}                      => {native-country=United-States} 0.7881127  0.9217231 0.8550428
## [6] {native-country=United-States} => {race=White}          0.7881127  0.8781940 0.8974243
## [7] {race=White}                      => {capital-gain=None}     0.7817862  0.9143240 0.8550428
## [8] {capital-gain=None}                => {race=White}          0.7817862  0.8521883 0.9173867
## [9] {race=White}                      => {capital-loss=None}    0.8136849  0.9516307 0.8550428
## [10] {capital-loss=None}                => {race=White}          0.8136849  0.8535653 0.9532779
## [11] {native-country=United-States} => {capital-gain=None}    0.8219565  0.9159062 0.8974243
## [12] {capital-gain=None}                => {native-country=United-States} 0.8219565  0.8959761 0.9173867
## [13] {native-country=United-States} => {capital-loss=None}    0.8548380  0.9525461 0.8974243
## [14] {capital-loss=None}                => {native-country=United-States} 0.8548380  0.8967354 0.9532779
## [15] {capital-gain=None}                => {capital-loss=None}    0.8706646  0.9490705 0.9173867
## [16] {capital-loss=None}                => {capital-gain=None}    0.8706646  0.9133376 0.9532779
## [17] {capital-gain=None,
##      native-country=United-States} => {capital-loss=None}    0.7793702  0.9481891 0.8219565
## [18] {capital-loss=None,
##      native-country=United-States} => {capital-gain=None}    0.7793702  0.9117168 0.8548380
## [19] {capital-gain=None,
##      capital-loss=None}                => {native-country=United-States} 0.7793702  0.8951440 0.8706646
```

```
inspect(apriori(Adult, parameter = list(supp = 0.75), appearance = list(rhs = "capital-gain=None", defa
```

```
## Apriori
##
## Parameter specification:
```

```

## confidence minval smax arem aval originalSupport maxtime support minlen
##      0.8      0.1      1 none FALSE          TRUE      5      0.75      1
## maxlen target  ext
##      10 rules TRUE
##
## Algorithmic control:
## filter tree heap memopt load sort verbose
##      0.1 TRUE TRUE  FALSE TRUE      2      TRUE
##
## Absolute minimum support count: 36631
##
## set item appearances ...[1 item(s)] done [0.00s].
## set transactions ...[115 item(s), 48842 transaction(s)] done [0.06s].
## sorting and recoding items ... [4 item(s)] done [0.00s].
## creating transaction tree ... done [0.01s].
## checking subsets of size 1 2 3 done [0.00s].
## writing ... [5 rule(s)] done [0.00s].
## creating S4 object ... done [0.00s].
##      lhs                                rhs      support confidence coverage      lift c
## [1] {}                                => {capital-gain=None} 0.9173867  0.9173867 1.0000000 1.0000000 4
## [2] {race=White}                      => {capital-gain=None} 0.7817862  0.9143240 0.8550428 0.9966616 3
## [3] {native-country=United-States} => {capital-gain=None} 0.8219565  0.9159062 0.8974243 0.9983862 4
## [4] {capital-loss=None}                => {capital-gain=None} 0.8706646  0.9133376 0.9532779 0.9955863 4
## [5] {capital-loss=None,
##      native-country=United-States} => {capital-gain=None} 0.7793702  0.9117168 0.8548380 0.9938195 3

```