Ex.No.5 **ASSOCIATION RULE MINING – APRIORI ALGORITHM**

Date: 29-08-23

Aim

To implement Apriori algorithm in finding the frequent data sets through R programming.

Procedure

1. To do programming in R, first install "RStudio" and "R" in the system. RStudio is an integrated development environment [IDE] for R and python.
2. Select the File in taskbar →open New file →R script or use shortcut "ctrl+shift+N"
3. Install the 'arules,arulesViz, RColorBrewer' package and load it in R.
4. Import the built-in dataset 'groceries'.
5. Apply the Apriori Algorithm on the groceries dataset.
6. Write the program in the script and save it using the extension R.
7. Run the program by clicking Run option or use the shortcut "ctrl+enter".
8. See the output in the console tab.

Concepts Involved

- Applying the Apriori's algorithm -Association rule mining on the data set.

APRIORI ALGORITHM

Apriori algorithm is related to the frequent itemset generation. The primary requirements to find the association rules in data mining are:

- **Brute Force:** Analyze all the rules and find the support and confidence levels for the individual rule. Afterward, eliminate the values which are less than the threshold support and confidence levels.

A. **Generate:**
Create a table containing support count of each item present in dataset – Called candidate set.(C1)
Compare candidate set item's support count with minimum support count. This gives us item set.(L1)

B. **Join :**
Generate candidate set C2 using L1 (this is called join step). Condition of joining Lk-1 and Lk-1 is that it should have (K-2) elements in common.

C. **Prune:**
Check all subsets of an itemset are frequent or not and if not frequent remove that itemset.
compare candidate (C2) support count with minimum support count(here min_support=2 if support_count of candidate set item is less than min_support then remove those items) this gives us itemset L2.

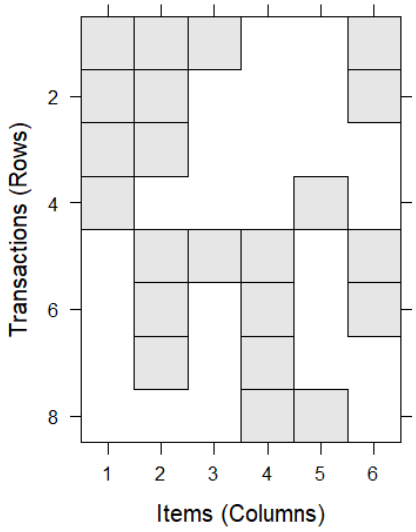
Like this, do the same process until there are no frequent data sets.

Script

```
#create a list of basket
market_basket <-
  list(
    c("apple", "beer", "rice", "meat"),
    c("apple", "beer", "rice"),
    c("apple", "beer"),
    c("apple", "pear"),
    c("milk", "beer", "rice", "meat"),
    c("milk", "beer", "rice"),
    c("milk", "beer"),
    c("milk", "pear"))
#set transaction names
names(market_basket) <- paste("T", c(1:8), sep = "")
#transform data
trans <- as(market_basket, "transactions")
#inspect data
dim(trans)
itemLabels(trans)
summary(trans)
image(trans)
```

Output

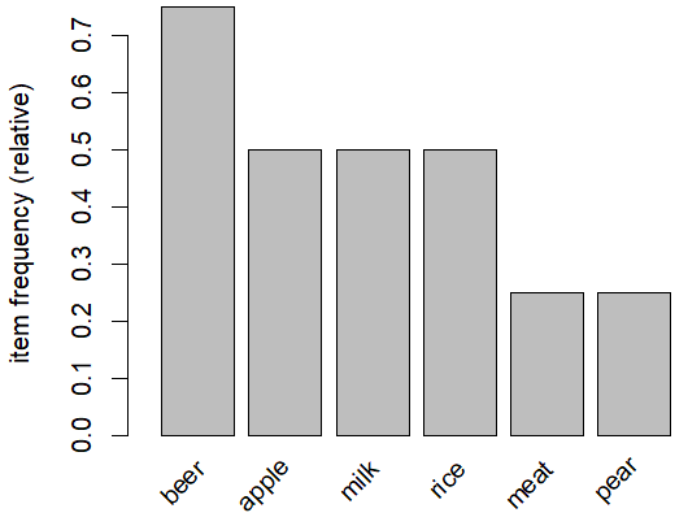
```
[1] 8 6

[1] "apple" "beer"  "meat"  "milk"  "pear"  "rice"

transactions as itemMatrix in sparse format with
 8 rows (elements/itemsets/transactions) and
 6 columns (items) and a density of 0.4583333

most frequent items:
   beer   apple    milk    rice    meat (Other)
      6       4       4       4       2       2

element (itemset/transaction) length distribution:
sizes
2 3 4
4 2 2

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   2.00    2.00    2.50    2.75    3.25    4.00

includes extended item information - examples:
  labels
1  apple
2   beer
3   meat

includes extended transaction information - examples:
  transactionID
1            T1
2            T2
3            T3
```



Script

```
#display relative item frequency
itemFrequencyPlot(trans, topN=10, cex.names=1)
```

Output



Script

```
#min support 0.3, min confidence 0.5
rules <- apriori(trans,
                 parameter = list(supp=0.3, conf=0.5,
                                  maxlen=10,
                                  target= "rules"))
summary(rules)
inspect(rules)
```

Output

```
> summary(rules)
set of 10 rules

rule length distribution (lhs + rhs):sizes
1 2
4 6

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    1.0     1.0     2.0     1.6     2.0     2.0

summary of quality measures:
    support         confidence        coverage            lift
count
 Min.   :0.375   Min.   :0.5000   Min.   :0.5000   Min.   :1.000
Min.   :3.0
 1st Qu.:0.375   1st Qu.:0.5000   1st Qu.:0.5625   1st Qu.:1.000
1st Qu.:3.0
 Median :0.500   Median :0.5833   Median :0.7500   Median :1.000
Median :4.0
 Mean   :0.475   Mean   :0.6417   Mean   :0.7750   Mean   :1.067
Mean   :3.8
 3rd Qu.:0.500   3rd Qu.:0.7500   3rd Qu.:1.0000   3rd Qu.:1.000
3rd Qu.:4.0
 Max.   :0.750   Max.   :1.0000   Max.   :1.0000   Max.   :1.333
Max.   :6.0

mining info:
  data ntransactions support confidence
 trans             8     0.3        0.5

call
 apriori(data = trans, parameter = list(supp = 0.3, conf = 0.5,
maxlen = 10, target = "rules"))
> inspect(rules)
     lhs         rhs     support confidence coverage lift     cou
nt
[1]  {}       => {apple} 0.500   0.5000000  1.00     1.000000 4
[2]  {}       => {milk}  0.500   0.5000000  1.00     1.000000 4
[3]  {}       => {rice}  0.500   0.5000000  1.00     1.000000 4
[4]  {}       => {beer}  0.750   0.7500000  1.00     1.000000 6
[5]  {apple} => {beer}  0.375   0.7500000  0.50     1.000000 3
[6]  {beer}  => {apple} 0.375   0.5000000  0.75     1.000000 3
[7]  {milk}  => {beer}  0.375   0.7500000  0.50     1.000000 3
[8]  {beer}  => {milk}  0.375   0.5000000  0.75     1.000000 3
[9]  {rice}  => {beer}  0.500   1.0000000  0.50     1.333333 4
[10] {beer}  => {rice}  0.500   0.6666667  0.75     1.333333 4
```

Script

```
#Min Support 0.3, confidence as 0.5.
rules <- apriori(trans,
        parameter = list(supp=0.3, conf=0.5,
                maxlen=10,
                minlen=2,
                target= "rules"))
inspect(rules)
```

Output

```
> inspect(rules)
    lhs         rhs     support confidence coverage lift     coun
t
[1] {apple} => {beer}  0.375   0.7500000  0.50     1.000000 3
[2] {beer}  => {apple} 0.375   0.5000000  0.75     1.000000 3
[3] {milk}  => {beer}  0.375   0.7500000  0.50     1.000000 3
[4] {beer}  => {milk}  0.375   0.5000000  0.75     1.000000 3
[5] {rice}  => {beer}  0.500   1.0000000  0.50     1.333333 4
[6] {beer}  => {rice}  0.500   0.6666667  0.75     1.333333 4
```

Script

```
#Set LHS and RHS
beer_rules_rhs <- apriori(trans,
                parameter = list(supp=0.3, conf=0.5,
                        maxlen=10,
                        minlen=2),
                appearance = list(default="lhs", rhs="beer"))
inspect(beer_rules_rhs)
beer_rules_lhs <- apriori(trans,
                parameter = list(supp=0.3, conf=0.5,
                        maxlen=10,
                        minlen=2),
                appearance = list(lhs="beer", default="rhs"))
inspect(beer_rules_lhs)
```

Output

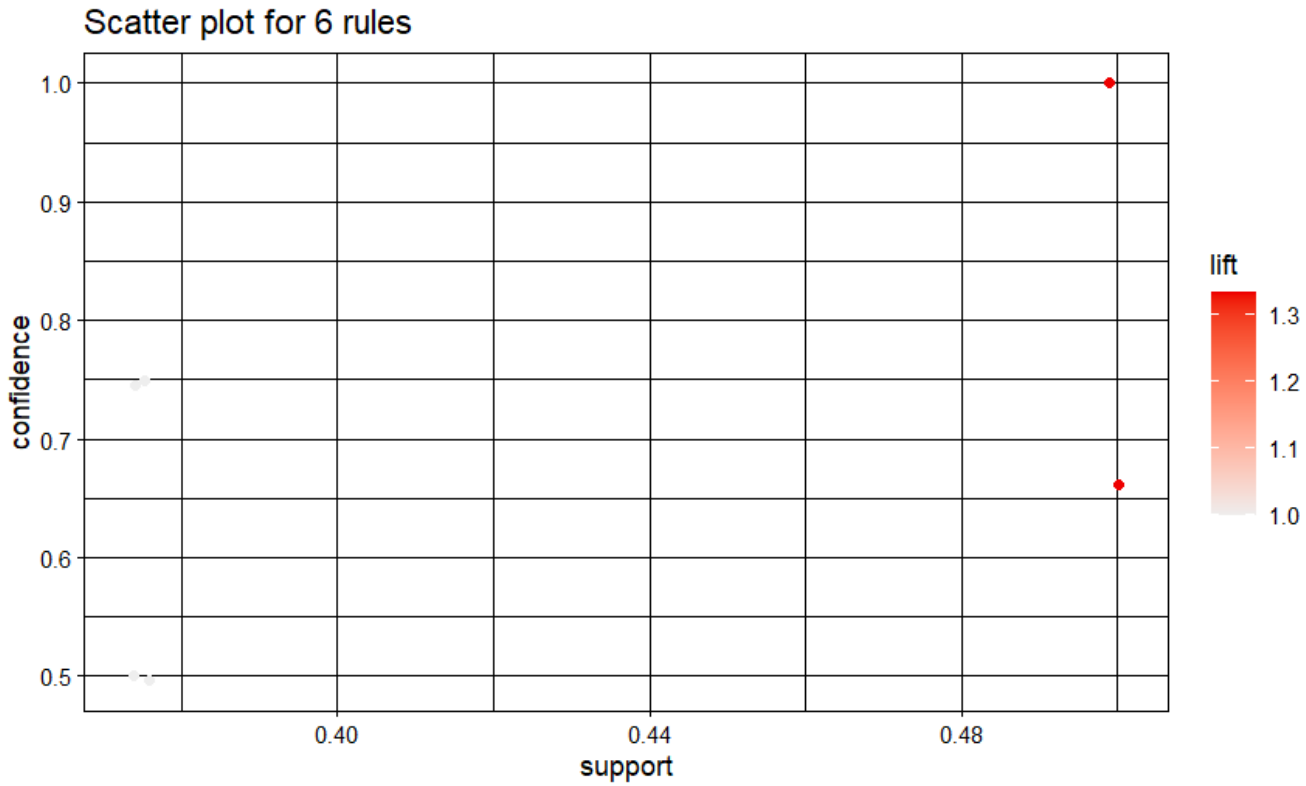
```
> inspect(beer_rules_rhs)
    lhs         rhs    support confidence coverage lift     count
[1] {apple} => {beer} 0.375   0.75       0.5      1.000000 3
[2] {milk}  => {beer} 0.375   0.75       0.5      1.000000 3
[3] {rice}  => {beer} 0.500   1.00       0.5      1.333333 4
> inspect(beer_rules_lhs)
    lhs         rhs     support confidence coverage lift     count
[1] {beer} => {apple} 0.375   0.5000000  0.75     1.000000 3
[2] {beer} => {milk}  0.375   0.5000000  0.75     1.000000 3
[3] {beer} => {rice}  0.500   0.6666667  0.75     1.333333 4
```

Script

#Visualizing association Rules

plot(rules)

Output



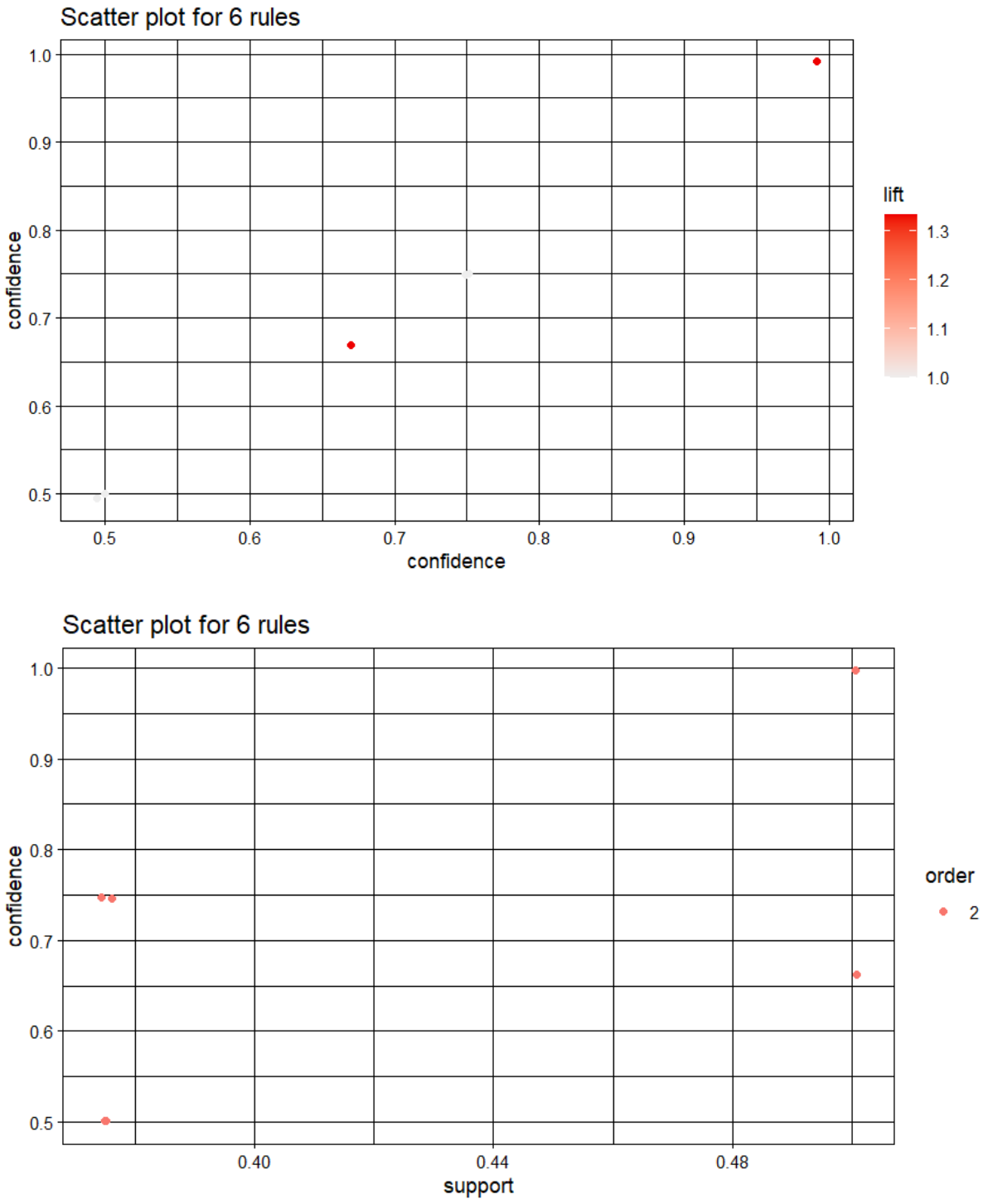
Script

#Confidence as a measure of interest

plot(rules, measure = "confidence")

plot(rules, method = "two-key plot")

Output

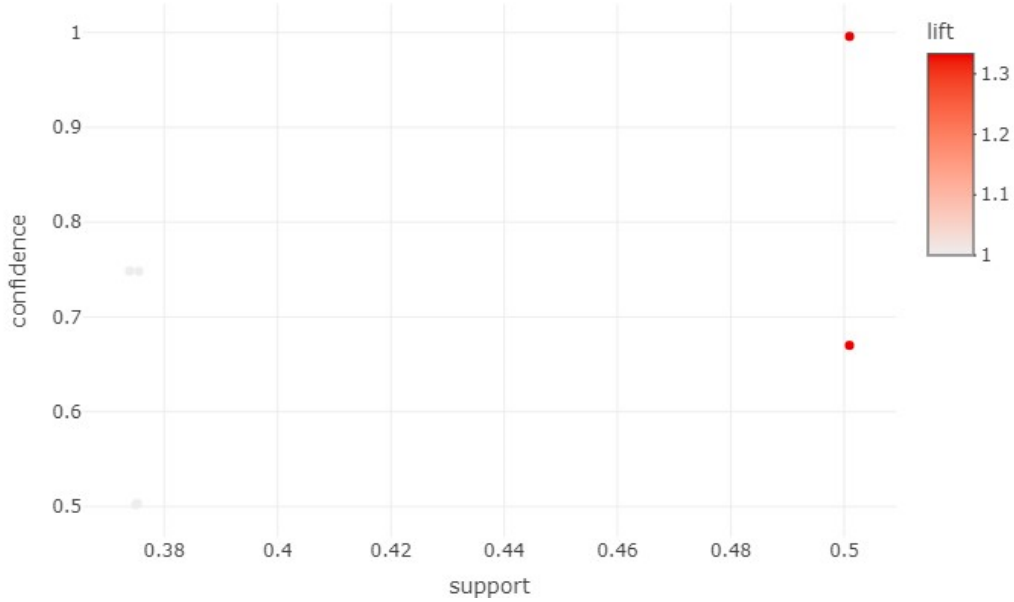


Script

#Interactive Scatter Plot

plot(rules, engine = "plotly")

Output



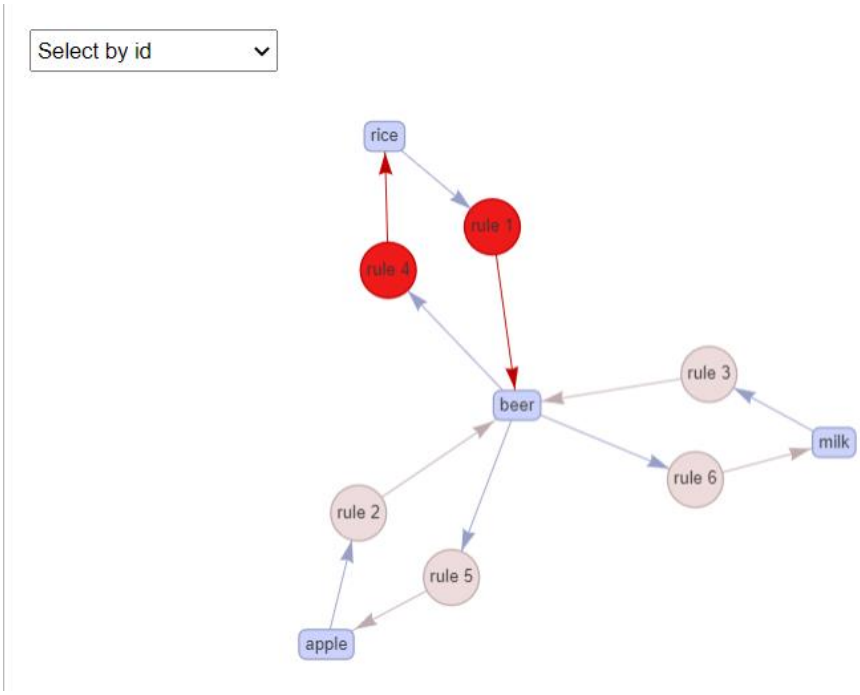
Script

#Graph based Visualization

subrules <- head(rules, n = 10, by = "confidence")

plot(subrules, method = "graph", engine = "htmlwidget")

Output

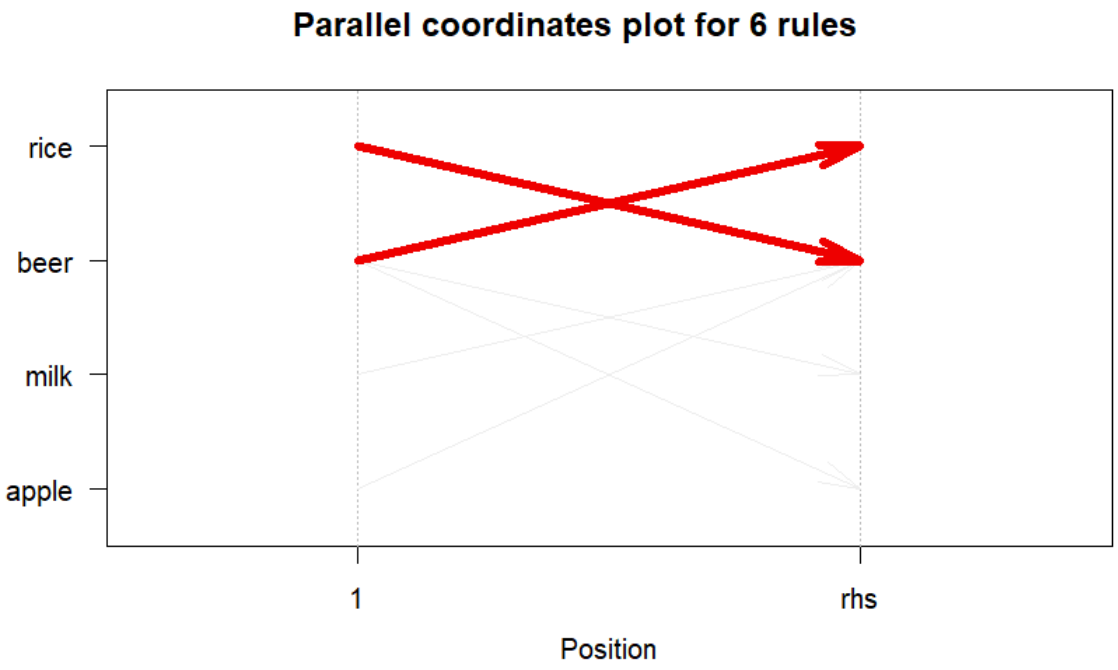


Script

#Parallel coordinate plot

plot(subrules, method="paracoord")

Output



Result

Thus the Apriori algorithm has been successfully implemented using R programming.