Statistical Computing with R: Masters in Data Sciences 503 (S28) Third Batch, SMS, TU, 2024

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Review Preview: Unsupervised models

- Association rules learning
  - Market-Basket analysis
- Monte Carlo simulations
  - Good old days!
- Class imbalance problem
  - Statistical approach
  - Data science approach

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 result:

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 analyis

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.

- 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
$=P(A \cap B)$ = **frequency(A,B)/N**

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

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

Lift=Confidence/Expected Confidence
$=P(A \cap B)/P(A).P(B)$ = **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.

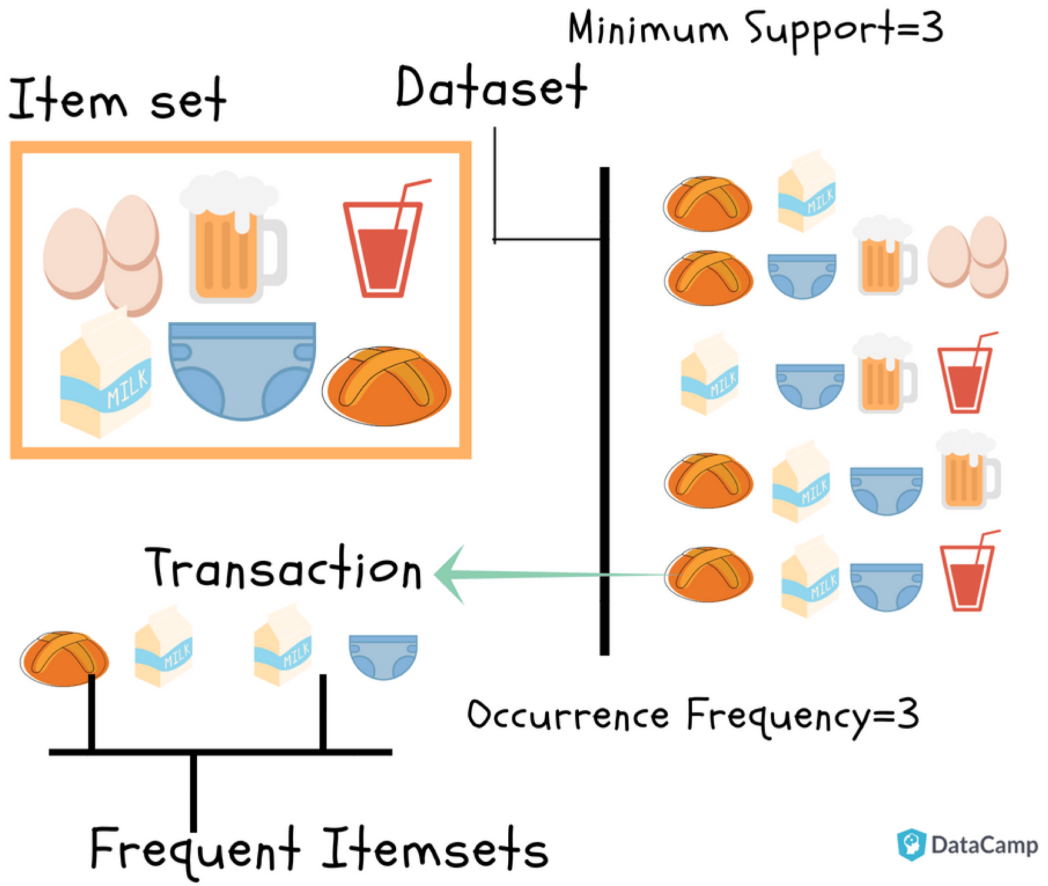
- **Coverage:**

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(Break=>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”

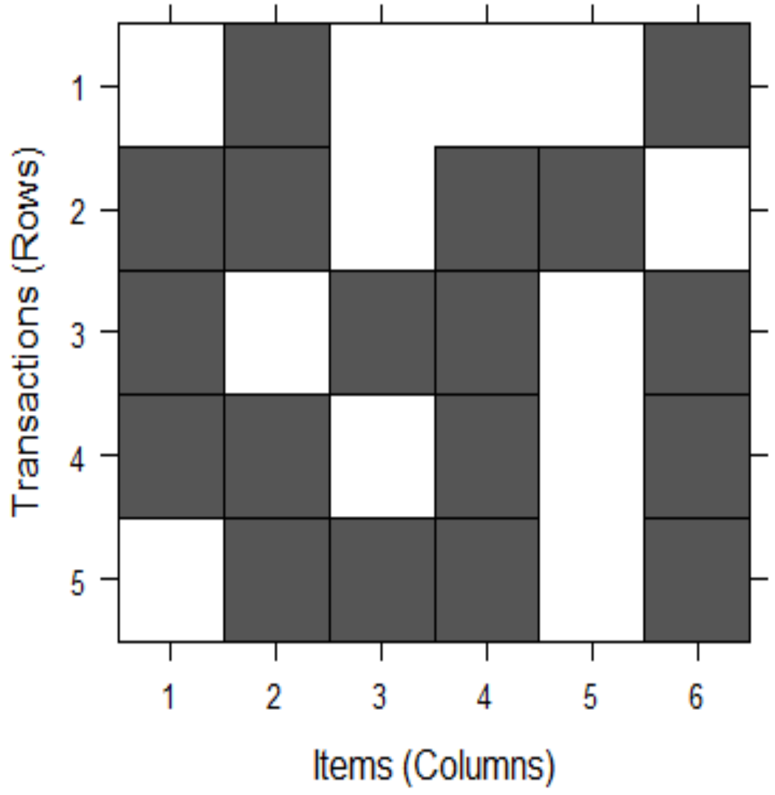
- inspect(trans)

	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

Plot of “trans”

#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 in “trans” with minimum support of 0.3 and min. confidence of 0.5:

#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**

target ext
rules TRUE

Algorithmic control:

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

Summary of the “rules”:

summary(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

Inspection of the “rules” with minlen:

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
•	[3]	{}	=>	{bread}	0.8	0.8000000	1.0	1.0000000	4
•	[4]	{}	=>	{diapers}	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
•	[7]	{cola}	=>	{diapers}	0.4	1.0000000	0.4	**1.2500000**	2
•	[8]	{diapers}	=>	{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
•	[11]	{beer}	=>	{bread}	0.4	0.6666667	0.6	0.8333333	2
•	[12]	{bread}	=>	{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

```
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

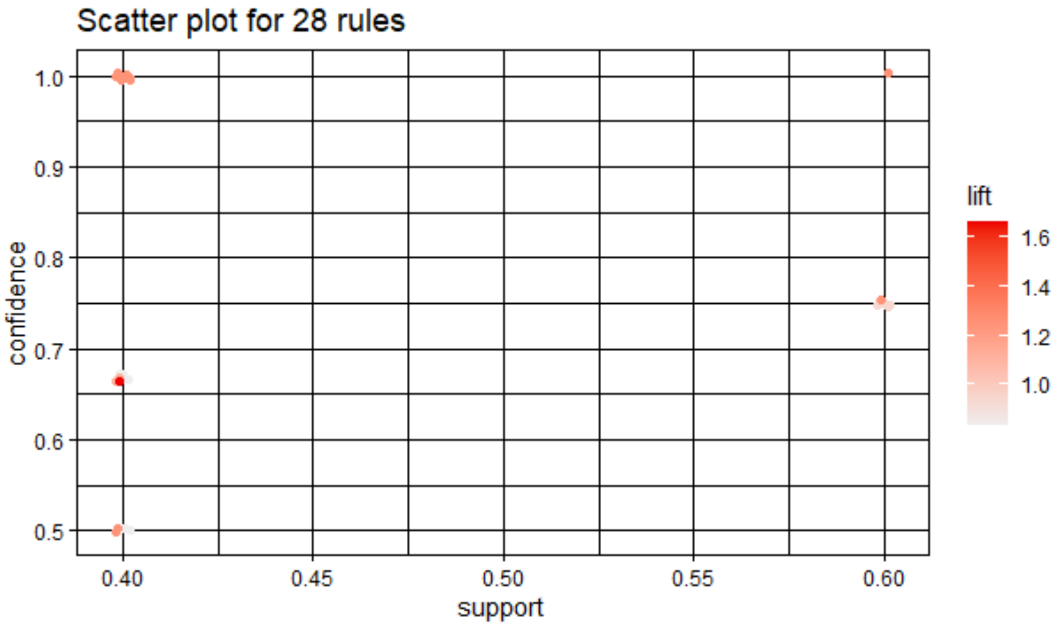
show the support, lift and confidence for all rules

- 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

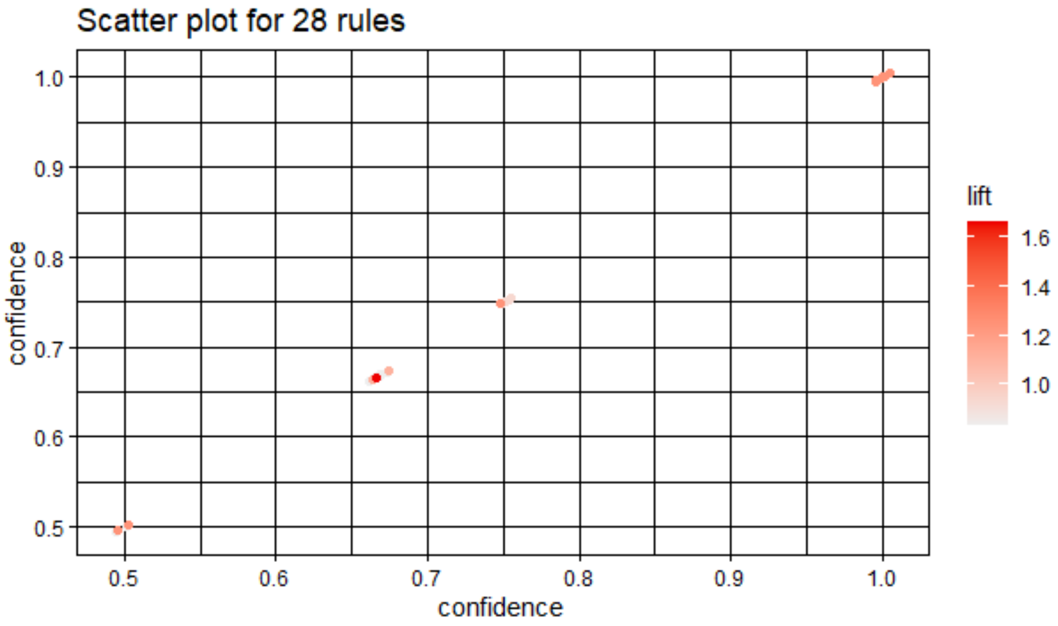
Plotting rules with “arulesViz” package:

- library(arulesViz)
- plot(rules)



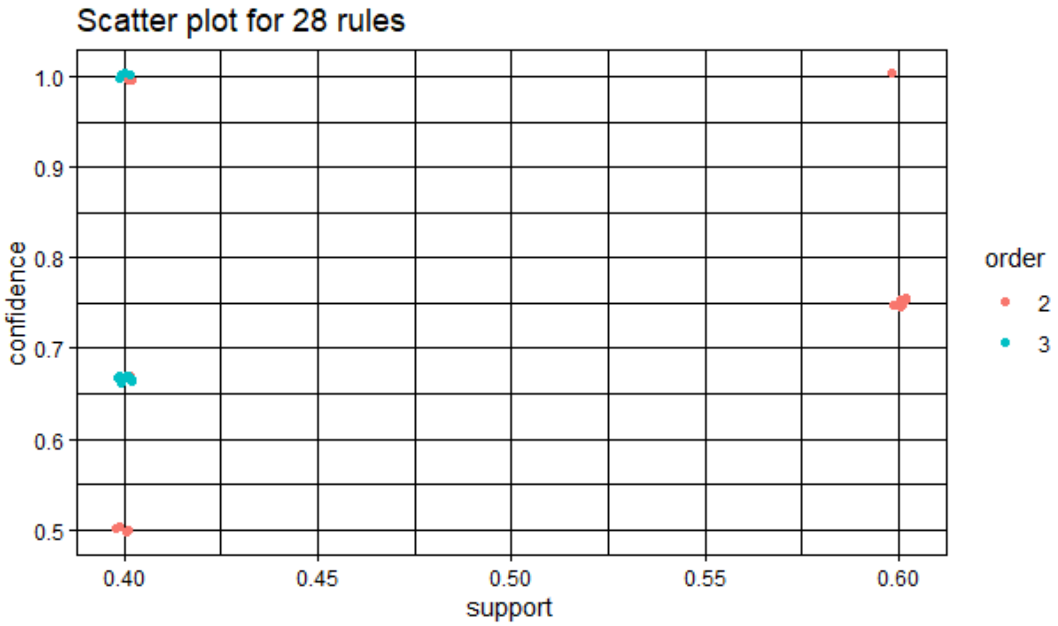
Plotting rules with “arulesViz” package:

- plot(rules, measure = "confidence")



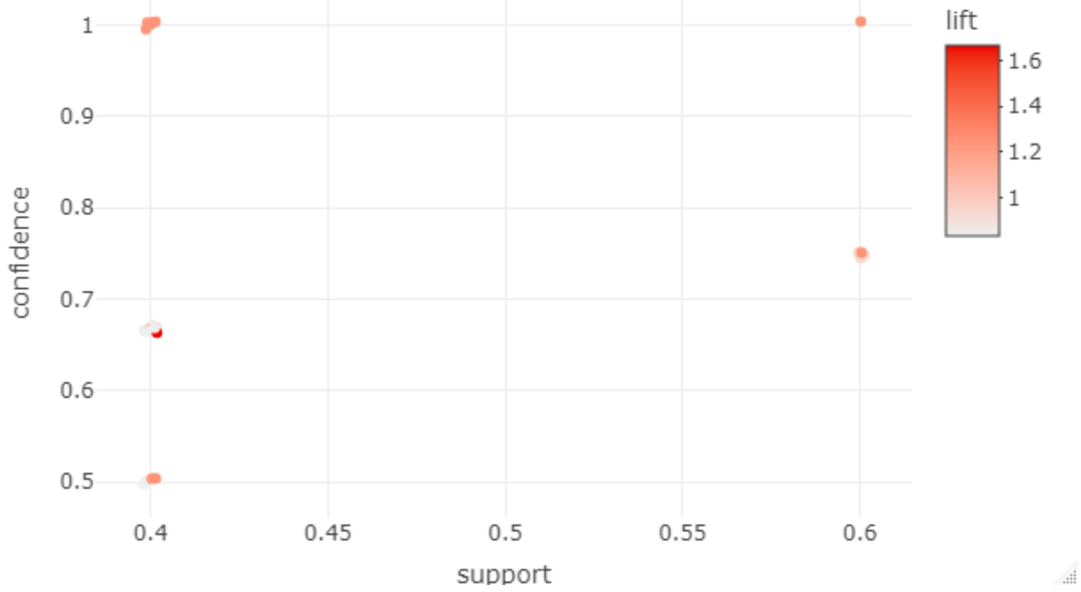
Plotting rules with “arulesViz” package:

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



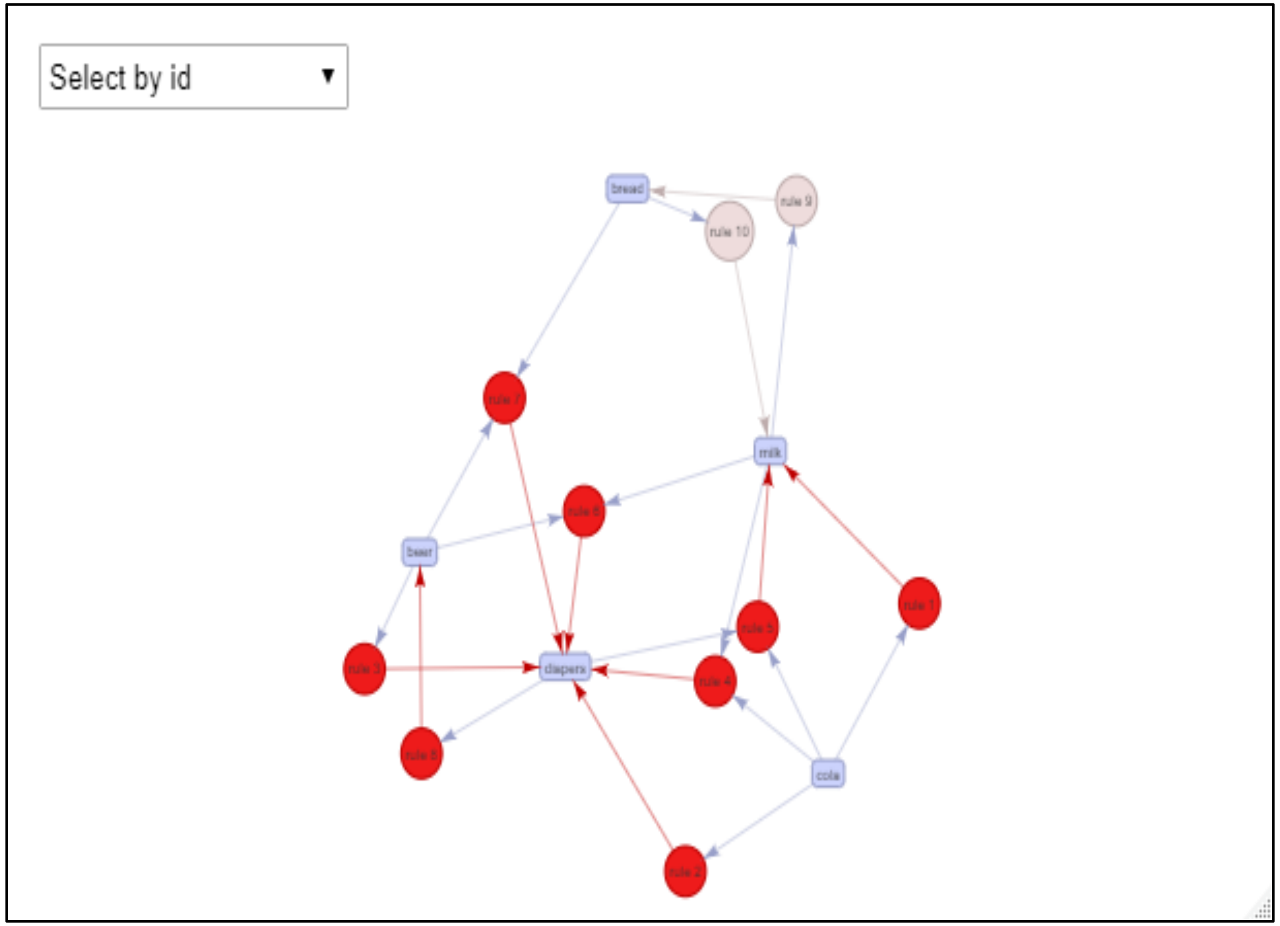
Interactive plot with “plotly” engine:

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



Graph based visualization:

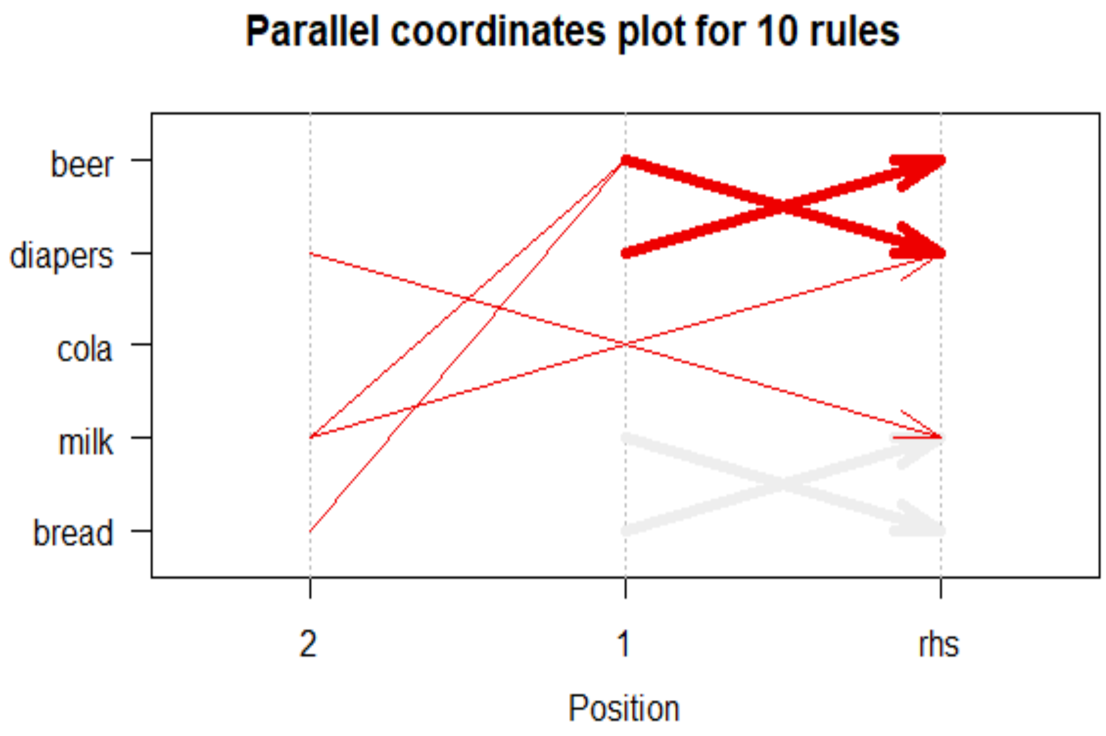
```
#Graph based visualization
subrules <- head(rules, n = 10, by = "confidence")
plot(subrules, method = "graph", engine = "htmlwidget")
```



Parallel coordinate plot for 10 rules:

#Paraller coordinate plot

- plot(subrules, method="paracoord")



More here:

- Like the one we did before:
- https://www.kirenz.com/post/2020-05-14-r-association-rule-mining/
- Real life example:
- https://www.youtube.com/watch?v=91CmrpD-4Fw

Question/queries?

- Next class

- Monte Carlo Simulations
- Class imbalance problem
  - Statistical approach
  - Data sciences approach

Thank you!

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