

# Market Basket Analysis with Apriori

An unsupervised learning technique to recognize purchasing patterns of consumers

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## INTRODUCTION

In today's data-driven world, almost every company has huge database of purchase transaction. Therefore, a big question arises that what products are more likely to be purchased together. To answer this, Market Basket Analysis with Apriori can be used.

It is an unsupervised learning technique that can be used to analyze the **purchasing patterns of consumers**. It can be used as a recommendation mechanism, for example, product recommendation, music recommendation, and others promotional strategies can be developed.

## METHODS

- Apriori is a pattern mining algorithm.
  - All subsets of a frequent itemset must be frequent
  - For any infrequent itemset, all its supersets must be infrequent.
- To apply the algorithm, at first, I transformed the dataset into transactional data. Apriori uses transactional data to design association models. In transactional data, there is a one-to-many relationship between the case identifier and the values for each case.
- The Apriori algorithm has been applied with support = 0.001, confidence = 0.8, and minlen=2.
- To check association for an specific item, the apriori has been applied with supp=0.001,conf = 0.05, minlen=2, and appearance = list(default="rhs",lhs=("rice")). The inspection of this rules only displays the association between 'Rice' and other items.

## RESULTS

- The dataset has 9835 rows (number of transactions) and 169 columns (unique products)
- After implementing apriori on the dataset, 410 rules are generated. A length of 5 items has the most rules. The summary of quality is measured by ranges of support, confidence, and lift.
- The **Figure 05** displays the Top 5 rules based on confidence. From the figure
  - 100% consumers who bought rice and sugar bought whole milk.
  - 100% consumers who bought butter domestic eggs, and soft cheese also bought whole milk.
- The **Figure 06** displays the Top 5 rules for a specific item 'Rice' based on confidence. From the figure,
  - 61.3% consumers who bought rice bought milk.
  - 30.6% consumers who bought rice bought yogurt.
- The **Figure 07** displays the Top 5 rules for a specific item 'Rice' based on lift. From the figure,
  - Consumers who bought rice are nearly 5.5 times more likely to buy hard cheese.
  - Consumers who bought rice are nearly 4 times more likely to buy chickens.

transactions as itemMatrix in sparse format with 9835 rows (elements/itemsets/transactions) and 169 columns (items) and a density of 0.02609146

most frequent items:

whole milk	other vegetables	rolls/buns	soda	yogurt (other)
2513	1903	1809	1715	1372
34055				

Figure 01: Summary of Raw Transactional Data

set of 410 rules

rule length distribution (lhs + rhs): sizes

3	4	5	6
29	229	140	12

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
3.000	4.000	4.000	4.329	5.000	6.000

summary of quality measures:

support	confidence	lift	count
Min.: 0.001017	Min.: 0.8000	Min.: 3.131	Min.: 10.00
1st Qu.: 0.001017	1st Qu.: 0.8333	1st Qu.: 3.312	1st Qu.: 10.00
Median: 0.001220	Median: 0.8462	Median: 3.588	Median: 12.00
Mean: 0.001247	Mean: 0.8663	Mean: 3.951	Mean: 12.27
3rd Qu.: 0.001322	3rd Qu.: 0.9091	3rd Qu.: 4.341	3rd Qu.: 13.00
Max.: 0.003152	Max.: 1.0000	Max.: 11.235	Max.: 31.00

mining info:

data	ntransactions	support	confidence
master2	9835	0.001	0.8

Figure 03: Summary of Rules after Applying Apriori

lhs	rhs	support	confidence	lift
{rice,sugar}	=> {whole milk}	0.001220132	1	3.913649
{canned fish,hygiene articles}	=> {whole milk}	0.001118454	1	3.913649
{butter,rice,root vegetables}	=> {whole milk}	0.001016777	1	3.913649
{flour,root vegetables,whipped/sour cream}	=> {whole milk}	0.001728521	1	3.913649
{butter,domestic eggs,soft cheese}	=> {whole milk}	0.001016777	1	3.913649

Figure 05: Association Check for Top 5 Rules by Confidence

lhs	rhs	support	confidence	lift
{rice}	=> {whole milk}	0.004677173	0.6133333	2.400371
{rice}	=> {other vegetables}	0.003965430	0.5200000	2.687441
{rice}	=> {root vegetables}	0.003152008	0.4133333	3.792102
{rice}	=> {yogurt}	0.002338587	0.3066667	2.198299
{rice}	=> {fruit/vegetable juice}	0.001931876	0.2533333	3.504266

Figure 06: Association Check for Top 5 Rules for Rice by Confidence

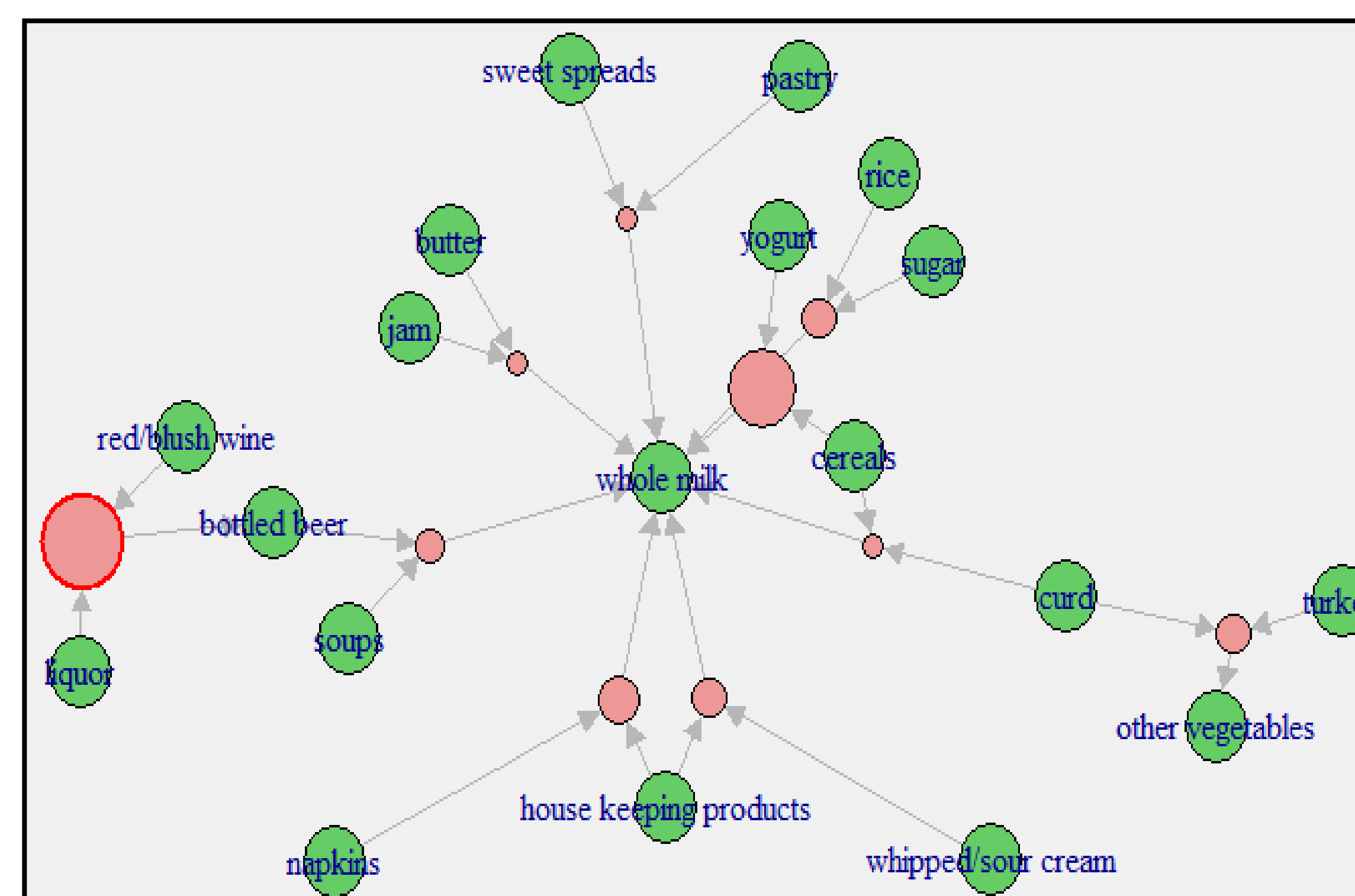


Figure 08: Overall Top 10 Association Rules

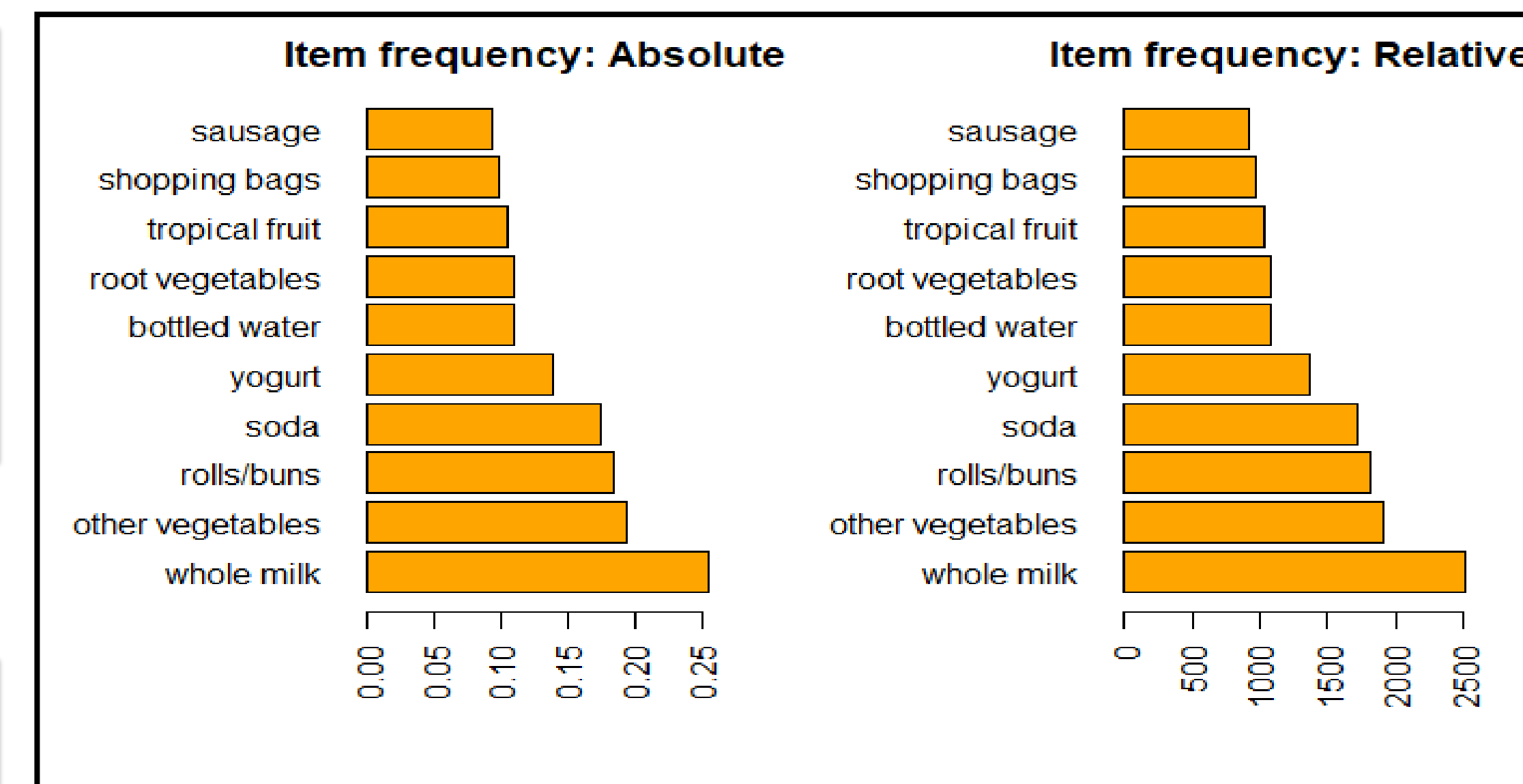


Figure 02: Absolute and Relative Distribution of Top 10 Selling Items

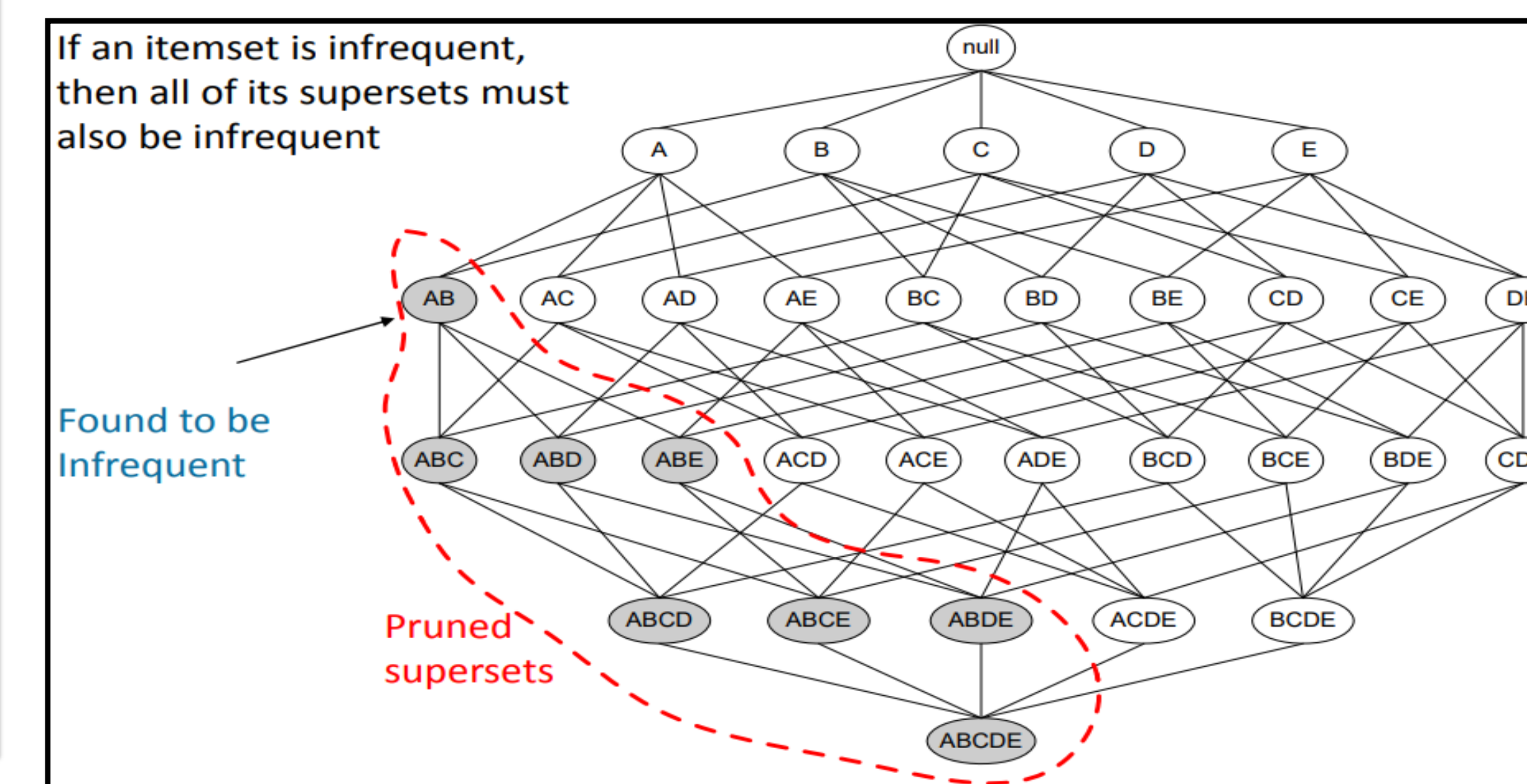


Figure 04: Apriori Principles (Source: Frequent Itemset Generation Using Apriori Algorithm by Chih-Ling Hsu)

lhs	rhs	support	confidence	lift
{rice}	=> {hard cheese}	0.001016777	0.1333333	5.441217
{rice}	=> {sugar}	0.001220132	0.1600000	4.725526
{rice}	=> {butter}	0.001830198	0.2400000	4.331009
{rice}	=> {chicken}	0.001321810	0.1733333	4.039652
{rice}	=> {hamburger meat}	0.001016777	0.1333333	4.010194

Figure 07: Association Check for Top 5 Rules for Rice by Lift

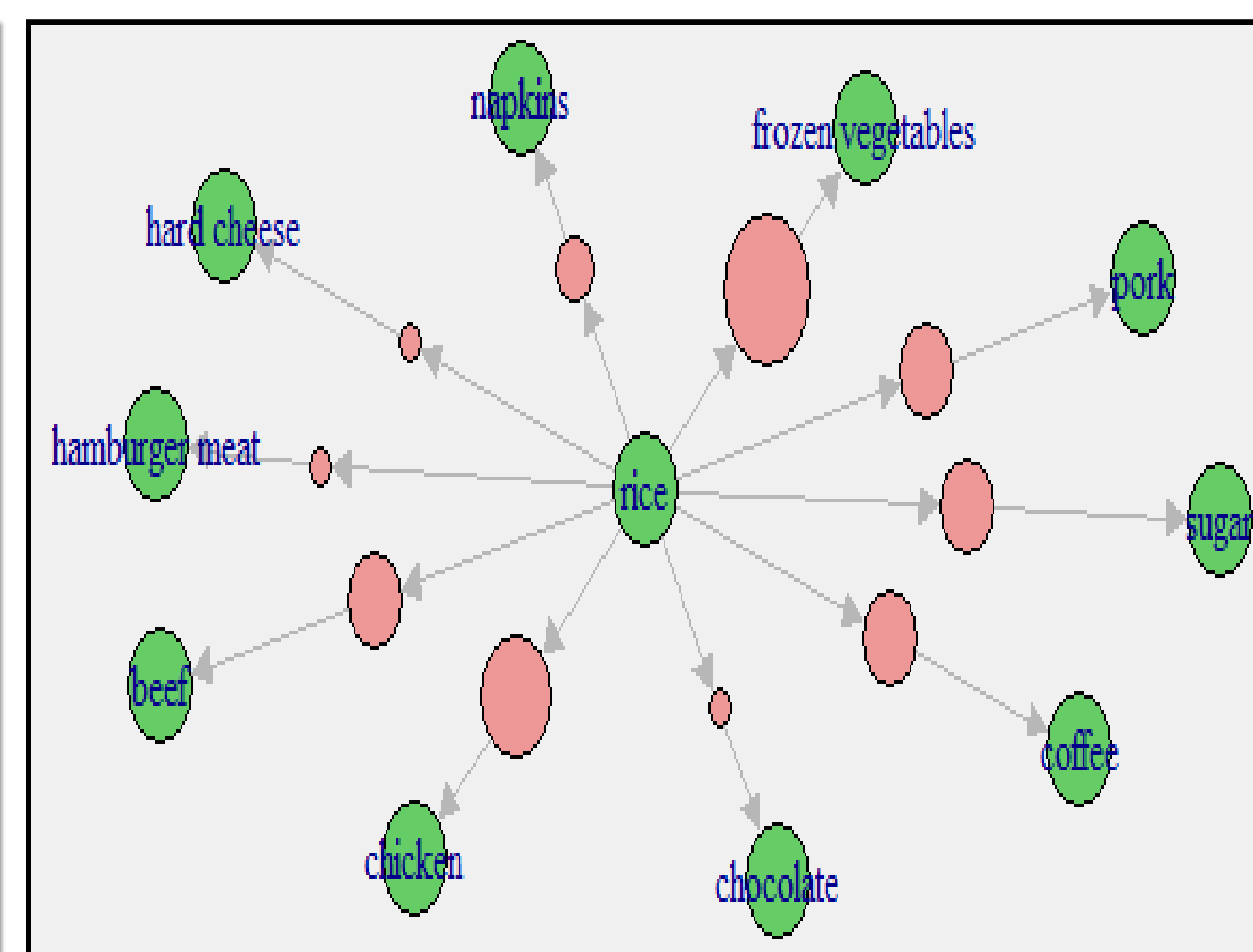


Figure 09: Overall Top 10 Association Rules for Rice

## DISCUSSION

- Support:** The fraction of transactions in data set that contain that product or set of products.
- Confidence:** It is conditional probability implies that a customer buy product A will also buy product B.
- Lift:** If someone buys Product A, what % of chance of buying product B would increase.
- Density:** It refers to the proportion of non-zero cells in the matrix..

From this Market Basket Analysis, a lot of different strategic questions can be answered. For example,

- What are the most purchased items? **Figure 02** displays the top 10 selling items
- What are the least selling items?
- What items should be kept together to boost sales?
- What items should not be kept together?
- Which products boost the sales of other products? Etc.

This model can also be applied in lot of other sectors. For example,

- Unusual credit card purchases to detect fraud.
- Finding potential clients in insurance industries.
- Finding the pattern of different diseases based on human behavior and provide health recommendation.

A major limitation of Association Technique with Apriori is that it is slow when there are a large number of transactions. Therefore, specifying the number of rules to be inspected is often necessary.

## R CODE

```
# Install package "arules"
install.packages("arules")
library(arules)

# create path
path <- "C:\\Users\\msalehin\\Desktop\\FALL 2017\\Programming in R\\R Project\\R Project"
setwd(path)

# import file
master1 <- read.csv("groceries.csv", header = FALSE)
summary(master1)
master2 <- read.transactions("groceries.csv", sep = ",")
summary(master2)

# Display Top 10 in Relative and Absolute Frequency in Chart
par(mfrow=c(1,2))
itemFrequencyPlot(master2,type="relative",topN=10,horiz=TRUE,col="orange", xlab='',
  main='Item frequency: Absolute')
itemFrequencyPlot(master2,type="absolute",topN=10,horiz=TRUE,col="orange",xlab='',
  main='Item frequency: Relative')

# Apply Apriori
Apply_Apriori1 <- apriori(master2, parameter = list(supp = 0.001, conf = 0.8, minlen=2))

# Display overall summary
summary(Apply_Apriori1)

# inspect top 5 rules by confidence and by lift
inspect(sort(Apply_Apriori1, by = 'confidence')[1:5])
inspect(sort(Apply_Apriori1, by = 'lift')[1:5])

# Apply Apriori for Specific item
Apply_Apriori2 <- apriori(master2, parameter=list(supp=0.001,conf = 0.05, minlen=2),
  appearance = list(default="rhs",lhs=("rice")), control = list(verbose=FALSE))

# inspect top 5 rules for specific tem by confidence and by lift
inspect(sort(Apply_Apriori2, by="confidence")[1:5])
inspect(sort(Apply_Apriori2, by="lift")[1:5])

# Install package "arulesviz"
install.packages("arulesviz")

# plot Top 10 Rules for Specific item
library(arulesviz)
plot(Apply_Apriori1[1:10],interactive=TRUE,method="graph",shading=NA)

# plot Top 10 Rules for specific item
library(arulesviz)
plot(Apply_Apriori2[1:10],interactive=TRUE,method="graph",shading=NA)
```