Statistical Computing with R: Masters in Data Sciences 503, S27 First Batch, SMS, TU, 2021

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Review Preview:

- Unsupervised models
- Association rules learning
  - Market-Basket analysis
- Monte Carlo simulations
  - Good old methods!
- Class imbalance problem
  - Statistical approach
  - Data science approach
- Missing data
  - Supervised learning
  - Unsupervised learning

Association rules learning/mining:

https://towardsdatascience.com/association-rule-mining-in-r-ddf2d044ae50

- Association Rule Mining (also called as Association Rule Learning) is a common technique used **to find associations (co-occurrence) between many variables**.
- It is often used by grocery stores, e-commerce websites, and anyone with large **transactional** databases.
- A most common example that we encounter in our daily lives: Amazon knows what else you want to buy when you order something on their site.
- The same idea extends to Spotify too: They know what song you want to listen to next.
- All of these incorporate, at some level, data mining concepts and association rule mining algorithms.

Association rules: example problem

https://www.datacamp.com/community/tutorials/market-basket-analysis-r

- You get a client who runs a retail store and gives you **data for all transactions that consists of items bought in the store by several customers over a period of time**.
- Your client then asks you to use that data to help boost their business.
- Your client will **use your findings to not only change/update/add items in inventory but also use them to change the layout of the physical store or rather an online store**.
- To find results that will help your client, you will use **Market Basket Analysis (MBA)** which uses **Association Rule Mining** on the given transaction data.

Use of association rules mining results:

https://www.datacamp.com/community/tutorials/market-basket-analysis-r

- Changing the store layout according to trends
- Customer behavior analysis
- Catalogue design
- Cross marketing on online stores
- What are the trending items customers buy
- Customized emails with add-on sales
- etc.

Association rule mining: If => Then analysis

https://www.datacamp.com/community/tutorials/market-basket-analysis-r

- Association Rule Mining is used when you want to **find an association between different objects** in a set, find frequent patterns in a transaction database, relational databases or any other information repository.
- The applications of Association Rule Mining are found in Marketing, Basket Data Analysis (or Market Basket Analysis) in retailing, clustering and classification.
- It can tell you what items do customers frequently buy together by generating a set of rules called **Association Rules**.
- In simple words, it gives you output as rules in form **if this then that**.

What is **apriori algorithm** and rule? http://r-statistics.co/Association-Mining-With-R.html

- Association mining is usually done on transactions data from a retail market or from an online e-commerce store.
- Since most transactions data **is large**, the apriori algorithm makes it easier to find these patterns or rules quickly.
- Using all the rules in the data with apriori() is not a good idea!
- A rule is a notation that represents which item/s is frequently bought with what item/s.
- It has an **LHS** and an **RHS** part and can be represented as follows:

  itemsetA => itemsetB

- This means, the item/s on the **right** were frequently purchased along with items on the **left**.

How to measure the strength of a rule? http://r-statistics.co/Association-Mining-With-R.html

- The **apriori algorithm** generates the most relevant set of rules from a given transaction data.
- **It also shows the support, confidence and lift of those rules.**
- These three measures can be used to decide the relative strength of the rules.
- How are they computed?

Lets consider the rule **A => B** in order to compute these metrics.

Support=Number of transactions with both A and B/Total number of transactions
=P(A∩B) = **frequency(A,B)/N**

Confidence=Number of transactions with both A and B/Total number of transactions with A
=P(A∩B)/P(A) = **frequency(A,B)/frequency(A)**

ExpectedConfidence=Number of transactions with B/Total number of transactions
=P(B)=**frequency(B)/N**

Lift=Confidence/Expected Confidence
=P(A∩B)/P(A).P(B) = **Support(A,B)/Support(A).Support(B)**

Association rule: Support and confidence

- Association rules are given in the form as below:

  A=>B[Support , Confidence]

- The part **before =>** is referred to as if (Antecedent) and the part **after =>** is referred to as then (Consequent).

- Where A and B are sets of items in the transaction data. A and B are disjoint sets.

Computer=>Anti−virusSoftware

[Support=20%,confidence=60%]

Above rule says:

- 20% transaction show Anti-virus software is bought with purchase of a Computer **(support)**

- 60% of customers who purchase Anti-virus software is bought with purchase of a Computer **(confidence)**

Lift:

- *Lift* is the factor by which, the co-occurence of A and B exceeds the expected probability of A and B co-occuring, **had they been independent**.

- So, higher the lift, higher the chance of A and B occurring together.

- **lift = 1**: implies no association between items

- **lift > 1**: greater than 1 means that item B is likely to be bought if item A is bought

- **lift < 1**: less than 1 means that item B is unlikely to be bought if item A is bought.

Note:

- **Frequent Itemsets:**

Item-sets whose support is greater or equal than minimum support threshold (min_sup).

- **min_sup is set on user choice.**

- **Strong rules:**

If a rule A=>B[Support, Confidence] satisfies **min_sup** **and** **min_confidence** then it is a strong rule.

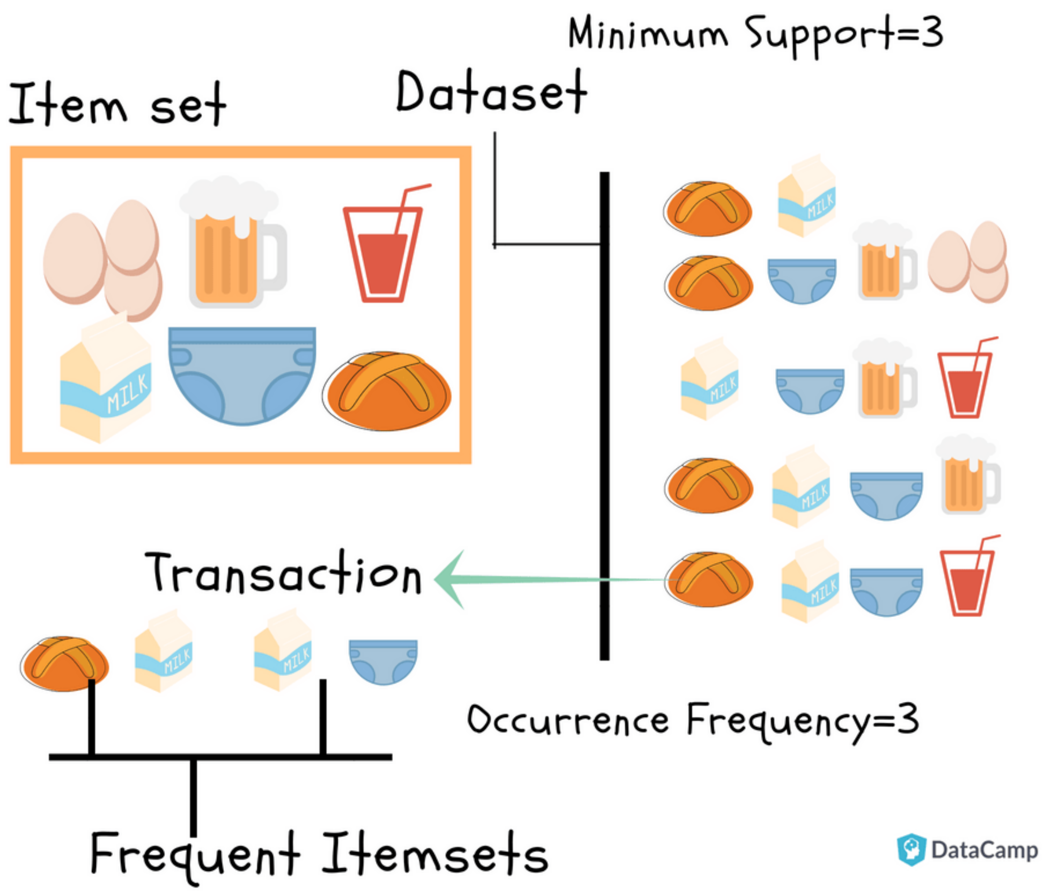
- **Coverage:**

Coverage (also called cover or LHS-support) is the support of the left-hand-side of the rule, i.e., *supp(X)*.

It represents a measure of “to how often the rule can be applied”.

Example:

https://www.datacamp.com/community/tutorials/market-basket-analysis-r



ID	Items
1	{Bread, Milk}
2	{Bread, Diapers, Beer, Eggs}
3	{Milk, Diapers, Beer, Cola}
4	{Bread, Milk, Diapers, Beer}
5	{Bread, Milk, Diapers, Cola}
...	...

market basket transactions

{Diapers, Beer} Example of a frequent itemset

{Diapers} → {Beer} Example of an association rule

Calculate the following for {Bread => Milk}:

- Support for (Bread)
- Support for (Milk)
- Support for (Break, Milk)

- Confidence (Bread => Milk)

- ExpectedConfidence(Bread=>Milk)

- Lift (Bread => Milk)

- Coverage(Bread=>Milk) = support(lhs)

- Support for (Bread)=4/5 =f(B)/N=0.8
- Support for (Milk)=4/5=f(M)/N=0.8
- Support(B,M) = f(B,M)/N=3/5=0.6

- Confidence (Bread => Milk) =3/4=0.75
- ExpectedConfidence=P(M)=4/5=0.8

- Lift (Bread => Milk)

=Confidence/ExpectedConfidence=0.75/0.80

=0.9375

OR

=support(A,B)/support(A).support(B)
=(0.6)/[(0.8).(0.8)] = 0.6/0.64 = 0.9375

Let’s do it in R!

 # create a list of baskets

```
market_basket <-
list(
c("bread", "milk"),
c("bread", "diapers", "beer", "Eggs"),
c("milk", "diapers", "beer", "cola"),
c("bread", "milk", "diapers", "beer"),
c("bread", "milk", "diapers", "cola")
  )
```

 # set transaction names (T1 to T5)

```
names(market_basket) <- paste("T", c(1:5), sep
= "")
```

```
> # create a list of baskets
  > market_basket <-
  +   list(
    +     c("bread", "milk"),
    +     c("bread", "diapers", "beer", "Eggs"),
    +     c("milk", "diapers", "beer", "cola"),
    +     c("bread", "milk", "diapers", "beer"),
    +     c("bread", "milk", "diapers", "cola")
    +   )
>
  > # set transaction names (T1 to T5)
  > names(market_basket) <- paste("T", c(1:5),
sep = "")
```

Let’s use “arules” package and get some outputs:

- library(arules)

#Transformation

- trans <- as(market_basket, "transactions")

#Dimensions

- dim(trans)

#Item labels

- itemLabels(trans)

#Summary

- summary(trans)

#Plot

- image(trans)

#Transformation to transactions data

trans <- as(market_basket, "transactions")

 # dim(trans)

- [1] 5 6 #5 transactions, 6 items

#Item labels

> itemLables(trans)

[1] "beer" "bread" "cola" "diapers" "Eggs" "milk“

Let’s use “arules” package and get some outputs:

#Summary
- summary(trans)

transactions as itemMatrix in sparse format with
5 rows (elements/itemsets/transactions) and
6 columns (items) and a **density of 0.6 (non-zero cells)**

most frequent items:

bread	diapers	milk	beer	cola	(Other)
4	4	4	3	2	1

element (itemset/transaction) length distribution:
sizes

2	4	(Itemset)
1	4	(transactions)

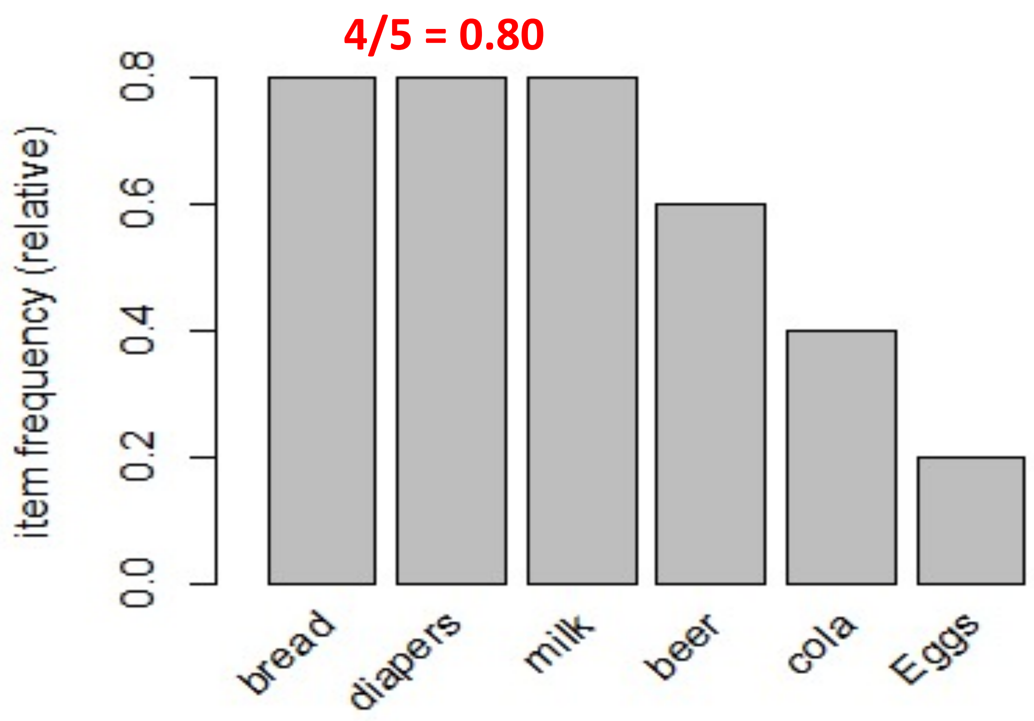
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
2.0	4.0	**4.0**	3.6	4.0	**4.0**

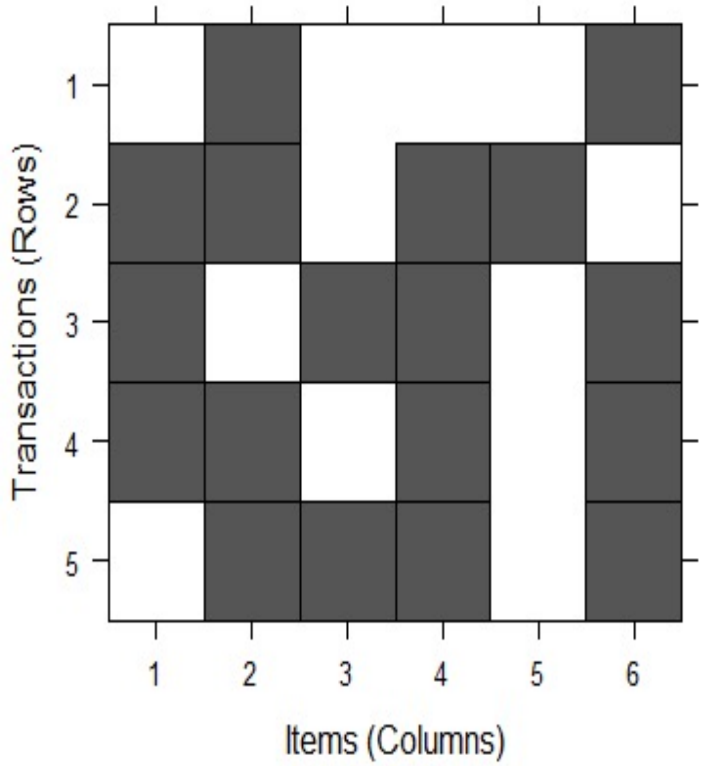
Let’s inspect the “trans”

- inspect(trans)

	items	transactionID
[1]	{bread, milk}	T1
[2]	{beer, bread, diapers, Eggs}	T2
[3]	{beer, cola, diapers, milk}	T3
[4]	{beer, bread, diapers, milk}	T4
[5]	{bread, cola, diapers, milk}	T5

Relative Frequency plot and plot of “trans”





#Relative frequency plot
itemFrequencyPlot(trans, topN=10, cex.names=1)

#Plot
image(trans)

Apriori algorithm: why?

- **Frequent Itemset Generation** is the most computationally expensive step because it requires a full database scan.

- In above example, we have seen the example of only 5 transactions, but in **real-world transaction data for retail can exceed up to GB s and TBs of data** for which an optimized algorithm is needed to prune out Item-sets that will not help in later steps.

- **For this APRIORI Algorithm is used to create new rules.**
- Since Support and Confidence measure how interesting the rule is, we will use them to create rules.
- **New rule is set by the minimum support and minimum confidence thresholds.**
- The closer to threshold the more the rule is of use to the client.
- These thresholds set by client help to compare the rule strength according to your own or client's will.

Apriori algorithm of "trans" without/with min. support of 0.3 and min. confidence of 0.5:

rules <- apriori(trans) **#set of 31 rules!**

Be careful using it with large transactions!

inspect(rules) **#3 empty LHS rules!**

#Min Support 0.3, confidence as 0.5.

```
rules <- apriori(trans,
parameter = list(supp=0.3, conf=0.5,
                 maxlen=10,
                 target= "rules"))
```

Note: maxlen = maximum length of the transaction! We could have used maxlen = 4 here as we know it but this will not be known in real-life!

Apriori

- Parameter specification:

confidence	minval	smax	arem	aval	originalSupport	maxtime	support	minlen	maxlen
0.5	0.1	1	none	FALSE	TRUE	5	0.3	**1**	**10**

Algorithmic control:

filter	tree	heap	memopt	load	sort	verbose
0.1	TRUE	TRUE	FALSE	TRUE	2	TRUE

rule length distribution (lhs + rhs):

sizes

1	2	3	
4	16	12	Total=32

Summary of the “rules”:

summary(rules)

set of 32 rules **#4 empty lhs rules**

#summary of quality measures:

support	confidence	coverage	lift
Min. :**0.4000**	Min. :**0.5000**	Min. :**0.4000**	Min. :**0.8333**
1st Qu.:0.4000	1st Qu.:0.6667	1st Qu.:0.6000	1st Qu.:0.8333
Median :0.4000	Median :0.7500	Median :0.6000	Median :1.0000
Mean :0.4938	Mean :0.7474	Mean :0.6813	Mean :1.0473
3rd Qu.:0.6000	3rd Qu.:0.8000	3rd Qu.:0.8000	3rd Qu.:1.2500
Max. :**0.8000**	Max. :**1.0000**	Max. :**1.0000**	Max. :**1.6667**

 # mining info:

- data ntransactions support confidence
- trans 5 0.3 0.5

rule length distribution (lhs + rhs):sizes

- 1 2 3
- 4 16 12

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.00	2.00	2.00	2.25	3.00	3.00

Inspection of the 32 “rules” with min. support = 0.3 & min. confidence = 0.5 in R:

Inspect (rules)

#Output from R:

		lhs		rhs	support	confidence	coverage	lift	count
•	[1]	{}	=>	{beer}	0.6	0.6000000	1.0	1.0000000	3
•	[2]	{}	=>	{milk}	0.8	0.8000000	1.0	1.0000000	4
•	…								
•	[5]	{cola}	=>	{milk}	0.4	1.0000000	0.4	**1.2500000**	2
•	[6]	{milk}	=>	{cola}	0.4	0.5000000	0.8	**1.2500000**	2
•	…								
•	[9]	{beer}	=>	{milk}	0.4	0.6666667	0.6	0.8333333	2
•	[10]	{milk}	=>	{beer}	0.4	0.5000000	0.8	0.8333333	2
•	…								
•	[13]	{beer}	=>	{diapers}	0.6	1.0000000	0.6	**1.2500000**	3
•	[14]	{diapers}	=>	{beer}	0.6	0.7500000	0.8	**1.2500000**	3
•	[15]	{milk}	=>	{bread}	0.6	0.7500000	0.8	0.9375000	3
•	**[16]**	**{bread}**	**=>**	**{milk}**	**0.6**	**0.7500000**	**0.8**	**0.9375000**	**3**
•	**….**								
•	**[32]**								

We can remove the “empty” rules with “minlen”:

#Removing empty rules

rules <- apriori(trans,
parameter = list(supp=0.3, conf=0.5,
maxlen=10,
minlen=2,
target= "rules"))

- **set of 28 rules**
- rule length distribution (lhs + rhs):
  sizes
- 2 3
- 16 12
-

	lhs		rhs	support	confidence	coverage	lift	count
[1]	{cola}	=>	{milk}	0.4	1.0000000	0.4	1.2500000	2
[2]	{milk}	=>	{cola}	0.4	0.5000000	0.8	1.2500000	2
[3]	{cola}	=>	{diapers}	0.4	1.0000000	0.4	1.2500000	2
…								
[17]	{cola, milk}	=>	{diapers}	0.4	1.0000000	0.4	1.2500000	2
[18]	{cola, diapers}	=>	{milk}	0.4	1.0000000	0.4	1.2500000	2
[19]	{diapers, milk}	=>	{cola}	0.4	0.6666667	0.6	1.6666667	2

Let’s set RHS rule for “trans” data:

#For example, to analyze what items customers buy before buying {beer},

#we set **rhs=beer** and default=lhs:

beer_rules_rhs <- apriori(trans,

parameter = list(supp=0.3, conf=0.5,

maxlen=10,

minlen=2),

appearance = list(default="lhs", rhs="beer"))

#Inspect

- inspect(beer_rules_rhs)

	lhs	rhs	support	confidence	coverage	lift	count
[1]	{bread}	=> {beer}	0.4	0.5000000	0.8	0.8333333	2
[2]	{milk}	=> {beer}	0.4	0.5000000	0.8	0.8333333	2
[3]	{diapers}	=> {beer}	0.6	0.7500000	0.8	**1.2500000**	3
[4]	{bread, diapers}	=> {beer}	0.4	0.6666667	0.6	**1.1111111**	2
[5]	{diapers, milk}	=> {beer}	0.4	0.6666667	0.6	**1.1111111**	2

Let’s set LHS rule for “trans” data:

#For example, to analyze what items customers buy before buying {beer},

#we set **lhs=beer** and default=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 the result:

inspect(beer_rules_lhs)

	lhs		rhs	support	confidence	coverage	lift	count
[1]	{beer}	=>	{bread}	0.4	0.6666667	0.6	0.8333333	2
[2]	{beer}	=>	{milk}	0.4	0.6666667	0.6	0.8333333	2
[3]	{beer}	=>	{diapers}	0.6	1.0000000	0.6	**1.2500000**	3

Product recommendation rule:

#Product recommendation rule

- rules_conf <- sort (rules, by="confidence", decreasing=TRUE)

#inspect the rule

show the support, lift and confidence for all rules

- inspect(head(rules_conf))

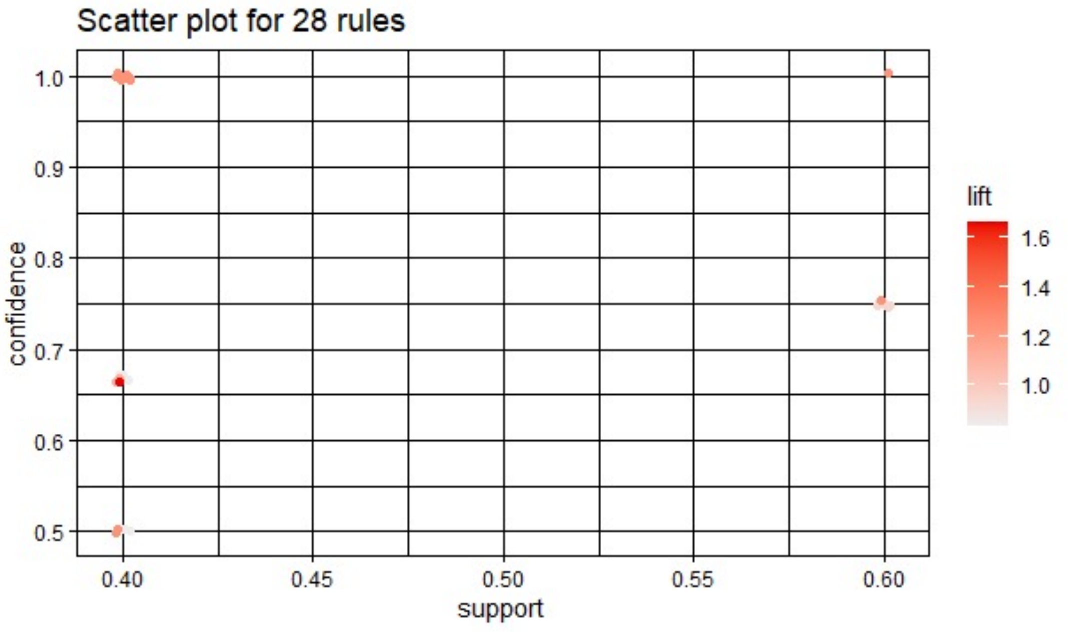
	lhs		rhs	support	confidence	coverage	lift	n
[1]	{cola}	=>	{milk}	0.4	1	0.4	**1.25**	2
[2]	{cola}	=>	{diapers}	0.4	1	0.4	**1.25**	2
[3]	{beer}	=>	{diapers}	0.6	1	0.6	**1.25**	3
[4]	{cola, milk}	=>	{diapers}	0.4	1	0.4	**1.25**	2
[5]	{cola, diapers}	=>	{milk}	0.4	1	0.4	**1.25**	2
[6]	{beer, milk}	=>	{diapers}	0.4	1	0.4	**1.25**	2

- We can check the whole list but it will be wise to use head to check the first 6 rules (**highly recommended when using the R markdown language or R notebook as knitting will be fast and easy to read/understand**)

- **We can sort it by "lift" too, if required!**

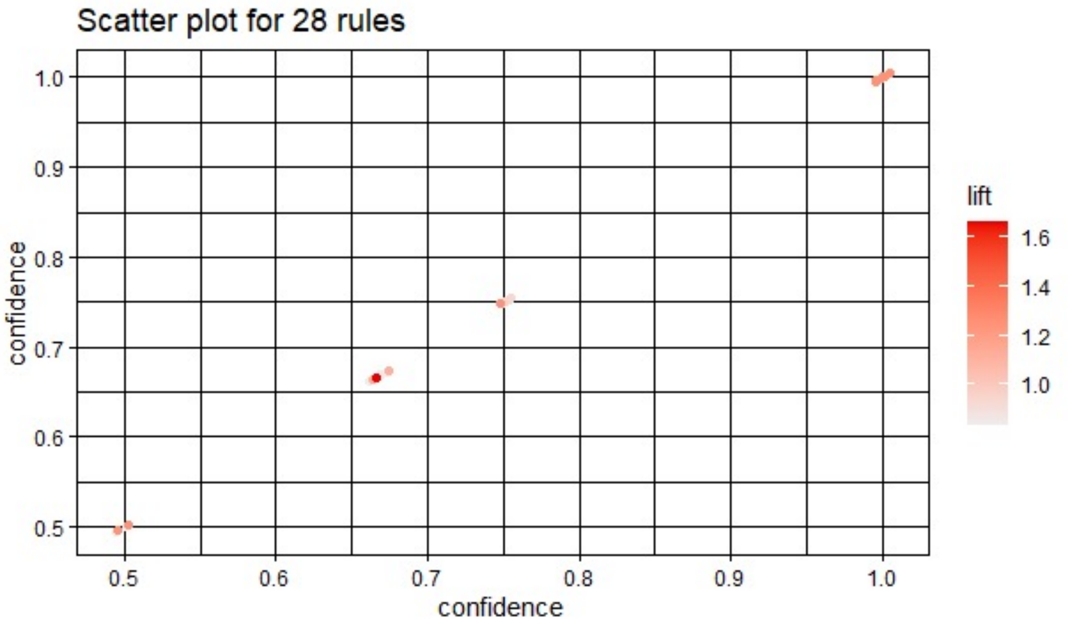
Plotting rules with “arulesViz” package:

- library(arulesViz)
- plot(rules)



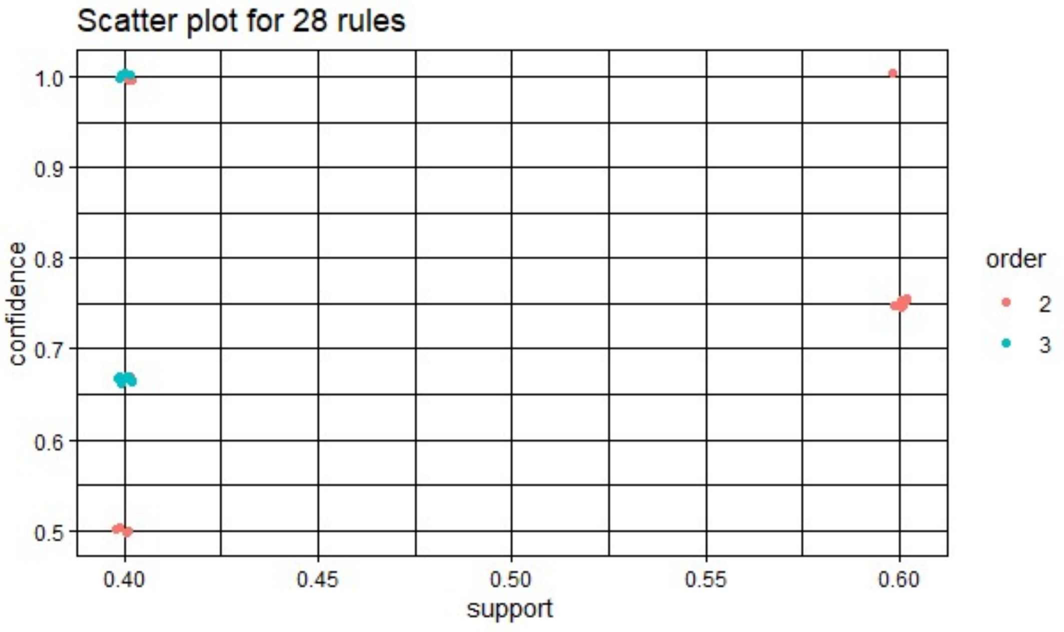
Plotting rules with “arulesViz” package:

- plot(rules, measure = "confidence")



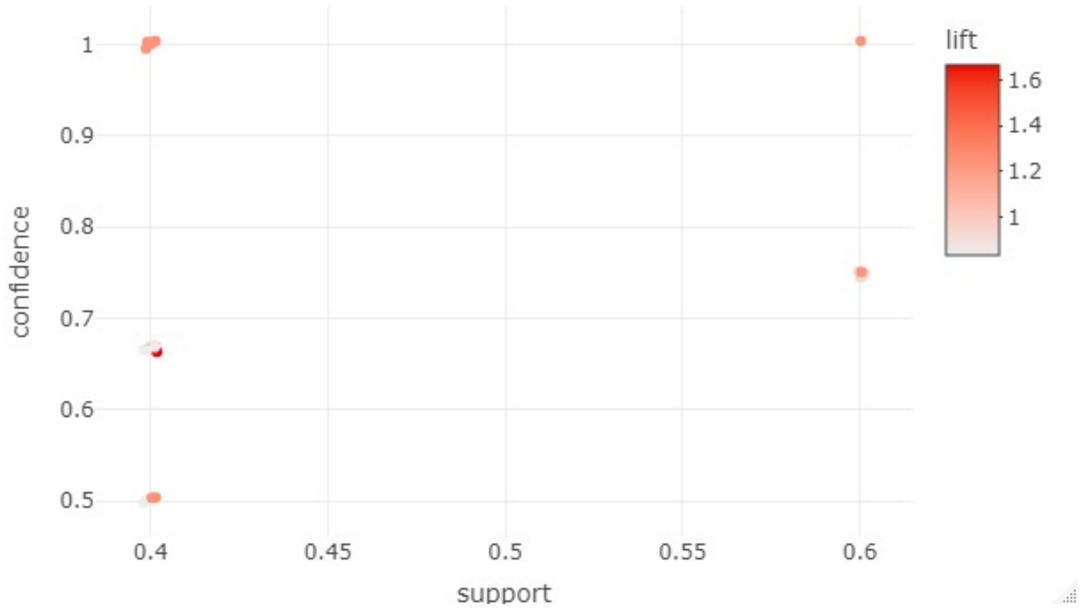
Plotting rules with “arulesViz” package:

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



Interactive plot with “plotly” engine:

- #Interactive plot
- plot(rules, engine = "plotly")

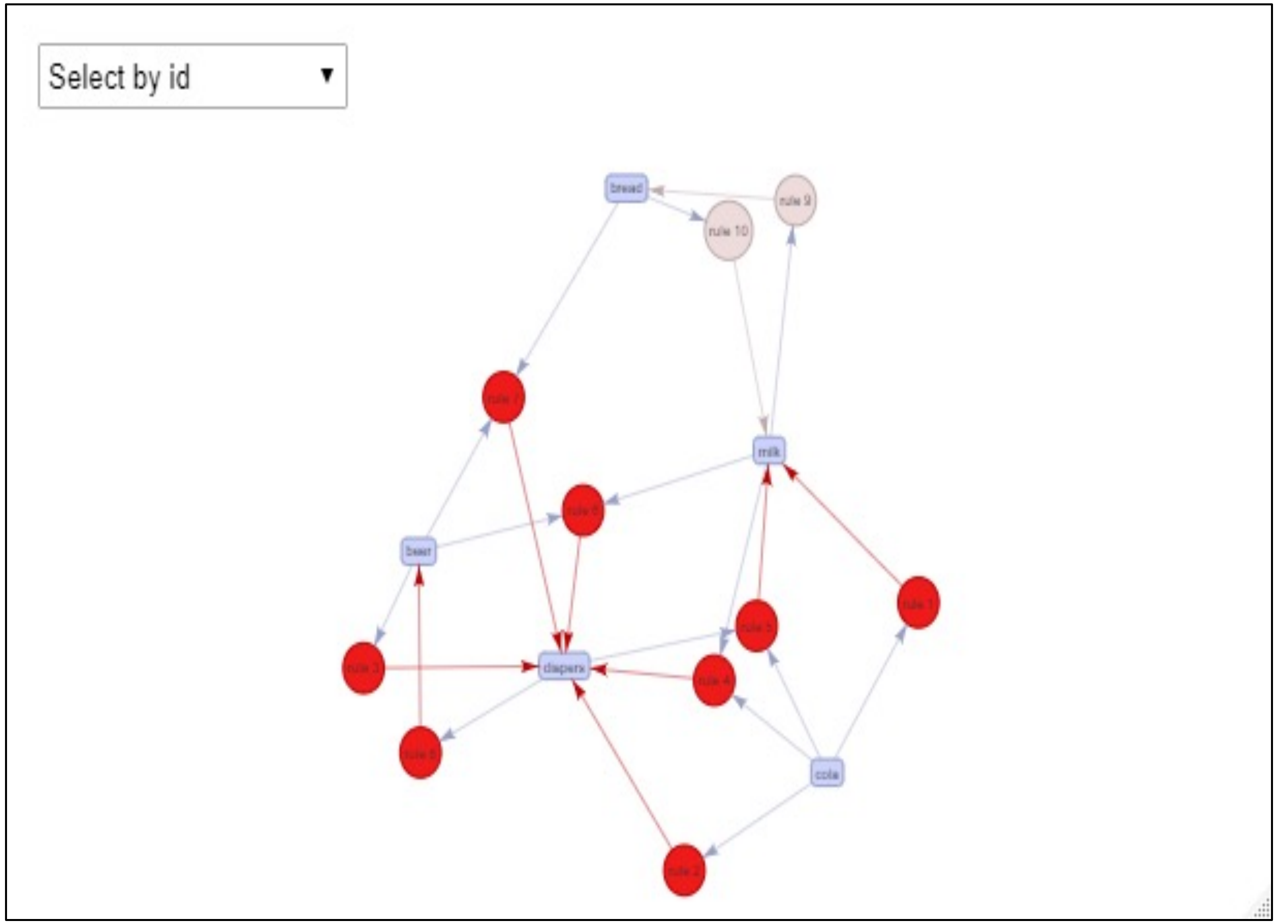


Graph based visualization:

#Graph based visualization

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

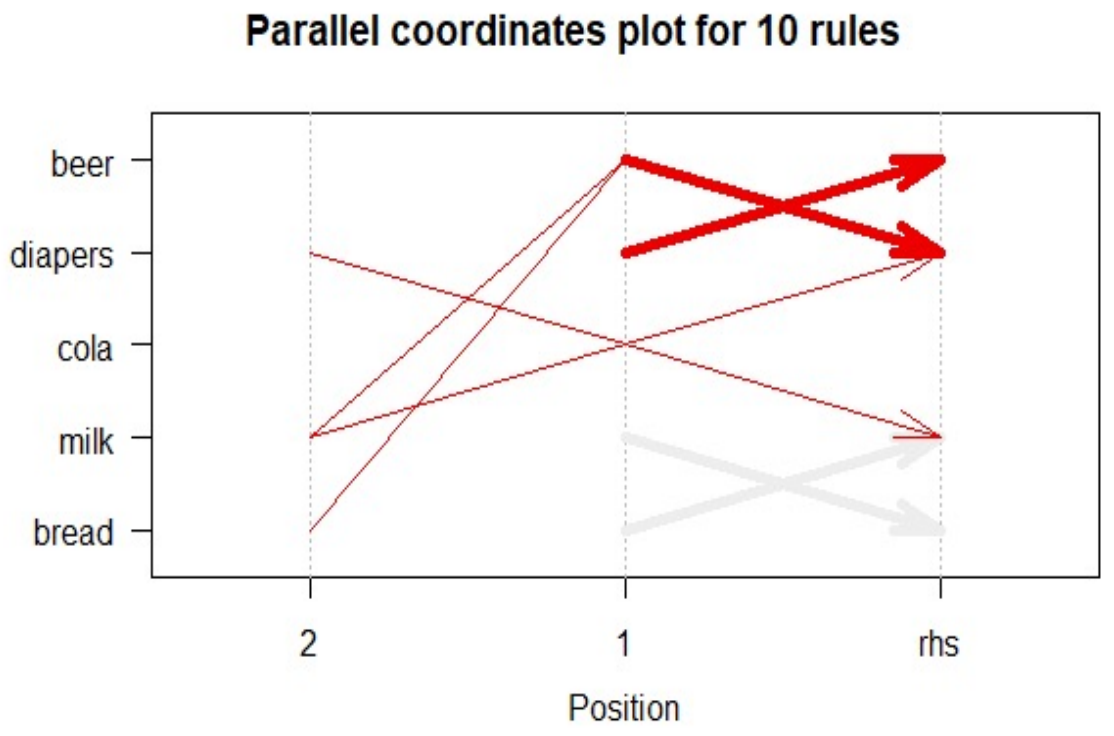
plot(subrules, method = "graph", engine = "htmlwidget")



Parallel coordinate plot for 10 rules:

#Parallel coordinate plot

- plot(subrules, method="paracoord")



Finally:

- Association rules mining/learning **must be done with the factor variables only**. So, continuous variable in the data must be converted to factor (categorical) variable ***before using the association rules***

- To learn more about the example we used and more, read:
- https://www-users.cse.umn.edu/~kumar001/dmbook/ch6.pdf
- To learn from the "real-life" example, watch:
- https://www.youtube.com/watch?v=91CmrpD-4Fw

Question/queries?

- Next class

- Monte Carlo Simulations
  - Good old methods!
- Class imbalance problem
  - Statistical approach
  - Data sciences approach
- Missing data
  - Supervised learning
  - Unsupervised learing

Thank you!

@shitalbhandary