Marketing and Retail Analytics Project

Cafe Coffee Night

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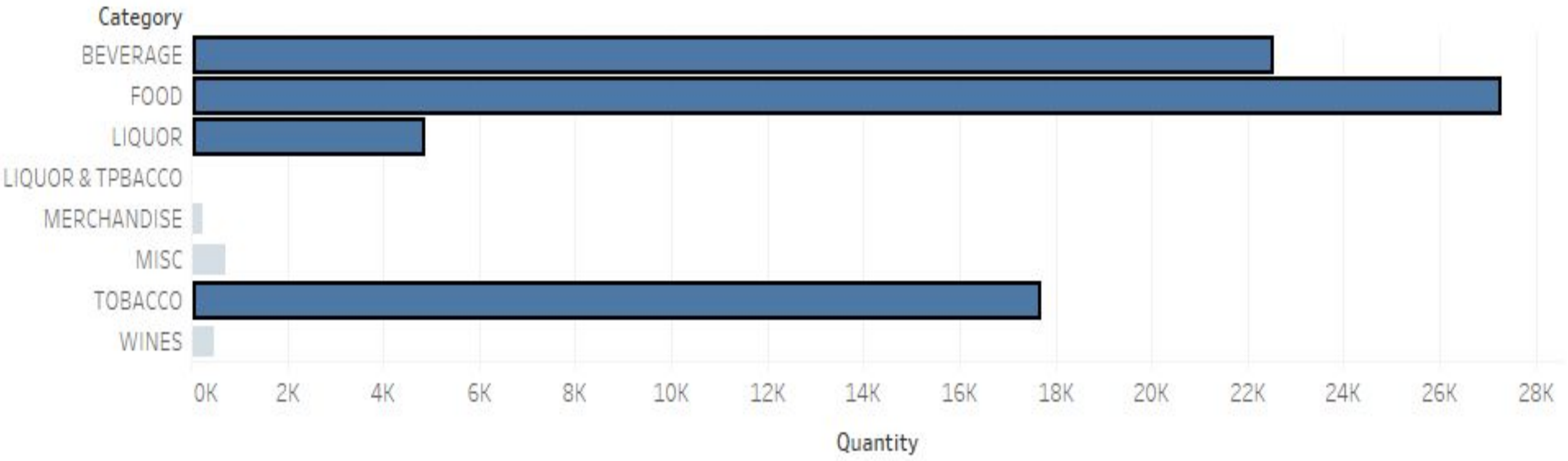
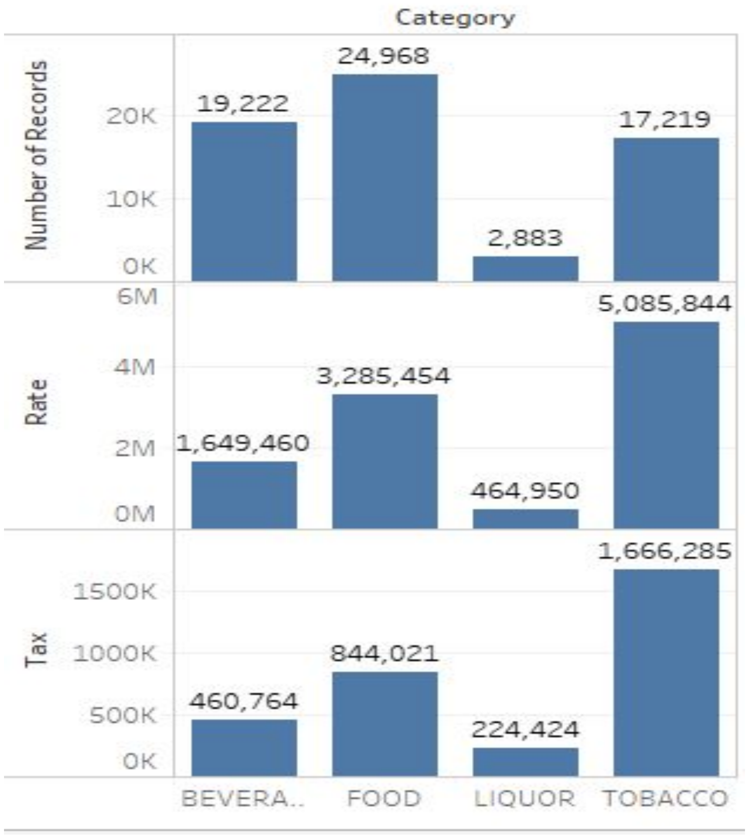
Exploratory data analysis

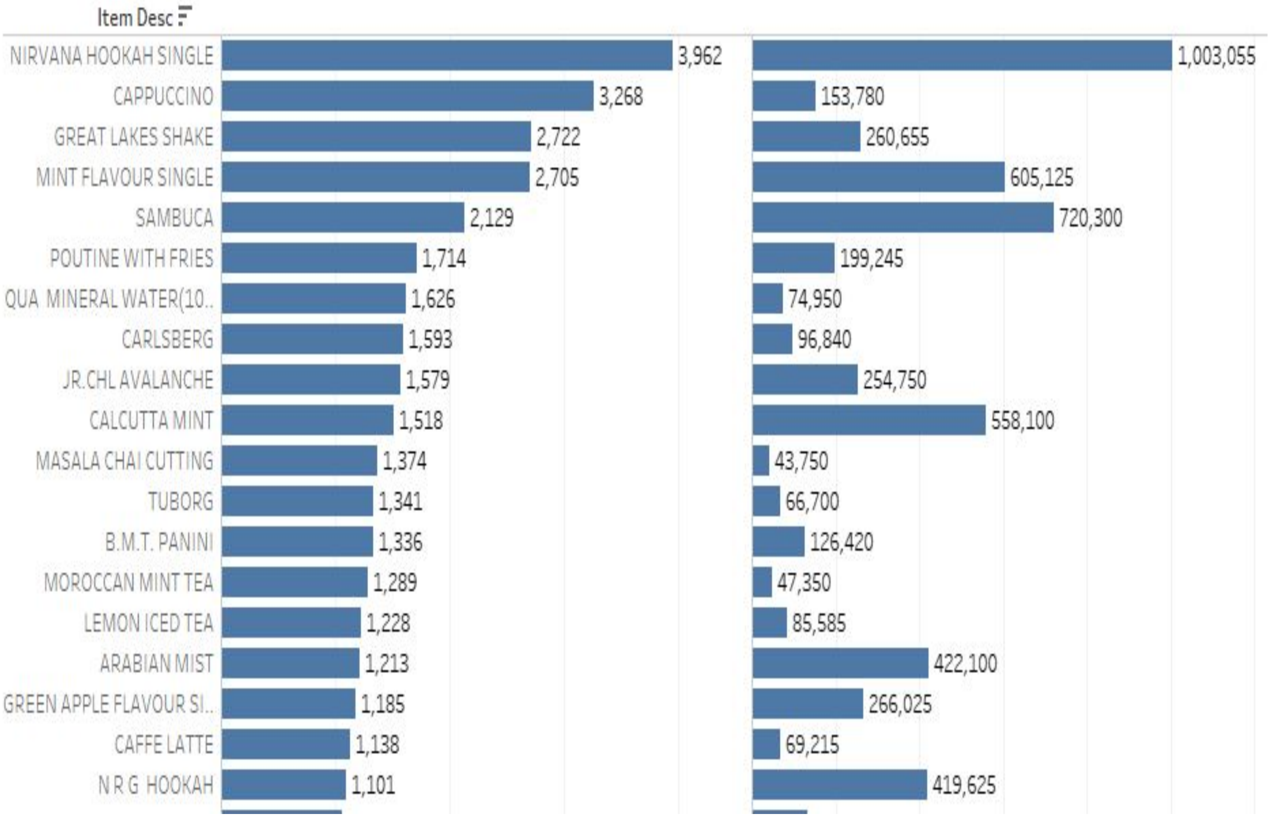
There are a total of 65,535 customers whose orders have been collected in a restaurant over a time period of 1 year .the different types of orders are categorised as beverages, food, liquor, merchandise ,misc and wine.



Basic information for number of customers for considered categories.

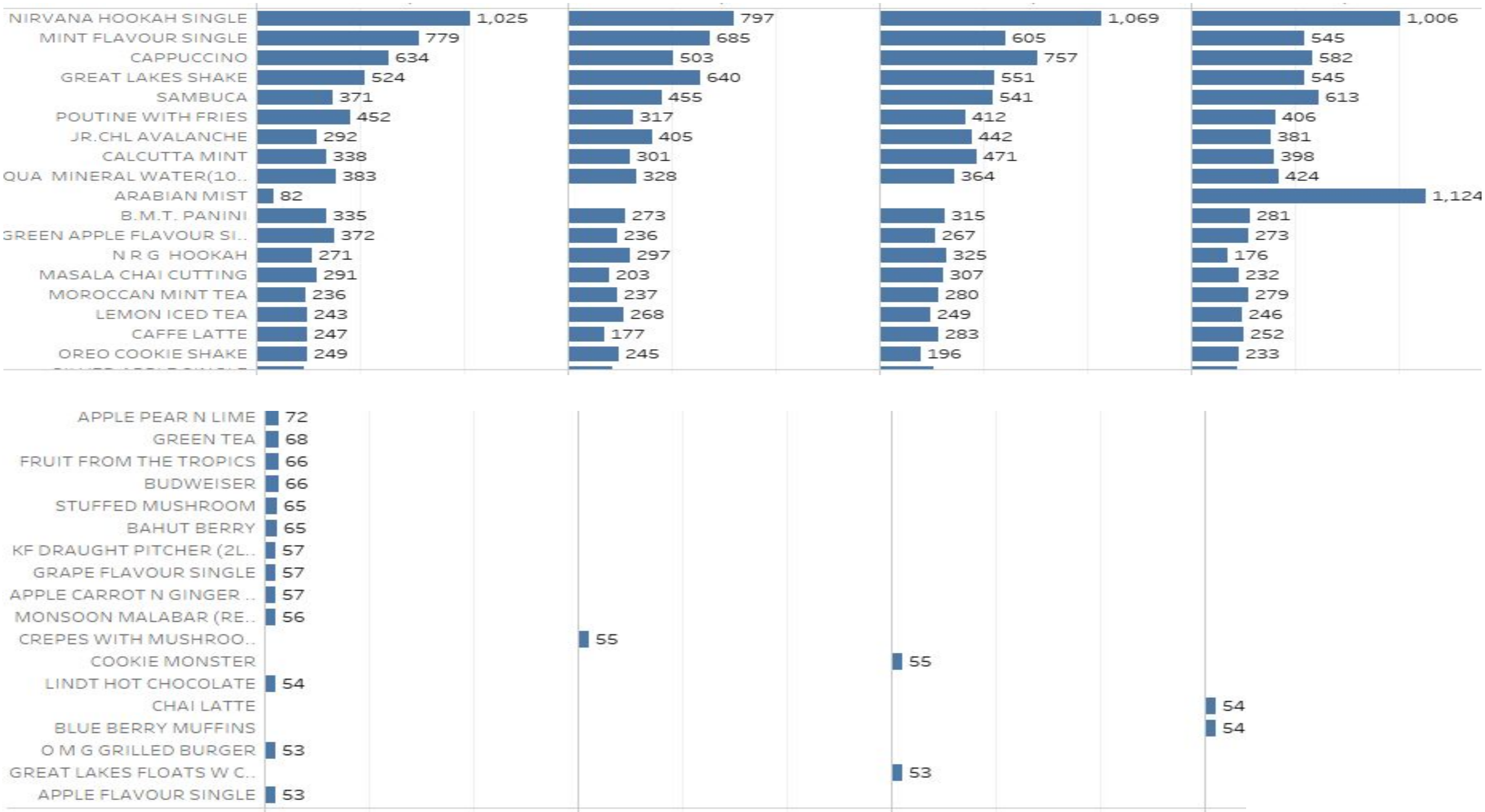


Some of the top and least Item desc ordered with total sum amount of the items



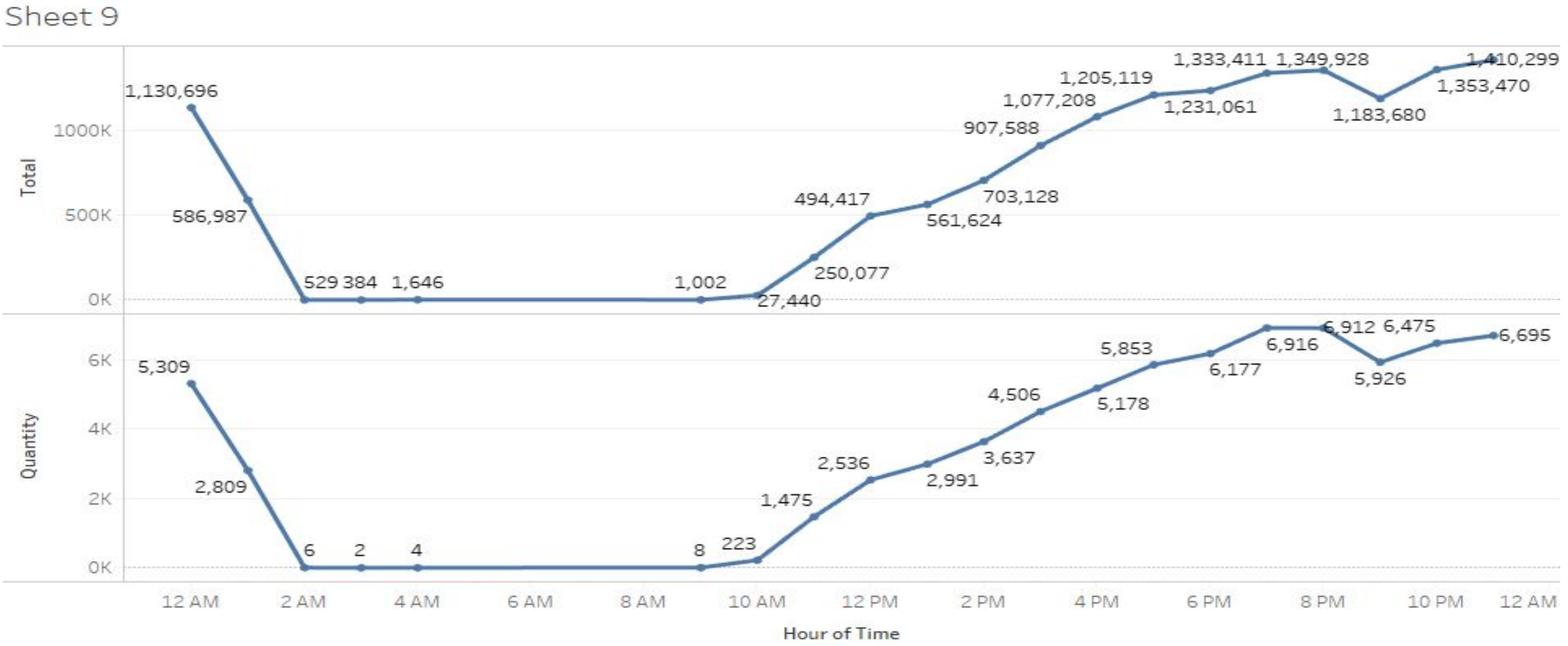
1+1 VLN CAB SAUV (BTL)	1	800
1+1 VLN SAUV BLANC (BTL)	1	800
2 AXE TWIST	1	140
2 DOM BEER + 1SPL SHEE..	1	500
2 OCEAN PINOTAGE (BTL)	1	1,900
4 SEASONS CLAS SYRAH(..	1	800
AL SIKANDARI HOOKAH D..	1	345
ASH TRAYS	1	150
B1G1 4SEASON CLAS SAU..	1	900
B1G1 4SEASON CLAS SAU..	1	200
BENARAS BLUE	1	351
BENARAS LIME	1	351
BENSON & HEGDES GOLD ..	1	92

Items across four quarters with good and bad sales



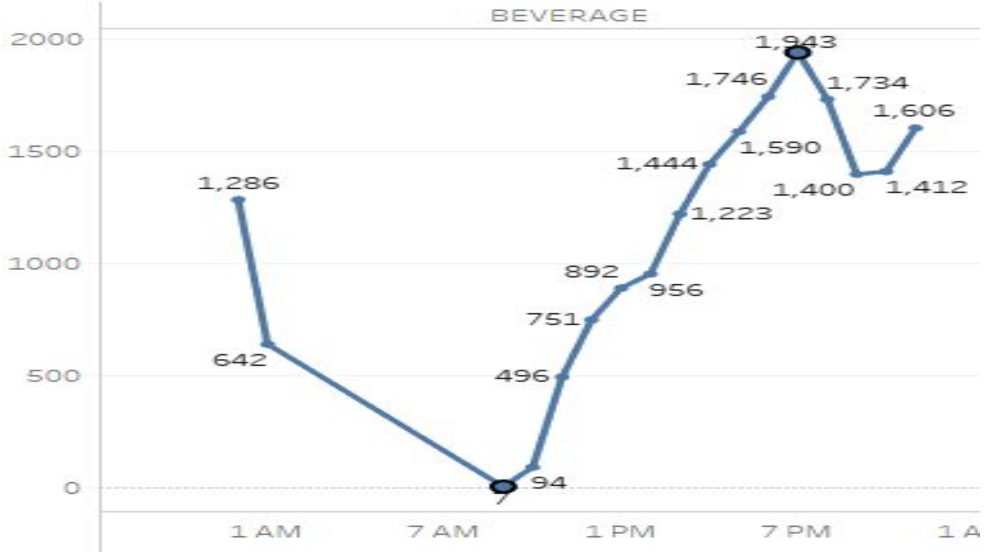
1.2 Trends of customer behaviour

The graph shows the different times of the day the customer flow is more and the total purchase amount



The restaurants start time is at around 10 A.M where the inflow of the customers begins to flow,but people are in good number at the time of lunch around 1 P.M and it keeps on increasing and is highest at 8 P.M i.e a lot of people clearly come over dinner or the evening time and it also works well as night restaurant till 12 A.M but after it keeps on decreasing and almost no one around 2 A.M .So the restaurant can work as a 12 hour clock rather than round the clock

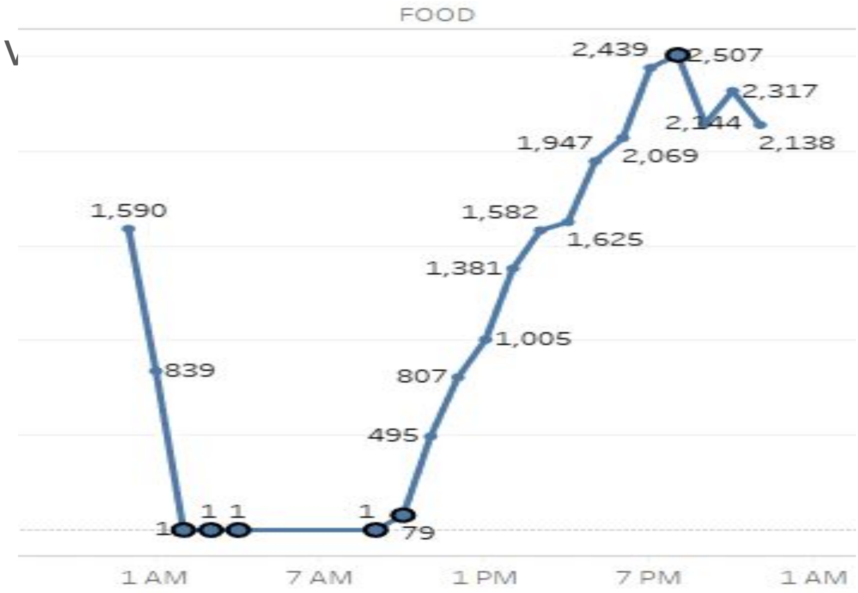
Some of the categories listed which people ordered at different times of the day



Highest orders :8 P.M (Beverages)

Lowest orders :9 P.M

Max orders: evening to midnight



Highest orders : 8 P.M (Food)

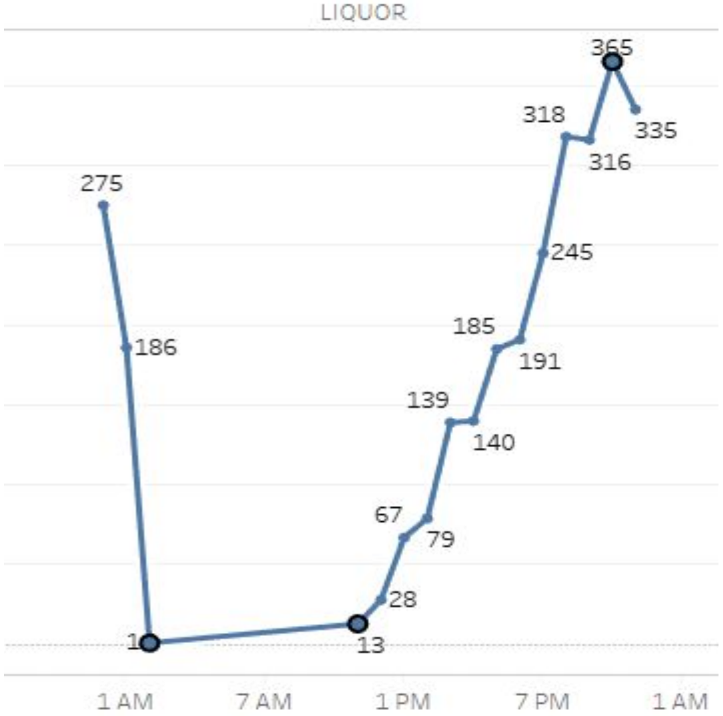
Lowest orders:1 A.M to 11 A.M

Max orders : evening to midnight

Highest orders : 11 P.M (Liquor)

Lowest orders : 1 A.M to 1 P.M

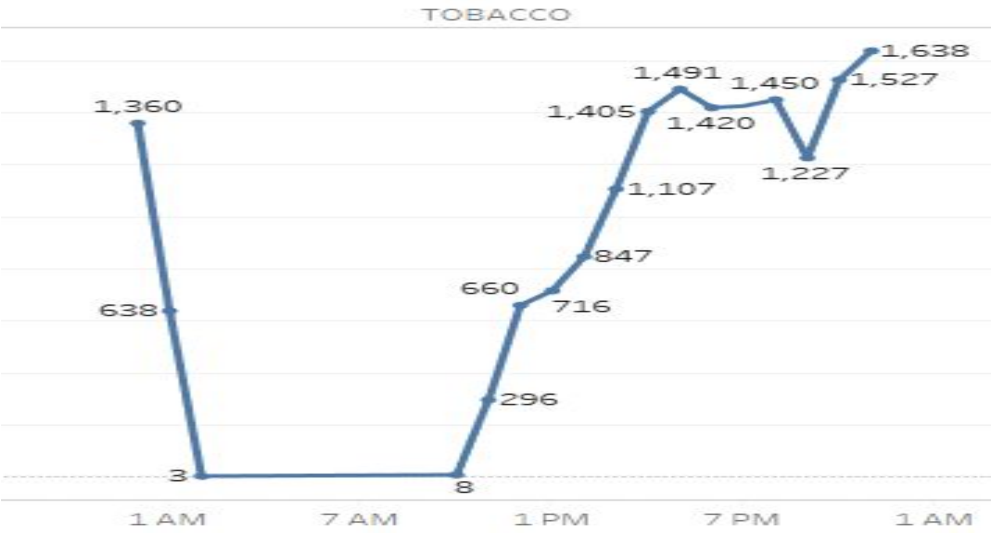
Max orders : mostly midnight



Highest order : 12 A.M (tobacco)

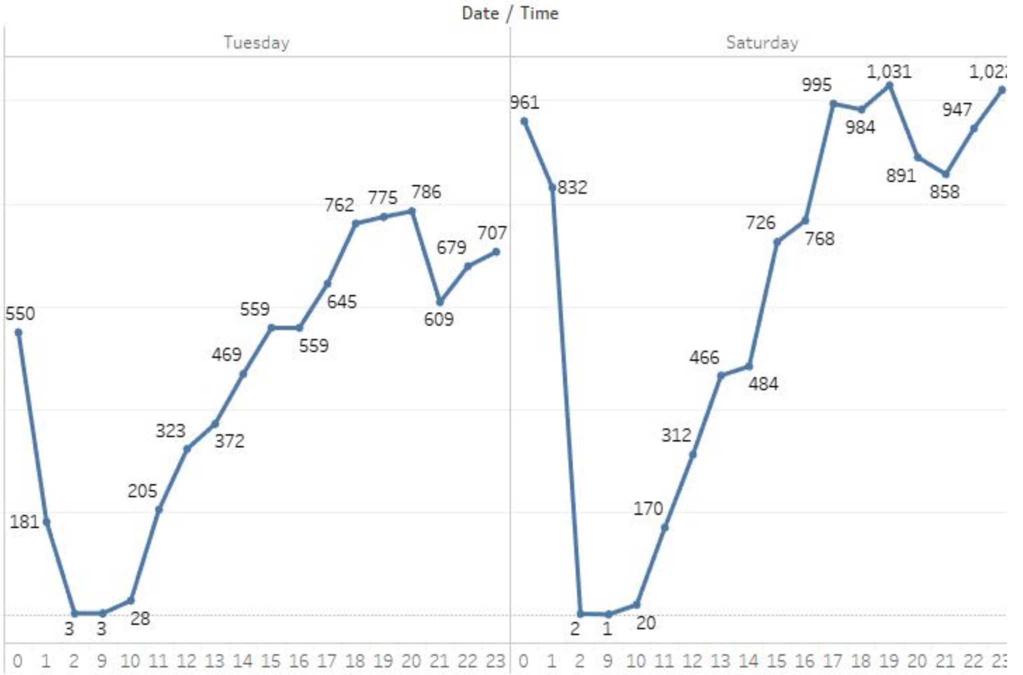
Lowest order : 1 A.M to 12 P.M

Max orders : noon to overnight



So clearly the customers inflow is way more over evenings and nights and way less in the mornings from around 2 A.M to 12 P.M So, clearly the restaurant is not preferred in the mornings so it can be a 12-hour restaurant so that the restaurant can be recommended the best for the customers for eve and nights

The weekends are filled with many customers than the weekdays and as we have already seen there has been lot of people in the evenings and nights i.e from around 4 P.M to around 12 A.M

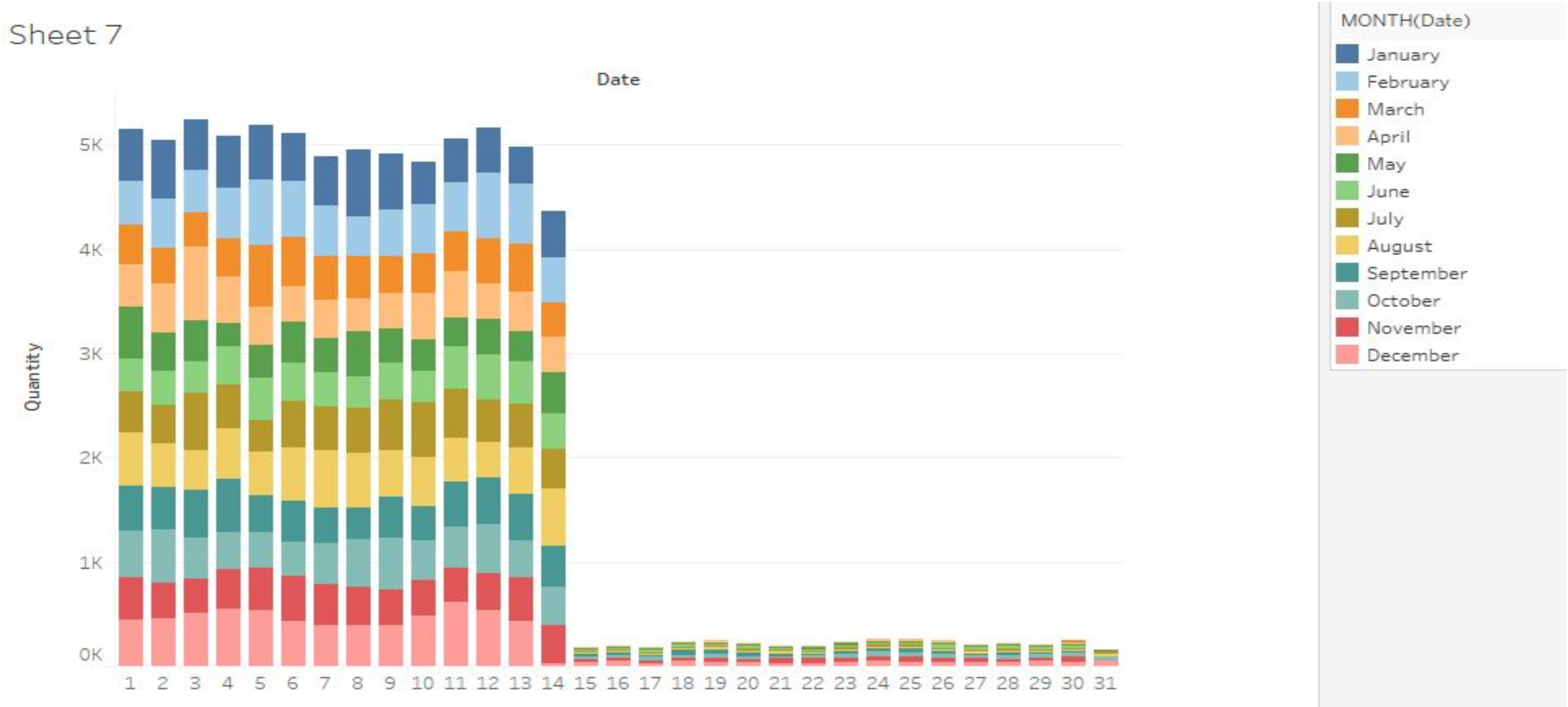


The lowest(tuesday) and highest(Sat)

days for flow of customers

1.3 Trends across months

This is a different trend where only the first 15 days there are more customers but the last 15 days of the month there are very less customers



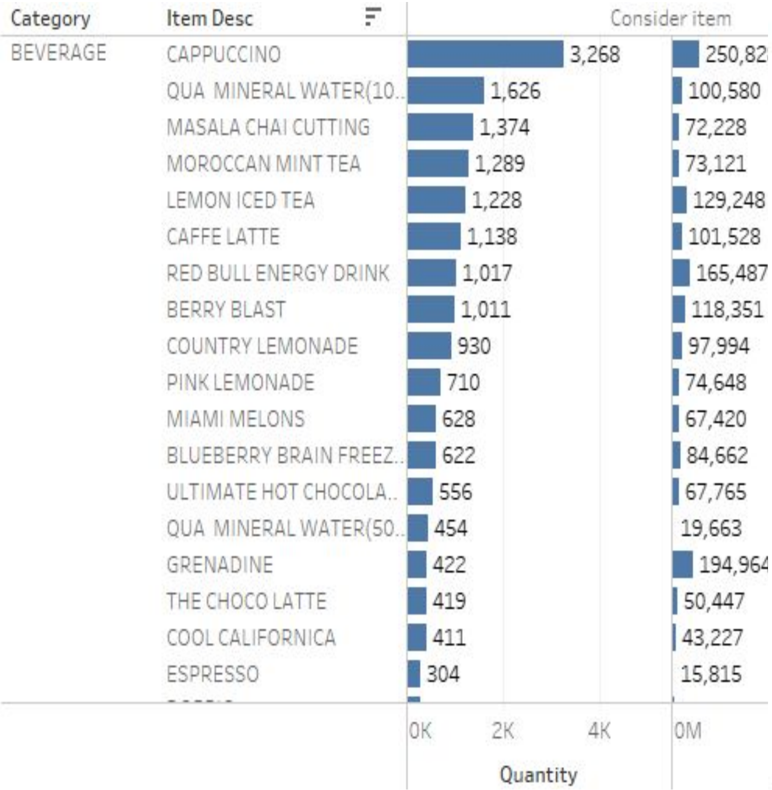
1.4 Menu items suggestions

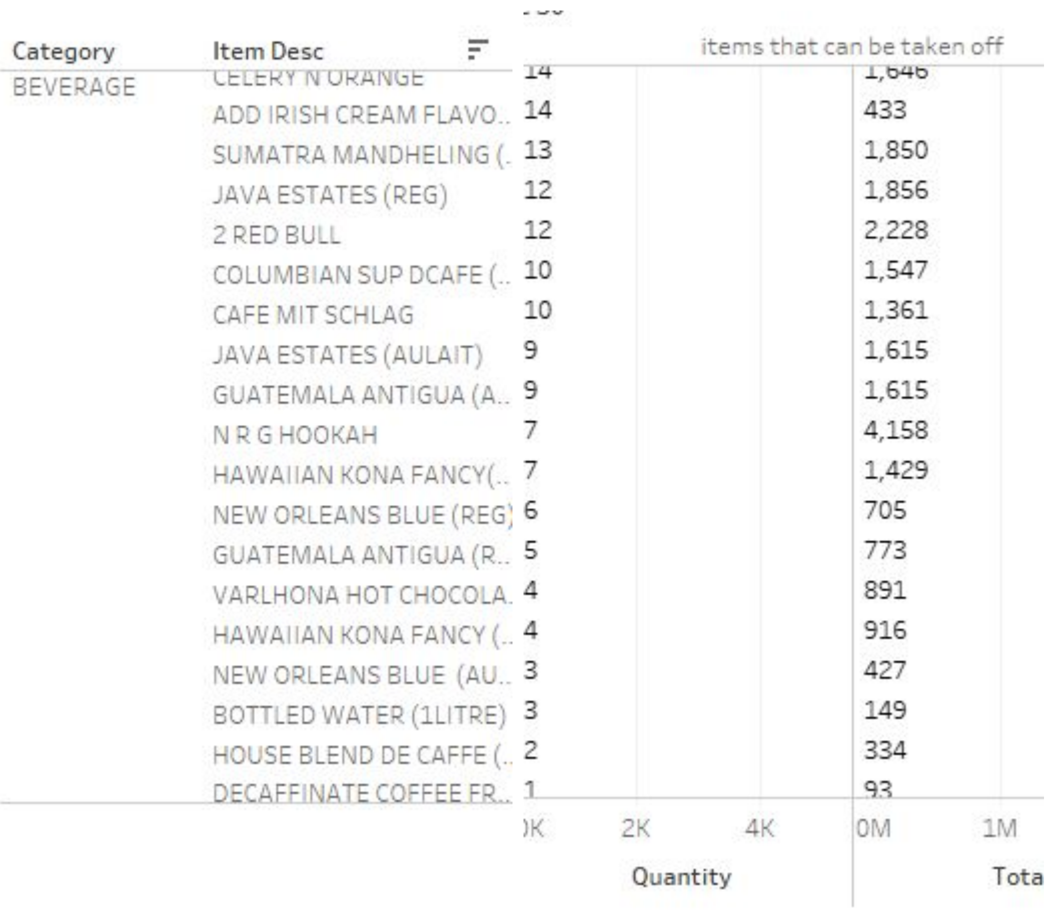
The following suggestions are made using Tableau as a working tool where the category and item description are considered as dimensions and total items and total sum of money for the items are considered as measures and a function is made with regarding to measures and items menu was considered accordingly across different categories . Since if more quantities are sold and high amount is acquired with regard to it the profits are more and also the transportation charges for the useless items will be reduced and all the top items will be even more sold .

The function used is IF SUM([Quantity])>35 OR SUM([Total])> 5000 THEN 'Consider item' ELSE 'items that can be taken off ' END

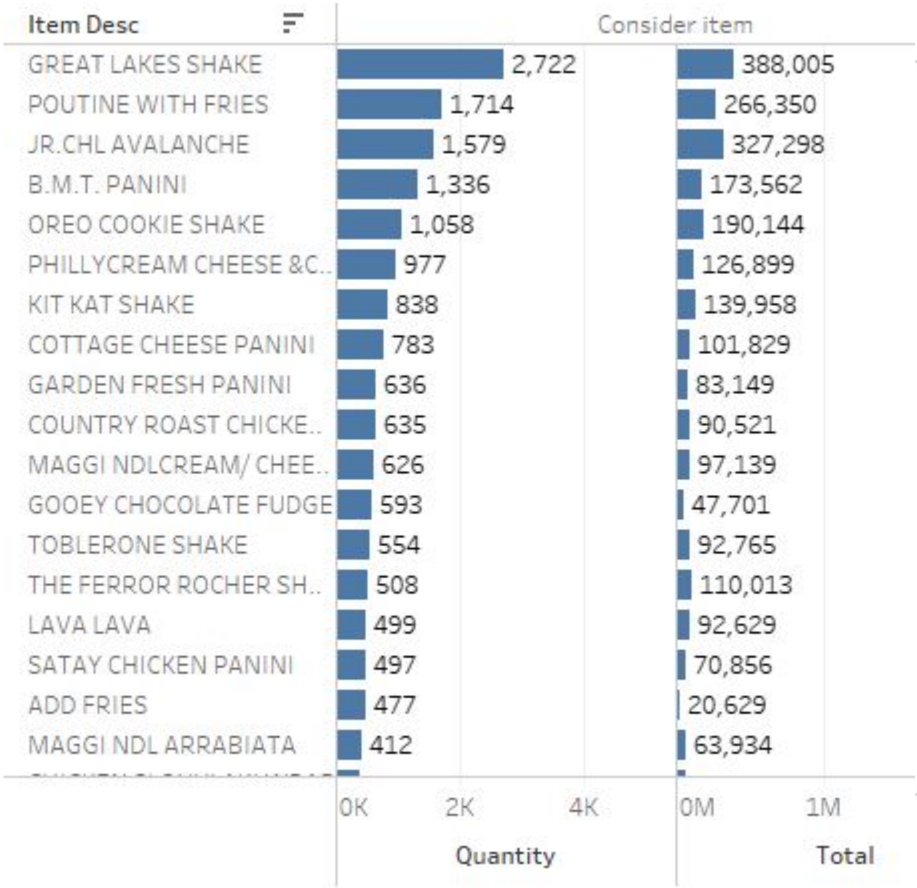
So based on different categories some of the items preferred and not preferred are :

Bevarages

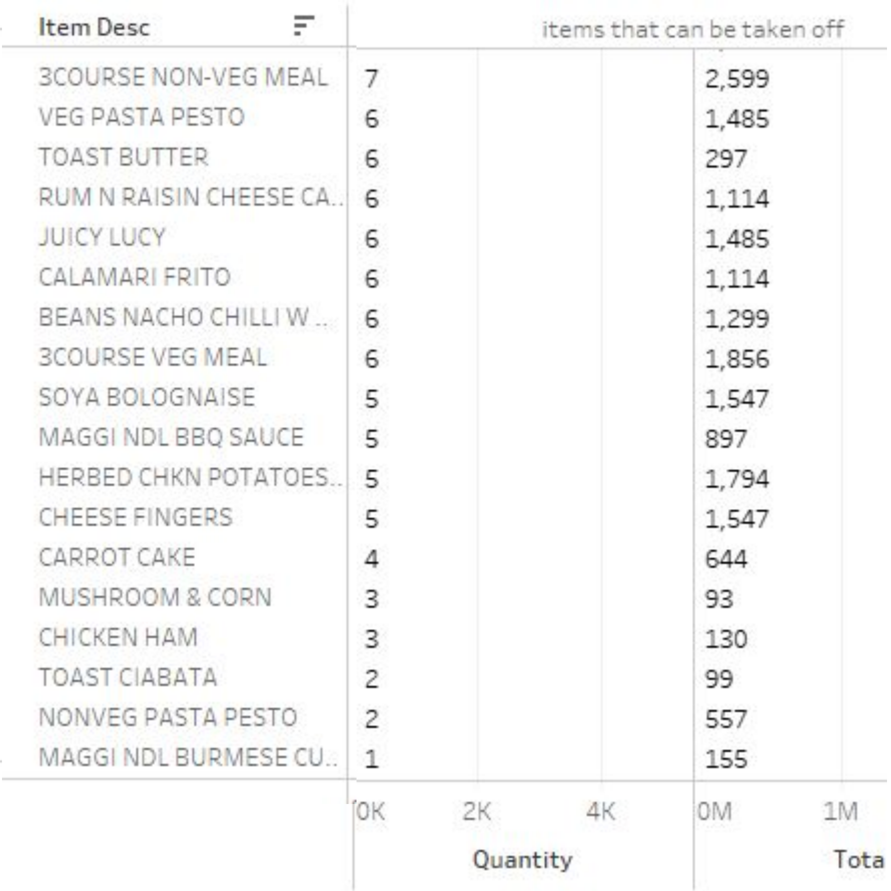

Category
Item Desc
Consider item
BEVERAGE
CAPPUCCINO 3,268 250,82
QUA MINERAL WATER(10.. 1,626 100,580
MASALA CHAI CUTTING 1,374 72,228
MOROCCAN MINT TEA 1,289 73,121
LEMON ICED TEA 1,228 129,248
CAFFE LATTE 1,138 101,528
RED BULL ENERGY DRINK 1,017 165,487
BERRY BLAST 1,011 118,351
COUNTRY LEMONADE 930 97,994
PINK LEMONADE 710 74,648
MIAMI MELONS 628 67,420
BLUEBERRY BRAIN FREEZ.. 622 84,662
ULTIMATE HOT CHOCOLA.. 556 67,765
QUA MINERAL WATER(50.. 454 19,663
GRENADINE 422 194,964
THE CHOCO LATTE 419 50,447
COOL CALIFORNICA 411 43,227
ESPRESSO 304 15,815
0K
2K
4K
0M
Quantity


Category
Item Desc
items that can be taken off
BEVERAGE
CELERY N ORANGE 14 1,646
ADD IRISH CREAM FLAVO.. 14 433
SUMATRA MANDHELING (.. 13 1,850
JAVA ESTATES (REG) 12 1,856
2 RED BULL 12 2,228
COLUMBIAN SUP DCAFE (.. 10 1,547
CAFE MIT SCHLAG 10 1,361
JAVA ESTATES (AULAIT) 9 1,615
GUATEMALA ANTIGUA (A.. 9 1,615
N R G HOOKAH 7 4,158
HAWAIIAN KONA FANCY(.. 7 1,429
NEW ORLEANS BLUE (REG) 6 705
GUATEMALA ANTIGUA (R.. 5 773
VARLHONA HOT CHOCOLA.. 4 891
HAWAIIAN KONA FANCY (.. 4 916
NEW ORLEANS BLUE (AU.. 3 427
BOTTLED WATER (1LITRE) 3 149
HOUSE BLEND DE CAFFE (.. 2 334
DECAFFINATE COFFEE FR.. 1 93
2K
4K
0M
1M
Quantity
Tota

Food



Item Desc
Consider item
GREAT LAKES SHAKE 2,722 388,005
POUTINE WITH FRIES 1,714 266,350
JR.CHL AVALANCHE 1,579 327,298
B.M.T. PANINI 1,336 173,562
OREO COOKIE SHAKE 1,058 190,144
PHILLYCREAM CHEESE &C.. 977 126,899
KIT KAT SHAKE 838 139,958
COTTAGE CHEESE PANINI 783 101,829
GARDEN FRESH PANINI 636 83,149
COUNTRY ROAST CHICKE.. 635 90,521
MAGGI NDLCREAM/ CHEE.. 626 97,139
GOOEY CHOCOLATE FUDGE 593 47,701
TOBLERONE SHAKE 554 92,765
THE FERROR ROCHER SH.. 508 110,013
LAVA LAVA 499 92,629
SATAY CHICKEN PANINI 497 70,856
ADD FRIES 477 20,629
MAGGI NDL ARRABIATA 412 63,934
0K 2K 4K
Quantity
0M 1M
Total



Item Desc
items that can be taken off
3COURSE NON-VEG MEAL 7 2,599
VEG PASTA PESTO 6 1,485
TOAST BUTTER 6 297
RUM N RAISIN CHEESE CA.. 6 1,114
JUICY LUCY 6 1,485
CALAMARI FRITO 6 1,114
BEANS NACHO CHILLI W.. 6 1,299
3COURSE VEG MEAL 6 1,856
SOYA BOLOGNAISE 5 1,547
MAGGI NDL BBQ SAUCE 5 897
HERBED CHKN POTATOES.. 5 1,794
CHEESE FINGERS 5 1,547
CARROT CAKE 4 644
MUSHROOM & CORN 3 93
CHICKEN HAM 3 130
TOAST CIABATA 2 99
NONVEG PASTA PESTO 2 557
MAGGI NDL BURMESE CU.. 1 155
0K 2K 4K
Quantity
0M 1M
Tota

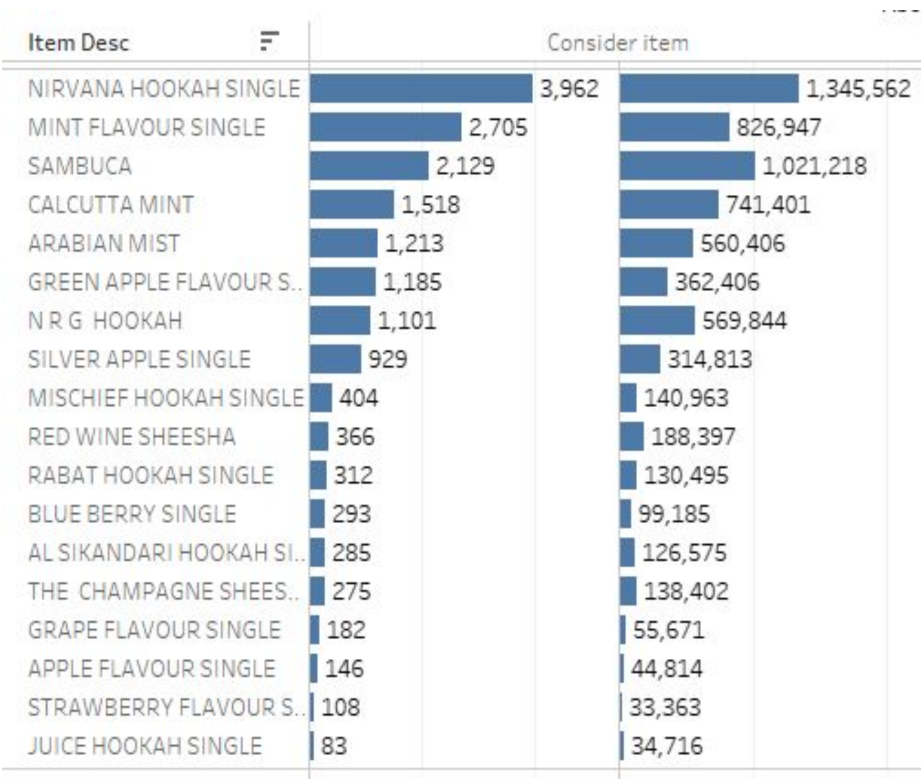
Liquor

Category	Item Desc	Consider item: Quantity	Consider item: Total	items that can be taken off: Quantity	items that can be taken off: Total
LIQUOR	TUBORG	1,341	176,006		
	KF DRAUGHT (1/2LTR)	708	116,144		
	KF DRAUGHT (1LTR)	479	147,105		
	KF DRAUGHT PITCHER (2L..	222	121,172		
	BUDWEISER	149	19,538		
	1+1 KF 1/2 LITER	136	22,312		
	1+1 KF 1 LITER	48	14,175		
	HOEGAARDEN (GLS)	31	9,877		
	HOEGAARDEN MUG (1 LIT..	26	21,131		
	CARLSBERG 2+1	21	8,250		
	HOEGAARDEN MUG (1/2 L..	13	5,972		
	BEER TANK 3.5 LITRE	11	8,663		
	STELLA ARTOIS MUG (1/2 ..			10	4,594
	STELLA ARTOIS MUG (1 LT..	8	6,825		
	1+1 KF 2 LITER			7	3,675
	STELLA ARTOIS (GLS)			5	1,509
	SCHNEIDER BUCKET - 6			2	3,150
	BROOKLYN BUCKET - 4			2	2,100

Quantity axis: 0K, 2K, 4K; Total axis: 0M, 1M, 2M

We're not considering Merchandise and liqur & tbacco since it doesn't yield high profits

Tobacco



Item Desc	items that can be taken off	
CASABLANKA HOOKAH SI		
BENSON & HEDGES LIGHT	17	1,753
GOLD FLAKE KINGS-BIG	11	964
LATE HARVEST SULA CHE..	10	2,394
GOLD FLAKE KING RED	7	735
GOLD FLAKE KING BLUE	6	630
BENSON & HEDGES SPL	6	608
SPICE SHEESHA	5	2,970
LATE HARVEST SULA CHE..	4	2,394
CLASSIC MENTHOL	4	362
BLUE LAGOON SHEESHA	4	2,376
GOLD FLAKE LIGHTS-BIG	3	263
CLASSIC ULTRA MILD	2	199
APPLE FLAVOUR DOUBLE	2	739
GREAT LAKES HOOKAH SI..	1	389
GOLD FLAKE ULTRA LIGHT	1	88
CLASSIC MENTHOL RUSH	1	100
BENSON & HEGDES GOLD	1	110
AL SIKANDARI HOOKAH D..	1	455

Wines

Above 50

Item Desc	Consider item		items that can be taken off	
VLN CAB SAUV (GLS)	90	19,870		
SULA BLUSH ZINFANDEL(..	46	11,592		
1+1 WINE GLASS	43	10,018		
VLN SAUV BLANC (GLS)	40	8,820		
VLN CAB SAUV CLASIQ (GL..	30	8,190		
VLN CHENIN BLANC (GLS)	28	6,174		
1+1 VLN CAB SAUV CLASI..			22	4,851
1+1 VLN CHENIN BLANC (..			21	4,631
DIA SPARKLING WINE(GLS)			20	3,150
SANGRIA ROSE (GLS)			18	3,969
1+1 GLS 4SEASONS WHITE			13	3,276
B1G1 ZINZI RED (GLS)			12	2,268
1+1 VLN CAB SAUV (GLS)			12	2,646
1+1 GLS 4SEASON RED			11	2,426
B1G1 ZINZI WHITE (GLS)			10	1,890
1+1 VLN SAUV BLANC (GLS)			10	2,205
4 SEASONS CLAS SYRAH(..			7	1,544
VLN CHENIN BLANC (BTL)			4	4,032

Item Desc	items that can be taken off	
4 SEASONS CLAS SYRAH(..	7	1,544
VLN CHENIN BLANC (BTL)	4	4,032
SANGRIA ROSE (CARAFE)	4	4,095
DIA SPARKLING WINE(BTL	4	2,520
4 SEASONS CLAS SAUV(GL	4	1,008
VLN CAB SAUV CLASIQ (BT	3	3,780
VLN CAB SAUV (BTL)	3	3,024
SULA BLUSH ZINFANDEL (.	3	3,402
B1G1 ZINZI WHITE (BTL)	3	2,646
B1G1 ZINZI RED (BTL)	3	2,646
VLN SAUV BLANC (BTL)	2	2,016
B1G1 4SEASON CLAS SYR..	2	441
4 SEASONS CLAS SAUV(B..	2	2,268
1+1 WINE BOTTLE	2	2,145
1+1 VLN CAB SAUV CLASI..	2	2,016
1+1 BTL4 SEASON WHITE	2	2,268
SULA BRUT (BTL)	1	1,512
GOSSIPS CHARD AUS (BTL)	1	2,756

Menu Analysis

The menu analysis is understanding which is the best combination of item descriptions used by the customer at the restaurant .So for this we take the sheet3 of the excel sheet given Cafe Coffee Night-1.xls .and converted to a csv file called cafe.csv and used for menu analysis .The analysis is done using R software and the libraries used are

```
library(arules)
library(arulesViz)
```

For this Apriori function is used which will run the transactions file by specifying minimum values for support and confidence and the data has to be in basket form .

```
dataset = read.csv('cafe.csv', header = FALSE)
dataset = read.transactions('cafe.csv', sep = ',', rm.duplicates = TRUE)
```

The different formulae used for understanding market basket analysis

$$\text{Confidence} = \frac{(A+B)}{A} \qquad \text{Support} = \frac{(A+B)}{\text{Total}} \qquad \text{Lift} = \left(\frac{\left(\frac{(A+B)}{A}\right)}{\left(\frac{B}{\text{Total}}\right)}\right)$$

Support: Its the default popularity of an item

Confidence: Likelihood that customer who bought both A and B

Lift should be greater than 1 only then the items are considered good and support and confidence are taken very less values to create rules and further create the menu combo

First let us consider by looking at the data to understand how the transactional data looks like and clearly we can see a lot of people buying beverages, food and tobacco mostly .

We can also do the analysis by tableau by considering Category in row and column and dropping ID or bill number on the detail then the combined orders of different categories can be known summary(dataset)

```
> summary(dataset)
transactions as itemMatrix in sparse format with
 65535 rows (elements/itemsets/transactions) and
 69314 columns (items) and a density of 8.016369e-05

most frequent items:
      1       2       3   323.4     297 (Other)
  49672   29769   13919    7753    7181  255849

element (itemset/transaction) length distribution:
sizes
    2     4     6     7     8     9    10    11    12
    1 38186    94 11618 12106  2702   782    31    15

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  2.000   4.000   4.000   5.556   7.000  12.000
```

itemFrequencyPlot(dataset, topN = 10)

Training Apriori on the dataset

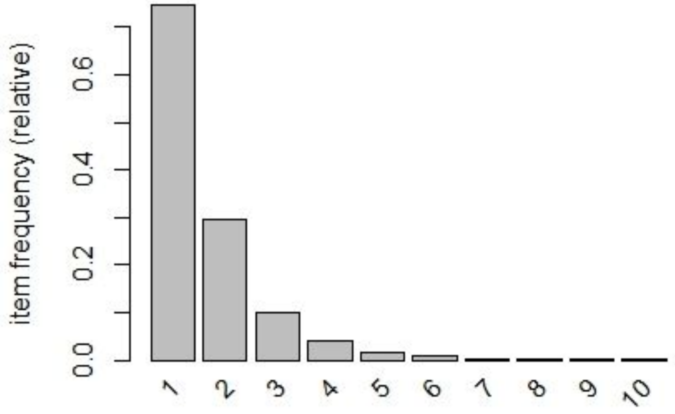
rules = apriori(data = dataset, parameter = list(support = 0.05, confidence = 0.1))

Visualising the results

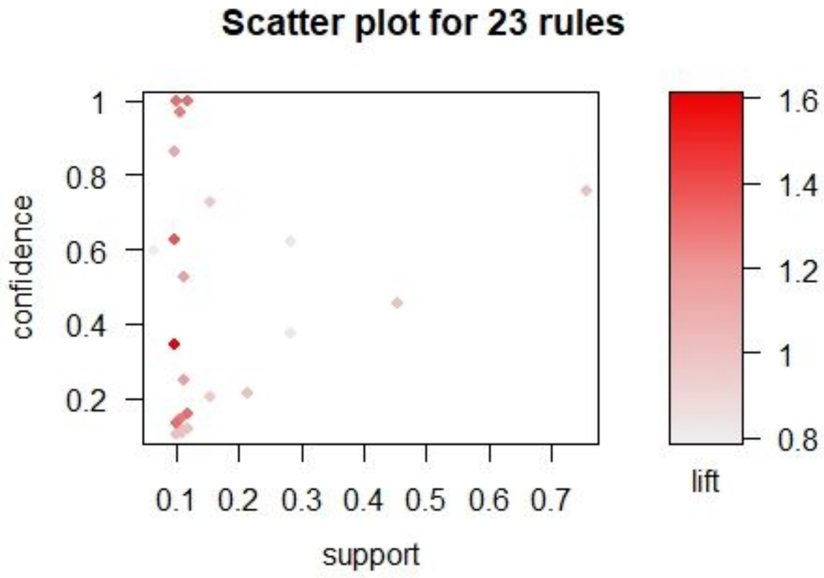
inspect(sort(rules, by = 'lift')[1:20])

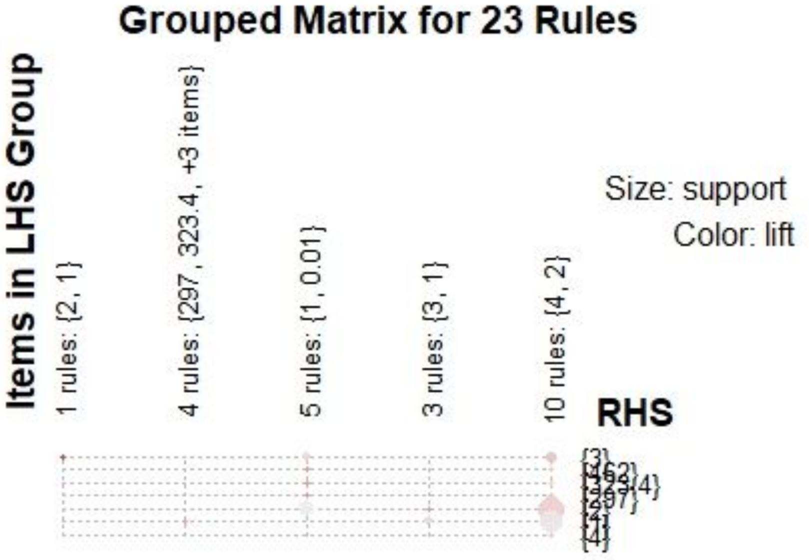
There are a total of 23 rules used

```
> rules = apriori(data = dataset, parameter = list(support = 0.05, confidence = 0.1))
Apriori

Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen maxlen target   ext
        0.1    0.1    1 none FALSE            TRUE       5    0.05      1     10  rules FALSE

Algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE

Absolute minimum support count: 3276

set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[69314 item(s), 65535 transaction(s)] done [0.20s].
sorting and recoding items ... [8 item(s)] done [0.01s].
creating transaction tree ... done [0.02s].
checking subsets of size 1 2 3 done [0.00s].
writing ... [23 rule(s)] done [0.00s].
creating S4 object  ... done [0.01s].
```

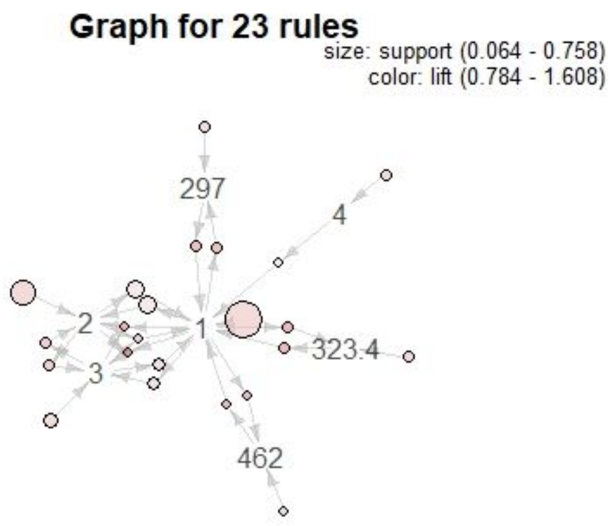


```
plot(rules)

plot(rules, method = "grouped", control = list(k = 5))
```





plot(rules, method="graph", control=list(type="items"))



While inspecting only the sets with a lift above 1 are considered as highlighted below since only those combinations are worth considering

```
> inspect(sort(rules, by = 'lift')[1:20])
     lhs          rhs       support   confidence lift      count
[1]  {1,2}     => {3}       0.0966659 0.3416199  1.6084533  6335
[2]  {1,3}     => {2}       0.0966659 0.6276006  1.3816320  6335
[3]  {1}       => {462}     0.1006027 0.1327307  1.3193550  6593
[4]  {462}     => {1}       0.1006027 1.0000000  1.3193550  6593
[5]  {323.4}   => {1}       0.1183032 1.0000000  1.3193550  7753
[6]  {1}       => {323.4}   0.1183032 0.1560839  1.3193550  7753
[7]  {1}       => {297}     0.1059281 0.1397568  1.2754438  6942
[8]  {297}     => {1}       0.1059281 0.9667177  1.2754438  6942
[9]  {2}       => {3}       0.1120470 0.2466660  1.1613806  7343
[10] {3}       => {2}       0.1120470 0.5275523  1.1613806  7343
[11] {2,3}     => {1}       0.0966659 0.8627264  1.1382424  6335
[12] {}        => {462}     0.1006027 0.1006027  1.0000000  6593
[13] {}        => {297}     0.1095750 0.1095750  1.0000000  7181
[14] {}        => {323.4}   0.1183032 0.1183032  1.0000000  7753
[15] {}        => {4}       0.1071641 0.1071641  1.0000000  7023
[16] {}        => {3}       0.2123903 0.2123903  1.0000000 13919
[17] {}        => {2}       0.4542458 0.4542458  1.0000000 29769
[18] {}        => {1}       0.7579461 0.7579461  1.0000000 49672
[19] {1}       => {3}       0.1540246 0.2032131  0.9567906 10094
[20] {3}       => {1}       0.1540246 0.7251958  0.9567906 10094
```

The first combination shows beverages and food with liquor

The second one shows beverages and liquor with food

The third one beverages with tobacco

So we will make a combo in such a way that the best seller of beverages and food is mixed with liquor so

1.Cappucino,Nirvana hookah single and poutine with fries
2.Qua Mineral water ,great cl avalanche and tuborg

And the rest as given before in the charts the list goes on with the combinations of next bestsellers in each of the category and also according to cost along with a discount more combos can be created and a better sale will created