Intro to ML Final Exam 2

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Raw .Rmd code available at —– https://github.com/abhinav-sharma-6167/Intro-to-ML-2

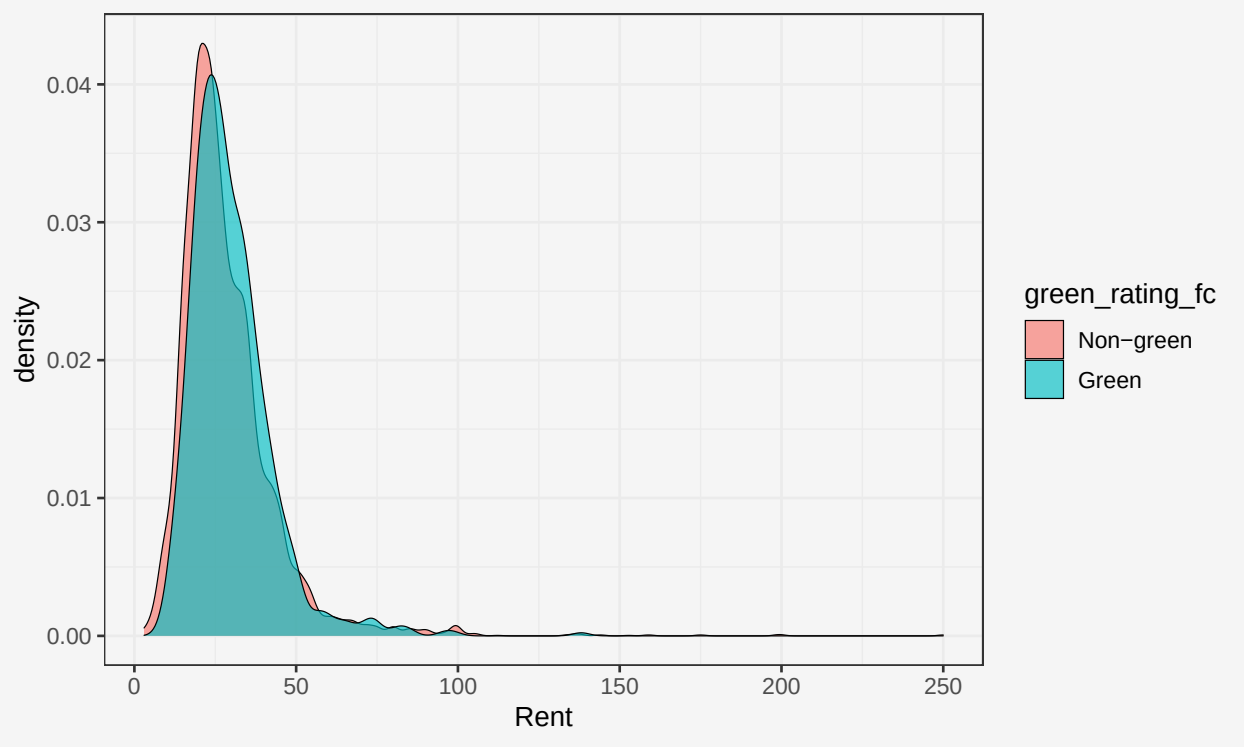
Setup - Loading libraries and setting working directory. Key libraries include ggplot2, plotly for exploration; data.table and dplyr data wrangling. Setting up custom ggplot theme for all plotting purposes.

1. Visual story telling part 1: green buildings

The details given in the case helps us get a sense of the problem. To quickly summarize, the data encompasses of 7,894 commercial rental properties of which 685 are green buildings.To avail a control set for the 685 properties, the creators of this data leveraged all non-rated buildings within a quarter-mile radius of the green-certified building. On average we have 12 non-rated nearby properties for each green property. The idea is green houses would be more attractive living options given lower recurring costs, better indoor environments, longer economically valuable lives and in general, the good PR they enjoy. The goal is to validate whether investing in a green building be worth it, from an economic perspective. Specifically, in a new 15-story mixed-use building on East Cesar Chavez, just across I-35 from downtown with baseline construction costs being $100 million and a 5% expected premium for green certification.

Building upon this premise, we now start exploring the data. We start by checking the number of green houses and distributions of the variables used in stat-guru's analysis to stress-test the assumptions made.

```
Percentage of green buildings :
 8.68 %
```



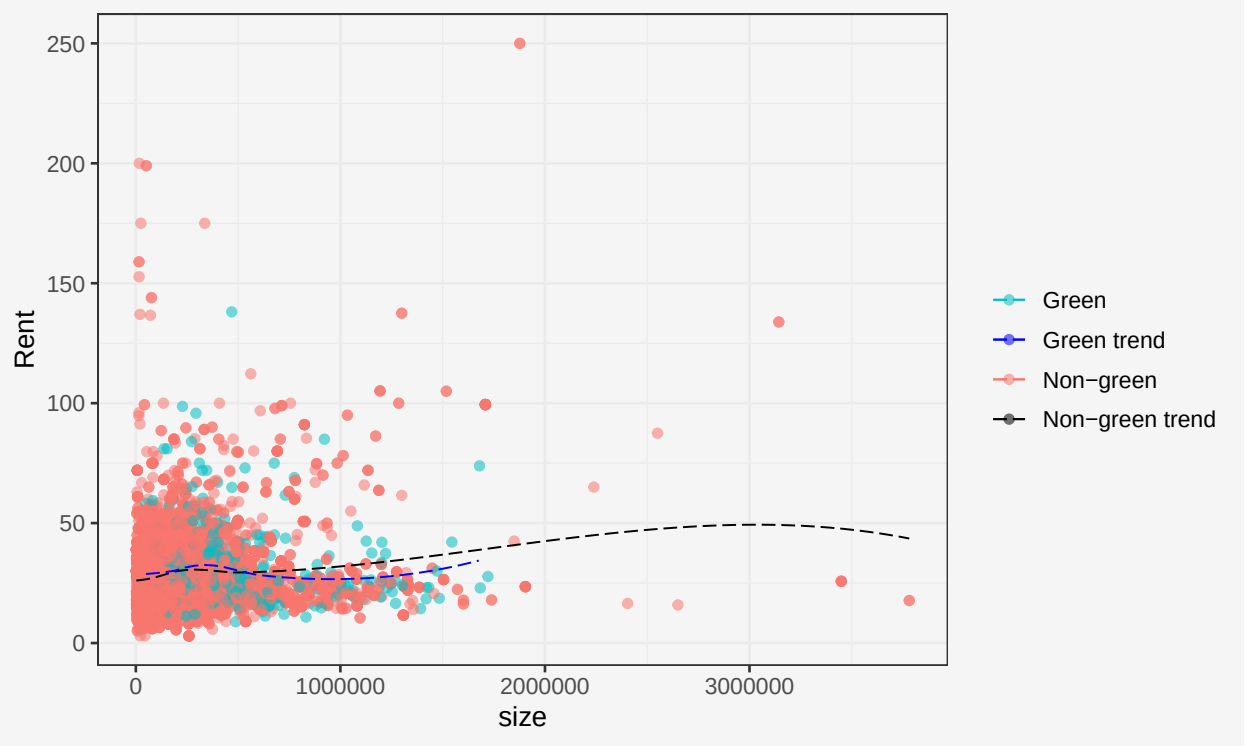

```
Summary Stats :

   green_rating Mean_Rent Med_Rent SD_Rent IQR_Rent
1:            1     30.03    27.60   12.96    14.04
2:            0     28.44    25.03   15.33    14.75
```

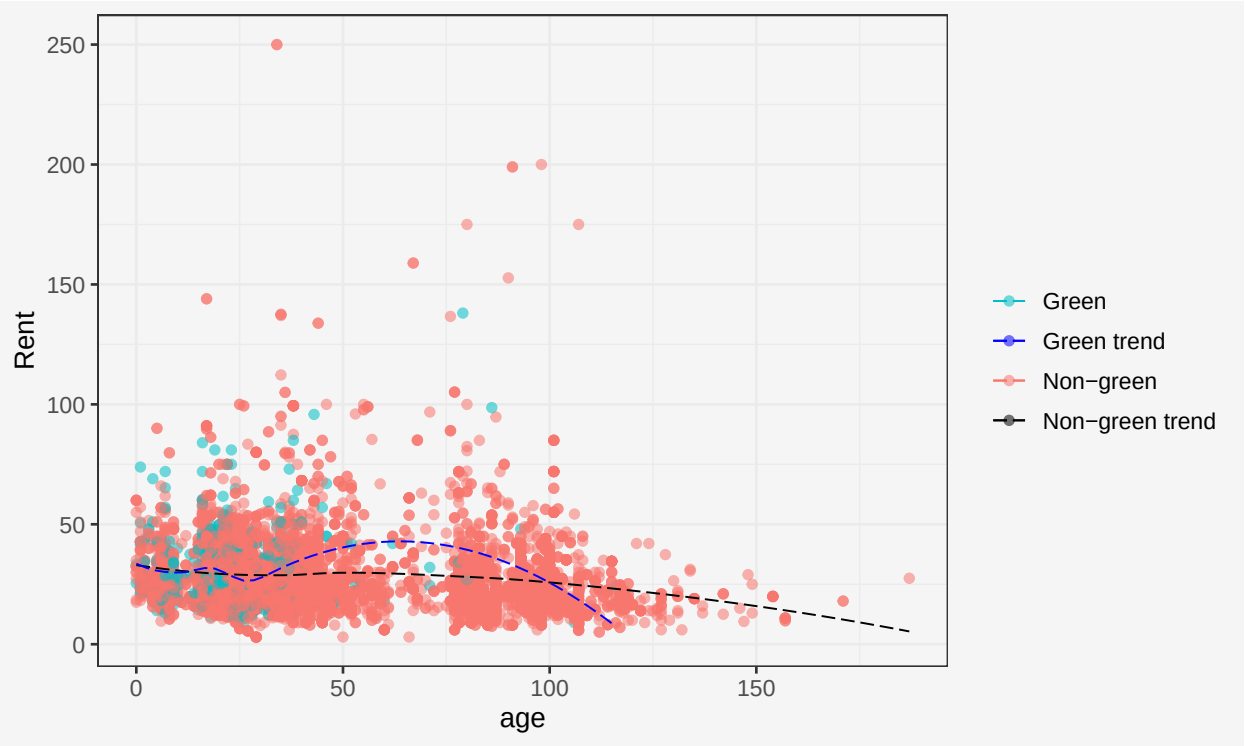
We see Rent for green houses is slightly larger than other houses. The rent variable is extremely right skewed so it makes sense to use median as the measure for centrality instead of mean. The statistical summary suggests Rent distribution is slightly more spread out for non-green buildings given it has higher SD and IQR. However, the graph looks pretty much the same for both categories implying, non-green building Rent has more outliers compared to green buildings.

However, this difference in medians could arise due to multiple confounding variables. Few hypotheses for this price change could be : 1. Properties with higher size may have higher rent 2. Older houses might have lower rent 3. Renovated houses may have higher rent 4. Houses in better class society and with more amenities may have higher rent 5. Houses with more Gas and Electricity costs may have higher rent, given they have more high energy-consuming facilities 6. Only specific type of green buildings (say LEED) may offer difference in rent

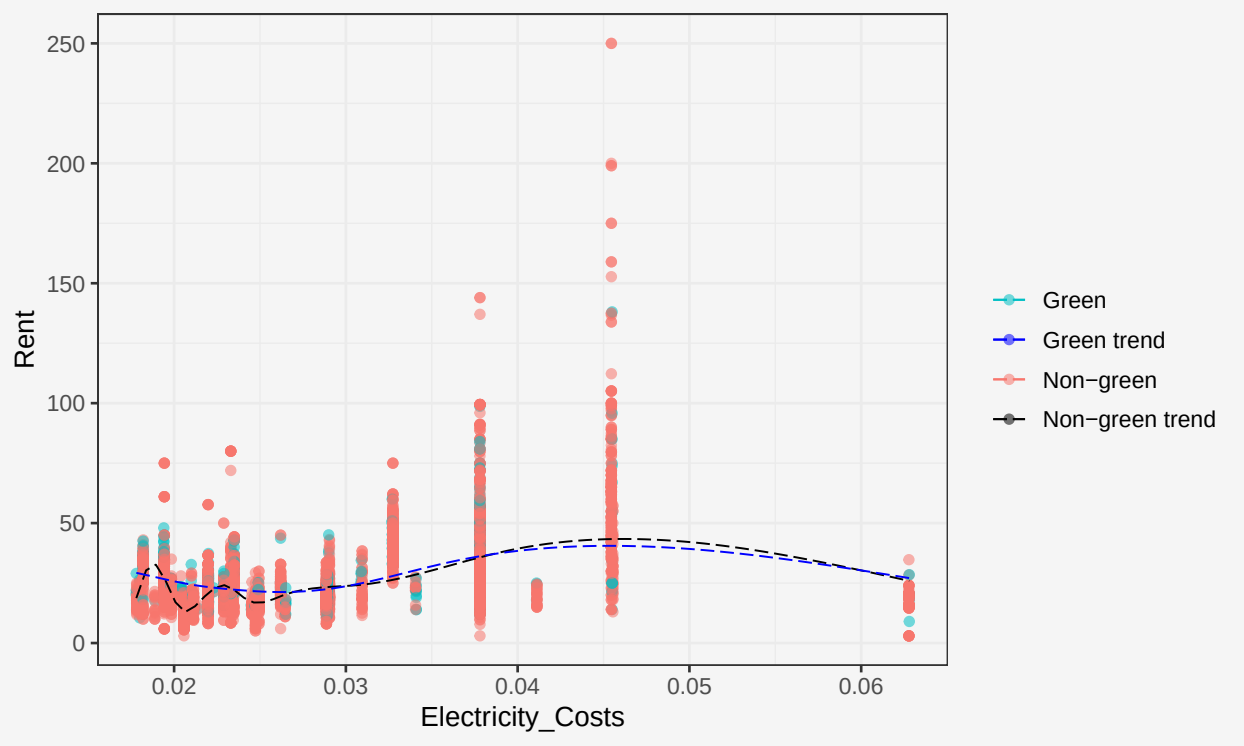
Let's explore them one by one. We use the non-parametric Generalized Additive Model (GAM) based smoothening to capture the non-linearity in the trends in our scatter plots.

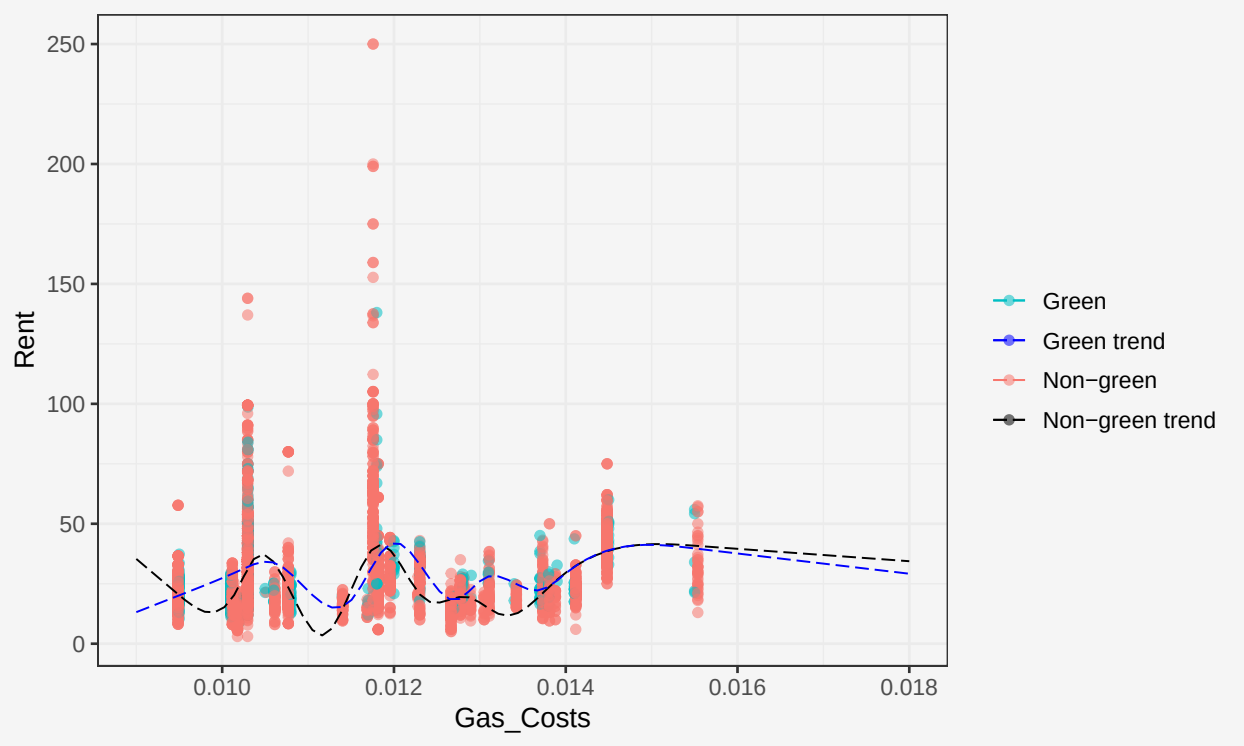


We observe almost no difference in Rent for green buildings vs other uptil size 900000, post which rent of non-green buildings slightly increases. However, this difference could be due to more outliers for non-green category and the confidence intervals of the fitted curves would intersect, negating any significance associated with this difference.



We see for houses aged 40-90 have some differenciation in rent with respect to houses being green vs non-green

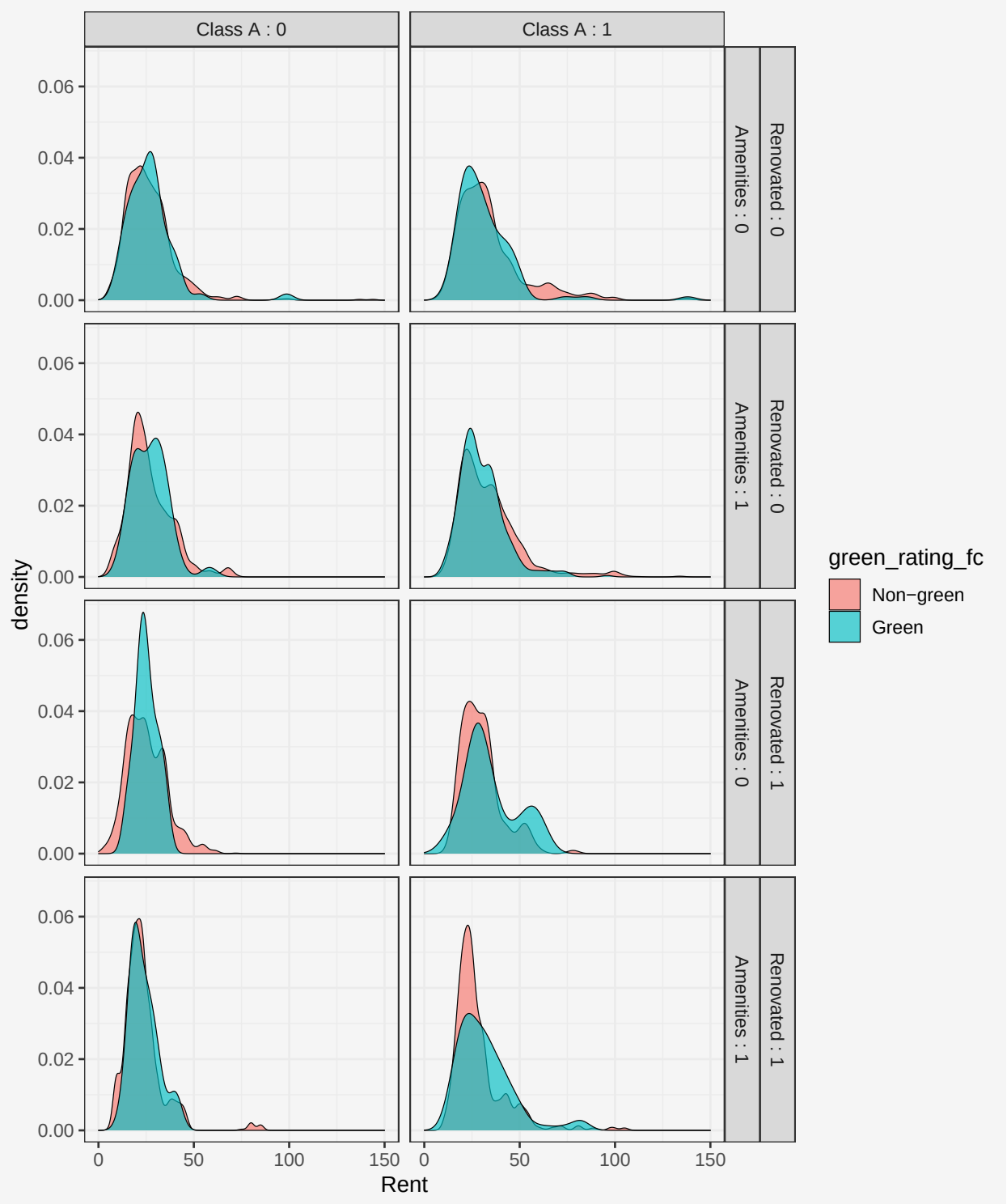




There's hardly any difference in Gas and electricity utilization, apart from a small segment of Gas costs between 0.011-0.012 where green buildings have lesser gas costs.

Even with continuous variables, we get the sense that the difference between prices of green building vs not wouldn't be as straightforwards as difference of median rents of the two categories. The localized regression trendlines convey that for certain properties of a house, some of the price difference could be explained by confounding variables such as age, gas costs.

We also explore categorical variables and check whether different categories lead to change in Rent.



Rent of house being green vs non-green differs widely in distribution, specifically in cases where house is renovated, is in upper class society and has additional amenities. Given, East Cesar Chavez looks very developed and say, the house has undergone renovations and includes amenities, the stat-guru's assumption of all green houses having incremental rent of \$2.6 than their non-green houses is erroneous.

```
The median price difference in such a case would be : $ 0.75
```

This implies that the duration of cost recuperation would be higher than 7.7 years. Assuming, the real difference in medians upon accounting for all confounding variables was $ 0.75, the premium of investment in a green building would be recovered in about 26.67 years. Hence, availing green status to ensure more probitability might not be a good strategy.

Because the proportion of green buildings in very less, thereby green vs non-green buildings have unequal sample sizes. We can use Anova to have a final comparison of means of unequal samples and remove Rent higher than 100 as outlier. We can include covariates we've explored in the EDA above such as recurring costs, size and age of building, class and amenities to quantify their effect sizes.

```
                              Feature      Coef    F_stat  P_val
 1: green_rating_fc                      6.5335   10.1345 0.0015
 2: size                                -0.0172  183.8325 0.0000
 3: age                                  0.0000   56.7926 0.0000
 4: renovated                            0.0353   99.2252 0.0000
 5: class_a                             -2.9395  234.2568 0.0000
 6: class_b                              6.9193   39.3476 0.0000
 7: amenities                            2.7857   14.0708 0.0002
 8: Gas_Costs                            0.6698    5.0544 0.0246
 9: Electricity_Costs                 -692.6059 1612.2222 0.0000
10: empl_gr                           756.3225    6.2707 0.0123
11: green_rating_fc:size                0.0354    4.5498 0.0330
12: green_rating_fc:age                 0.0000    2.1967 0.1384
13: green_rating_fc:renovated           0.0493    1.8038 0.1793
14: green_rating_fc:class_a             1.9534    2.0126 0.1560
15: green_rating_fc:class_b            -0.2348    0.2521 0.6156
16: green_rating_fc:amenities          -2.7601    1.0341 0.3092
17: green_rating_fc:Gas_Costs          -1.1879    0.0308 0.8607
18: green_rating_fc:Electricity_Costs  40.3885    0.4524 0.5012
19: green_rating_fc:empl_gr           -30.2841    2.5275 0.1119
20: Residuals                           0.0924        NA     NA
```

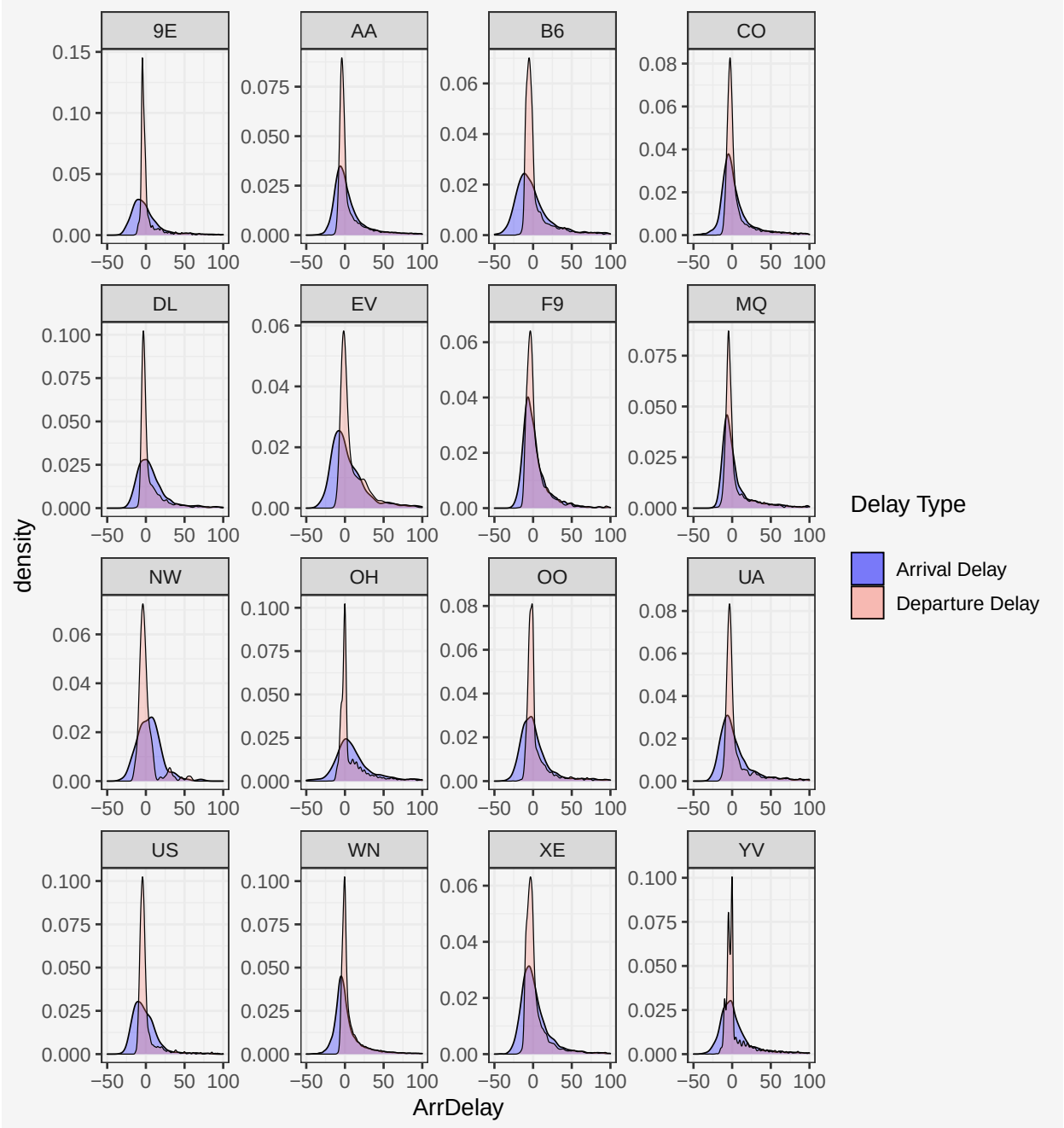
Supporting our EDA, we see all covariates have an impact on the rent of the building and solely attributing the rent to green status by differencing medians would be incorrect.

2. Visual story telling part 2: flights at ABIA

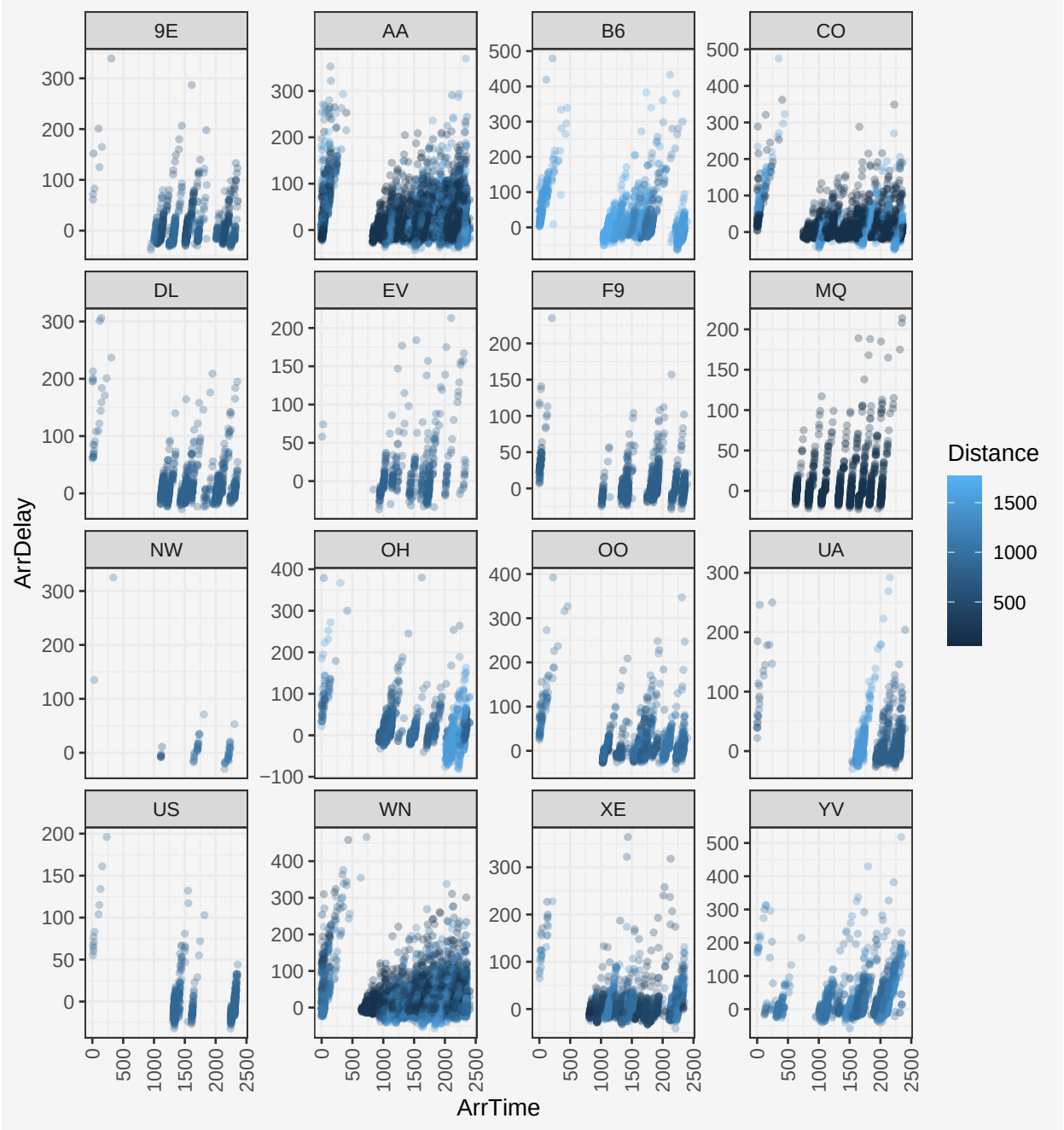
We start by exploring the data using summary functions such as str, summary, Hmisc::describe() and DescTools::Desc() to get a sense of the overall data.

Preliminary univariate EDA shows : 1. DepTime and ArrTime have 1.4% and 1.6% missing values respectively. Variables CarrierDelay, WeatherDelay, NASDelay, SecurityDelay and LateAircraftDelay all have 80.1% missing values. 2. There is some seasonality with respect to month with lesser flights towards year end in months Sept-Dec'08. Similarly there are fewer flights on weekends compared to weekdays. 3. Total 16 unique airline carriers with top three carriers operating most flights being Southwest (WN), American Airlines (AA) and Continental (CO) 4. ActualElapsedTime has bimodal distribution. ArrDelay, DepDelay distribution has very high kurtosis implying high number of outliers. Distance follows a spread-out distributions with 3 modes, meaning there could be some categorization such as local, national and international flights. Variables CarrierDelay, WeatherDelay, NASDelay, SecurityDelay and LateAircraftDelay 5. Most incoming flights to and from Austin are connected with the cities DAL, DFW, IAH, PHX etc.

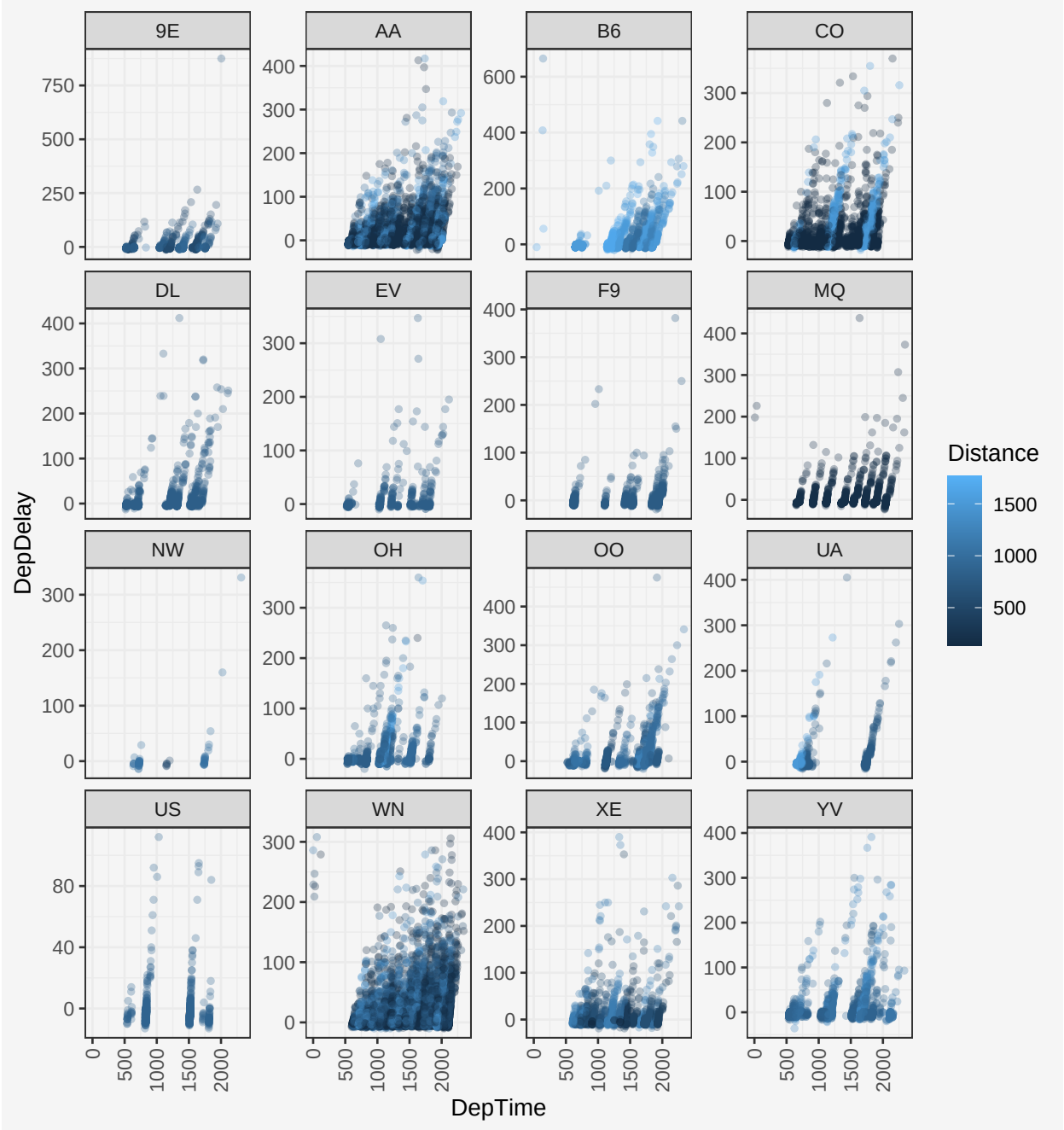
We start by studying if there is any pattern in Arrival and Departure delay by airline carriers.



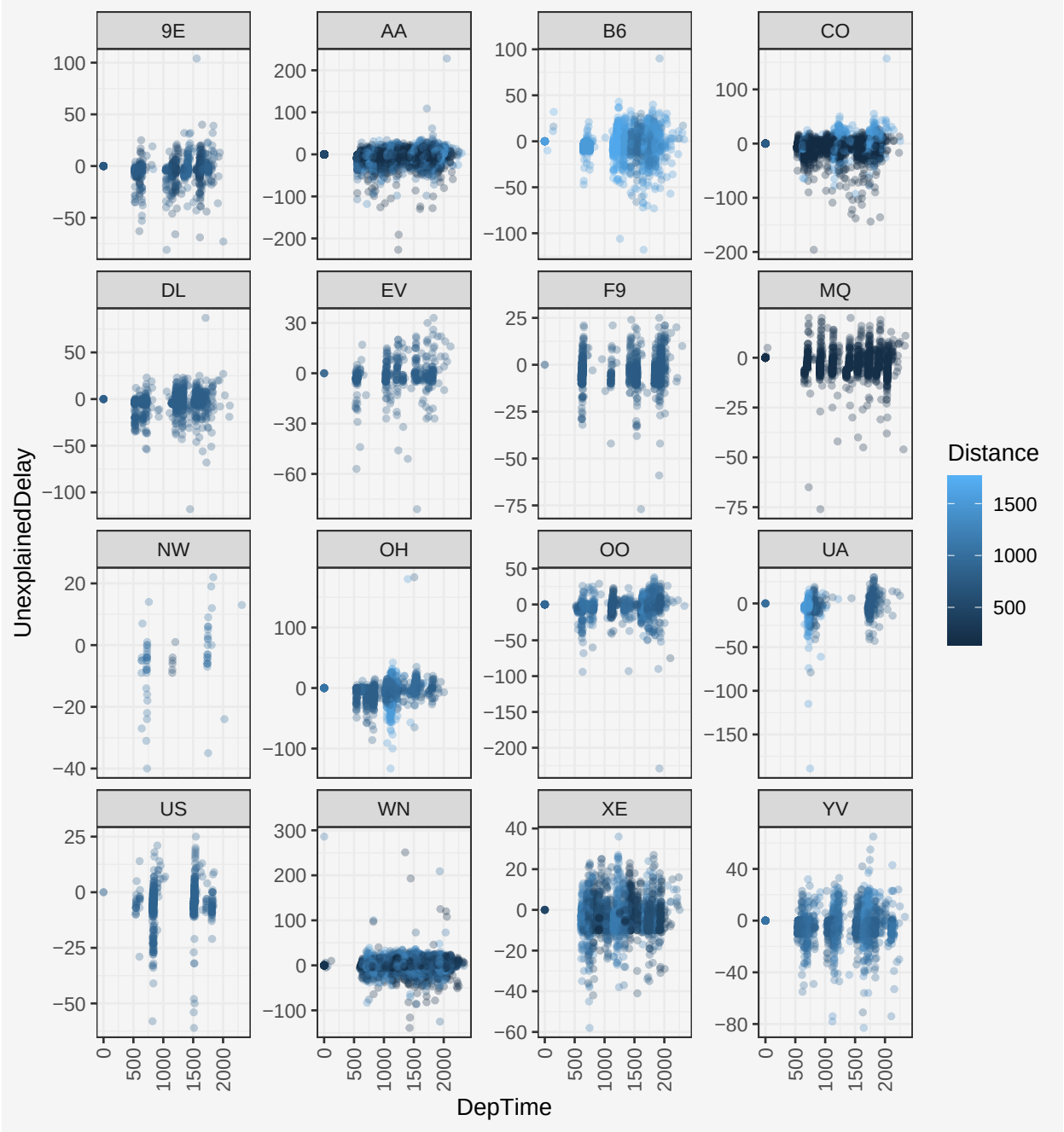
We observe that Departure delays for most carriers are often less in magnitude (be it positive or negative) than arrival delays, with an exception being F9 carrier where arrival vs departure delays are more of less the same.



Above graph shows Arrival Delays for flights arriving in Austin are particularly high when there are multiple flights of the same carrier arriving with very little time between each other.This could probably be explained by the air-space congestion issue. We also see marginally more delays when flights are for longer distances. Carriers YV and B6 have higher delays associated with them.



We avail the same insight for Departure delays being more in number and magnitude when time between multiple flights lined one after another is very less. Additionally, we check for delays that are unexplained by the parameters to validate if there are any patterns therein as well.

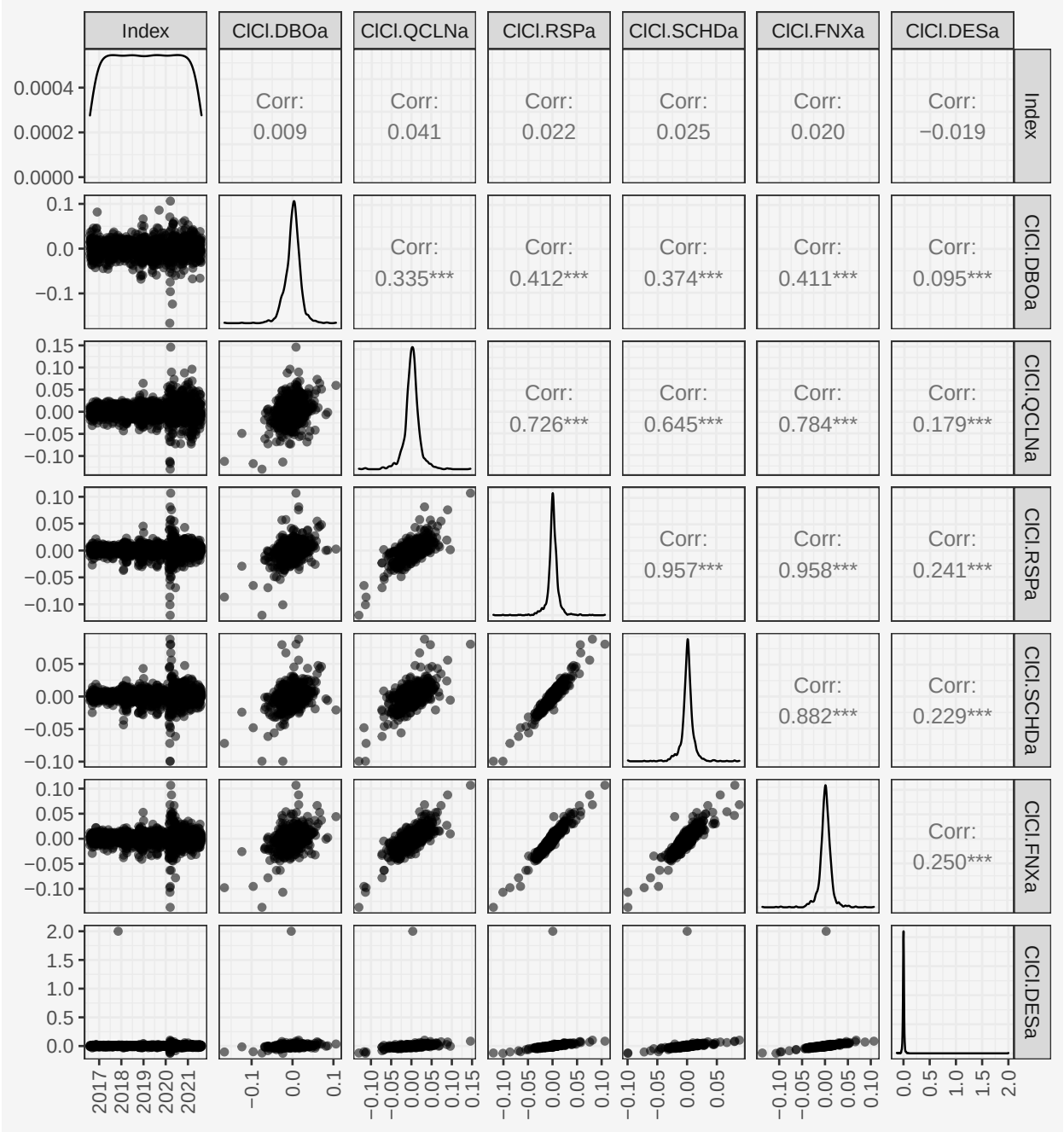


We see fewer patterns in Unexplained Delay but still flights right after one another seem to be prone to delays, specially in carriers such as MQ, WN etc.

3. Portfolio Modeling

Portfolio includes 6 ETF's which has a mix of two large cap blend equities, a mid cap blend equity, a small cap blend equity, oil/gas commodity ETF and alternative energy equities. Blend equity ETF's are a mixture of growth as well as value equities, thereby ensuring an overall diverse portfolio to reduce risk associated with the investment.

The stocks imported are energy, oil or gas commodities, large cap ETFs distributed between two securities, small and mid-cap respectively.



For the first possibility, 60% capital is allocated for large cap ETF, 10% capital to small and mid cap ETF's each, 10% each for alternative energy and oil/gas commodities. For this allocation, if we invest \$100k, we are 95% confident that our worst 20 trading day loss will not exceed \$8052.51 with an average profit of \$1683.2

```
Mean :  101683.2
```

```
Average Profit :  1683.177
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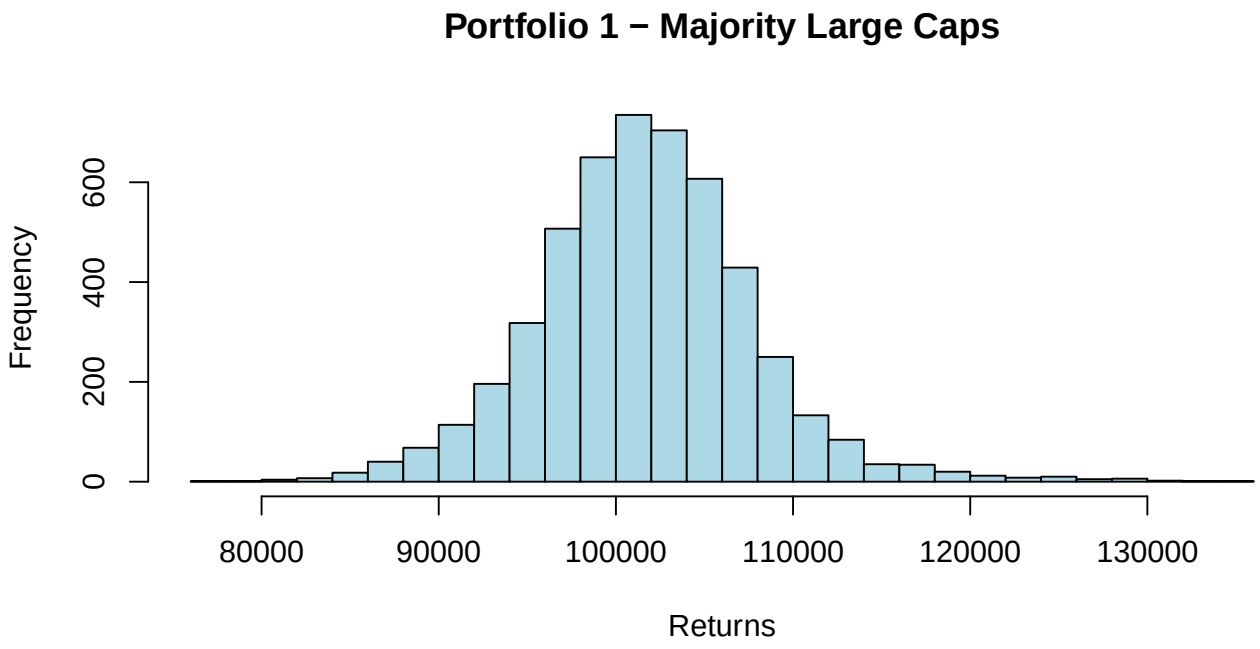
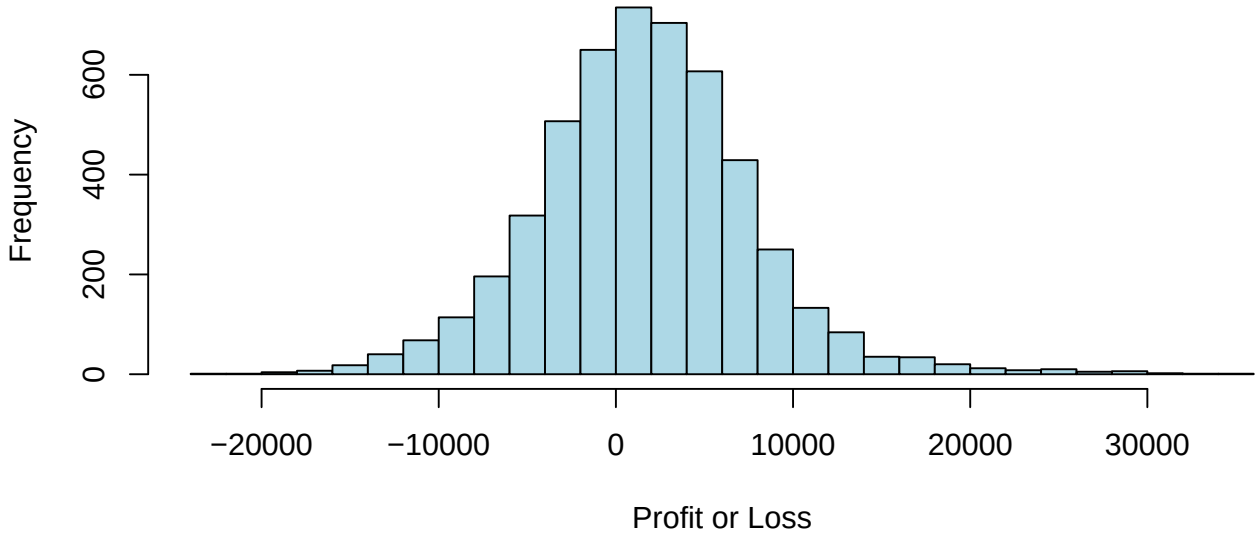
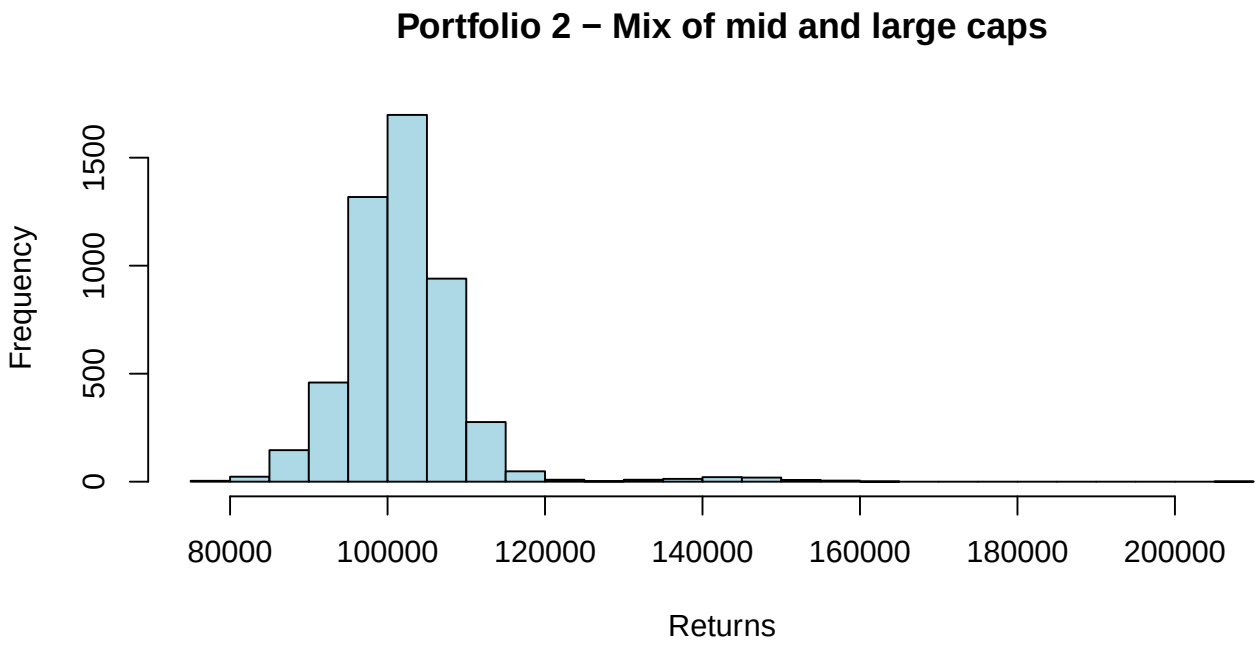
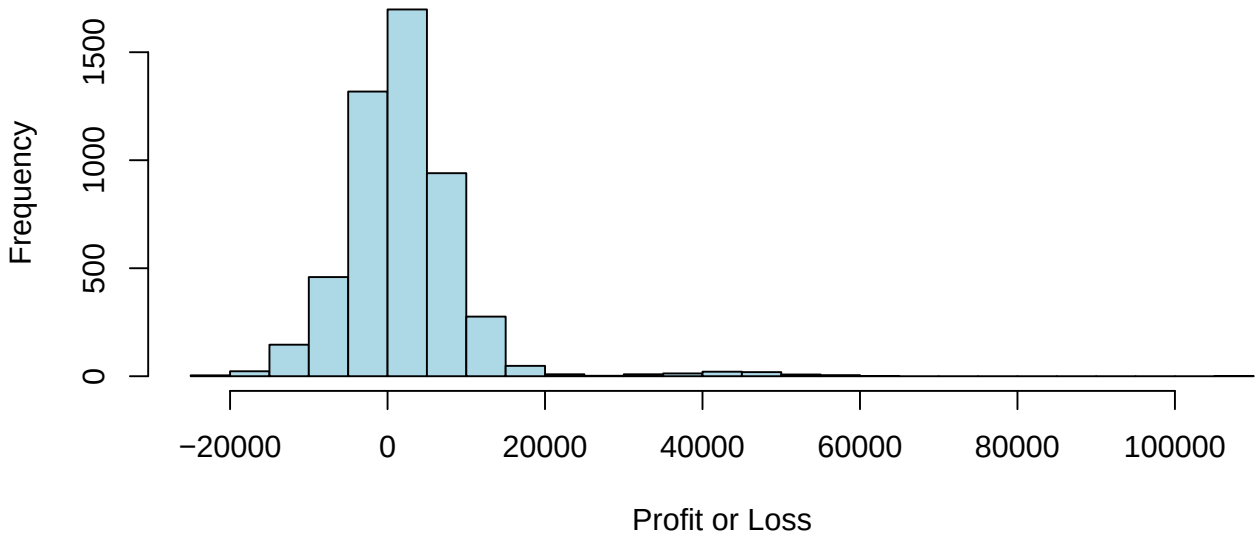





```
5% Value at Risk :  -8052.518
```

For the second possibility, 40% capital is allocated for large cap ETF, 20% capital to small and mid cap ETF's each, 10% each for alternative energy and oil/gas commodities. For this allocation, if we invest $100k, we are 95% confident that our worst 20 trading day loss will not exceed $8526.64 with an average profit of $2014.5



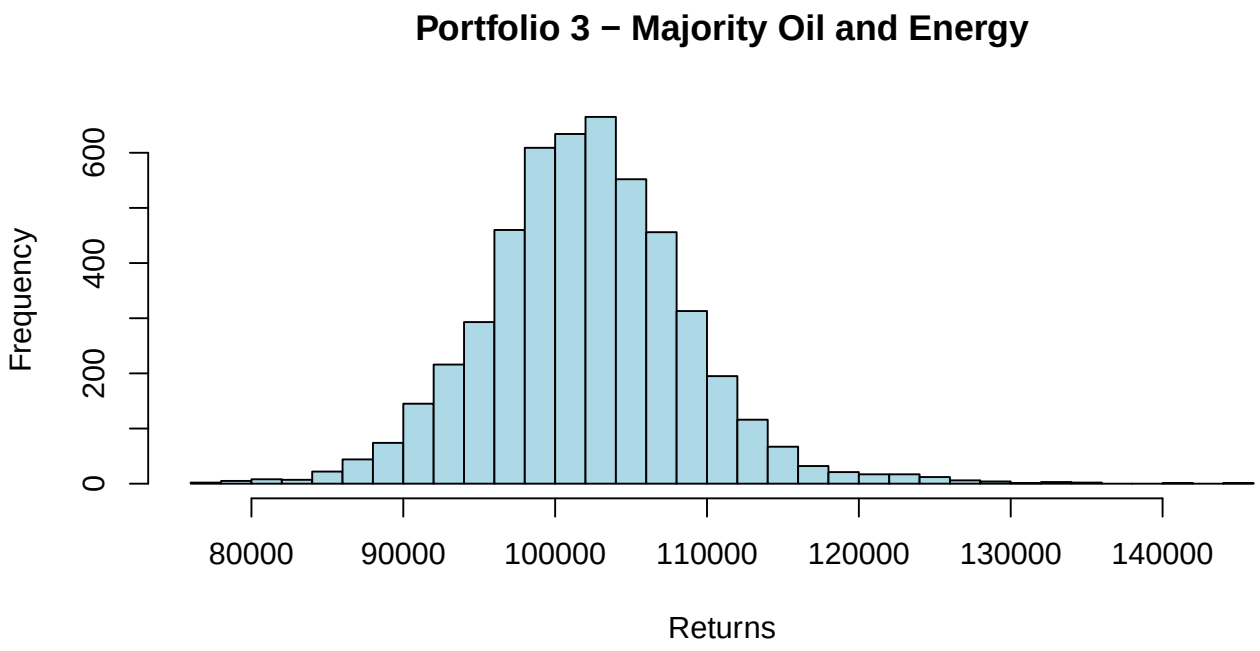


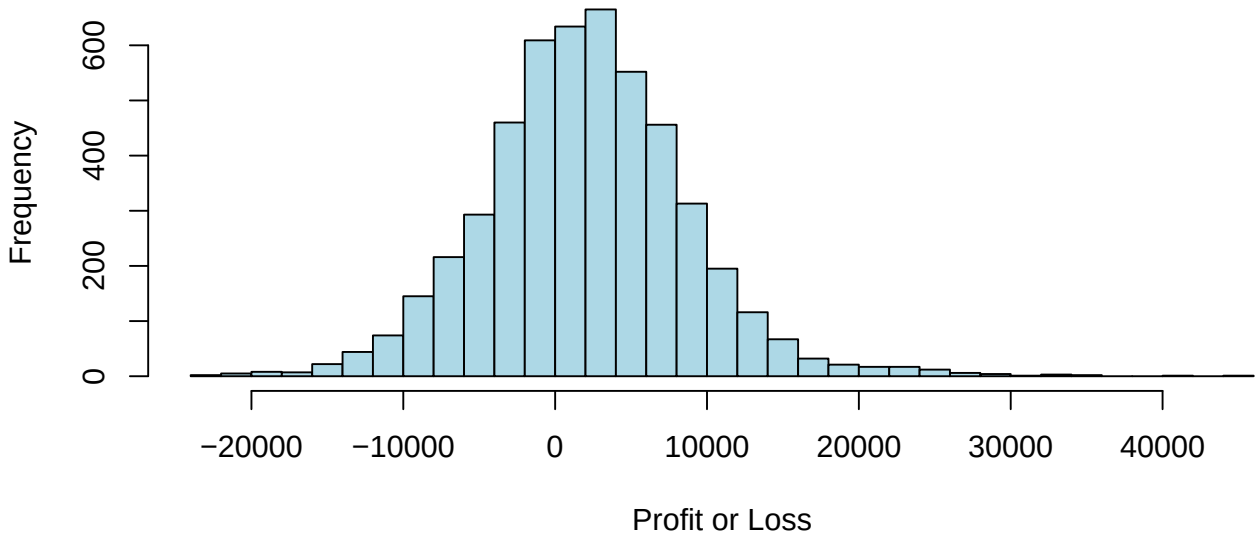

```
Mean :  102014.5

Average Profit :  2014.508

 5% Value at Risk :  -8526.643
```

For the third possibility, 20% capital is allocated for large cap ETF, 10% capital to small and mid cap ETF's each, 30% each for alternative energy and oil/gas commodities. For this allocation, if we invest $100k, we are 95% confident that our worst 20 trading day loss will not exceed $8625.87 with an average profit of $2058.61






```
Mean :  102058.6

Average Profit :  2058.611

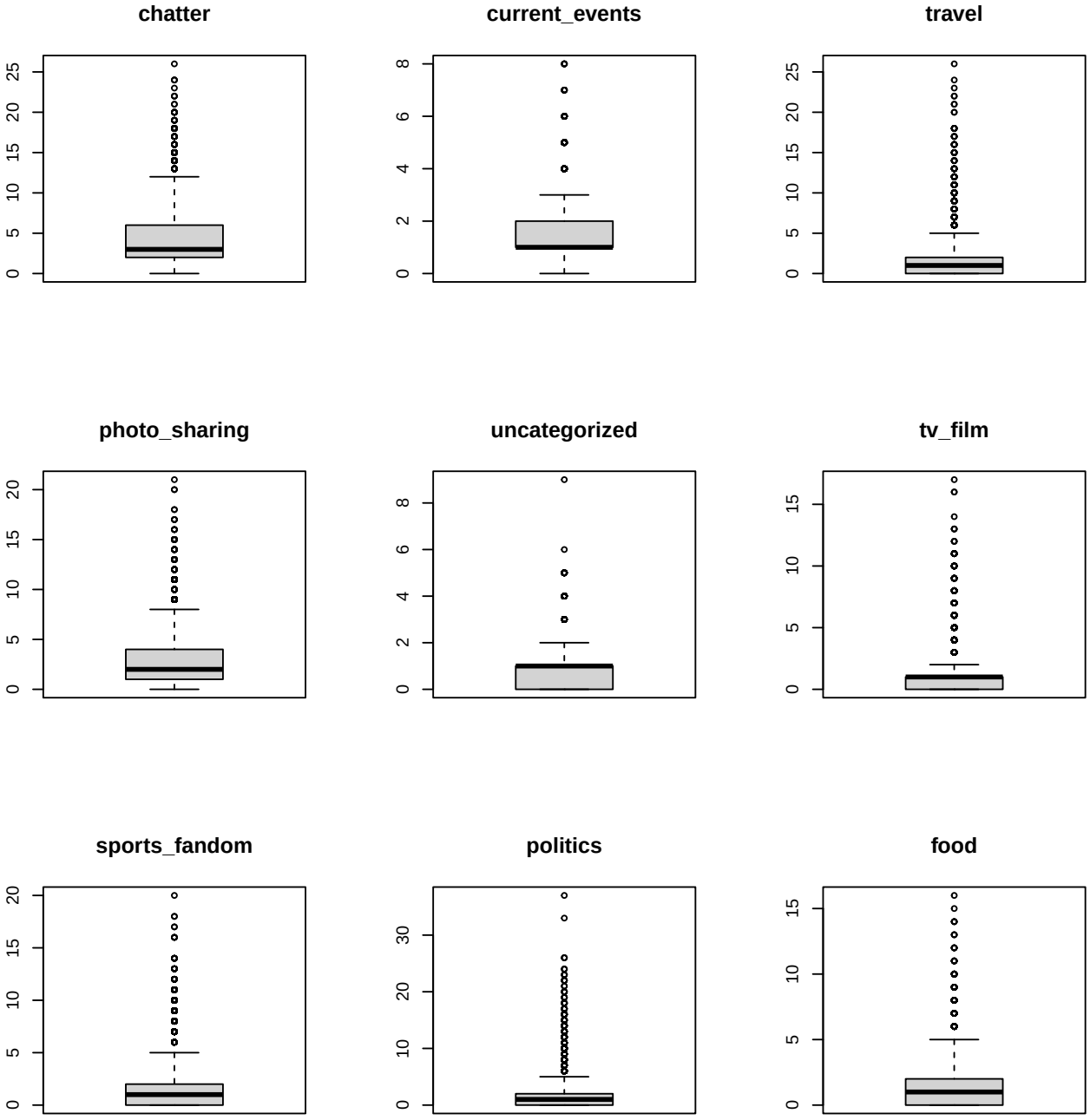
 5% Value at Risk :  -8625.87
```

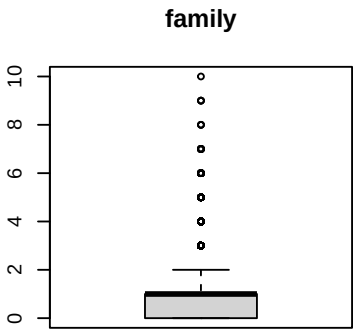
We tried a safe bet in a stable market, with major investments in large cap in Portfolio 1. Portfolio 2 had a well-balanced portfolio with equal proportion of initial wealth distributed amidst the large caps, mid and small caps to leverage diversification benefits. Portfolio 3 had more focus on high-risk high-reward bet on

oil, gas and alternative energy ETFs given their volatility. It turns out, we see best returns with our Oil and Energy heavy portfolio, however value which worst 20 trading day loss will not exceed with 95% confidence also increases the most for this portfolio, given aforementioned volatility.

4. Market Segmentation

We start by exploring the datasets using boxplots to get a sense of univariate distributions of each of the variables. Boxplots help us understand which variables have more outliers or too spread out distributions that might not be helpful in explaining variance in dependent variable.

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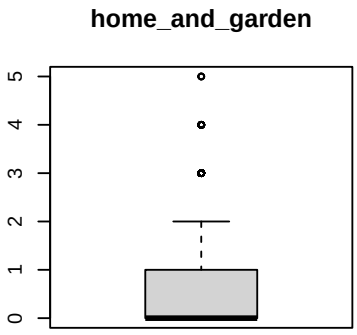
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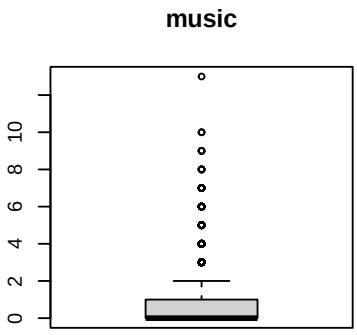
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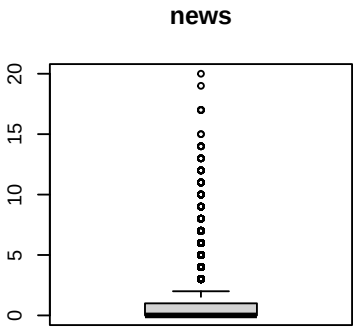
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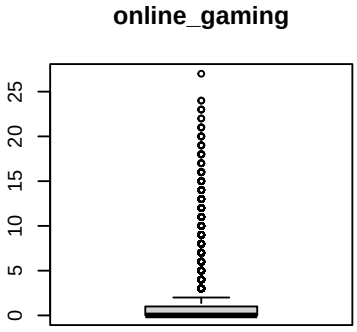
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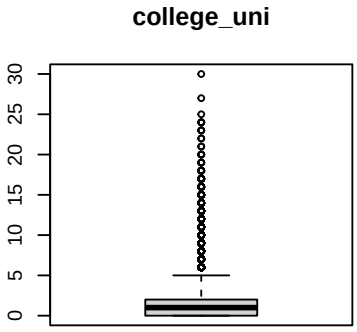
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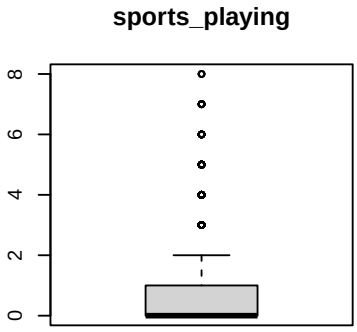
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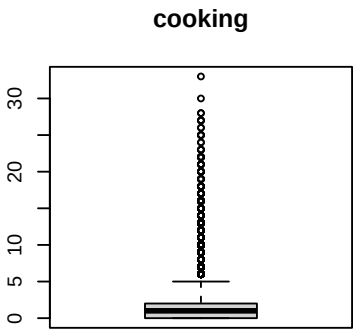
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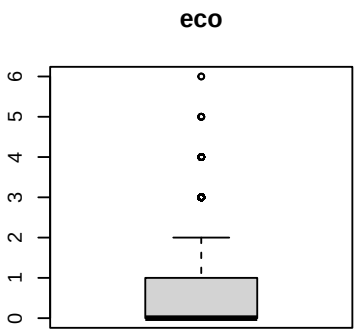
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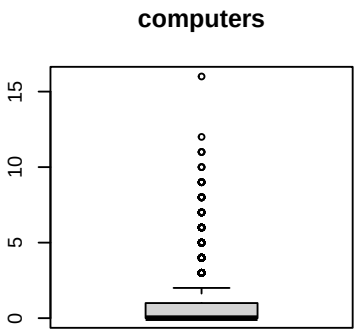
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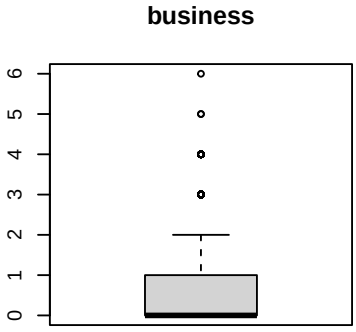
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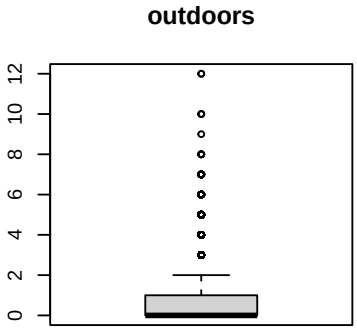
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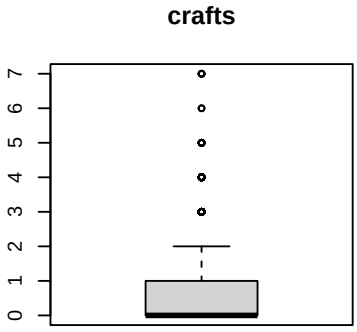
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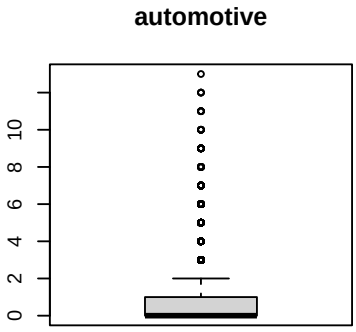
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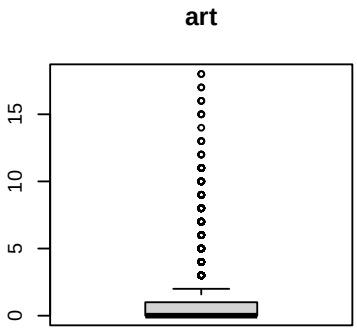
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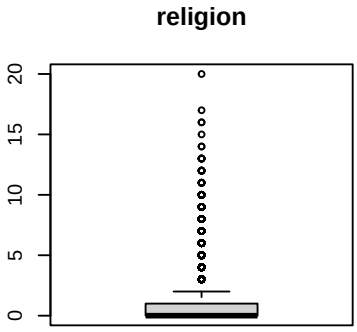
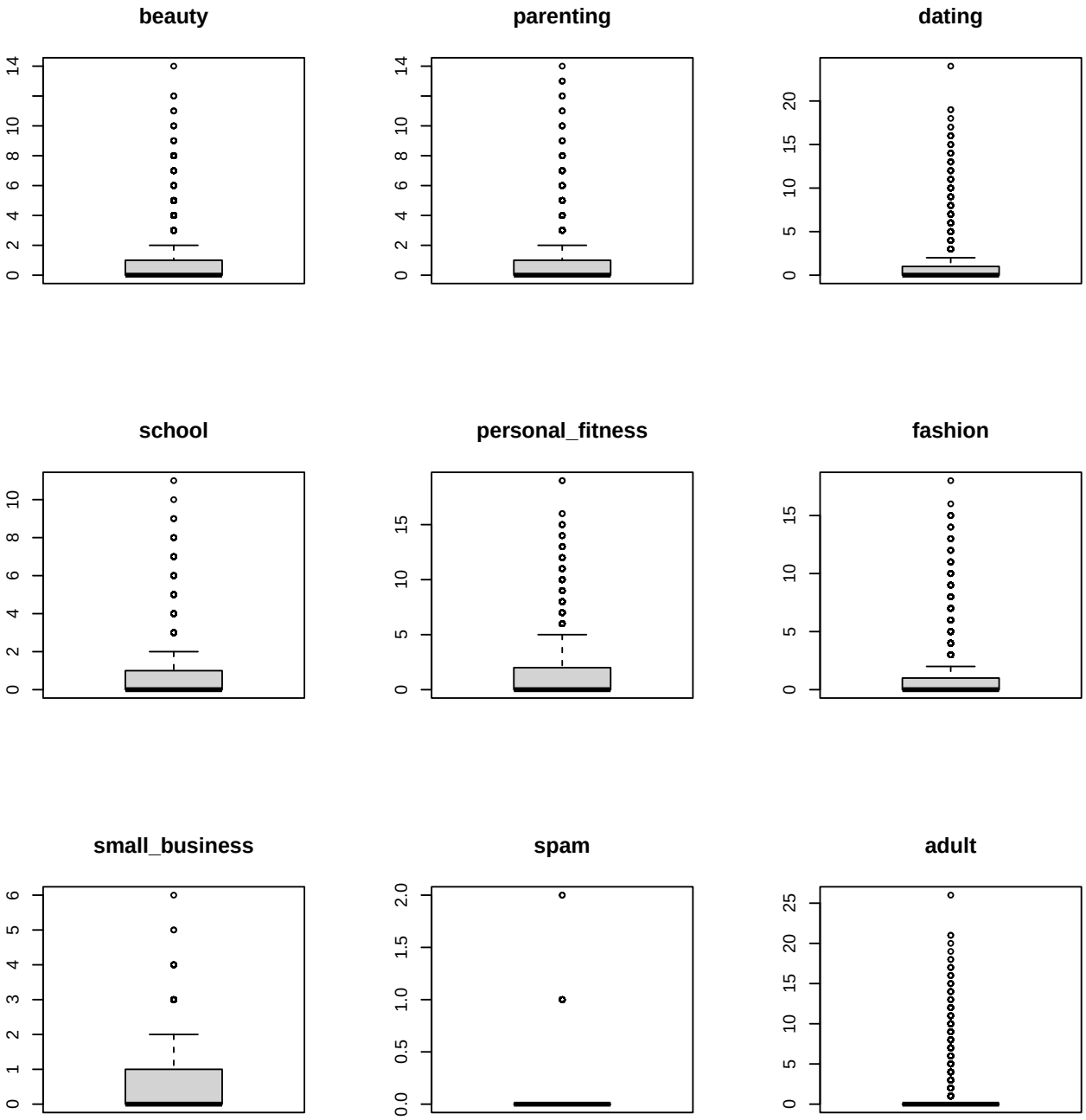
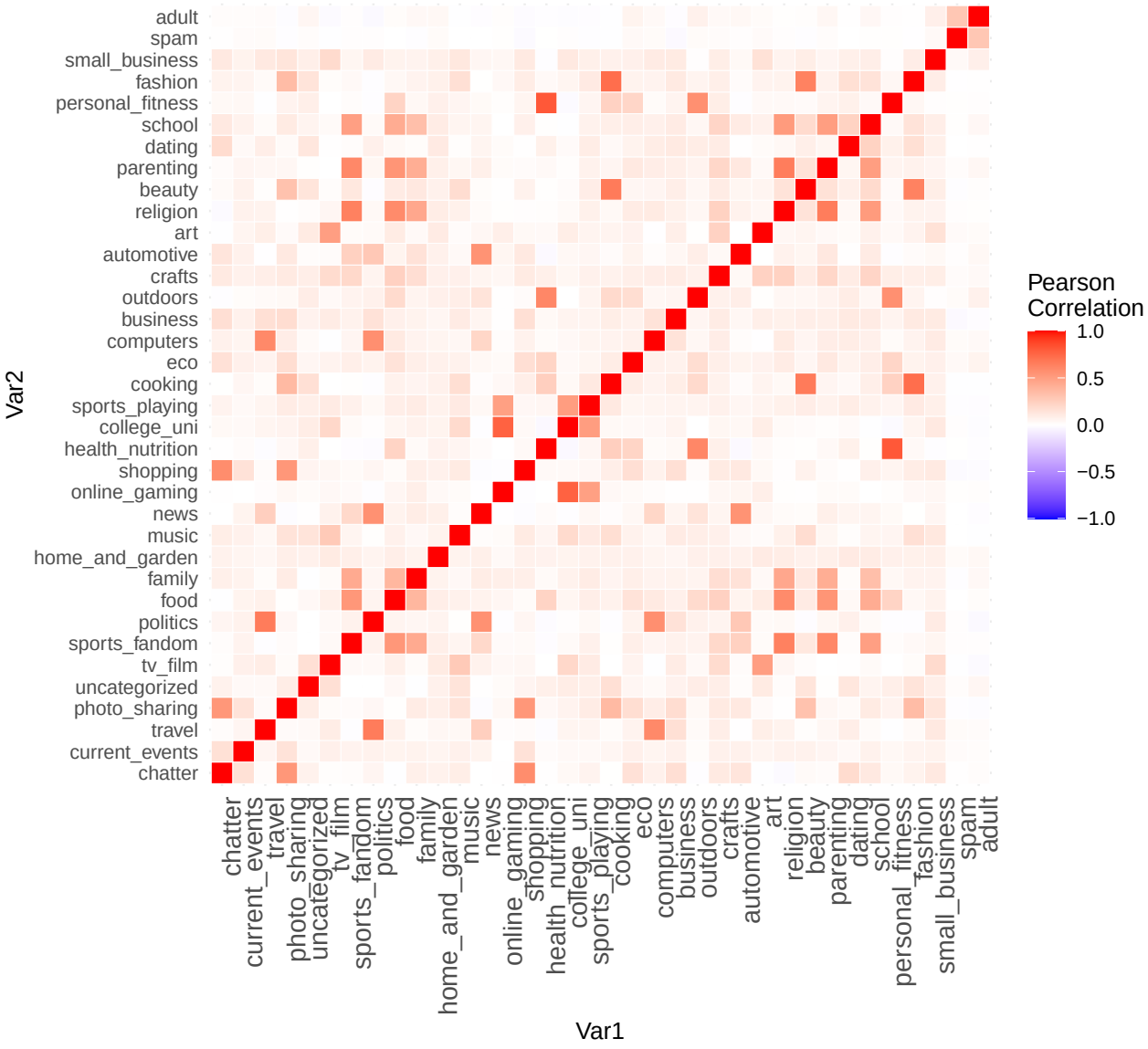
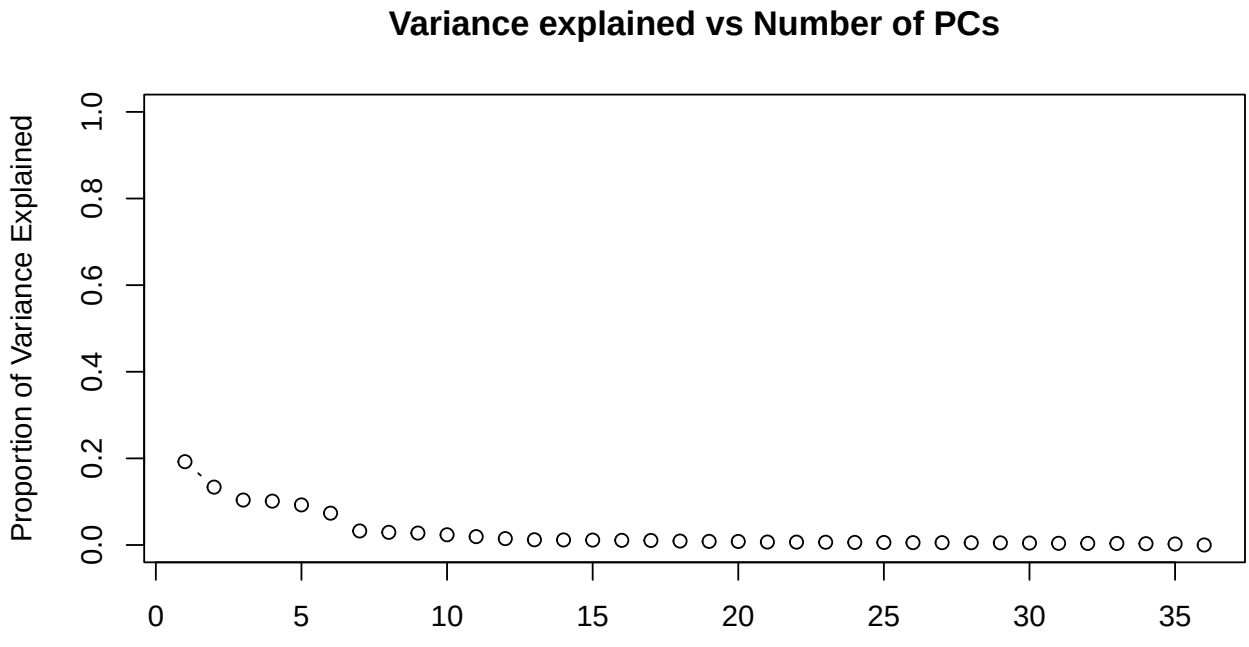
5
10
15

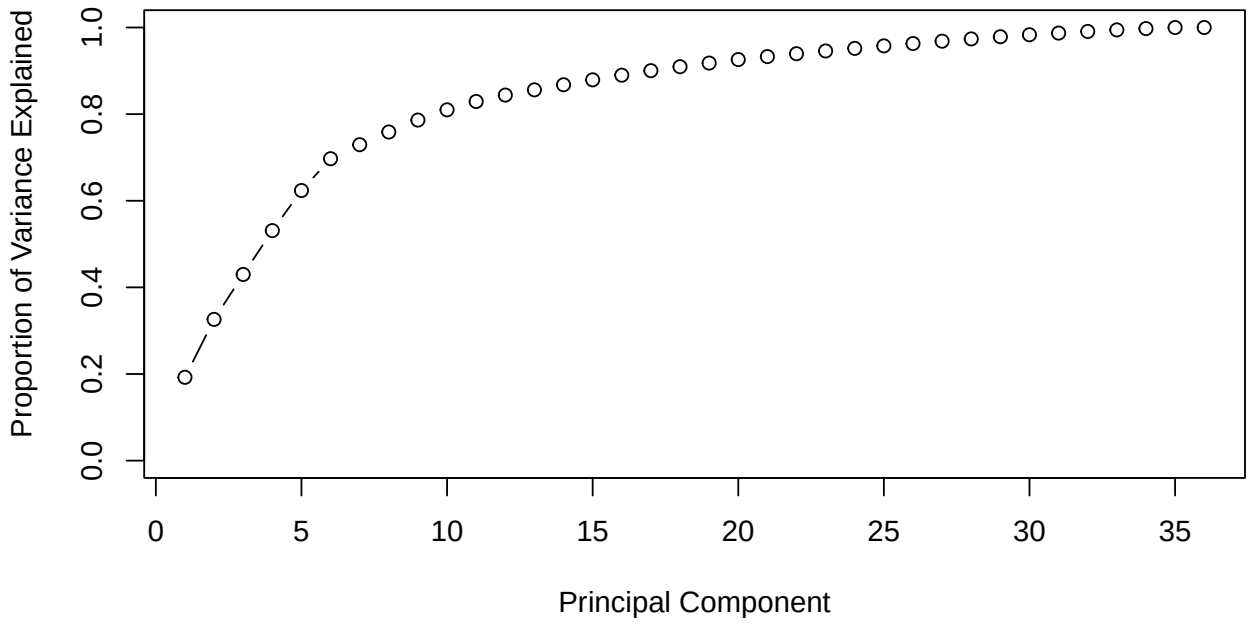

religion
0
5
10
15
20



Further on, we explore bivariate associations by a corrplot. While we see few correlations in the 0.3-0.7 range, very few values are higher than that.


adult
spam
small_business
fashion
personal_fitness
school
dating
parenting
beauty
religion
art
automotive
crafts
outdoors
business
computers
eco
cooking
sports_playing
college_uni
health_nutrition
shopping
online_gaming
news
music
home_and_garden
family
food
politics
sports_fandom
tv_film
uncategorized
photo_sharing
travel
current_events
chatter
Var2
chatter
current_events
travel
photo_sharing
uncategorized
tv_film
sports_fandom
politics
food
family
home_and_garden
music
news
online_gaming
shopping
health_nutrition
college_uni
sports_playing
cooking
eco
computers
business
outdoors
crafts
automotive
art
religion
beauty
parenting
dating
school
personal_fitness
fashion
small_business
spam
adult
Var1
Pearson Correlation
1.0
0.5
0.0
−0.5
−1.0





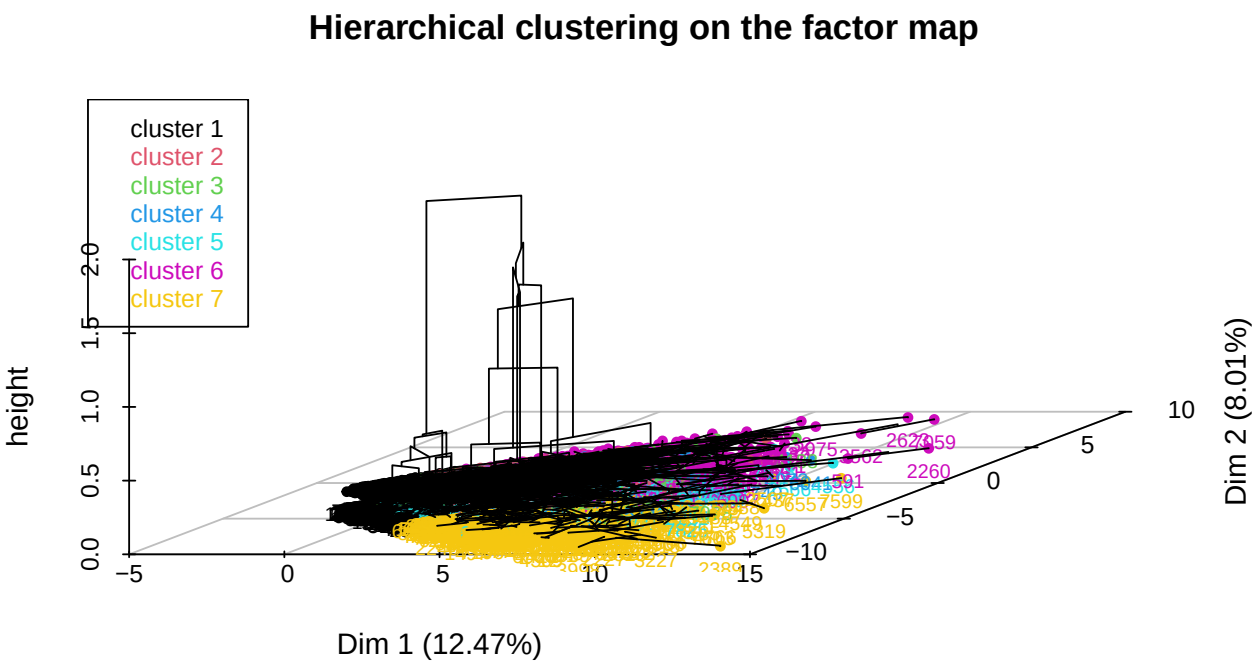

```
$loadings

Loadings:
               PC1    PC2    PC3    PC4    PC5    PC6    PC7
chatter                0.821                -0.148
current_events
travel                        0.497                      -0.475
photo_sharing          0.460                0.253
uncategorized
tv_film                                                   -0.270
sports_fandom                                      0.580  0.154
```

```
politics                       0.765
food                                                0.399 -0.132
family                                              0.189
home_and_garden
music
news                           0.328                       0.586
online_gaming                        -0.666
shopping               0.306
health_nutrition  0.883
college_uni                          -0.723               -0.108
sports_playing                       -0.142
cooking                                      0.832
eco
computers                      0.199                       -0.141
business
outdoors          0.156
crafts
automotive                                                   0.383
art                                                         -0.262
religion                                            0.503 -0.142
beauty                                       0.255
parenting                                           0.365
dating                                                      -0.118
school                                              0.230
personal_fitness  0.416
fashion                                      0.383
small_business
spam
adult

                 PC1   PC2   PC3   PC4   PC5   PC6   PC7
SS loadings    1.000 1.000 1.000 1.000 1.000 1.000 1.000
Proportion Var 0.028 0.028 0.028 0.028 0.028 0.028 0.028
Cumulative Var 0.028 0.056 0.083 0.111 0.139 0.167 0.194

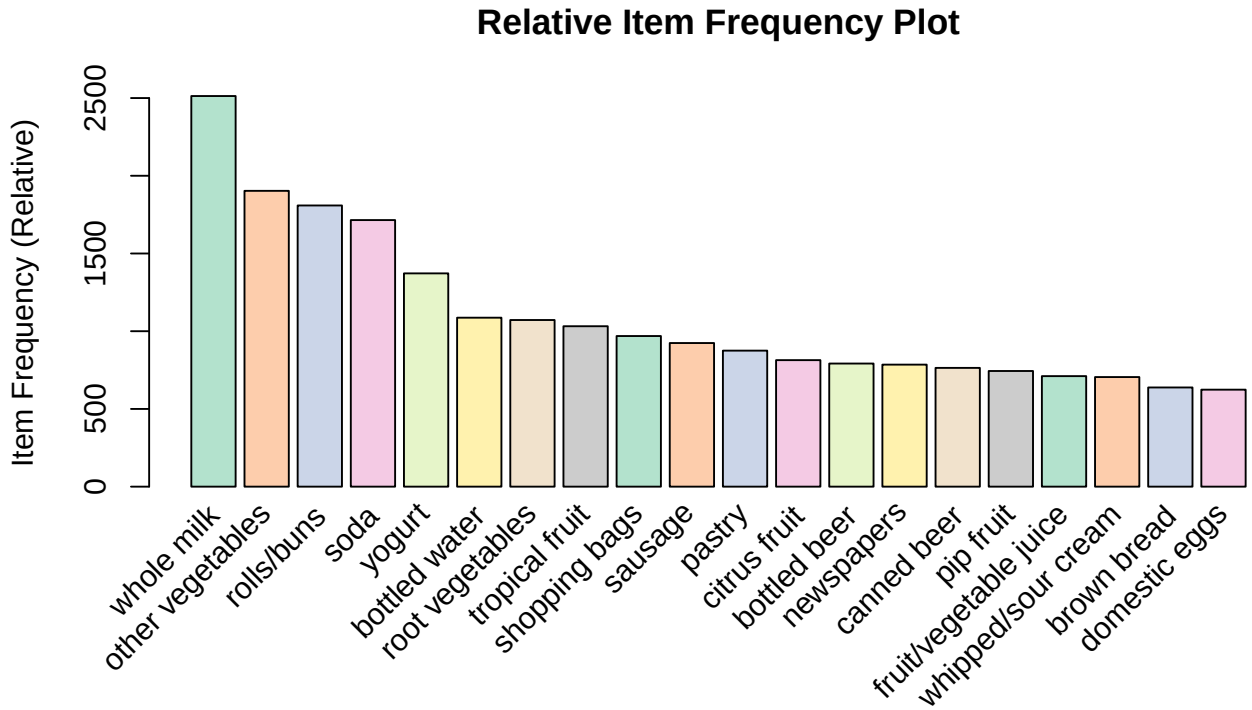
$rotmat
            [,1]        [,2]        [,3]        [,4]         [,5]         [,6]
[1,]  0.93099687  0.15515877 -0.01223470 -0.02462586  0.318667817  0.058614615
[2,] -0.27256380  0.82857806  0.21182179 -0.23088275  0.363471074  0.093216639
[3,]  0.08120565 -0.24578522  0.85159958 -0.34112087 -0.157724821  0.257888072
[4,]  0.08591401  0.30133687  0.35359131  0.82217701 -0.300919086 -0.006021501
[5,] -0.20243417 -0.37113982  0.17848672  0.36676882  0.801313251  0.094609361
[6,] -0.03167198  0.01468759 -0.26546436  0.08461340 -0.093689468  0.955180828
[7,]  0.05473136  0.01446981 -0.04903405 -0.10986101  0.005435302 -0.003335372
             [,7]
[1,] -0.058562899
[2,] -0.013837921
[3,]  0.005156792
[4,]  0.101116098
[5,]  0.062007337
[6,]  0.001508381
[7,]  0.991100729
```



Recommended number of clusters = 7.

5.

6. Association Mining Rules



However, I can call the same object in another chunk.

`Apriori`

```
Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen
       0.01    0.1    1 none FALSE            TRUE       5   0.002      1
 maxlen target  ext
     40  rules TRUE

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

Absolute minimum support count: 19

set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[169 item(s), 9835 transaction(s)] done [0.00s].
sorting and recoding items ... [147 item(s)] done [0.00s].
creating transaction tree ... done [0.00s].
checking subsets of size 1 2 3 4 5 done [0.00s].
writing ... [11060 rule(s)] done [0.00s].
creating S4 object  ... done [0.00s].

Apriori

Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen
        0.1    0.1    1 none FALSE            TRUE       5   0.002      1
 maxlen target  ext
     10  rules TRUE

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

Absolute minimum support count: 19

set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[169 item(s), 9835 transaction(s)] done [0.00s].
sorting and recoding items ... [147 item(s)] done [0.00s].
creating transaction tree ... done [0.00s].
checking subsets of size 1 2 3 4 5 done [0.00s].
writing ... [8340 rule(s)] done [0.00s].
creating S4 object  ... done [0.00s].

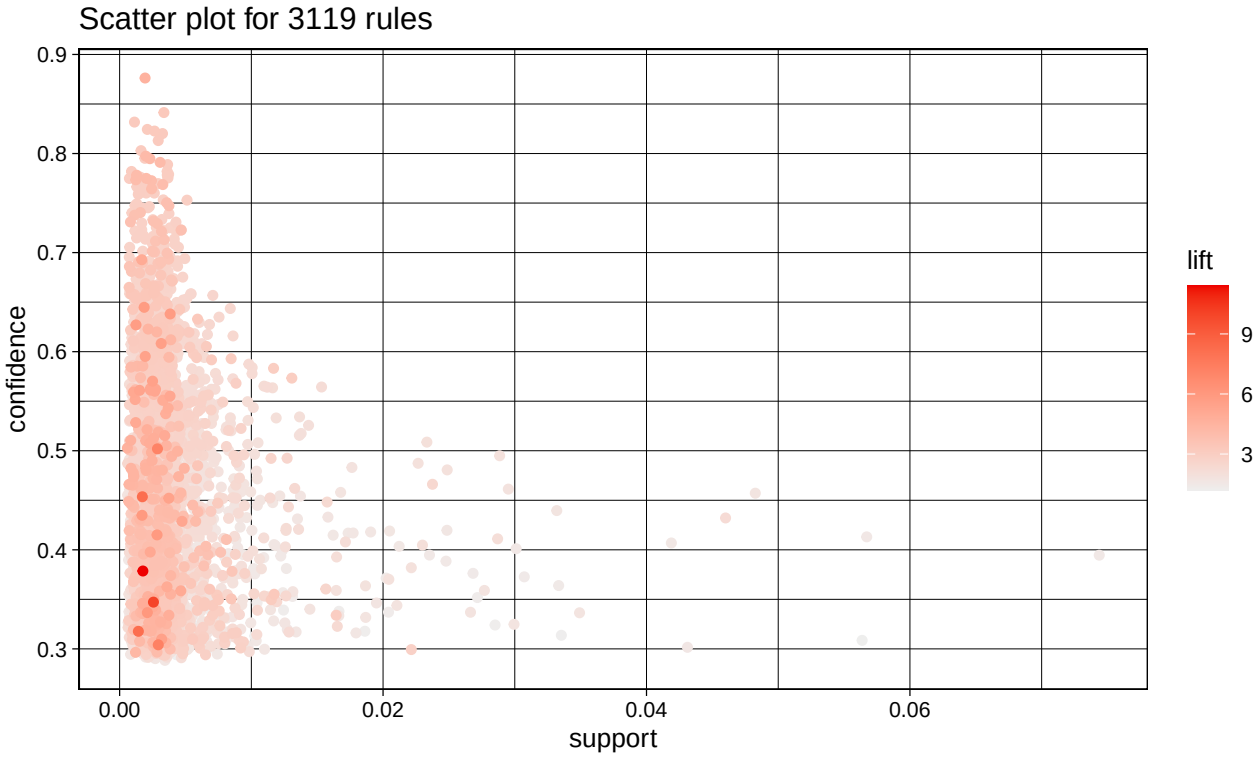
Apriori

Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen
        0.3    0.1    1 none FALSE            TRUE       5   0.002      1
 maxlen target  ext
     10  rules TRUE

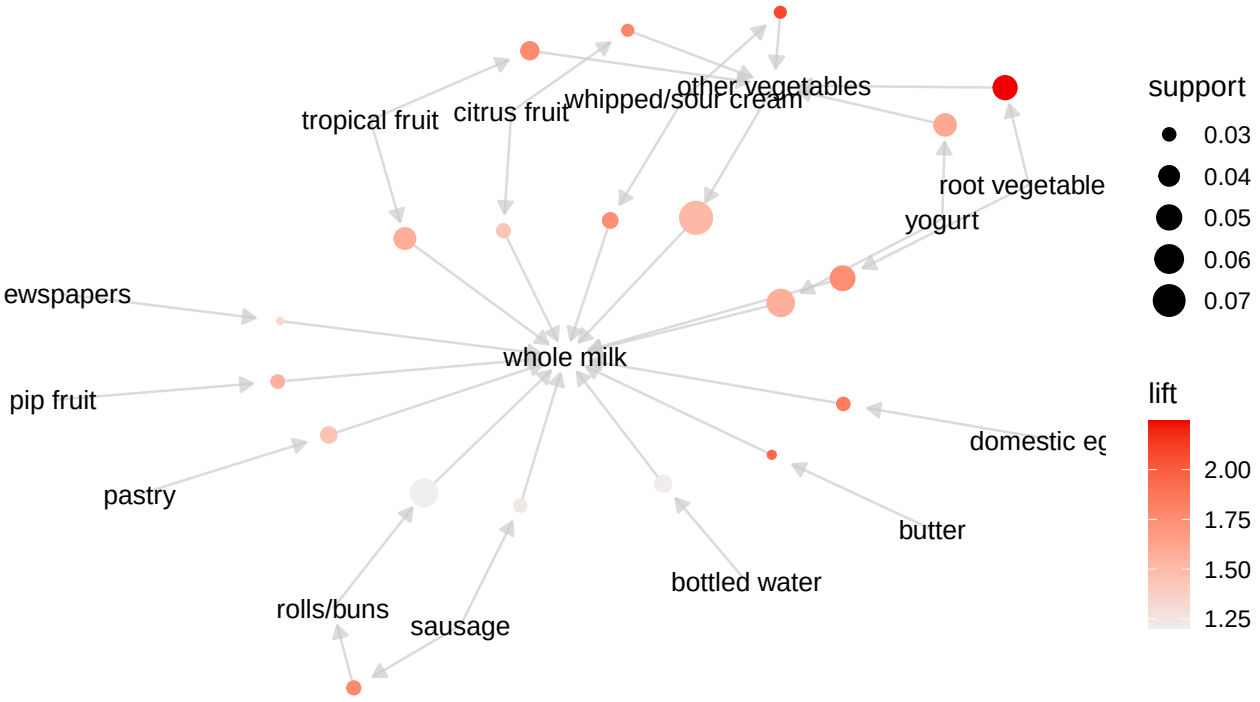
Algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE
```

```
Absolute minimum support count: 19

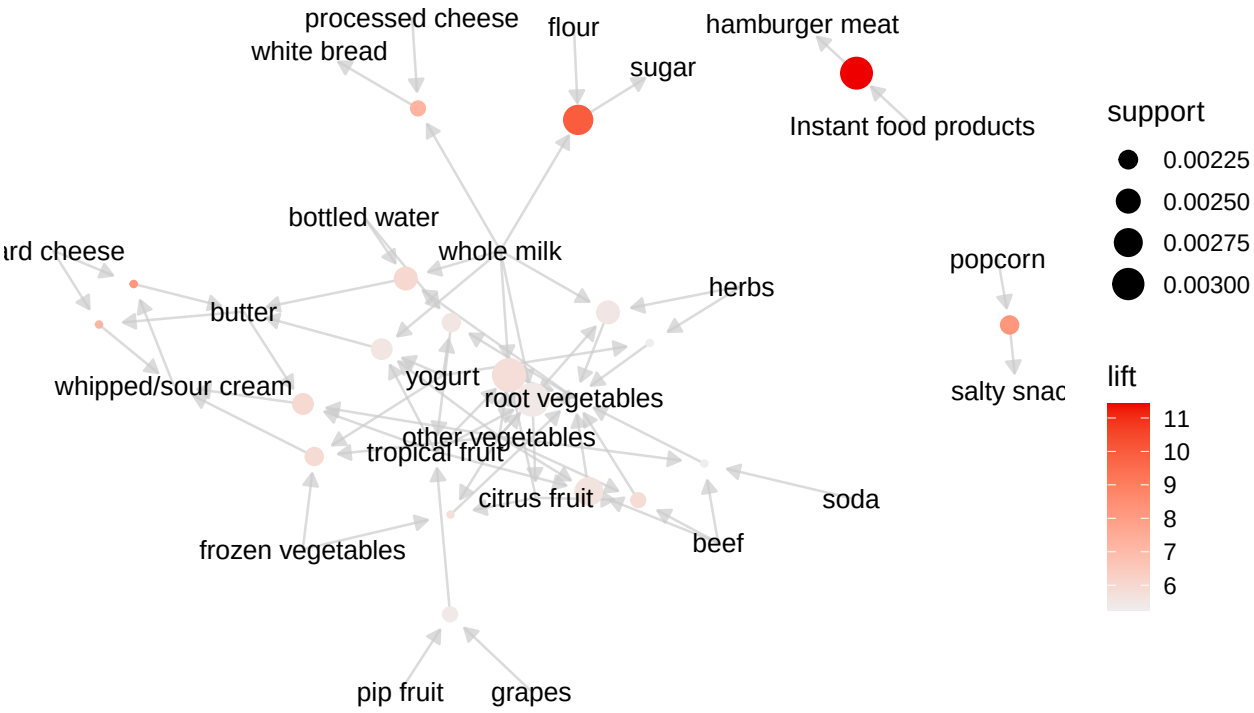
set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[169 item(s), 9835 transaction(s)] done [0.00s].
sorting and recoding items ... [147 item(s)] done [0.00s].
creating transaction tree ... done [0.00s].
checking subsets of size 1 2 3 4 5 done [0.00s].
writing ... [3119 rule(s)] done [0.00s].
creating S4 object  ... done [0.00s].
```




```
Available control parameters (with default values):
layout   =  list(fun = function (graph, dim = 2, ...)  {     if ("layout" %in% graph_attr_names(graph))
edges    =  <environment>
nodes    =  <environment>
nodetext     =  <environment>
colors   =  c("#EE0000FF", "#EEEEEEFF")
engine   =  ggplot2
max  =  100
verbose  =  FALSE
```




```
Available control parameters (with default values):
layout   =  list(fun = function (graph, dim = 2, ...)  {     if ("layout" %in% graph_attr_names(graph))
edges    =  <environment>
nodes    =  <environment>
nodetext     =  <environment>
colors   =  c("#EE0000FF", "#EEEEEEFF")
engine   =  ggplot2
max  =  100
verbose  =  FALSE
```


processed cheese
white bread
flour
sugar
hamburger meat
Instant food products
bottled water
whole milk
herbs
butter
popcorn
salty snac
whipped/sour cream
yogurt
root vegetables
other vegetables
tropical fruit
citrus fruit
soda
beef
frozen vegetables
pip fruit
grapes
support
0.00225
0.00250
0.00275
0.00300
lift
11
10
9
8
7
6