INDIAN INSTITUTE OF TECHNOLOGY ROORKEE
NPTEL
NPTEL ONLINE CERTIFICATION COURSE
Business Analytics & Data Mining Modeling
Using R – Part II
Lecture-04
Association Rules – Part IV
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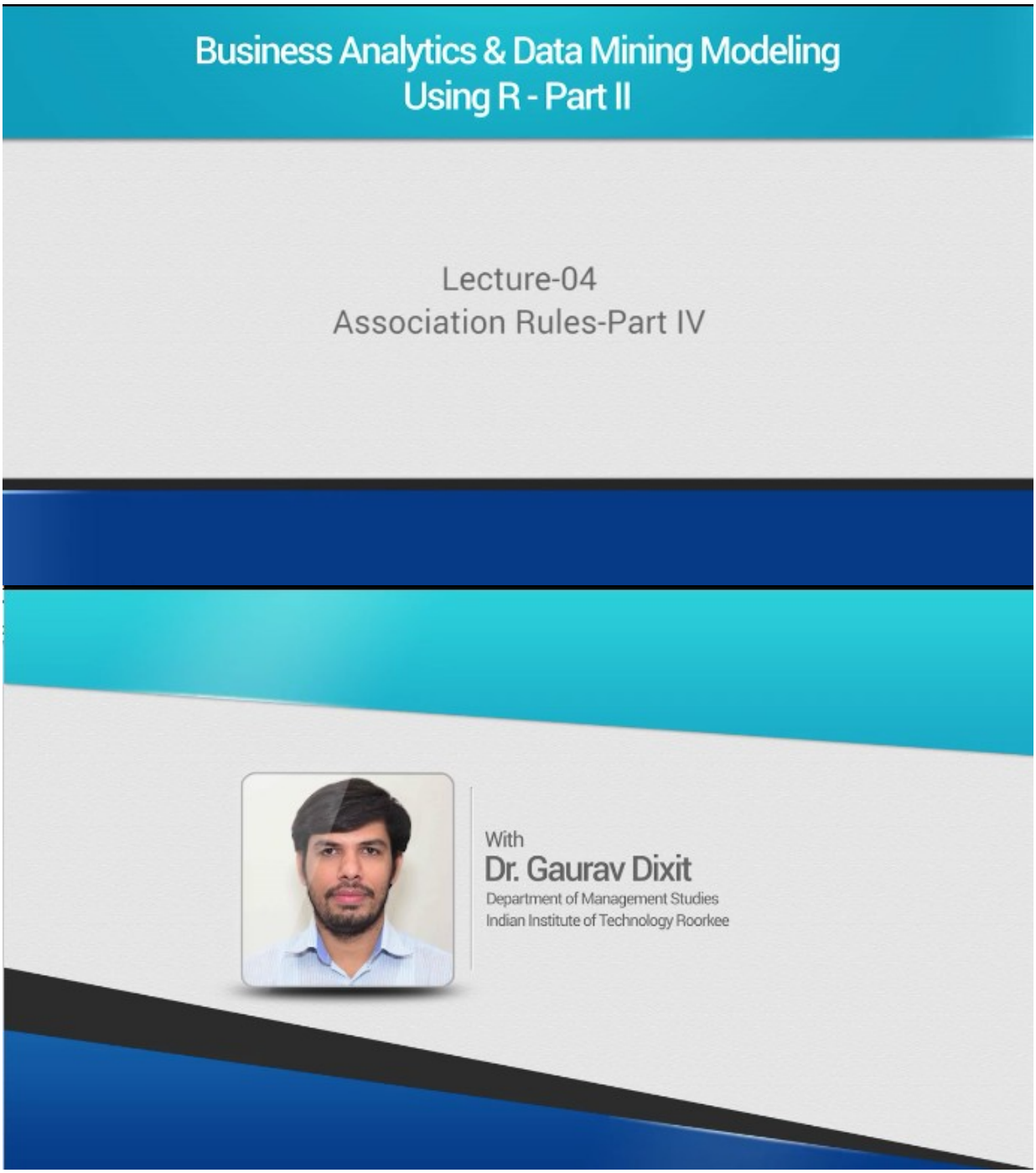


Welcome to the course Business Analytics and Data Mining Modeling Using R, Part 2. So in previous few lectures we have been discussing association rules, so let's do a small review of what we have discussed so far, so we started with our discussion on association rules what it is about the different names for this like affinity analysis, market basket analysis, we also talked

Association Rules

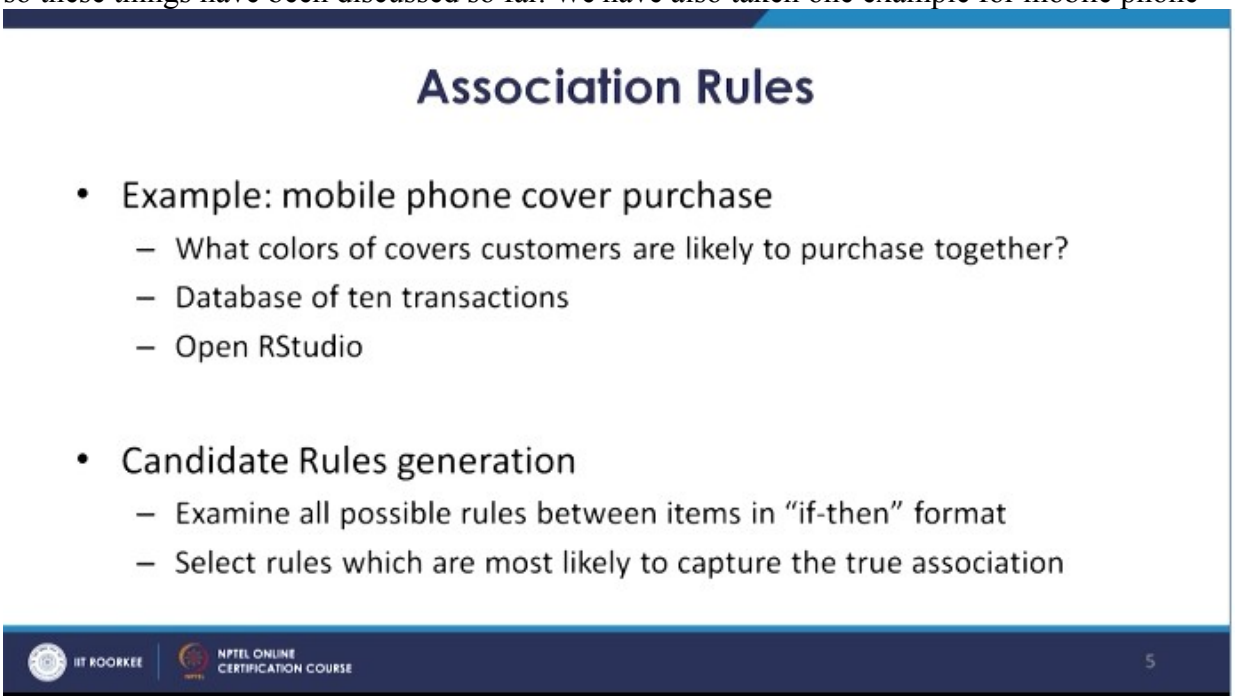
- Also called
  - Affinity Analysis
  - Market Basket Analysis
    - Due to its origin from the studies of customer purchase transactions databases
- Main Idea is
  - To identify item associations in transaction-type databases and
  - Formulate probabilistic association rules for the same
  - "what goes with what"

about the main idea is to find to identify item associations in transaction type databases and formulate probabilistic association rules for the same, so what goes with what, if you know a particular, typically the examples that we have been taking or in the you know marketing domain for you know when the customer is going for purchase in a supermarket or retail store, if a particular item X is being purchased then what else is also being purchased along with that item, so what goes with what kind of you know analysis we typically do in association rules. All these things we have talked about, so we talked about the if then statements that are typically use in association rules, we talked about two stage process, so first stage being rule generation where we apply Apriori algorithm, so we had discussed Apriori algorithm in previous lecture.

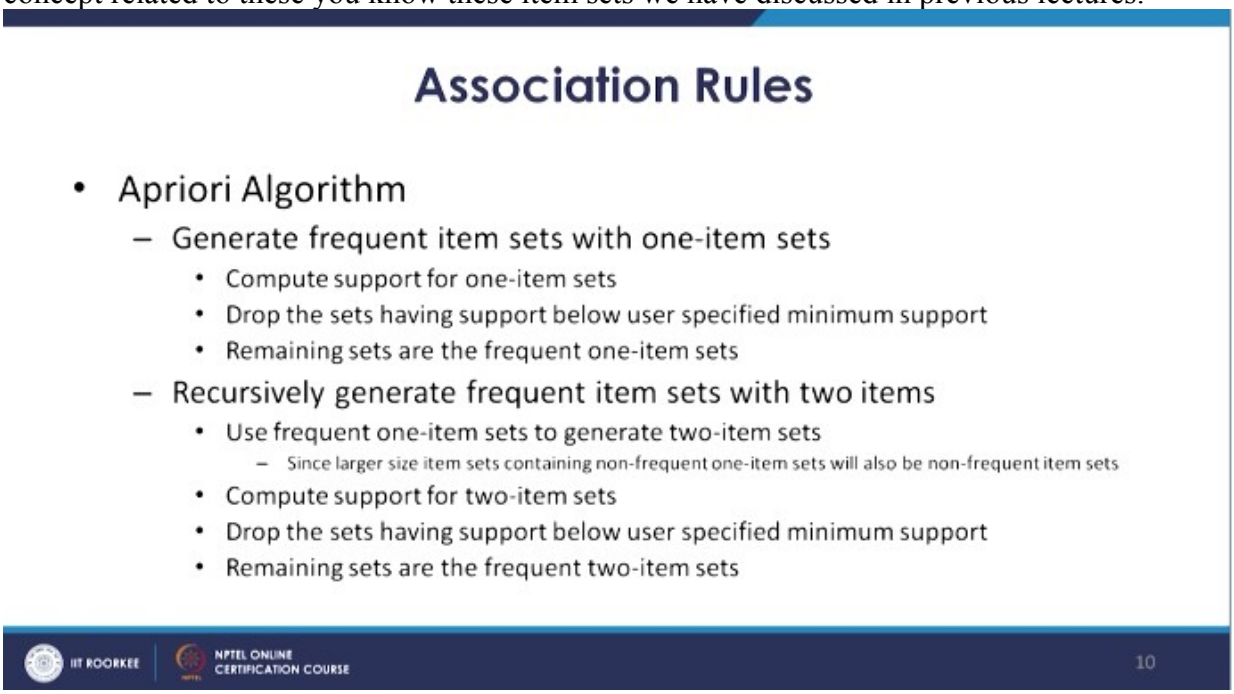
Association Rules

- Association rules
  - "if-then" statements computed from data
  - Example: online recommendation systems or recommender systems in online shopping websites of e-commerce companies like Amazon, Flipkart, and Snapdeal
- Two-stage process
  - Rule generation
    - Apriori Algorithm
  - Assessment of rule strength

We also talked about the rules that are generated in the first stage, how the strength of those rules are assessed, so that we can you know select the most important rules for implementation, so these things have been discussed so far. We have also taken one example for mobile phone

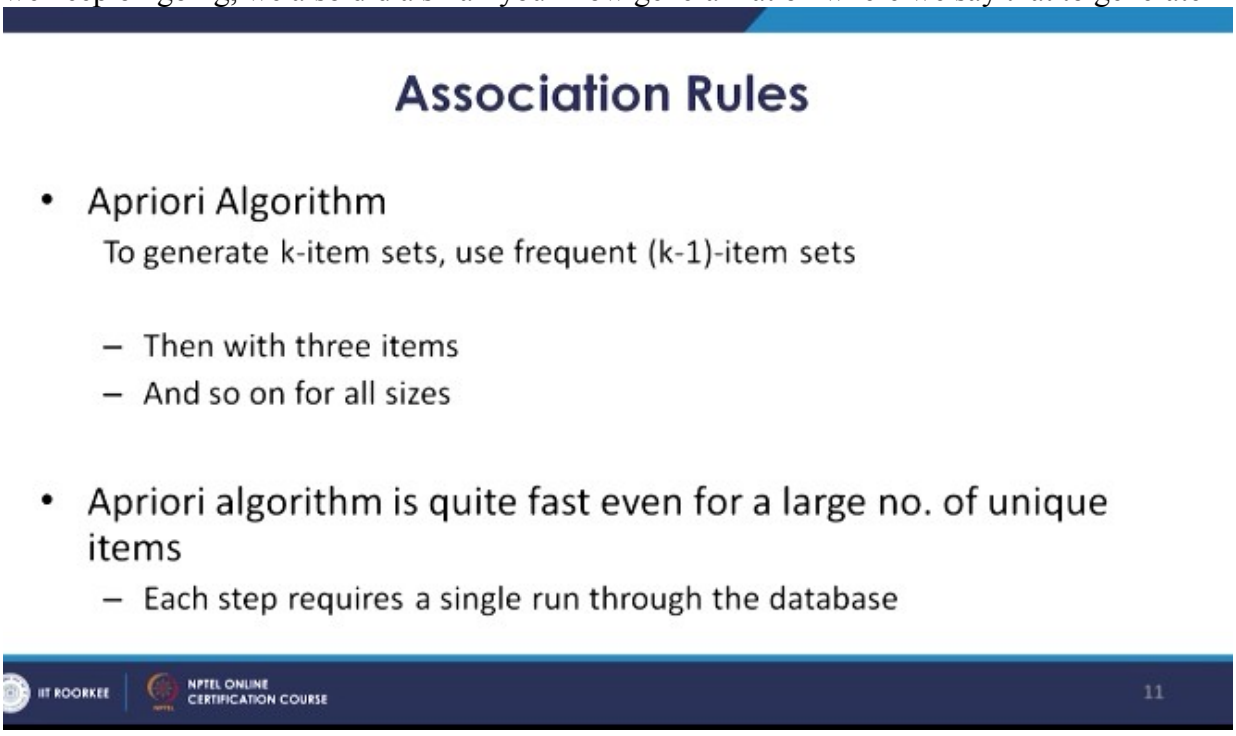


cover, we discussed two transaction data formats in the last lecture item list format, and binary matrix format so those things were also covered, so antecedent, consequent item sets and the concept related to these you know these item sets we have discussed in previous lectures.



We also talked about the frequent item set, after that you know previous lectures we have also discussed Apriori algorithm, the different steps for it, for example first we start with the generation of frequent item sets having just single item, then this particular list of frequent item

set with single item is taken for generating frequent item sets with two items and so on and so forth frequent item sets with three items, frequent item sets with four items, so in this fashion we keep on going, we also did a small you know generalization where we say that to generate K



item sets we use frequent K-1 item sets, we also talked about the Apriori algorithm and the you know lower computational intensity that is required because of you know, in each step we just need to go through once through the database, so all those things we have discussed so far.
We talked about few matrix for assessing rule strength, so in terms of rule generation we talked about support and its importance in generating rules, then we talked about these two matrix confidence and lift ratio which could be used to assess the strength of association rules, so we

Association Rules

- Assessing rule strength
  - Idea is to identify rules which capture strong association between antecedent and consequent item sets
  - Metrics to measure strength of this association as implied by a rule
    - Confidence
      - Ratio of no. of transactions with antecedent and consequent item sets to the no. of transactions with antecedent item set
    - Lift ratio

discussed and defined these two matrix in previous lectures confidence and lift ratio, so we then thought of support and confidence matrix in probability terms, so this part we were able to

Association Rules

- Revisit Support and Confidence
  - Support as P(antecedent and consequent)
  - Confidence as $\frac{P(\text{antecedent and consequent})}{P(\text{antecedent})}$

  or $P(\text{consequent} \mid \text{antecedent})$
- Typically, high value of confidence means strong association rule
  - It might fail in cases where antecedent and/or consequent item sets have high support leading to high confidence despite no real association

discuss that confidence can be defined as the conditional probability of you know occurrence of consequent item set given that antecedent item sets has occurred, so these things we were able to discuss.

Association Rules

- Lift ratio
  - Compare the confidence of a rule with its benchmark value
  - Benchmark value of a rule is confidence value computed by assuming no association between antecedent and consequent item sets
    - We assume that antecedent and consequent item sets occur independently

P(antecedent and consequent) = P(antecedent) x P(consequent)

$$\text{Confidence (benchmark)} = \frac{P(\text{antecedent}) \times P(\text{consequent})}{P(\text{antecedent})} = P(\text{consequent})$$

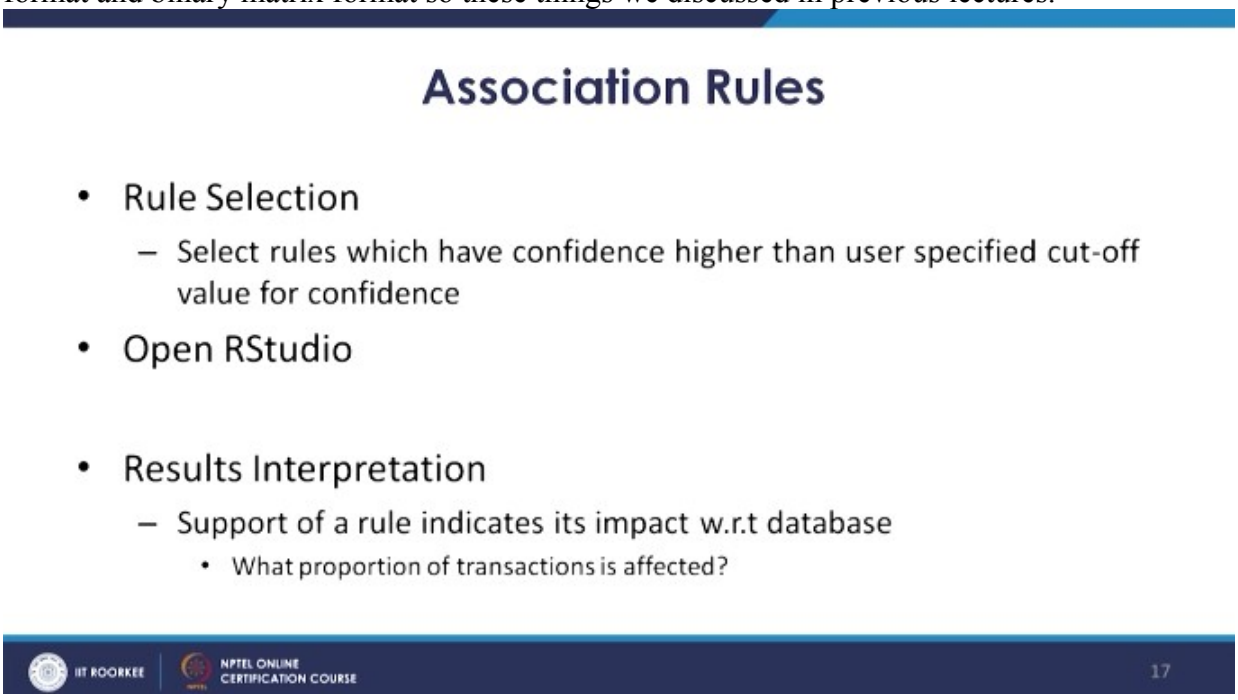
$$\text{Benchmark confidence} = \frac{\text{No.of transactions with consequent item set}}{\text{total no.of transactions}}$$

Then while our discussion on lift ratio we talked about the benchmark value, the benchmark confidence value and its importance, how it is calculated so we discussed the how the expressions for benchmark confidence can be you know, can be defined, so you know discussed in the previous lecture that we talked about benchmark confidence value can be determined as the probability of occurrence of consequent item sets, so those formulas were also discussed, we defined lift ratio, we also talked about the usefulness of a you know rule, using lift ratio value, so it should be greater than 1, so for any association rule to be useful it's should be, the lift ratio value should be greater than 1.

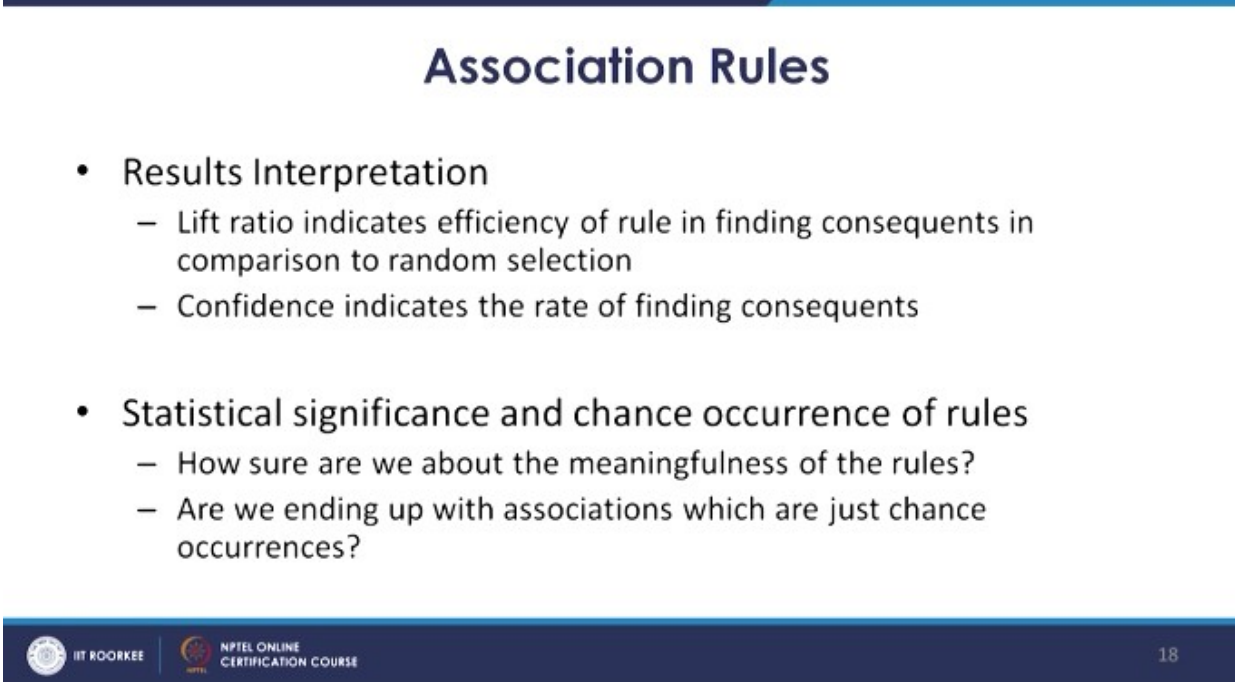
Association Rules

- Transaction Data formats
  - Item list format
    - Each row contains a list of purchased items and represents a transaction
  - Binary matrix format
    - Rows represent transactions
    - Columns represent items
    - Cells have either a 1 or a 0 indicating presence or absence of the item in the transaction
  - Open RStudio

In you know exercise in R studio environment we also went through some of the examples where we saw how the rules can be generated, and then how we can assess the strength of the rules, we sorted the list in particular you know lift ratio order for all the rules were sorted using lift ratio orders, so all those things we did, as I talked about transaction data format, item list format and binary matrix format so these things we discussed in previous lectures.

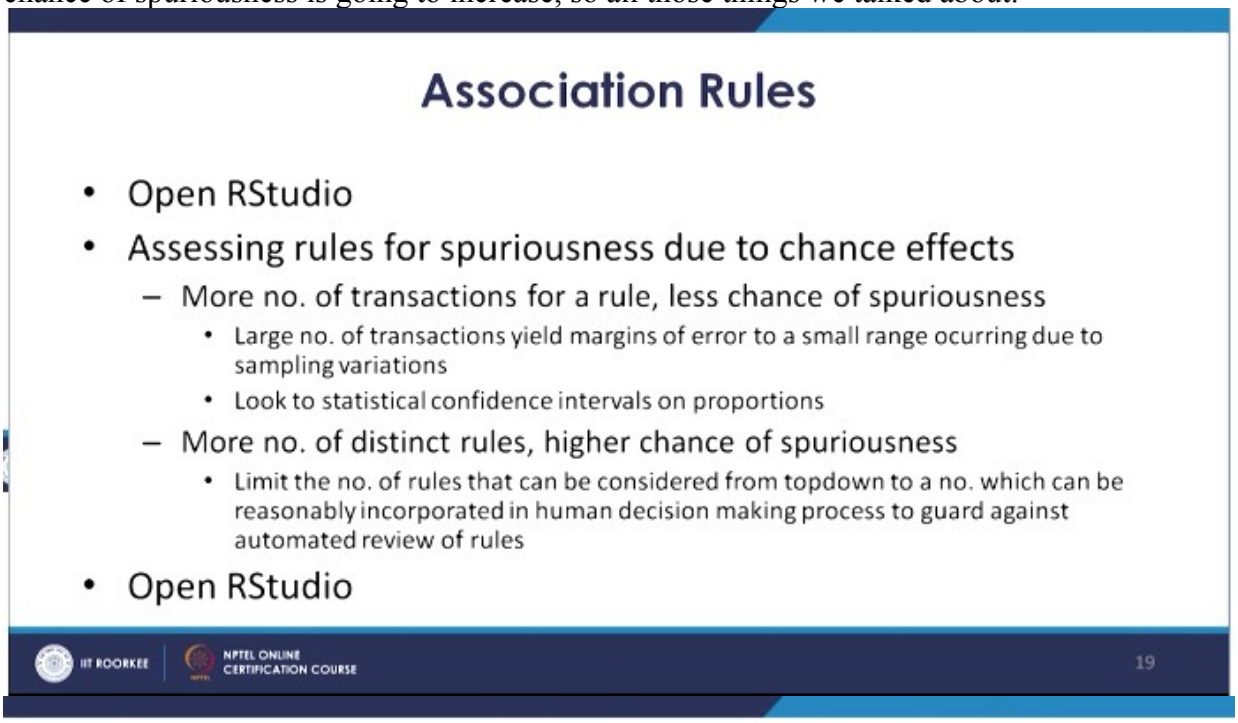


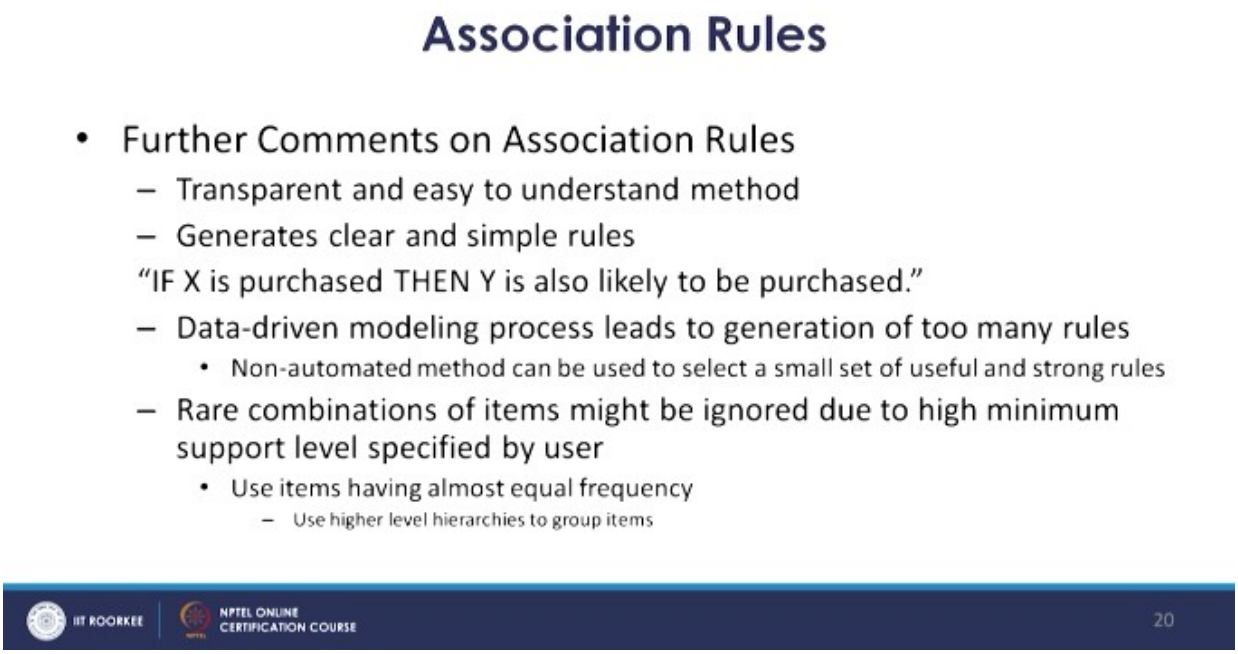
We also talked about the results interpretation part and how you know importance of support, confidence and lift value, we talked about that higher value of support and confidence value and



lift ratio are desired for you know selection of you know top association rules and later on implementation, so then we also talked about the statistical significance of these rules, the

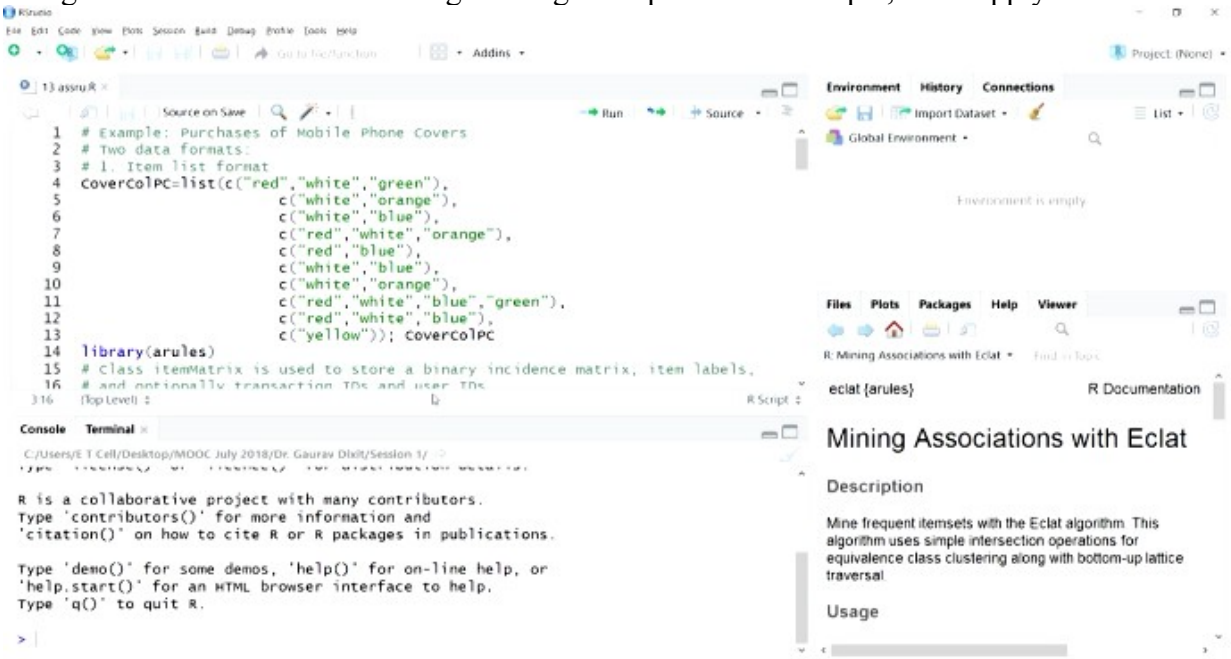
chance occurrence so we did an exercise where data was randomly generated and then association rule mining was applied, and we found that even with the randomly generated data we are able to find some strong association rules, so what about the significance? Whether you know these rules can be taken as at phase value or whether we should look for something more, so we discussed a few rules of thumb few points that could be consider, for example more number of transactions for a rule, and you know if there are more number of distinct rules then chance of spuriousness is going to increase, so all those things we talked about.





Before we move on to you know further comments on association rules, we talked about that you know one exercise that we are going to do using a, you know, a particular you know

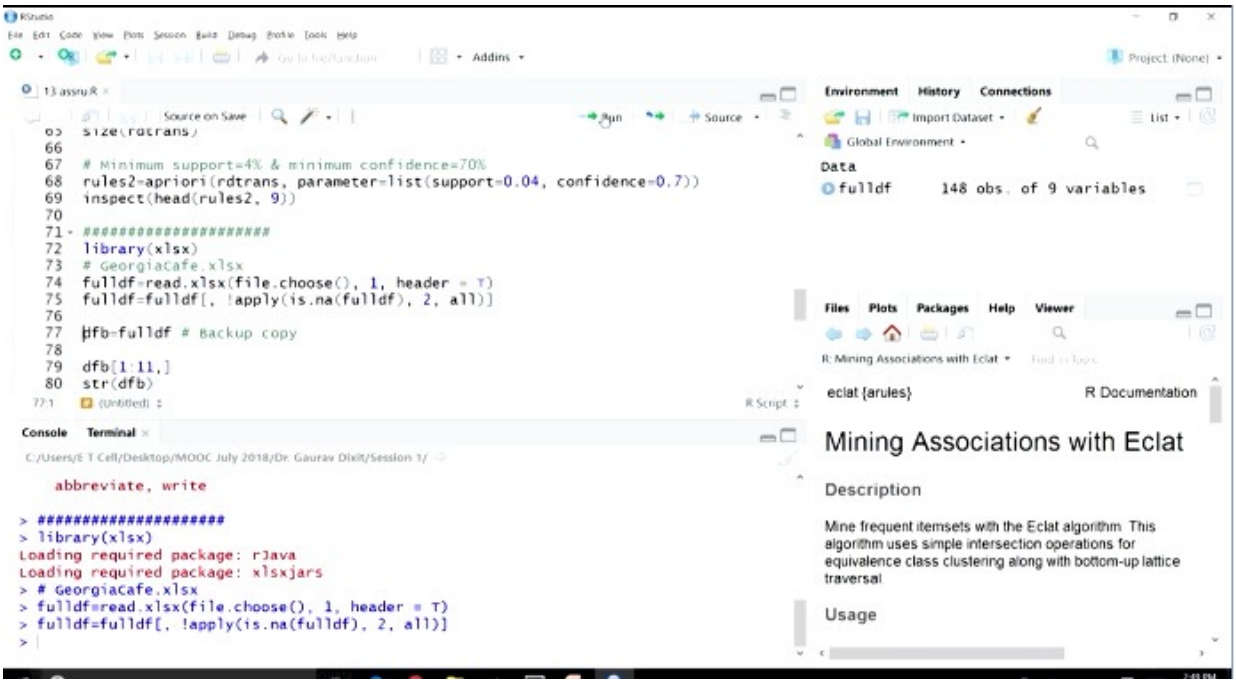
dataset, this dataset is also manufactured, but it is based on a more real life like situation, so we will go back to R studio and we'll go through this particular example, we'll apply association



rules and whatever concepts and exercises that we have done in previous lecture, we'll try to repeat that and discuss in more detail.

So let's scroll through the part which we want to cover, so let's load this library, so A rules is the package that we require to you know develop our models to do our association rules planning in R environment, so once this is done we'll move forward, so in the previous lecture we were trying to load another library, so were facing some problems installing that particular package, so this one, so the problem that we faced was that java was not installed in this particular system and that is why that R java library, though we were able to install it you were not able to load it into R studio environment, so since now we have already installed java in this particular system , now we should be able to load this particular library.

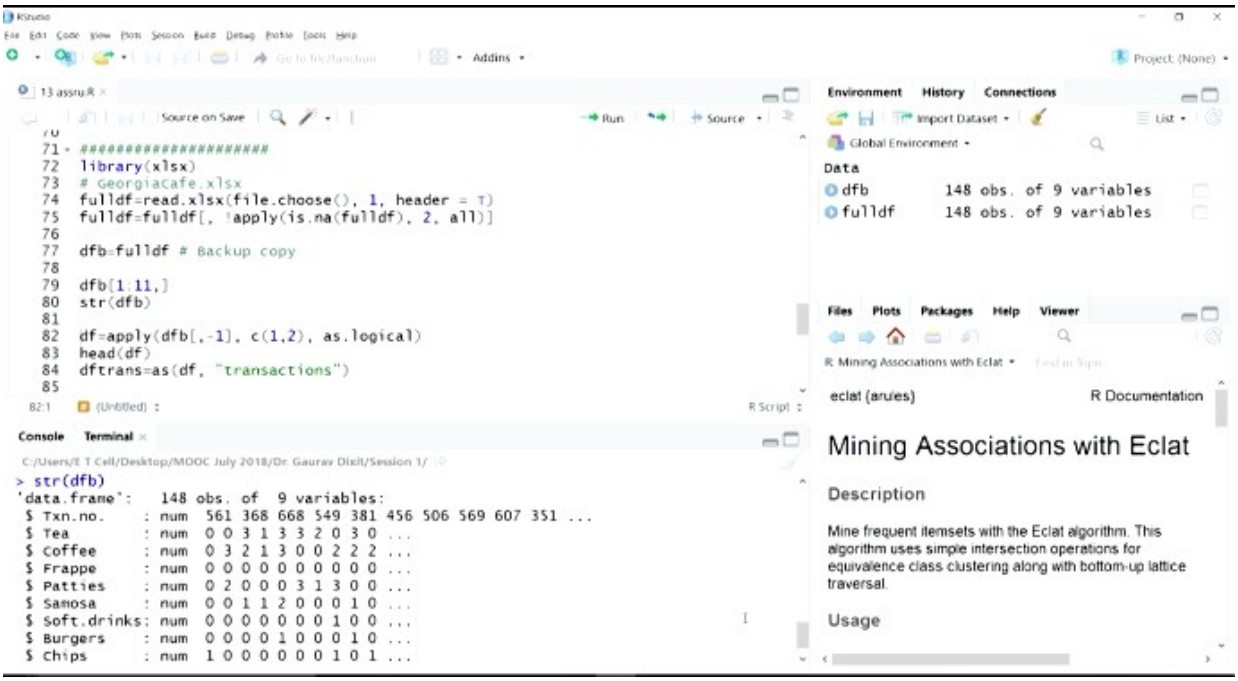
As you can see you know in this session we are able to load this library, now we talked about this Georgia cafe dataset, so let's import this dataset into the R environment, so let's run this code, so we have talked about this particular piece of code in previous code on business analytics and data mining modeling using R, so for more detail you know about these functions and how we are using them here you can always find in those video lectures, of course you have the advantage of help section here in this R studio environment and you can always look for the you know manuals for these functions read.xlsx or any other functions that we are using, so let's run this code and import this particular data, so we can see here Georgia café this, this one, so you can see in the environment section this particular file has been imported into R environment and you can see 148 observations of 9 variables.



So now let's remove any you know, any redundant columns here, so let's run this code. Now let's take a backup of this dataset that we've just imported, so in case you know if we planned to do some modification transformation in some of the variables, then it is always recommended to take back up before proceeding with those transformations.

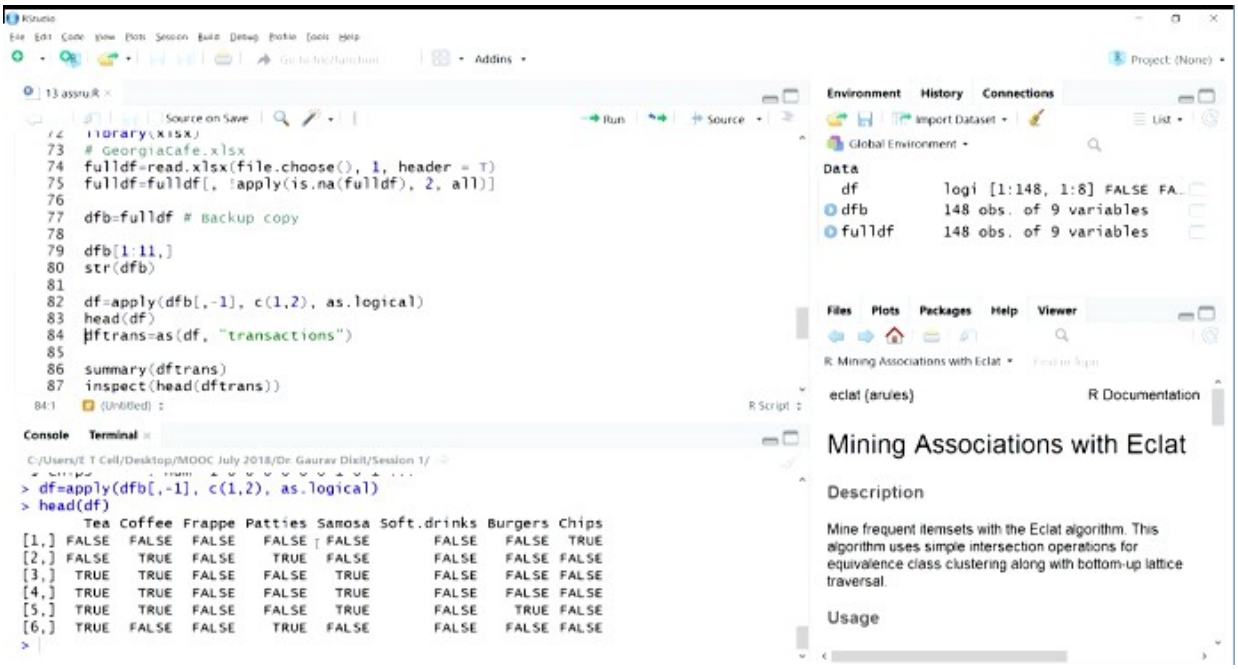
So now the next code is about the few observations, so let's look at these first few 11 observation of this dataset, so as you can see here first column is transaction number, so this particular dataset is about this Georgia café where customers can buy different you know snacks and beverage items as you can see in the columns itself, tea, coffee, frappe, patties samosa, soft drinks, burgers and chips, so these are some of the items that are being sold by this café and different customers they have purchased different items, so those transactions along with their transaction, number transaction ID's have been recorded, so each row is representing a transaction, so for example first row is transaction number is 561, and the you know items that they have purchased, so you can see they have purchased just the one item that is chips, one packet of it, and the numbers that you see in this particular dataset they are you know representing the number of you know units that they have purchased, right, so but however typically what we require is just the you know presence or absence of that item, so later on as we will see that we would be converting this particular data set into a format of ones and zeros, where one would be representing whether that item was part of that transaction or not, and you know 0 would be you know absence of it, and 1 would be presence of it.

Right now these numbers that you see 3, 2, 1 or 0 they are representing the number of these items that have been purchased, so this also has the information whether they have been purchased or not.

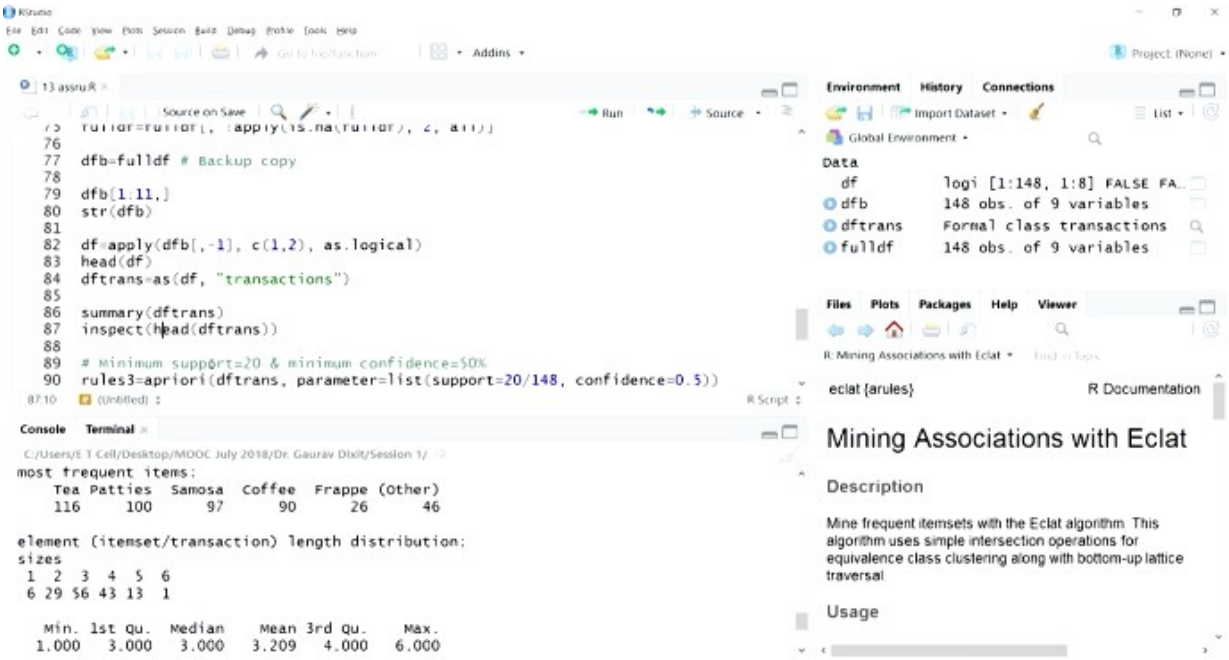


Let's look at the structure of this particular dataset, all the variables that are part of this you know data frame, so if we look at this particular data frame, as I talked about 148 observations, 9 variables, you can see transaction ID tea, coffee, so because all these are number of units that have been purchased, so you can see all these variables are numerical, so we are not required to do any transformation as such here, because as I talked about we would just be requiring ones and zeros.

So right now this particular dataset as you can see is in the numerical format, now we can use the apply function to convert all these values into the logical format, so the values would be true and false, so more detail about this particular function apply you can find out in the help section, so you can see the first argument is the you know data frame on which we want to apply you know this particular function, third argument is the name of the function that we want to apply, on the first argument that is the you know data frame, so as.logical so this function would actually colds the points into you know logical you know variables and you can see the second argument is talking about 1 and 2, 1 representing rows, and 2 representing columns, that means all the cells, on all the cells this particular function is going to be applied, so let's go through this.

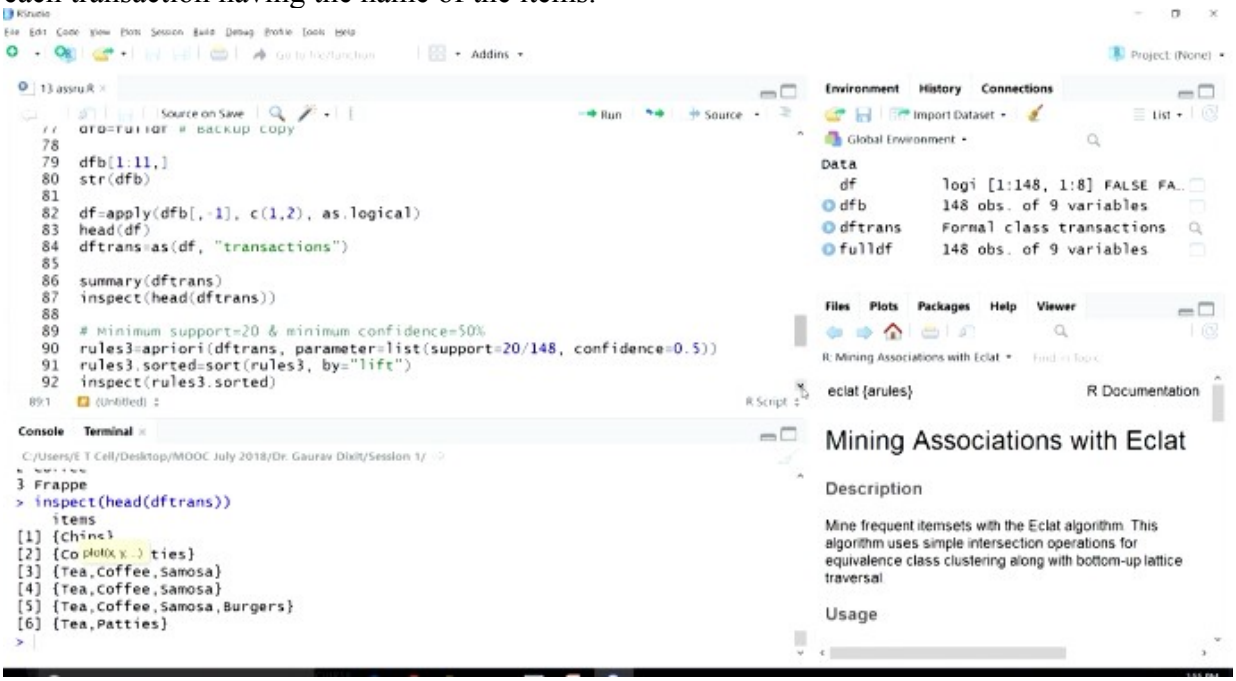


We are doing this, because we are interested in just the presence or absence of a particular item in a particular transaction, so let's run this, and let's look at the first 6 observations here, now you can see we have just the you know items that are available, so all the items are distinct, 1, 2, 3, 4, 5, 6, 7, 8, so we have 8 items, 8 distinct items and whether they are present in a particular transaction or absent that is being represented using these you know values, true or false.



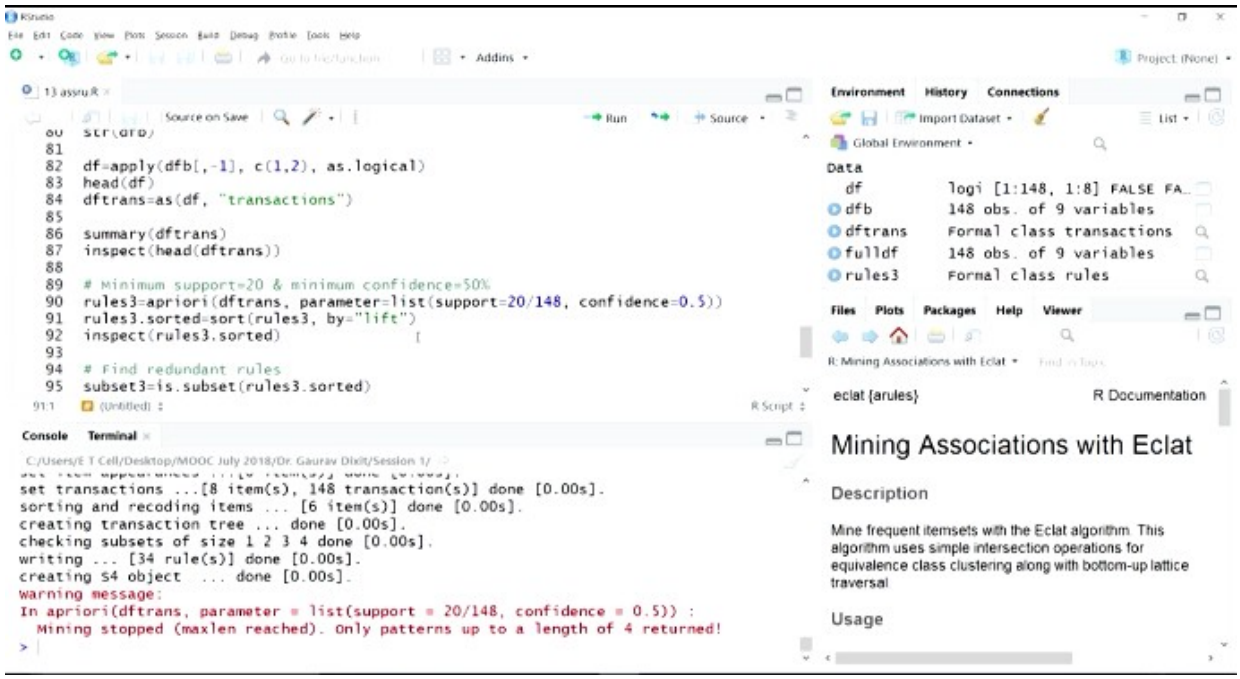
Now we can always convert this particular data frame into transactions format, so for this we can use as a function, so let's run this and we'll get to convert this particular dataset into transactions format. Now this is done, we can look at the summary of this, so you can see here, so the few details about this particular you know format is available, you can see most frequent items, you can see tea is the most frequent item followed by patties, samosa and all those, other

all other things, so as we talked about in previous lecture inspect is the function that could be used to look at the, look at the transactions database, so you can see. Now this format is the, you know item list format where each transaction is representing the name of the items that is there, so you can see in this we have just first 6 transaction, so first transaction is having just chips, second transaction is having coffee and patties, third transaction we have tea, coffee, samosa, so each of these transaction now, what we are seeing right now is the item list format, each transaction having the name of the items.

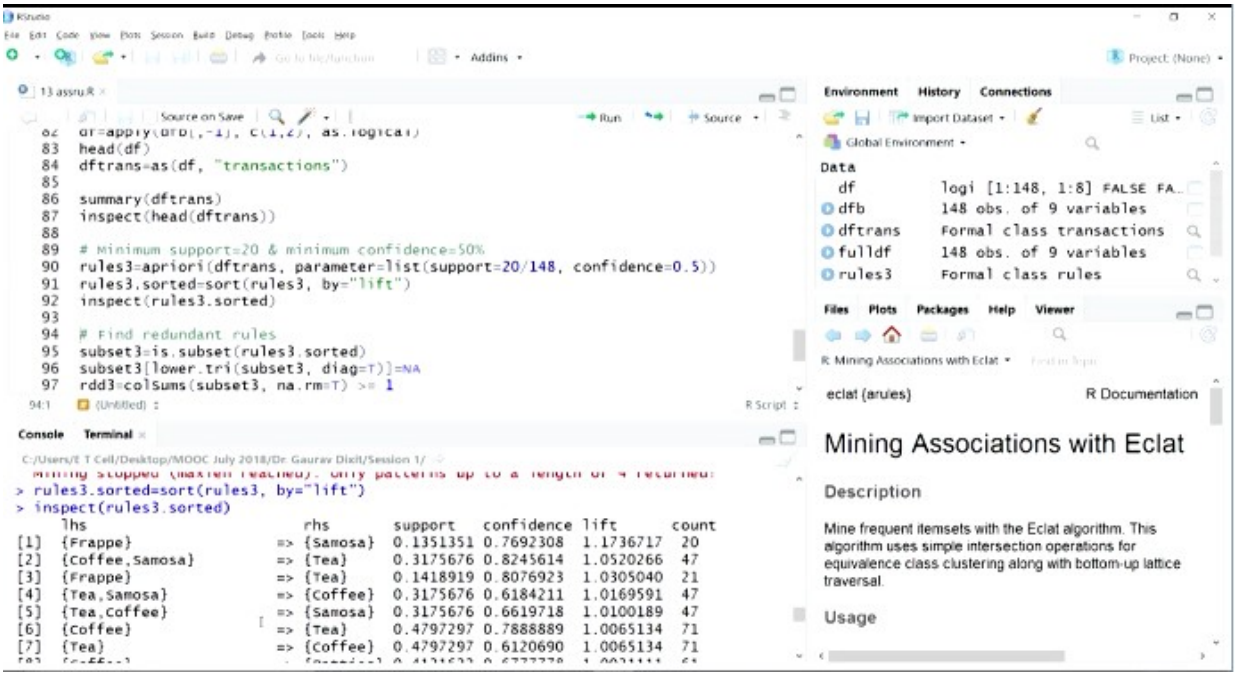


Now to proceed with our association rules mining, what we will do is we'll call this Apriori function, but before calling this function we need to establish our you know support level, minimum support level and minimum confidence level, so as you can see in the commented line I was specified support as 20 that is the number of transaction and the minimum confidence as 50 percentage, that is the percentage minimum accepted confidence value in percentage terms.

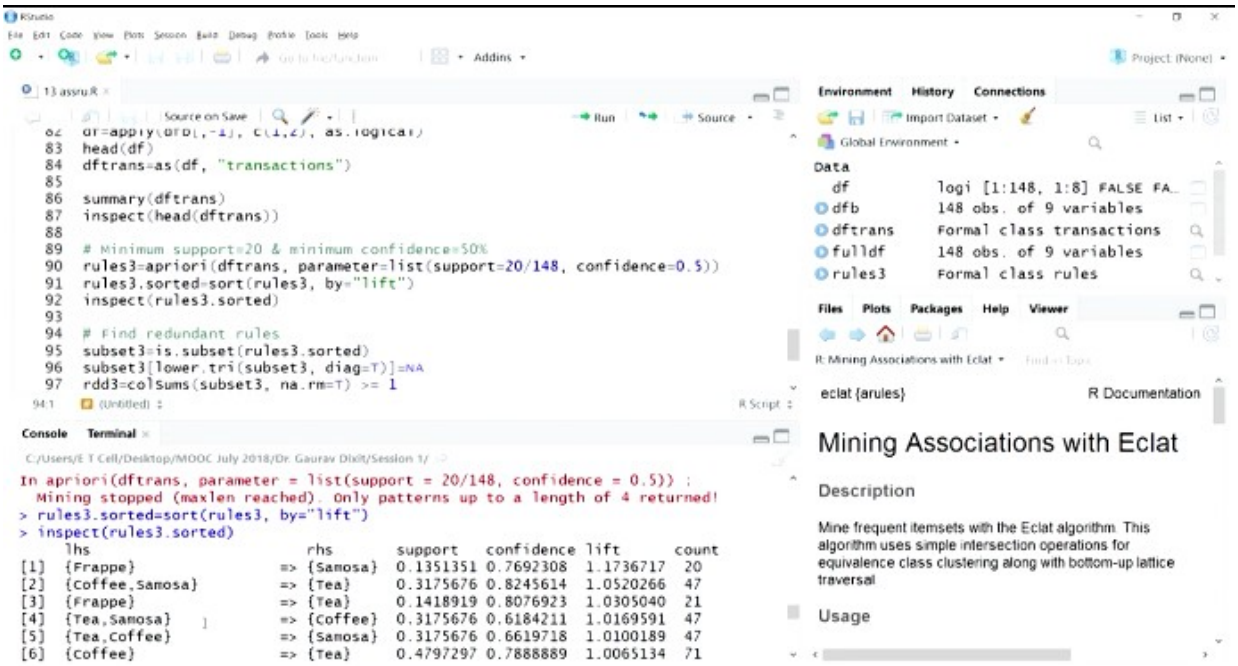
So now you can see in the next line I'm calling the function Apriori and I'm passing on the first argument, this transaction database that we have just created, then the parameter I'm specifying the you know, the minimum support level that is 20 divided by 148 and the confidence value, so you can see these values are in proportion terms, so appropriately they have been specified, so let's call this function.



Now once this is done we can always sort this particular you know output of Apriori function into you know, by lift values so let's run this, next line. And now we can use the inspect function to look at the details of the output, so now as you can see there are number of association rules have been displayed in this output, and you can see that all these association rules have been sorted in decreasing order of the lift value, so the first association rule is having the highest lift value, as you can see the lift value is 1.17 so from this database that we have Georgia café database that we have, we are not getting you know many assessment rules with you know higher lift values, so even the top association rules are having lift values around you know 1, and this is the only the first transaction is having just you know a bit higher lift value that is also not much high, it is just 1.17, so you can see that in this first transaction we have you know frappe and if the frappe is being purchased then samosa is also being purchased, so this is you know the first, the strongest association rule that we have from this database.

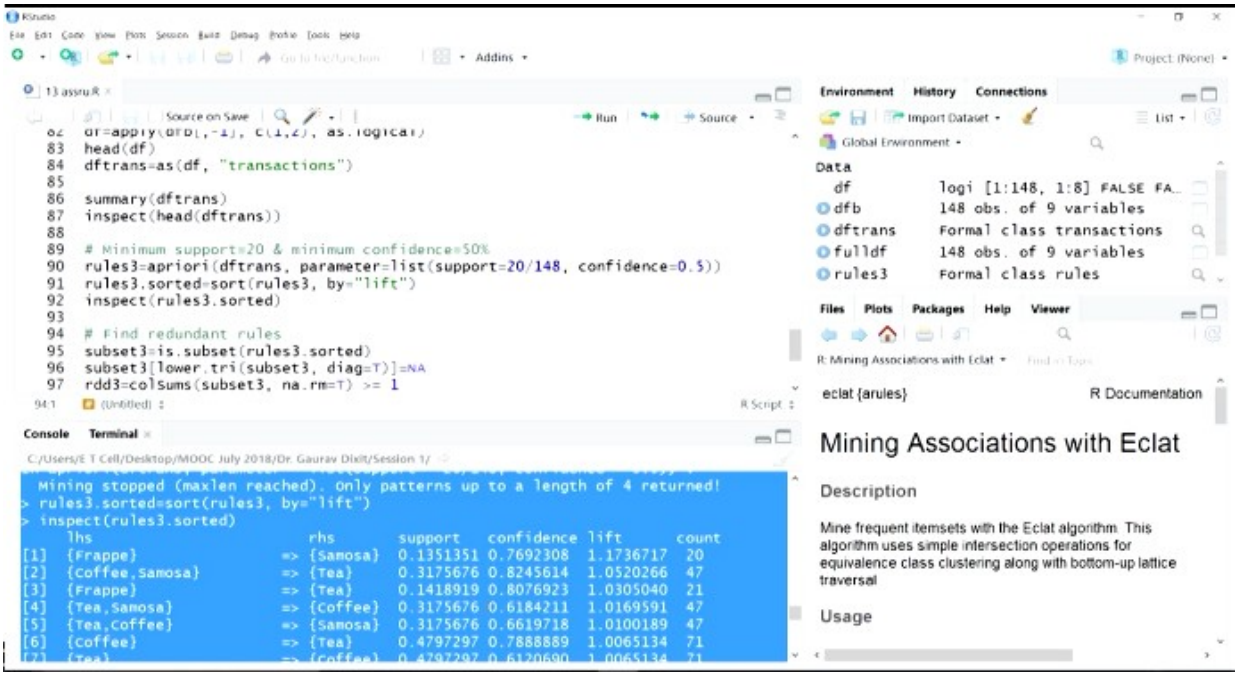


So as you can see is you know, frappe and samosa is being purchased, this is not something you know that we would ideally expect as to be a strong association rule, so all this is because of the manufactured dataset and so the real relationships might not anyway be captured. However, for an exercise we can see here other assessment rules so in this you would also see that some association rules are involving the same items, for example you would see that association rule number 4 and 5, tea, samosa, if tea and samosa are being purchased then coffee is being purchased, so the lift value is higher than 1 just above 1, and in the transaction, in the association rule number 5 you see that if tea and coffee are being purchased then samosa is also being purchased, so this is also having lift value of just above 1, so you would see that you know on the same items, you know are being used, so this is not unusual, so you know rather this is more favorable thing because you'll have to deal with, you can have more number of association rules and still it will be the you know, fewer number of items, so we can have this kind of situation where this one item set is leading to more than 1 association rules.



So other things also you can look at, so since this output has been sorted using lift values, so strongest you know association rules will come on top, so in terms of, as we talked about in the previous lectures we should always you know select the rules which can be you know reasonably incorporated in human decision making process, so probably if you have to select the rules from this output, the rules which can be implemented for their business and operational you know applicability, we will have to select few rules from the top, right, so if we look at the some of the rules from the top, then we see that as we talked about that we would prefer, all these values support, confidence and lift values to be on the higher side.

So we also talked about that we took a wide spuriousness to get more meaningful rules, we would like to have support count, support that is count, more number of transactions supporting particular rule, so we look at the first association rules the count is 20, however it is having higher lift value quite good you know high value of confidence, but slightly lower support, but if we look at the you know, if we look at the transaction association rule number 2 that is if coffee and samosa are being purchased then tea is also being purchased, so there we look at that 47 transactions, 47 you know transactions are supporting this particular rules, so in total we have 148 transactions and out of that about you know 31% of the transactions are supporting this rule, and we are also having the second highest lift value, we are also having a very high confidence value, it might be the highest also, if we are able to look at the you know, the full table, and sorted it out in confidence values, and then we can find out, so high confidence value, high support for the second association rules and of course you know high count, high lift value, relatively high lift value and higher you know confidence and support value, so from this we can see it is the second association rule that we might be willing to invest a bit more implement.

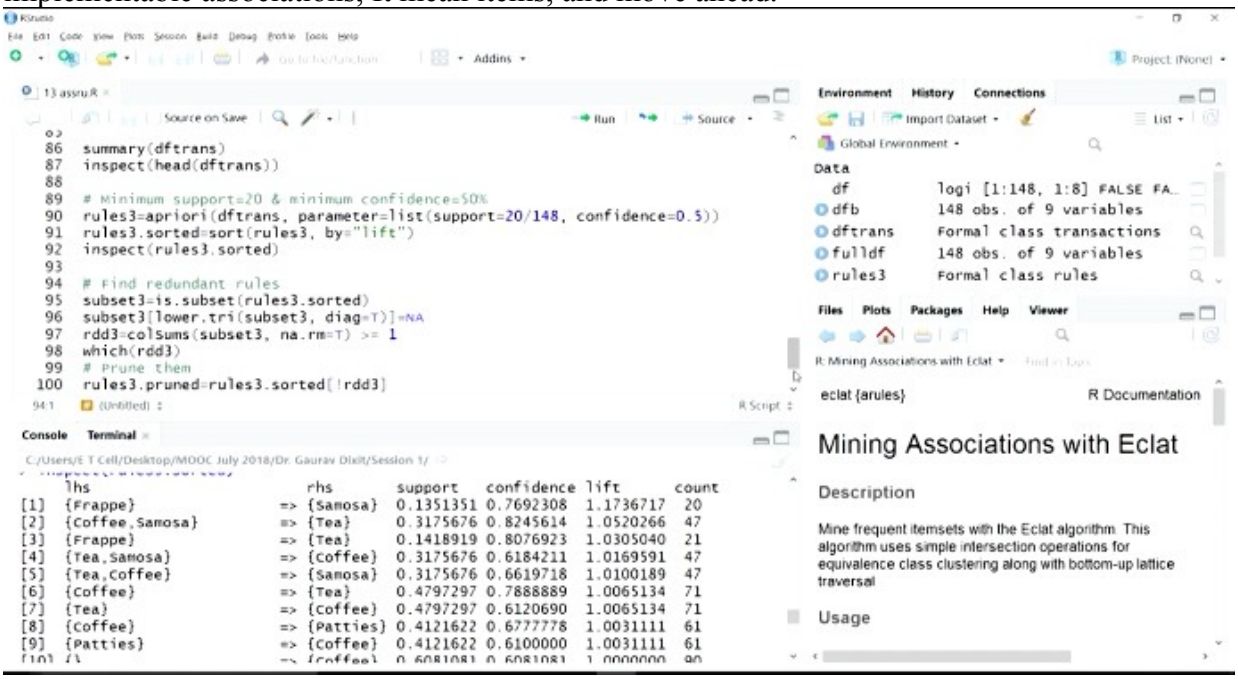


Now if we go down this table we see that there are few association rules like 6, 7, and 8, 9, so and even if we go down further we see that support level is increasing around this, so we see that association rule number 14, if samosa is being purchased then tea is also being purchased, not this one just above this, tea is being purchase, so you can see most of the transactions involve that tea is being purchased, so 116, patties 100 transactions, but if we are not interested in single item association rules then probably, then probably this transaction if samosa is being purchased then tea is being purchased, 76 transactions are supporting this association rules, however lift value is lower, so probably lift value is less than 1, so probably we'll not go with this, so we'll have to stick to the association rules which are having lift value higher than 1, so if we take that as the criteria, then we will have to consider the association rules up to 9, so association rules from 1 to 9 are to be considered if P follow this criteria that lift value has to be higher than 1, and within this if we see that rule number 6 and 7 they are having the highest support, right, they're having highest count 71 and 71, and we can see you know higher confidence value, high support value, higher count and also the lift value is greater than 1, so probably association rule number 6 and 7, these are the rules that we might be interested into implementing first, right, even though they do not have the highest lift value.

So if we look at these association rules, if coffee is being purchased then tea is being purchased, and if tea is being purchased then coffee is being purchased, if we look at this, so then essentially you know in terms of implementation we just get at the one decision rule, so you know this coffee and tea they are being purchased together so this particular information we can use in our business and operational you know implementation in our decisions.

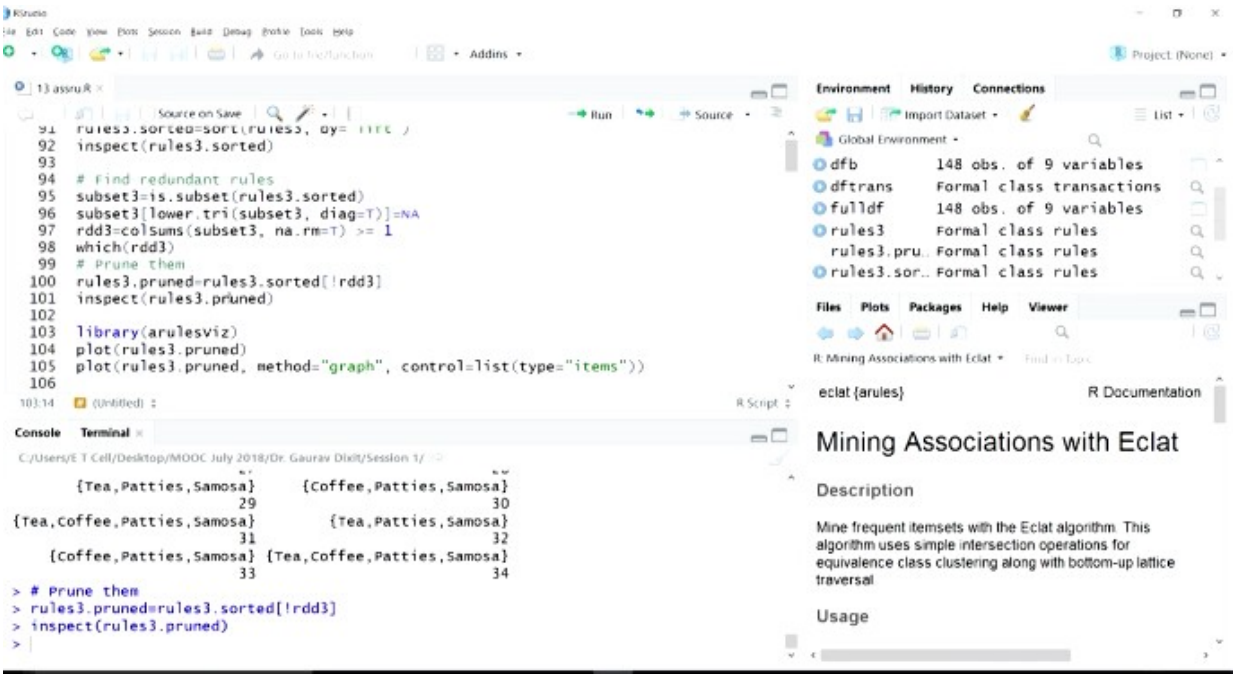
After this we can look at the rule number you know 4 and 5, rather we'll prefer the rule number 2 for it being the having the higher lift value, so after rule number 6 and 7 we'll probably go with rule number 2, that if coffee and samosa are being purchased then tea is also being purchased, and then after that if we still are looking for more rules to implement then probably 4 and 5, however again you can see 4 and 5 effectively they also converge to the same thing, so these rules also, you know, these rules involve just three items, tea, samosa and coffee, so if we are looking for just top three rules that we would like to implement, then first one would be

based on rule number 6 and 7, tea and coffee that association then tea, samosa and coffee that association would be third, the second one would be you know coffee, samosa, and tea, so if we look at the rule number 2 is also involving the same item, so essentially top things that we would like to implement from this output would be, first thing would be tea and coffee, then the second thing would be tea, coffee, and samosa, so based on this output as you can see we can restrict ourselves to you know some fewer number of rules, some you know few rules which are you know, you know satisfying all the criteria that we want, higher transaction support, higher number of transaction supporting them, higher support value, higher confidence value, and higher lift value, and then some of these you know rules will involve the same items, so using all this we would be able to get some you know few implementable you know information, implementable associations, It mean items, and move ahead.



So let's move forward, so some of these rules as we have seen that, some of these rules might be redundant, so some of this rules might be subset of some other rules, so how do we eliminate these redundant rules which are subset of some other rule, right, so we have some code for this, so you can see we are calling here is.subset function, so this function can be used to identify the you know item sets which are subset of some other set, so let's run this code.

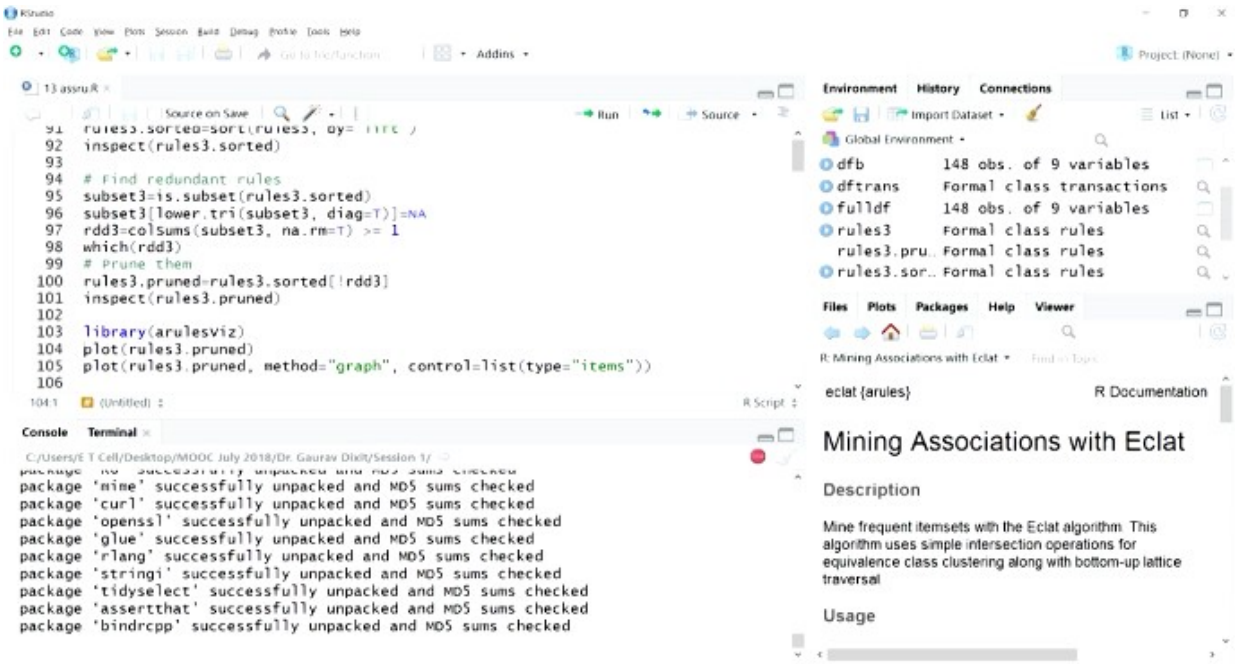
Now in the next line as you can see that because we'll get a you know so lower triangular values and upper triangular value would be same, so we would like to you know strike you know lower triangular using any values, the second line is doing precisely that, so let's run this. Then as you can see we are using colsums function, so it will sum all the you know subsets, all the item sets which are subset of 1 or more than 1 set, so all those you know item sets would be identified, so let's run this, so we can also, from here we can also see which of these you know subsets or which of these item sets are you know subsets of other item sets, so we can see big list is here, so we can always pruned this list and the remaining, we'll just have the remaining items which are distinct, so we run this, let's look at this, let's call this inspect and so right now probably you know, there was, in this particular run, there, we were not able to find some unique items, otherwise we would have got an output where some remaining subset would be there.



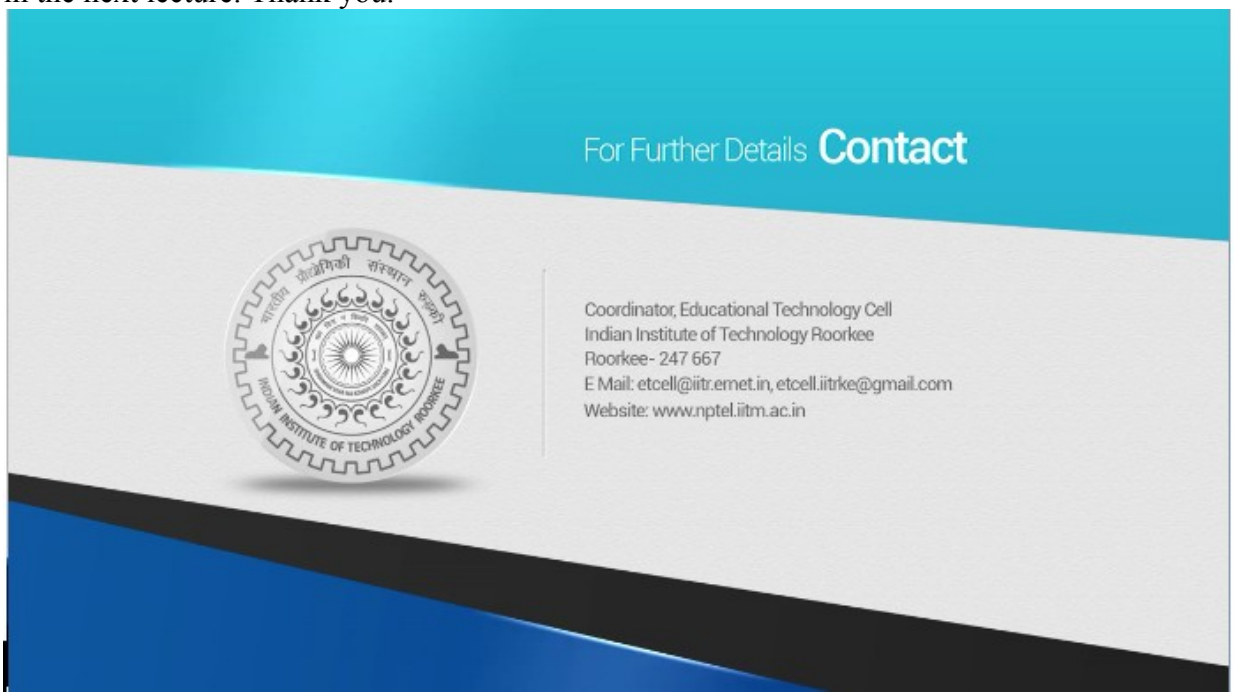
So then there is once these remaining rules are there then we can use this particular library A rules viz, so this is only for visualization purpose, so the rules they can be you know a graphic can be created which can, convey the information about these shortlisted rules in terms of you know the different shape of you know different shapes that are being used, their size of those shape and color of those shapes can be used to convey different kind of information, so for this we would be requiring this library, so let's try and load this, so this is not installed, so let's run this.

So we will have, we'll try and install this particular library install.packages, so within double quotes we will like to enter the name of it, so once this particular library is installed and then we can load it and you'll see in this run we have not been able to shortlist rules, we do not have an real output in this particular rules, otherwise we would be able to see that shortlist rule, they can be depicted using certain shapes and size of those shapes and color can convey certain information, right, so for example size you can convey the number of transaction that are involved, and the color can convey the you know lift value, so support, confidence and lift value can be you know depicted using some of these you know graphics and different visualization, so essentially it would be a multi-dimensional graphic.

So what we can do is, we can do one more run of this particular, you know we can apply association rules one more time and if some output is after pruning we get few rules shortlisted rule, then we can of course visualize them using these functions.



So right now this package is still being installed, so this is about to be completed I think this package installation is almost complete. Just about there the packages are being unpacked and installed, so it seems to be stuck somewhere, so as I talked about that, once this library is loaded and we have shortlisted some rules they can be visually seen the importance of those rules, their strength using different matrix that we have talked about, support, confidence, and lift value, so using shapes and colors we can create a multidimensional graphic using this particular code and we would be able to see it, so we'll stop here and we'll start our discussion on cluster, analysis in the next lecture. Thank you.



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Acknowledgement
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Subject Expert
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Produced by
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Binoy V.P
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Dr. NibeditaBisoyi
Neetesh Kumar
Jitender Kumar
Vivek Kumar
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