

Module 1

Semih Barutcu

6/1/2020

0

I used tidyverse package family to analyze the data.

```
library(pacman)
p_load(tidyverse, lubridate, skimr, summarytools, autoEDA, visdat, C50)
```

I saved 3 datasets as csv from excel spreadsheets source.

```
transactions <- read.csv("Transactions.csv", header = T, skip = 1)

cdemographics <- read.csv("CustomerDemographic.csv", header = T, skip = 1)

caddress <- read.csv("CustomerAddress.csv", header = T, skip = 1)

newcustomer <- read.csv("NewCustomerList.csv", header = T, skip = 1)
```

I arranged dates using lubridate package function mdy() to be able to use date features for my analyses.

```
transactions$transaction_date <- mdy(transactions$transaction_date)
cdemographics$DOB <- mdy(cdemographics$DOB)
newcustomer$DOB <- mdy(newcustomer$DOB)
```

Changing chr(character) variables to factor is applied using lapply() function after I listed these columns. Categorical data is much more useful to explore the data. I also removed “\$” sign from standard_cost variable to be able to get proper statistics as numeric values.

```
cols1 <- c("order_status", "brand", "product_line", "product_class", "product_size", "standard_cost")
transactions[cols1] <- lapply(transactions[cols1], factor)

cols2 <- c("gender", "job_title", "job_industry_category", "wealth_segment", "deceased_indicator", "owns")
cdemographics[cols2] <- lapply(cdemographics[cols2], factor)

cols3 <- c("address", "postcode", "state", "country")
caddress[cols3] <- lapply(caddress[cols3], factor)

cols4 <- c("gender", "job_title", "job_industry_category", "wealth_segment", "deceased_indicator", "owns")
newcustomer[cols4] <- lapply(newcustomer[cols4], factor)

# Nested gsub() function. First remove $ sign and after remove commas if exists
transactions$standard_cost <- as.numeric(gsub(",", "", gsub("\\$", "", transactions$standard_cost)))
```

1

All summary statistics are listed below.

All transactions were happened in 2017. 360 of the total 20000 transactions are missing online_order information. 179 of the orders were cancelled. 197 of the transactions are without a brand, product_line, product_class, product_size, standard_cost and product_first_sold_date.

3 of 4000 total observations are misidentified as F, Femal and M. There are 88 observations with gender U and 87 of observations do not have tenure information. 88 of customers do not have date of birth information. Job title is missing for 506 persons and job industry category is missing for 656.

New South Wales and Victoria states used with both full names and abbreviations. All 3999 address records are from Australia. 3 addresses are used for 2 times.

```
summary(transactions)
```

```
## transaction_id    product_id    customer_id    transaction_date
## Min.      :    1    Min.      : 0.00    Min.      : 1.0    Min.      :2017-01-01
## 1st Qu.: 5001    1st Qu.: 18.00    1st Qu.: 857.8    1st Qu.:2017-04-01
## Median :10000    Median : 44.00    Median :1736.0    Median :2017-07-03
## Mean    :10000    Mean    : 45.36    Mean    :1738.2    Mean    :2017-07-01
## 3rd Qu.:15000    3rd Qu.: 72.00    3rd Qu.:2613.0    3rd Qu.:2017-10-02
## Max.    :20000    Max.    :100.00    Max.    :5034.0    Max.    :2017-12-30
##
## online_order      order_status      brand      product_line
## Mode:logical      Approved :19821      : 197      : 197
## FALSE:9811        Cancelled: 179    Giant Bicycles:3312    Mountain: 423
## TRUE :9829        Norco Bicycles:2910    Road      : 3970
## NA's :360        OHM Cycles  :3043    Standard:14176
##                      Solex      :4253    Touring  : 1234
##                      Trek Bicycles :2990
##                      WeareA2B    :3295
## product_class    product_size    list_price    standard_cost
##      : 197      : 197    Min.      : 12.01    Min.      : 7.21
## high : 3013    large : 3976    1st Qu.: 575.27    1st Qu.: 215.14
## low  : 2964    medium:12990    Median :1163.89    Median : 507.58
## medium:13826    small : 2837    Mean    :1107.83    Mean    : 556.05
##                      3rd Qu.:1635.30    3rd Qu.: 795.10
##                      Max.    :2091.47    Max.    :1759.85
##                      NA's    :197
## product_first_sold_date
## Min.      :33259
## 1st Qu.:35667
## Median :38216
## Mean    :38200
## 3rd Qu.:40672
## Max.    :42710
## NA's    :197
```

```
summary(cdemographics)
```

```
## customer_id    first_name    last_name    gender
## Min.      :    1    Length:4000    Length:4000    F      :    1
## 1st Qu.:1001    Class :character    Class :character    Femal  :    1
## Median :2000    Mode  :character    Mode  :character    Female:2037
## Mean    :2000      M      :    1
## 3rd Qu.:3000      Male  :1872
## Max.    :4000      U      :    88
##
```

```
## past_3_years_bike_related_purchases      DOB
## Min.      : 0.00                        Min.      :1931-10-23
## 1st Qu.:24.00                        1st Qu.:1968-01-25
## Median :48.00                        Median :1977-07-25
## Mean      :48.89                        Mean      :1977-07-25
## 3rd Qu.:73.00                        3rd Qu.:1987-02-28
## Max.      :99.00                        Max.      :2002-03-11
##                                     NA's      :88
##                                     job_title    job_industry_category
##                                     : 506      Manufacturing      :799
## Business Systems Development Analyst: 45      Financial Services:774
## Social Worker                       : 44      n/a              :656
## Tax Accountant                      : 44      Health           :602
## Internal Auditor                    : 42      Retail           :358
## Legal Assistant                     : 41      Property         :267
## (Other)                             :3278     (Other)          :544
## wealth_segment deceased_indicator default      owns_car
## Affluent Customer: 979      N:3998      Length:4000      No :1976
## High Net Worth   :1021      Y: 2      Class :character Yes:2024
## Mass Customer    :2000      Mode  :character
##
##
## tenure
## Min.      : 1.00
## 1st Qu.: 6.00
## Median :11.00
## Mean      :10.66
## 3rd Qu.:15.00
## Max.      :22.00
## NA's      :87
```

```
summary(caddress)
```

```
## customer_id      address      postcode
## Min.      : 1      3 Mariners Cove Terrace: 2      2170      : 31
## 1st Qu.:1004      3 Talisman Place      : 2      2145      : 30
## Median :2004      64 Macpherson Junction : 2      2155      : 30
## Mean      :2004      0 3rd Road      : 1      2153      : 29
## 3rd Qu.:3004      0 American Ash Parkway : 1      2560      : 26
## Max.      :4003      0 Arapahoe Court      : 1      2770      : 26
##                                     (Other)      :3990      (Other):3827
## state      country      property_valuation
## New South Wales: 86      Australia:3999      Min.      : 1.000
## NSW      :2054      1st Qu.: 6.000
## QLD      : 838      Median : 8.000
## VIC      : 939      Mean      : 7.514
## Victoria      : 82      3rd Qu.:10.000
##                                     Max.      :12.000
##
```

```
summary(newcustomer)
```

```
## first_name      last_name      gender
```

```

## Length:1000      Length:1000      Female:513
## Class :character  Class :character  Male :470
## Mode :character   Mode :character   U    : 17
##
##
##
##
## past_3_years_bike_related_purchases      DOB
## Min. : 0.00                                Min. :1938-06-08
## 1st Qu.:26.75                            1st Qu.:1957-10-09
## Median :51.00                            Median :1972-03-24
## Mean :49.84                              Mean :1971-04-20
## 3rd Qu.:72.00                            3rd Qu.:1983-04-12
## Max. :99.00                              Max. :2002-02-27
## NA's :17
##
##          job_title      job_industry_category
##          :106      Financial Services:203
## Associate Professor : 15      Manufacturing :199
## Environmental Tech : 14      n/a :165
## Software Consultant : 14      Health :152
## Chief Design Engineer: 13      Retail : 78
## Assistant Manager : 12      Property : 64
## (Other) :826      (Other) :139
##
##          wealth_segment deceased_indicator owns_car      tenure
## Affluent Customer:241      N:1000      No :507      Min. : 0.00
## High Net Worth :251      Yes:493      1st Qu.: 7.00
## Mass Customer :508      Median :11.00
## Mean :11.39
## 3rd Qu.:15.00
## Max. :22.00
##
##
##          address      postcode      state      country
## 0 Bay Drive : 1      2145 : 9      NSW:506      Australia:1000
## 0 Dexter Parkway: 1      2232 : 9      QLD:228
## 0 Emmet Trail : 1      2148 : 7      VIC:266
## 0 Esker Avenue : 1      2168 : 7
## 0 Express Lane : 1      2750 : 7
## 0 Kipling Way : 1      3029 : 7
## (Other) :994      (Other):954
##
## property_valuation      X      X.1      X.2
## Min. : 1.000      Min. :0.4000      Min. :0.4000      Min. :0.4000
## 1st Qu.: 6.000      1st Qu.:0.5700      1st Qu.:0.6400      1st Qu.:0.7083
## Median : 8.000      Median :0.7500      Median :0.8375      Median :0.9375
## Mean : 7.397      Mean :0.7468      Mean :0.8372      Mean :0.9408
## 3rd Qu.: 9.000      3rd Qu.:0.9200      3rd Qu.:1.0100      3rd Qu.:1.1250
## Max. :12.000      Max. :1.1000      Max. :1.3750      Max. :1.7188
##
##
##          X.3      X.4      Rank      Value
## Min. :0.3400      Min. : 1.0      Min. : 1.0      Min. :0.3400
## 1st Qu.:0.6500      1st Qu.: 250.0      1st Qu.: 250.0      1st Qu.:0.6495
## Median :0.8500      Median : 500.0      Median : 500.0      Median :0.8600
## Mean :0.8686      Mean : 498.8      Mean : 498.8      Mean :0.8817
## 3rd Qu.:1.0600      3rd Qu.: 750.2      3rd Qu.: 750.2      3rd Qu.:1.0750
## Max. :1.7188      Max. :1000.0      Max. :1000.0      Max. :1.7188

```

```
##
```

I checked addresses below which exists 2 times in the data. They have different postcodes and customer IDs.

```
address %>% filter(address == "3 Mariners Cove Terrace")
```

```
##   customer_id          address postcode state  country
## 1      2333 3 Mariners Cove Terrace    3108   VIC Australia
## 2      2985 3 Mariners Cove Terrace    2216   NSW Australia
##   property_valuation
## 1                  10
## 2                  10
```

```
address %>% filter(address == "3 Talisman Place")
```

```
##   customer_id          address postcode state  country property_valuation
## 1         737 3 Talisman Place    4811   QLD Australia             2
## 2        2475 3 Talisman Place    4017   QLD Australia             5
```

```
address %>% filter(address == "64 Macpherson Junction")
```

```
##   customer_id          address postcode state  country
## 1        2320 64 Macpherson Junction    2208   NSW Australia
## 2        3540 64 Macpherson Junction    4061   QLD Australia
##   property_valuation
## 1                  11
## 2                   8
```

Gender and state variables corrections have been made below. I used factor function to get corrected categories.

```
cdemographics$gender[cdemographics$gender == "Femal" | cdemographics$gender == "F"] <- "Female"
```

```
cdemographics$gender[cdemographics$gender == "M"] <- "Male"
```

```
cdemographics$gender <- factor(cdemographics$gender)
```

```
address$state[address$state == "New South Wales"] <- "NSW"
```

```
address$state[address$state == "Victoria"] <- "VIC"
```

```
address$state <- factor(address$state)
```

```
summary(cdemographics$gender)
```

```
## Female   Male     U
##   2039   1873    88
```

```
summary(address$state)
```

```
## NSW  QLD  VIC
## 2140  838 1021
```

Age variable is added to cdemographics and newcustomer datasets.

```
cdemographics$age <- 2020 - year(cdemographics$DOB)
```

```
newcustomer$age <- 2020 - year(newcustomer$DOB)
```

Summaries of new age columns can be seen below.

```
summary(cdemographics$age)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's  
##    18.00   33.00   43.00   42.94   52.00   89.00    88
```

```
summary(newcustomer$age)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's  
##    18.00   37.00   48.00   49.21   63.00   82.00    17
```

2 EDA (Exploratory Data Analysis)

I started to investigate datasets with using automatic Exploratory Data Analysis tools.

dfsummary

```
cdemographics %>% dfSummary() %>% view()
```

```
## Switching method to 'browser'
```

```
## Output file written: C:\Users\sbaru\AppData\Local\Temp\RtmpukPlY7\file6b0c4dbab2c.html
```

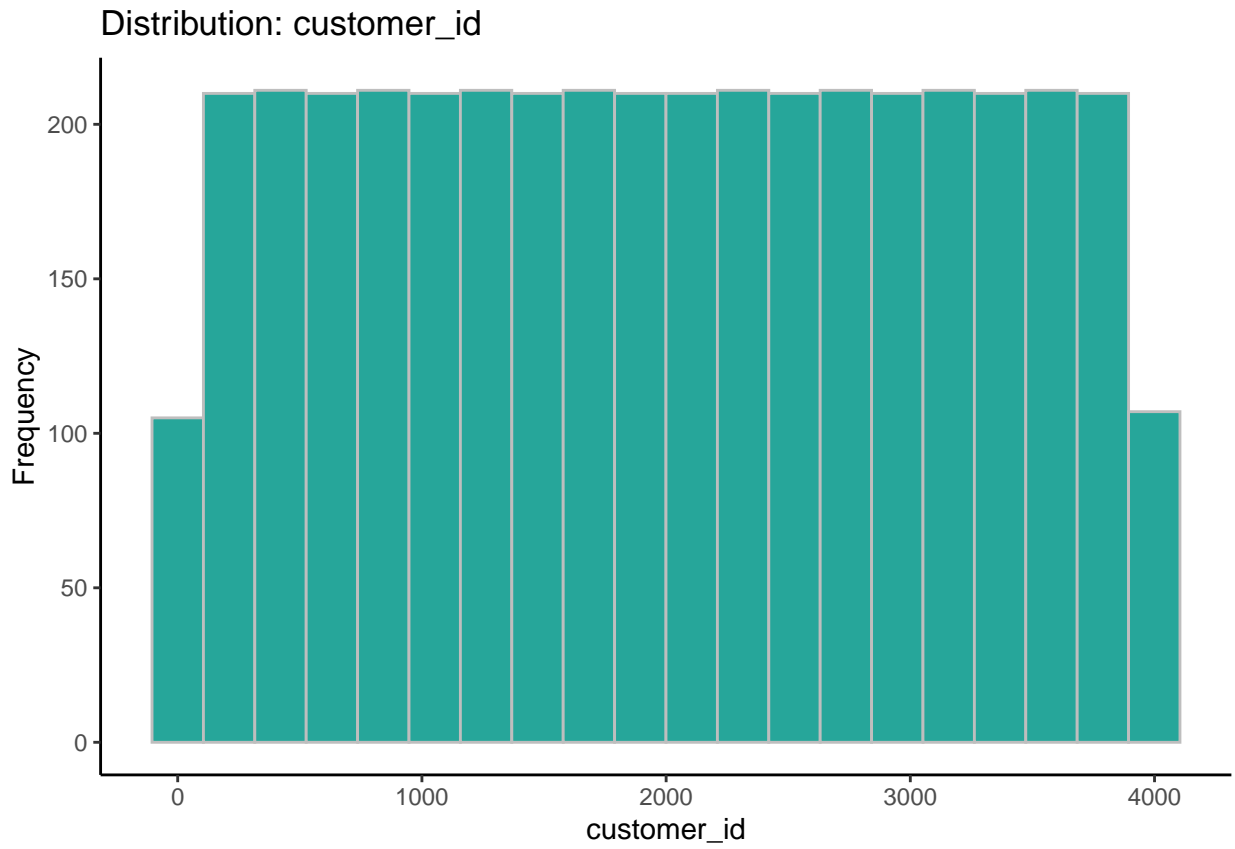
autoEDA

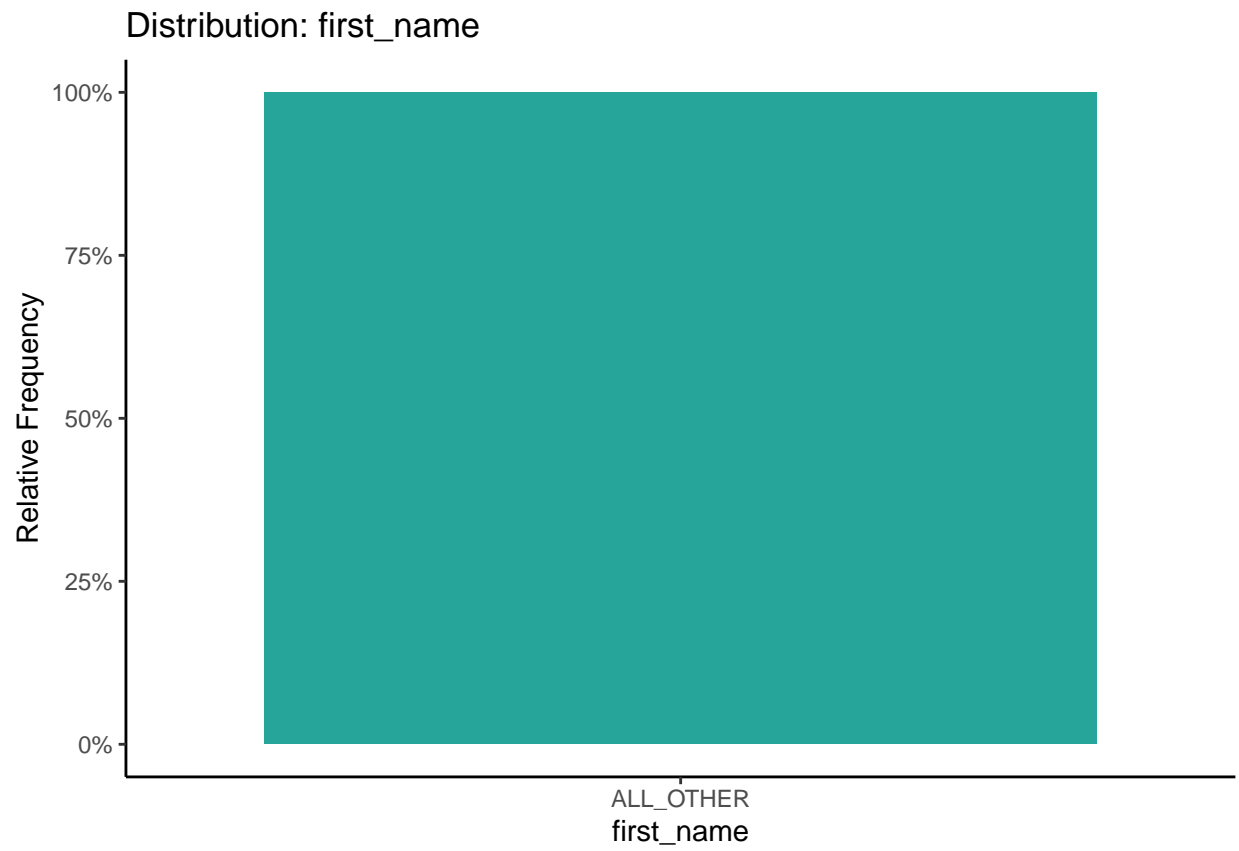
I arranged the code below as echo = F because it produces a graph for every column of datasets and make it the report hard to read. I use it as a prior investigation. Graphs, which make sense to me, are going to be plotted after auto EDA part.

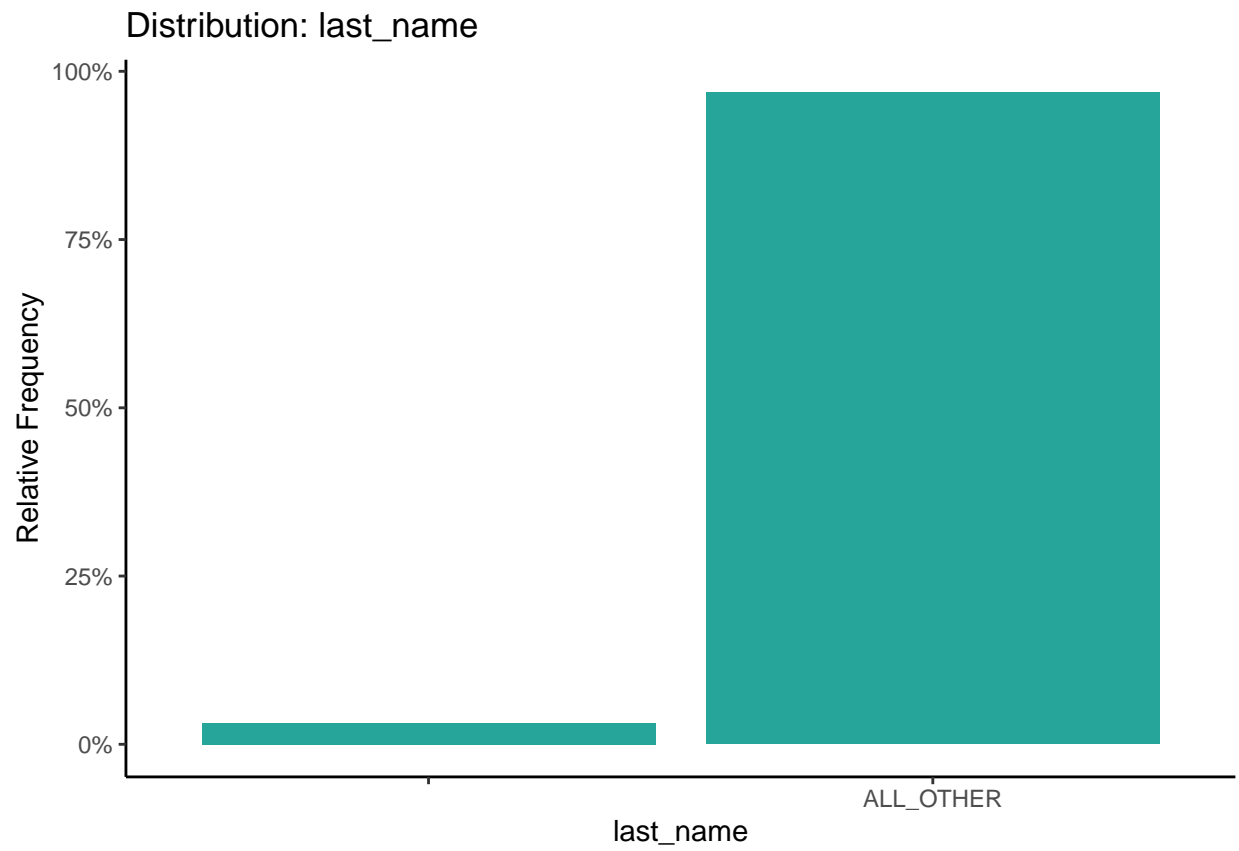
0th product have the most transactions record and its range shows a different trend than remainings. It has biggest price range between all the products.

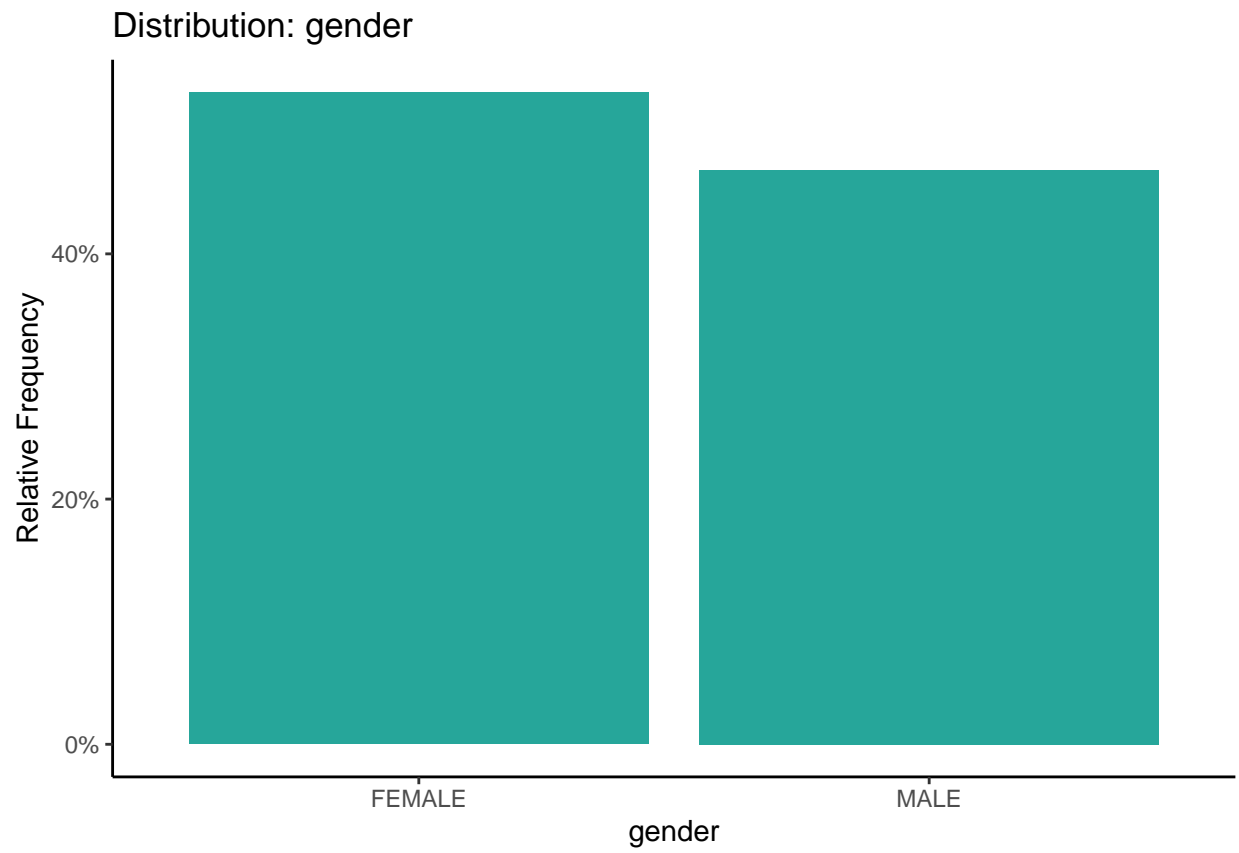
```
## Loading required package: RColorBrewer
```

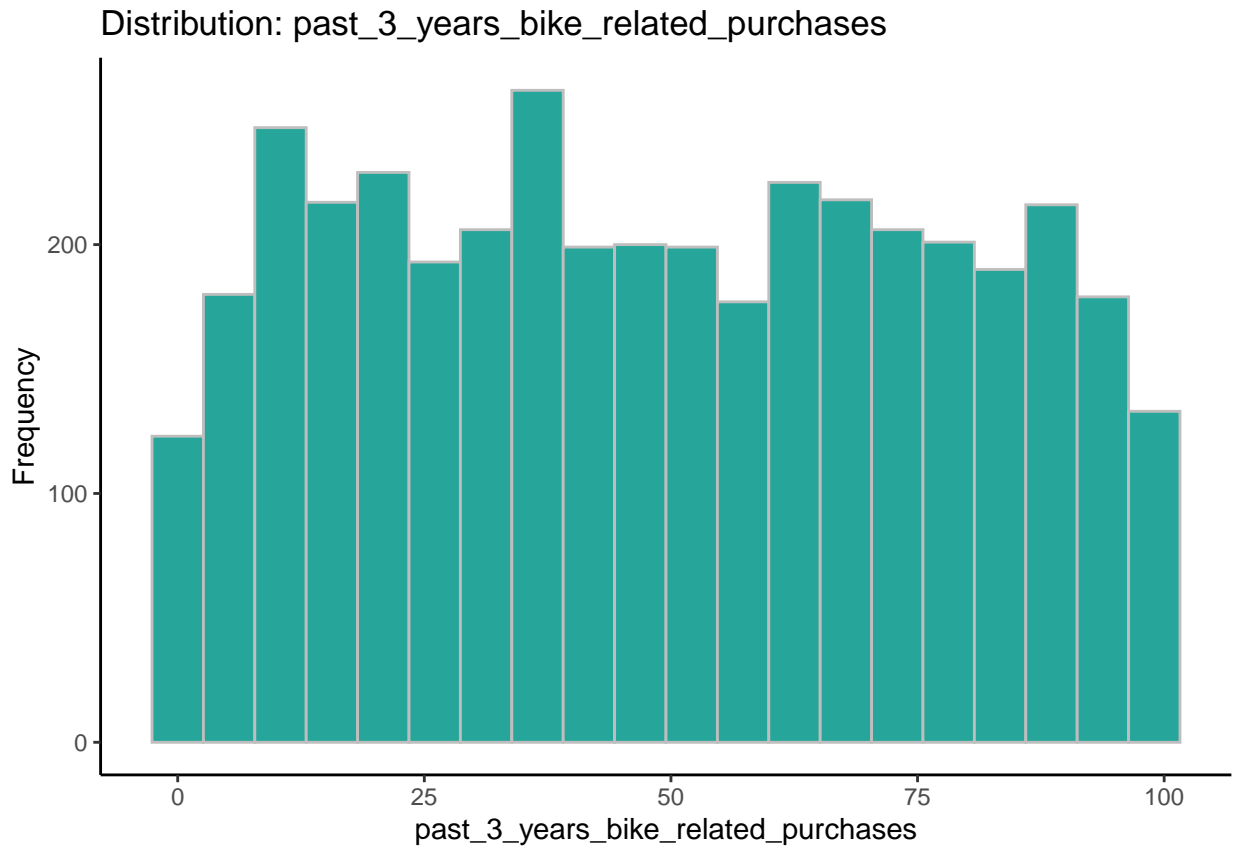
```
## autoEDA | Setting color theme  
## autoEDA | Removing constant features  
## autoEDA | 0 constant features removed  
## autoEDA | 0 zero spread features removed  
## autoEDA | Removing features containing majority missing values  
## autoEDA | 0 majority missing features removed  
## autoEDA | Cleaning data  
## autoEDA | Correcting sparse categorical feature levels  
## autoEDA | Performing univariate analysis  
## autoEDA | Visualizing data
```

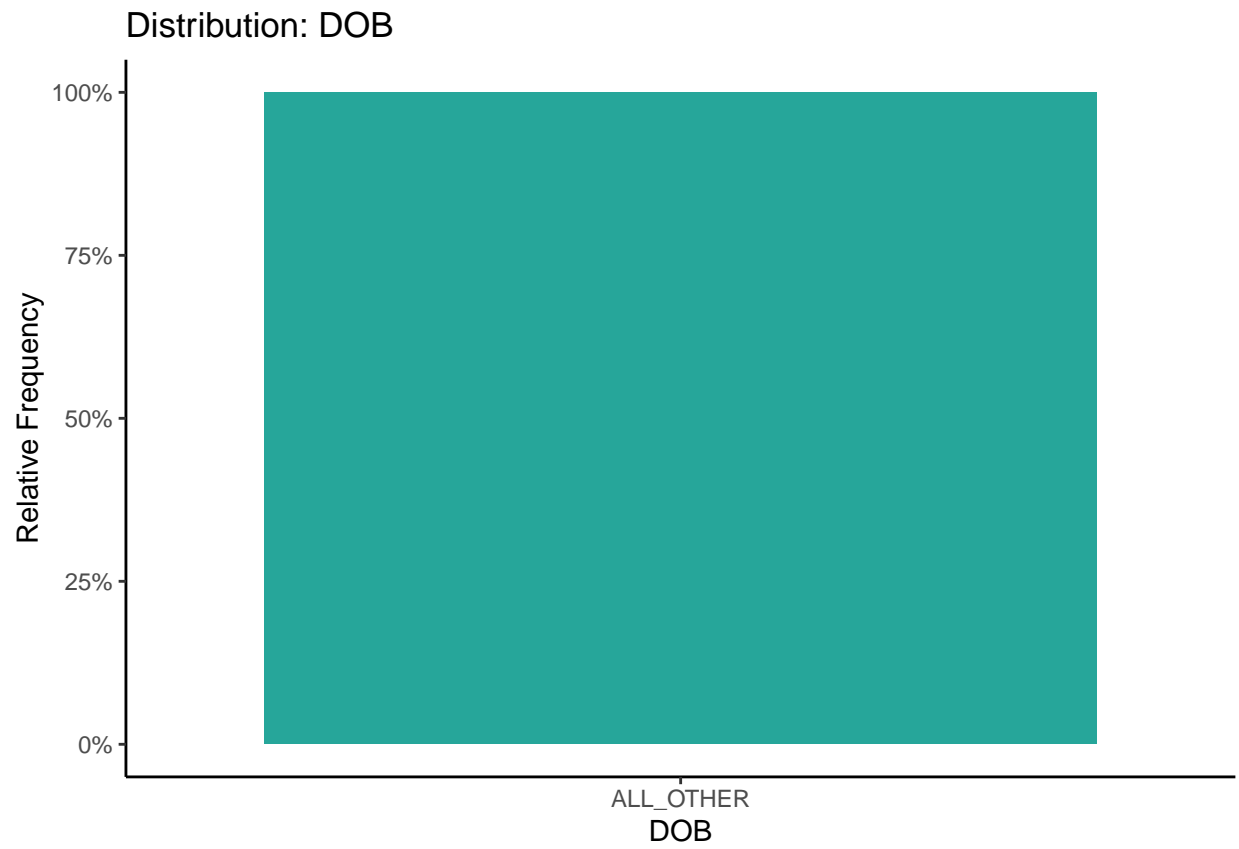


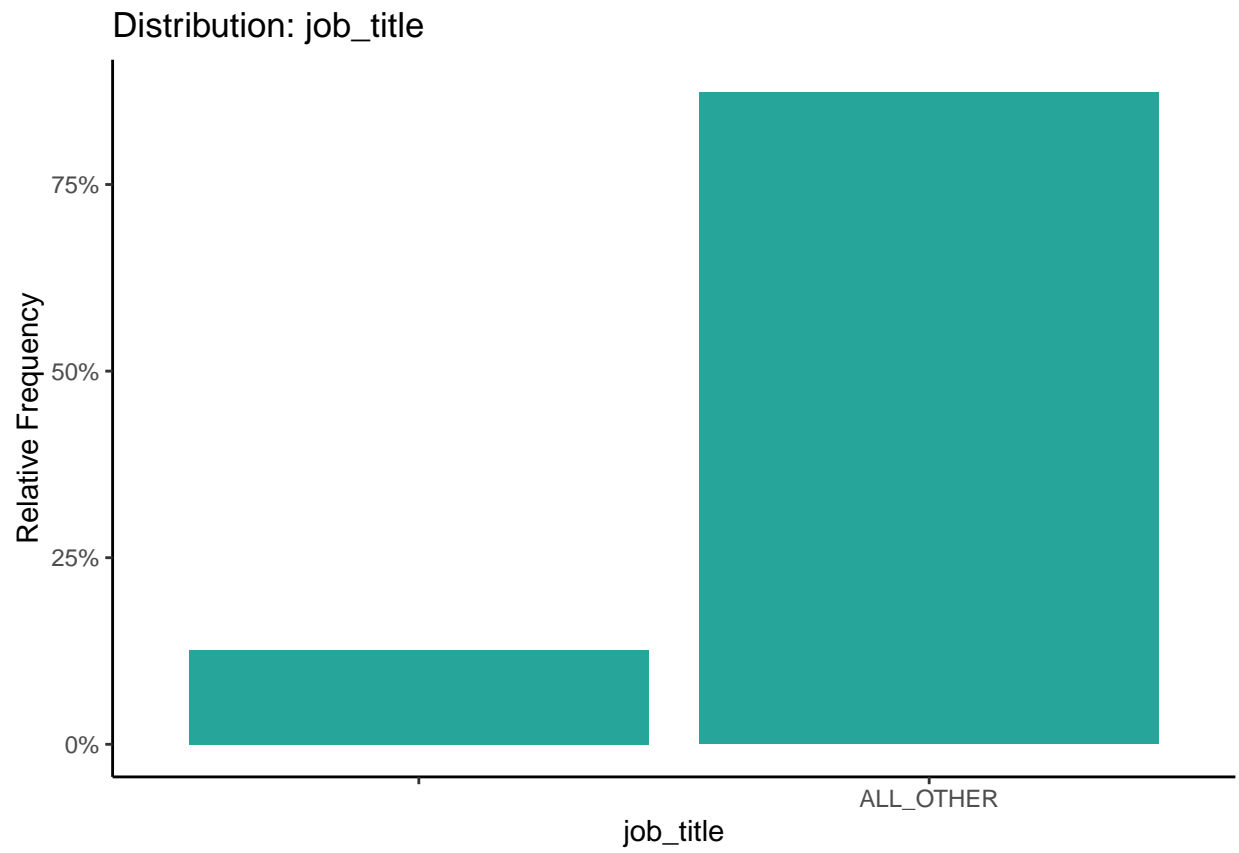


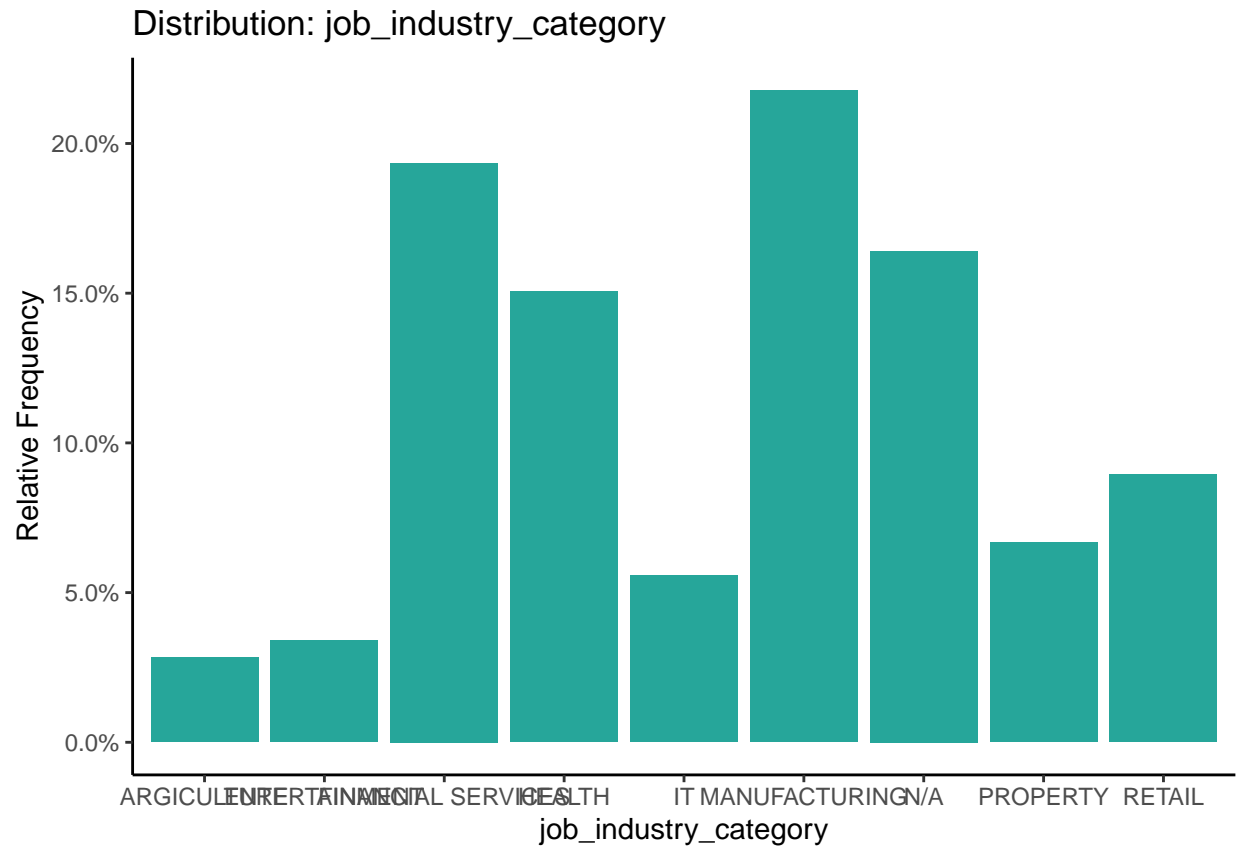


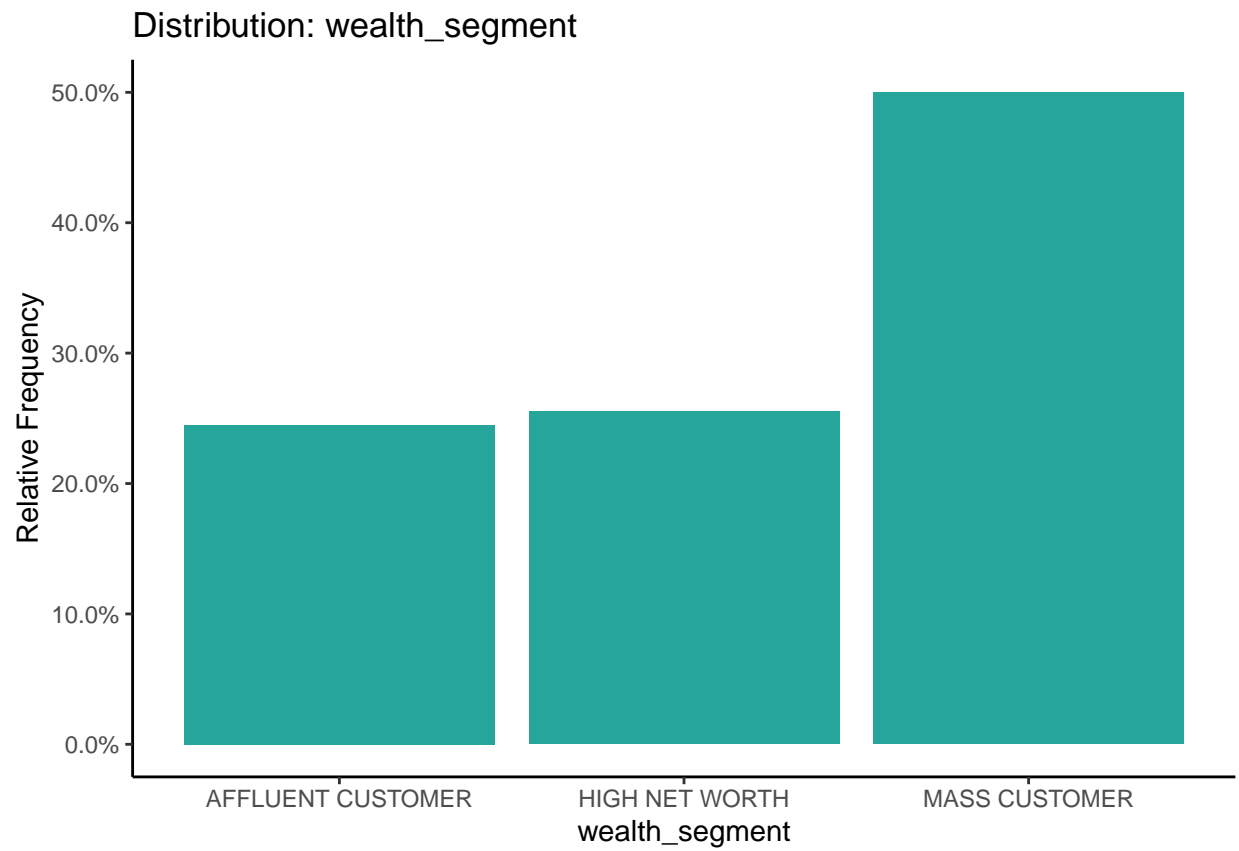


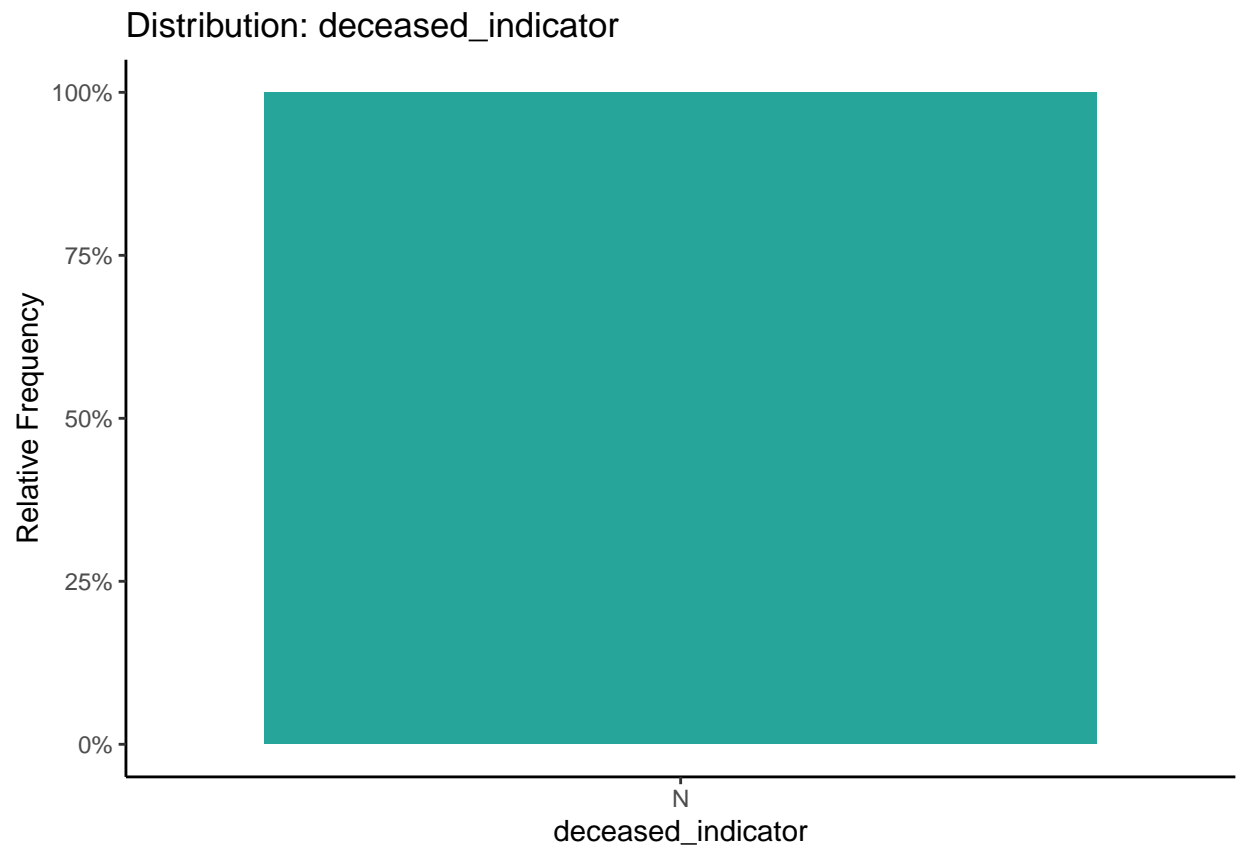


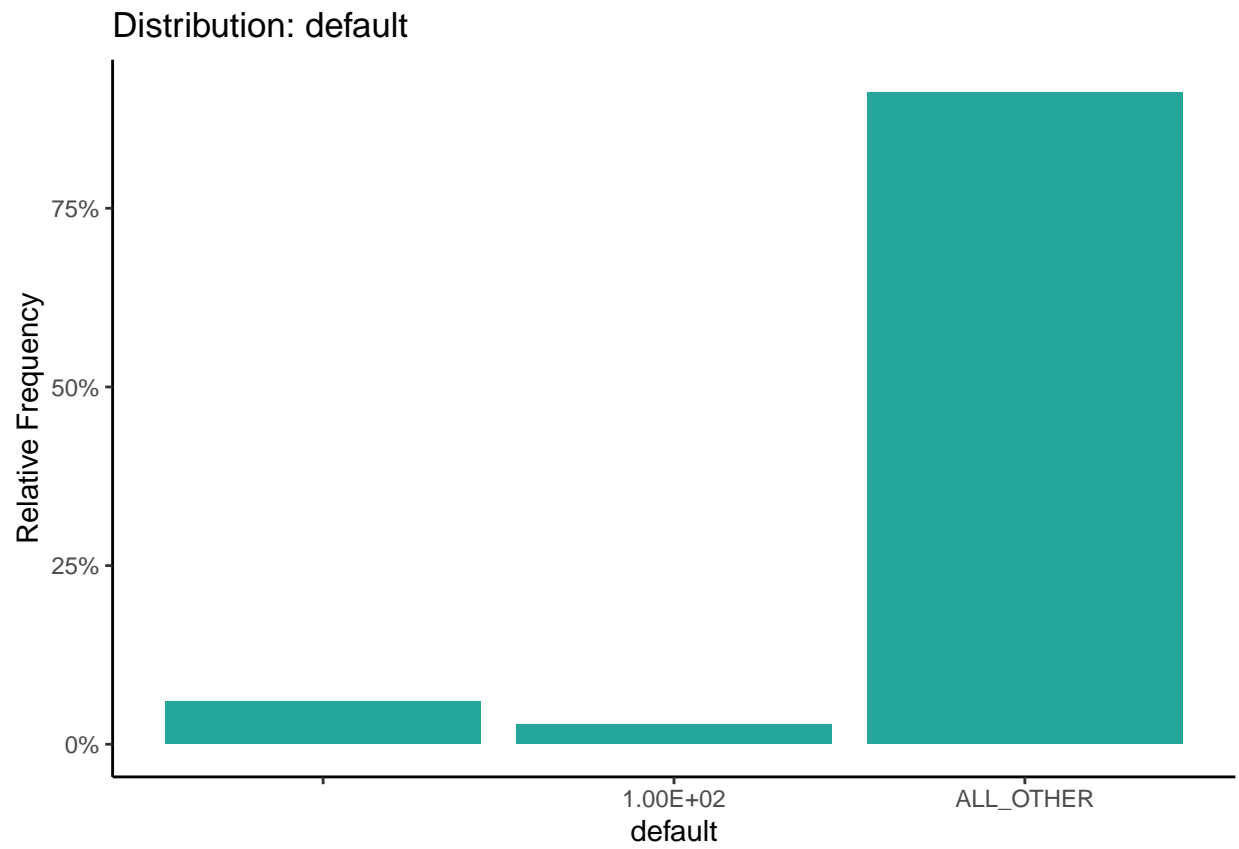


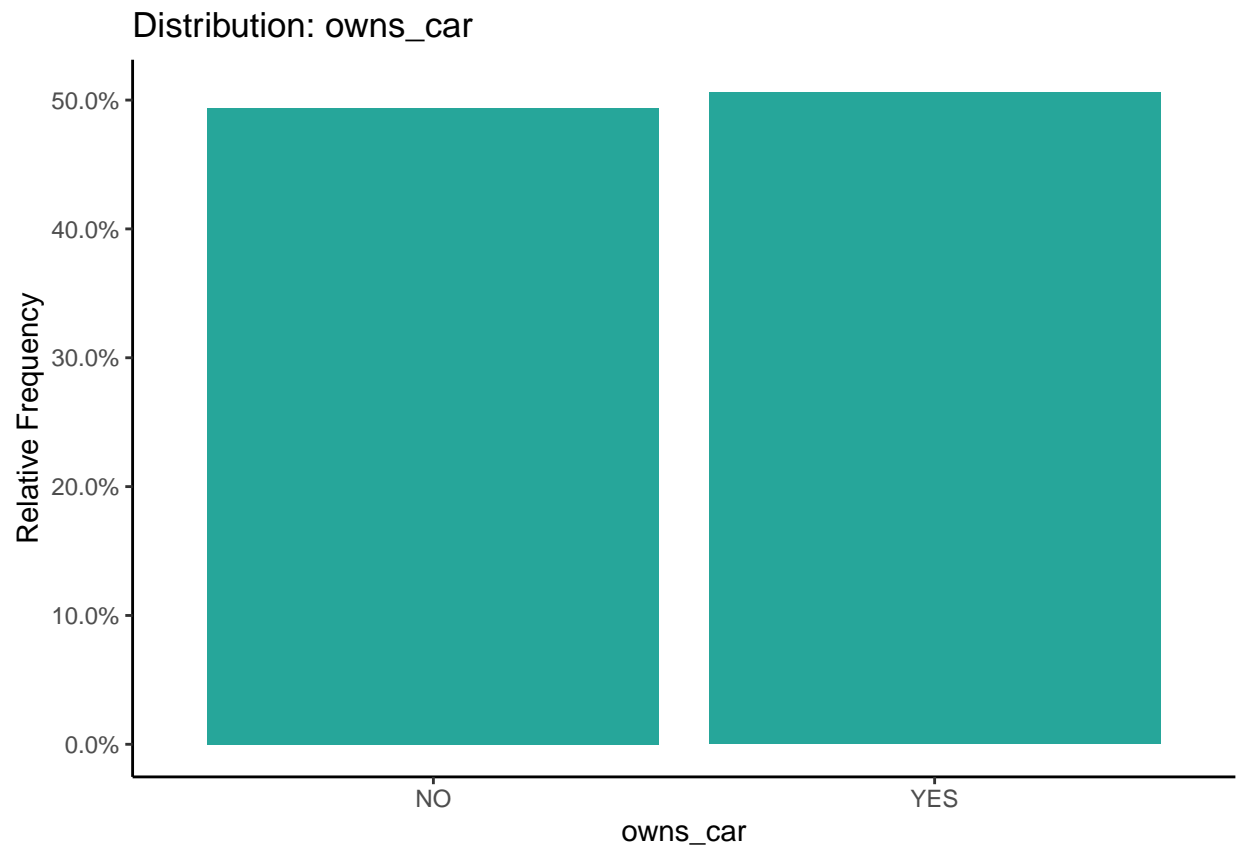


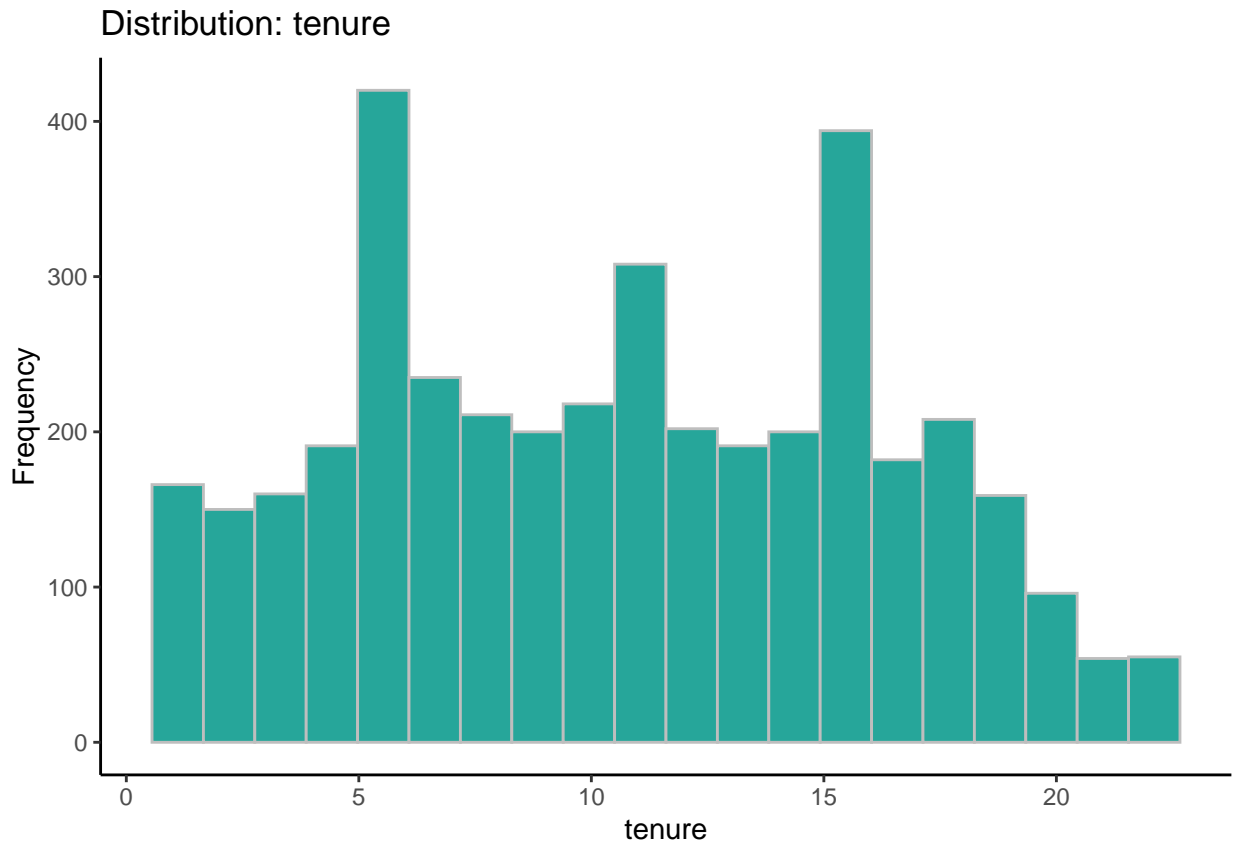


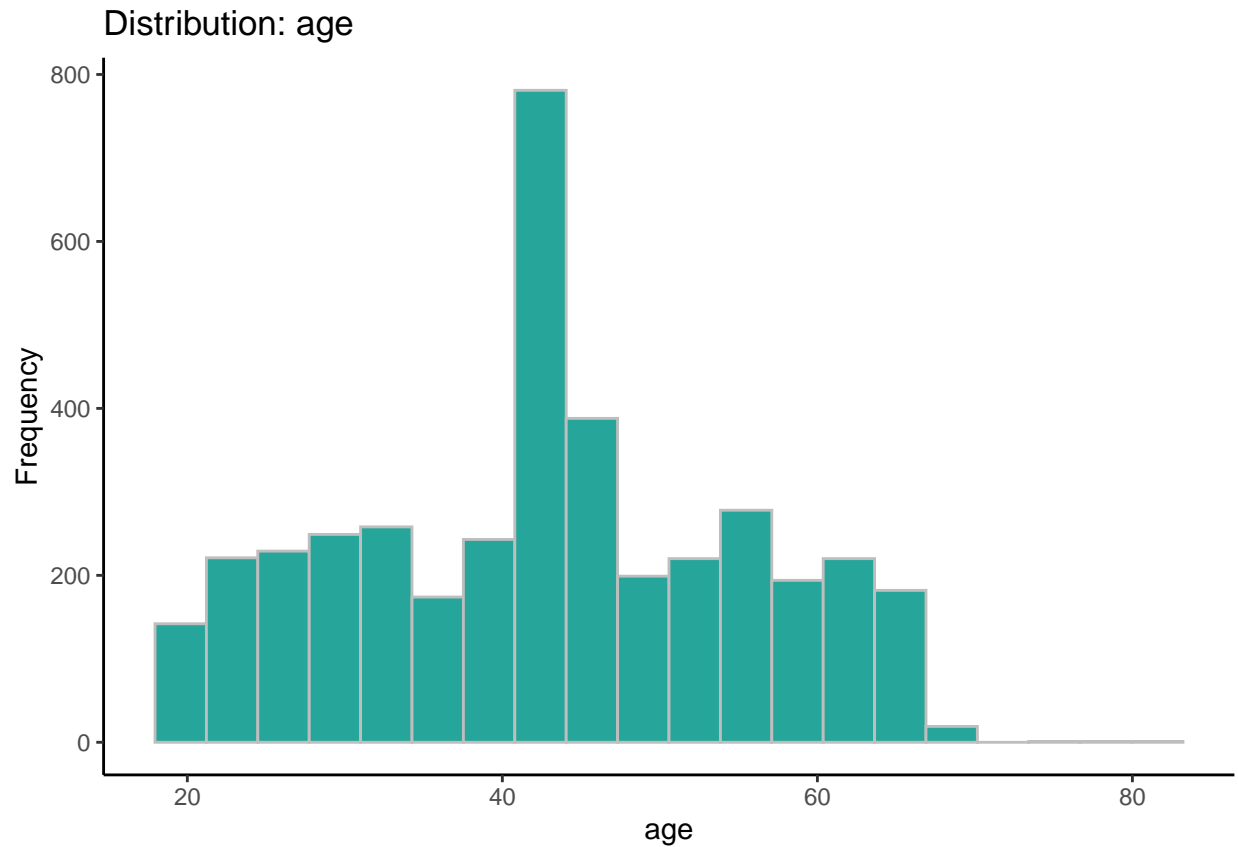












##	Feature	Observations	FeatureClass	FeatureType
## 1	customer_id	4000	numeric	Continuous
## 2	first_name	4000	character	Categorical
## 3	last_name	4000	character	Categorical
## 4	gender	4000	character	Categorical
## 5	past_3_years_bike_related_purchases	4000	numeric	Continuous
## 6	DOB	4000	character	Categorical
## 7	job_title	4000	character	Categorical
## 8	job_industry_category	4000	character	Categorical
## 9	wealth_segment	4000	character	Categorical
## 10	deceased_indicator	4000	character	Categorical
## 11	default	4000	character	Categorical
## 12	owns_car	4000	character	Categorical
## 13	tenure	4000	numeric	Continuous
## 14	age	4000	numeric	Continuous
##	PercentageMissing	PercentageUnique	ConstantFeature	ZeroSpreadFeature
## 1	0.00	100.00	No	No
## 2	0.00	78.47	No	No
## 3	0.00	93.15	No	No
## 4	0.00	0.08	No	No
## 5	0.00	2.50	No	No
## 6	2.20	86.20	No	No
## 7	0.00	4.90	No	No
## 8	0.00	0.25	No	No
## 9	0.00	0.08	No	No
## 10	0.00	0.05	No	No

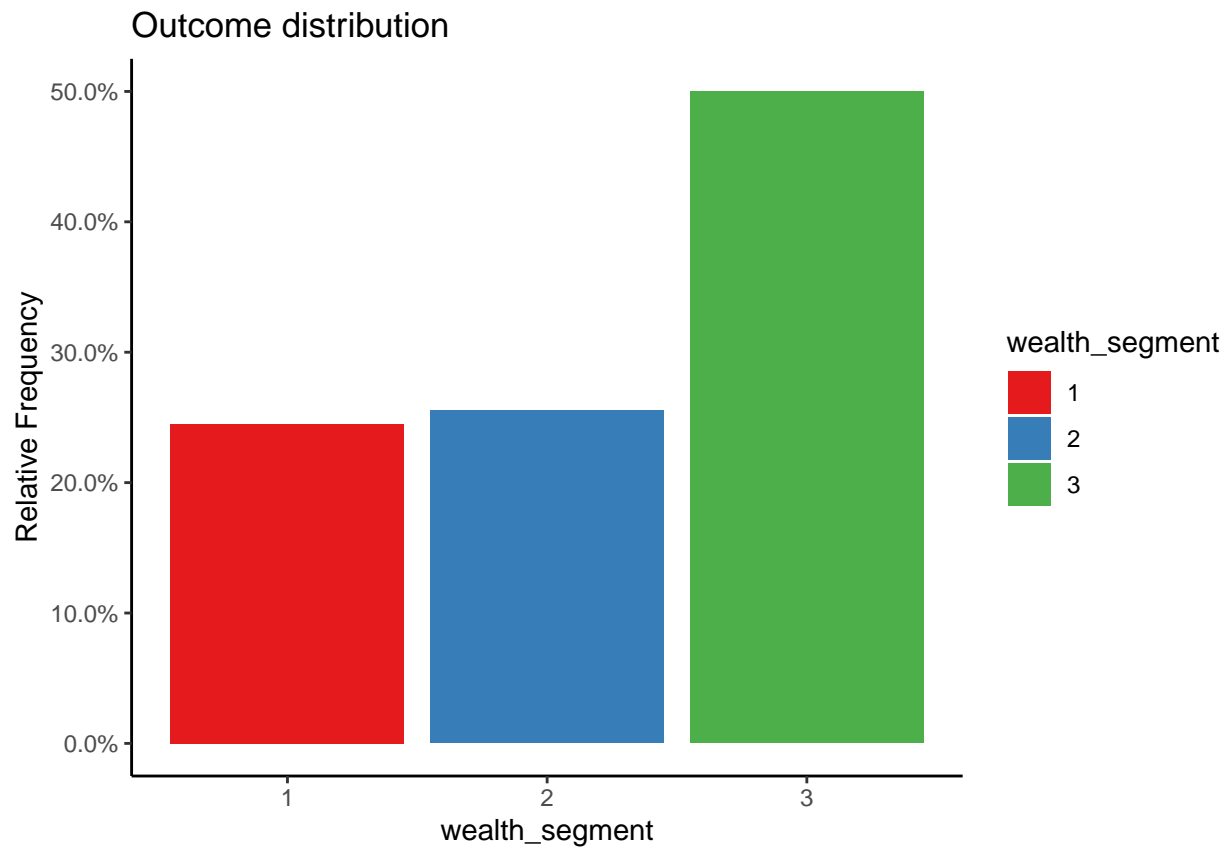
```

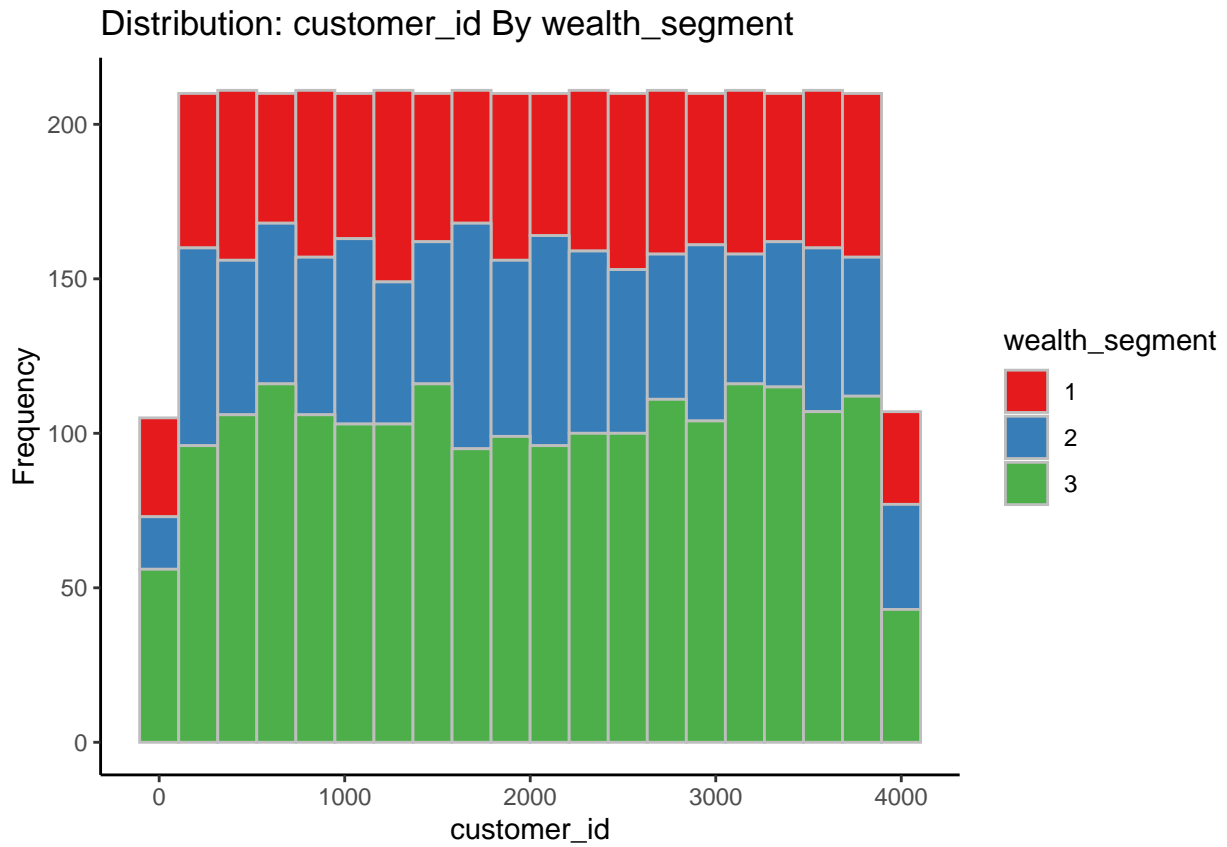
## 11          0.00          2.55          No          No
## 12          0.00          0.05          No          No
## 13          2.17          0.58          No          No
## 14          2.20          1.40          No          No
## LowerOutliers UpperOutliers ImputationValue MinValue FirstQuartile Median
## 1          0          0          2000.5          1          1000.75 2000.5
## 2          0          0          ALL_OTHER          0          0.00 0.0
## 3          0          0          ALL_OTHER          0          0.00 0.0
## 4          0          0          FEMALE          0          0.00 0.0
## 5          0          0          48          0          24.00 48.0
## 6          0          0          MISSING          0          0.00 0.0
## 7          0          0          ALL_OTHER          0          0.00 0.0
## 8          0          0          MANUFACTURING          0          0.00 0.0
## 9          0          0          MASS CUSTOMER          0          0.00 0.0
## 10         0          0          N          0          0.00 0.0
## 11         0          0          ALL_OTHER          0          0.00 0.0
## 12         0          0          YES          0          0.00 0.0
## 13         0          0          11          1          6.00 11.0
## 14         0          2          43          18          33.00 43.0
## Mean          Mode ThirdQuartile MaxValue LowerOutlierValue
## 1 2000.50          1          3000.25          4000          -1998.5
## 2 0.00          MAX          0.00          0          0.0
## 3 0.00          0.00          0          0.0
## 4 0.00          FEMALE          0.00          0          0.0
## 5 48.89          16          73.00          99          -49.5
## 6 0.00 1978-01-30          0.00          0          0.0
## 7 0.00          0.00          0          0.0
## 8 0.00 MANUFACTURING          0.00          0          0.0
## 9 0.00 MASS CUSTOMER          0.00          0          0.0
## 10 0.00          N          0.00          0          0.0
## 11 0.00          0.00          0          0.0
## 12 0.00          YES          0.00          0          0.0
## 13 10.66          7          15.00          22          -7.5
## 14 42.94          42          52.00          89          4.5
## UpperOutlierValue
## 1          5999.5
## 2          0.0
## 3          0.0
## 4          0.0
## 5          146.5
## 6          0.0
## 7          0.0
## 8          0.0
## 9          0.0
## 10         0.0
## 11         0.0
## 12         0.0
## 13         28.5
## 14         80.5

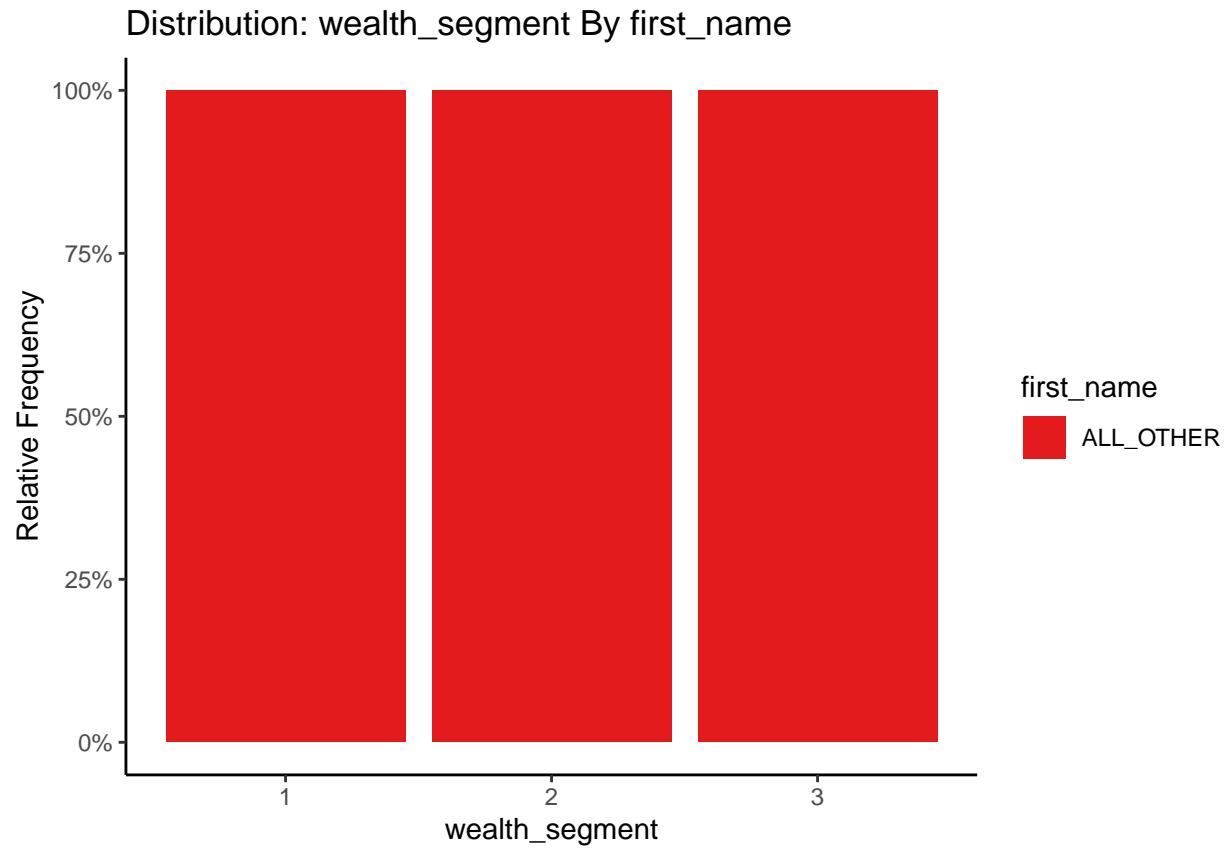
## autoEDA | Setting color theme
## autoEDA | Removing constant features
## autoEDA | 0 constant features removed
## autoEDA | Removing zero spread features

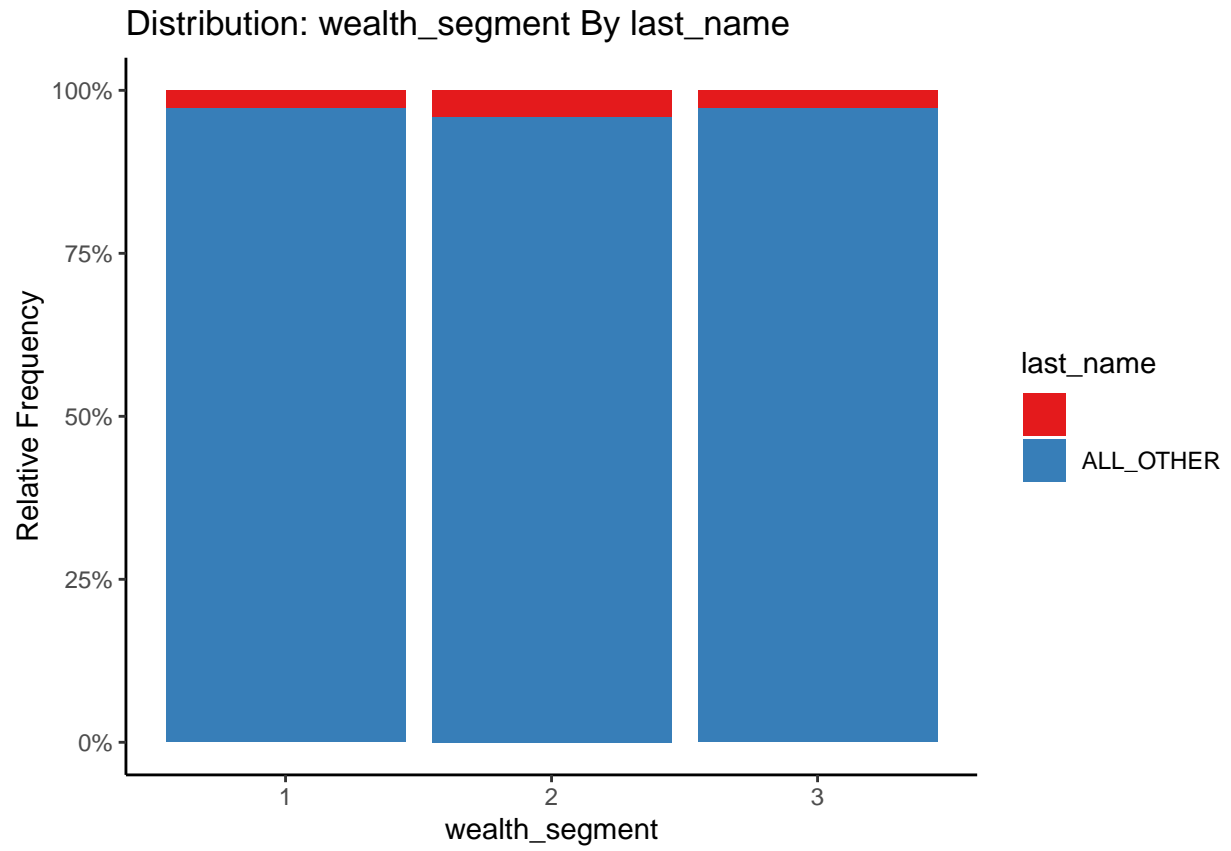
```

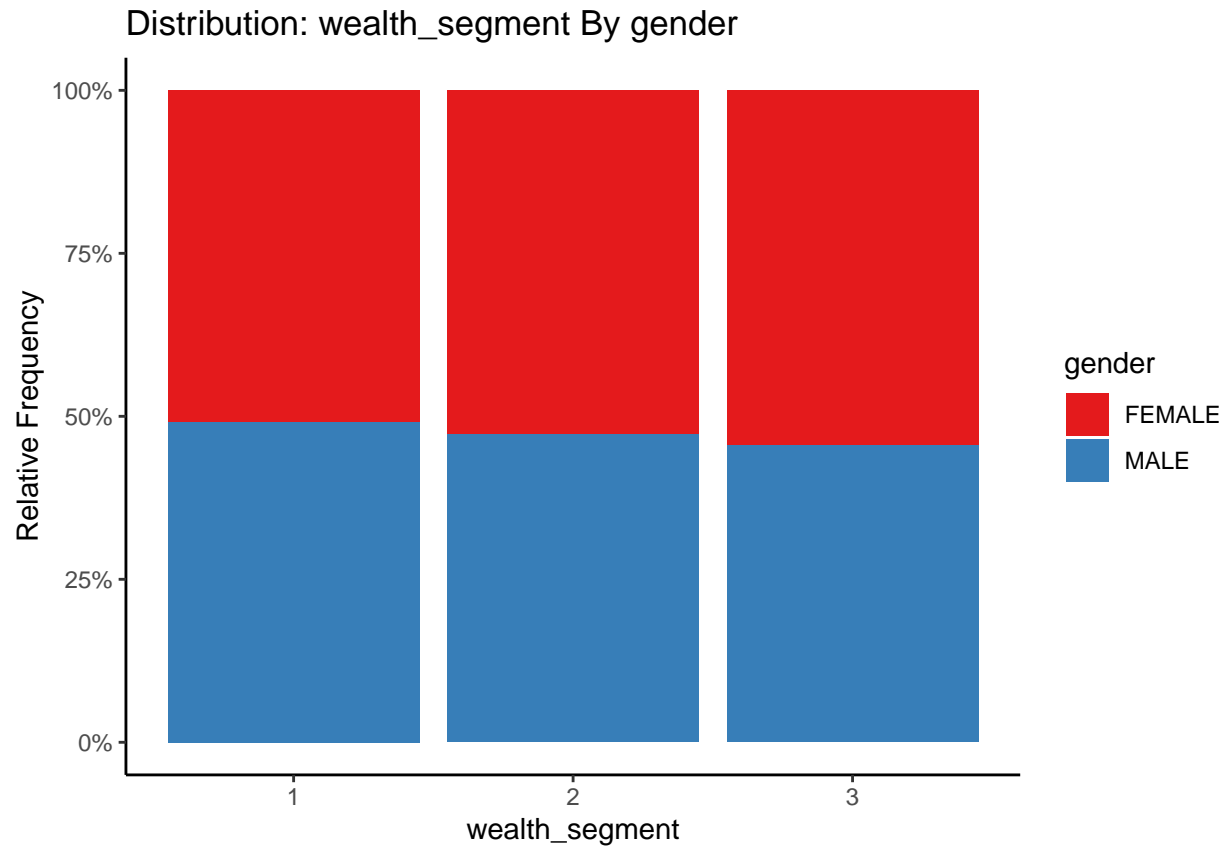
```
## autoEDA | 0 zero spread features removed
## autoEDA | Removing features containing majority missing values
## autoEDA | 0 majority missing features removed
## autoEDA | Cleaning data
## autoEDA | Correcting sparse categorical feature levels
## autoEDA | Sorting features
## autoEDA | Multi-class classification outcome detected
## autoEDA | Calculating feature predictive power
## autoEDA | Visualizing data
```

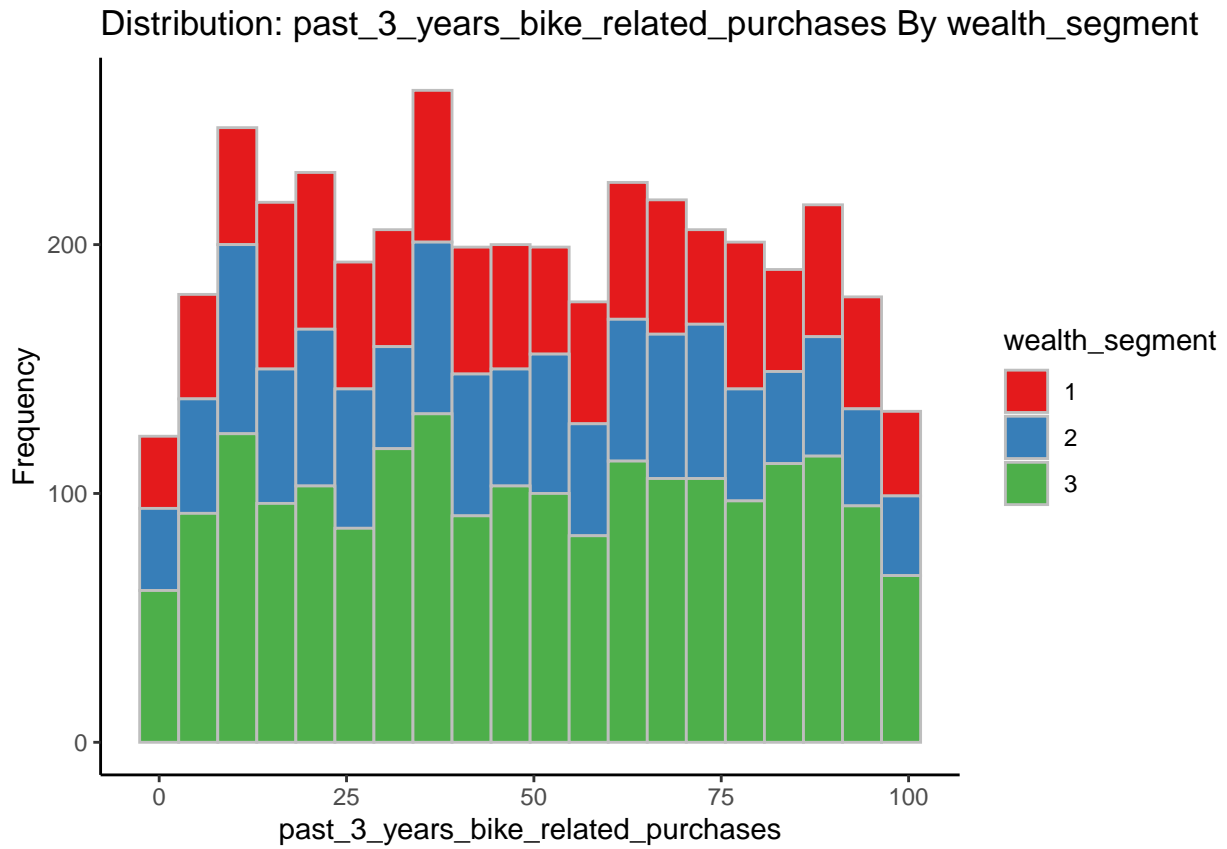


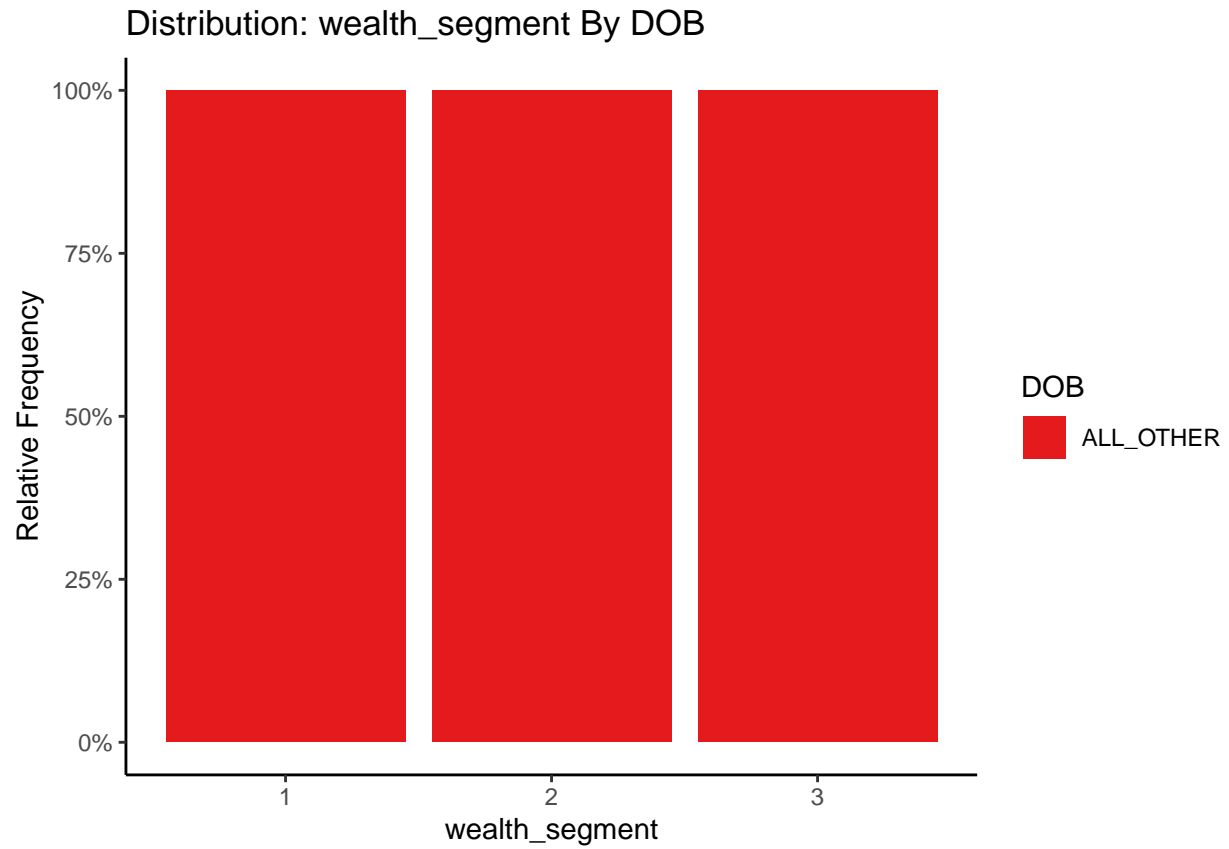


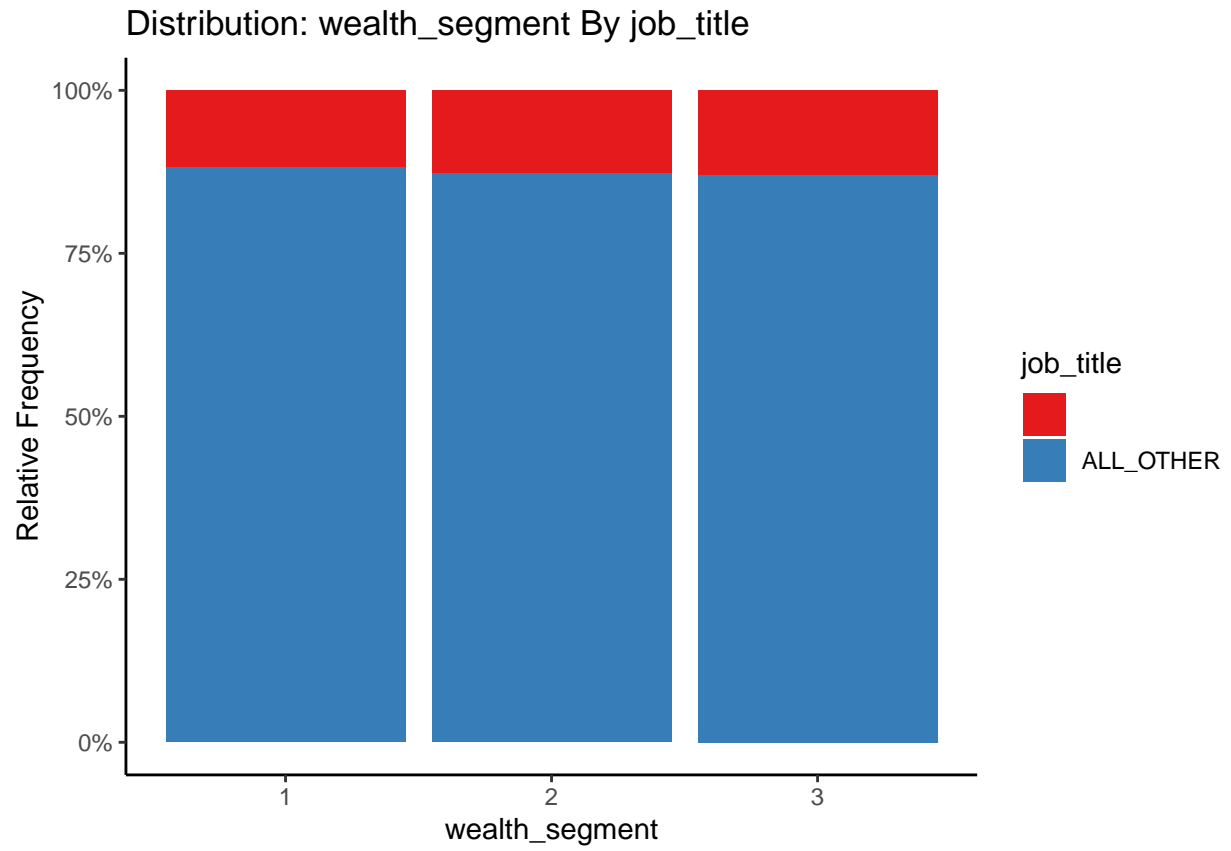


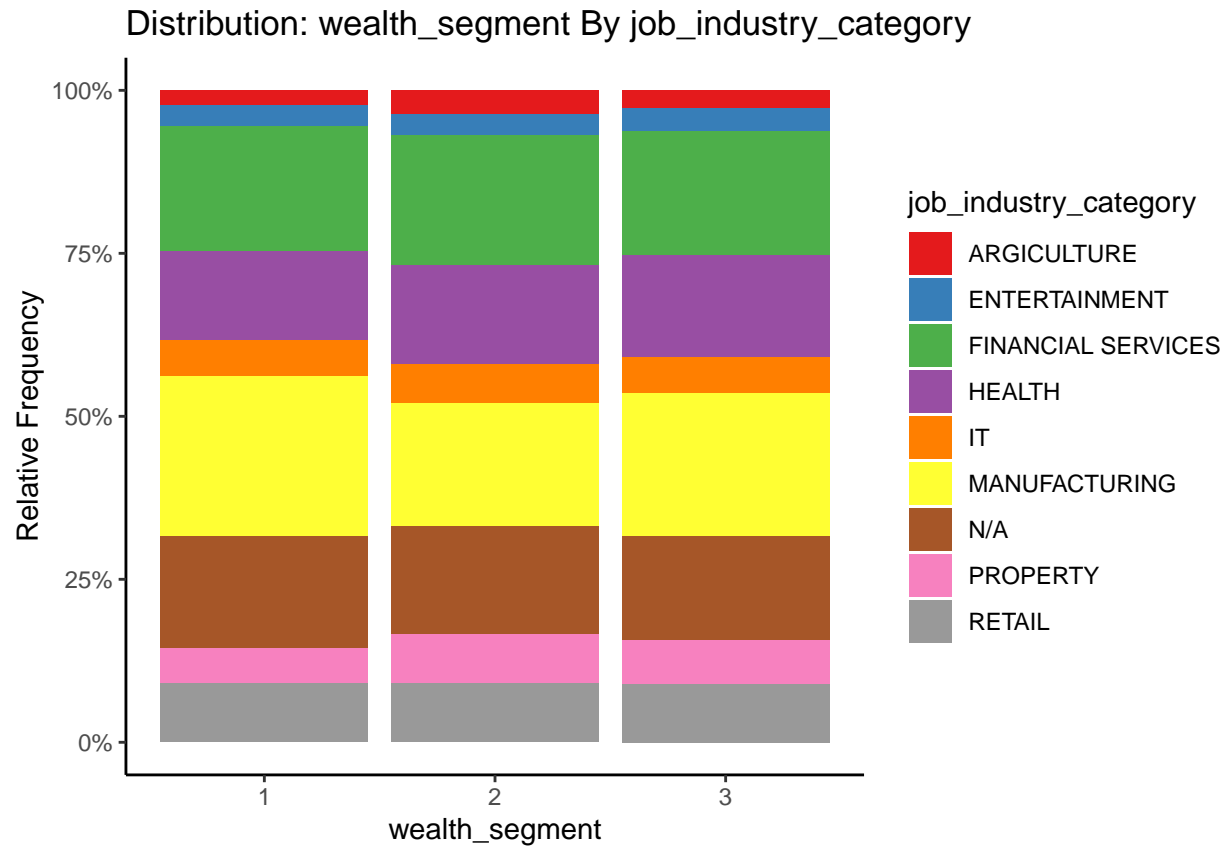


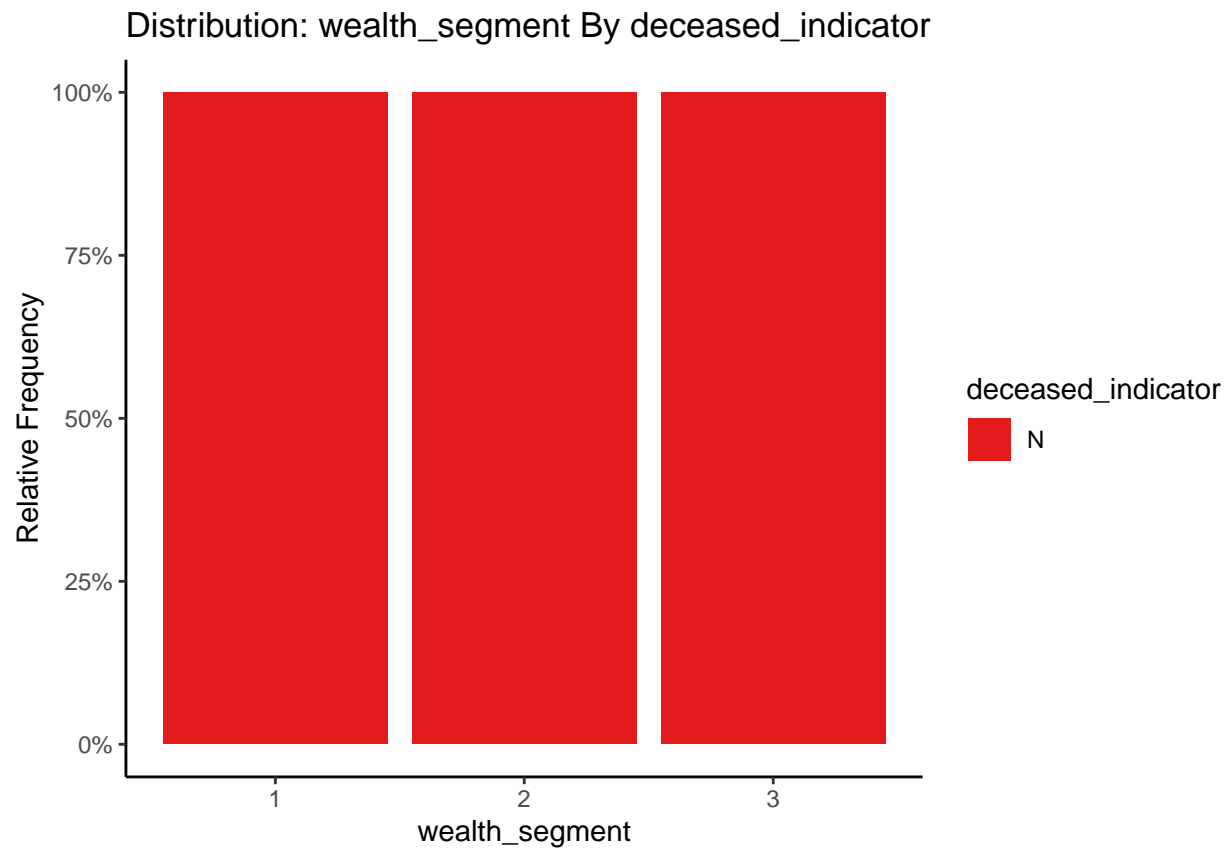


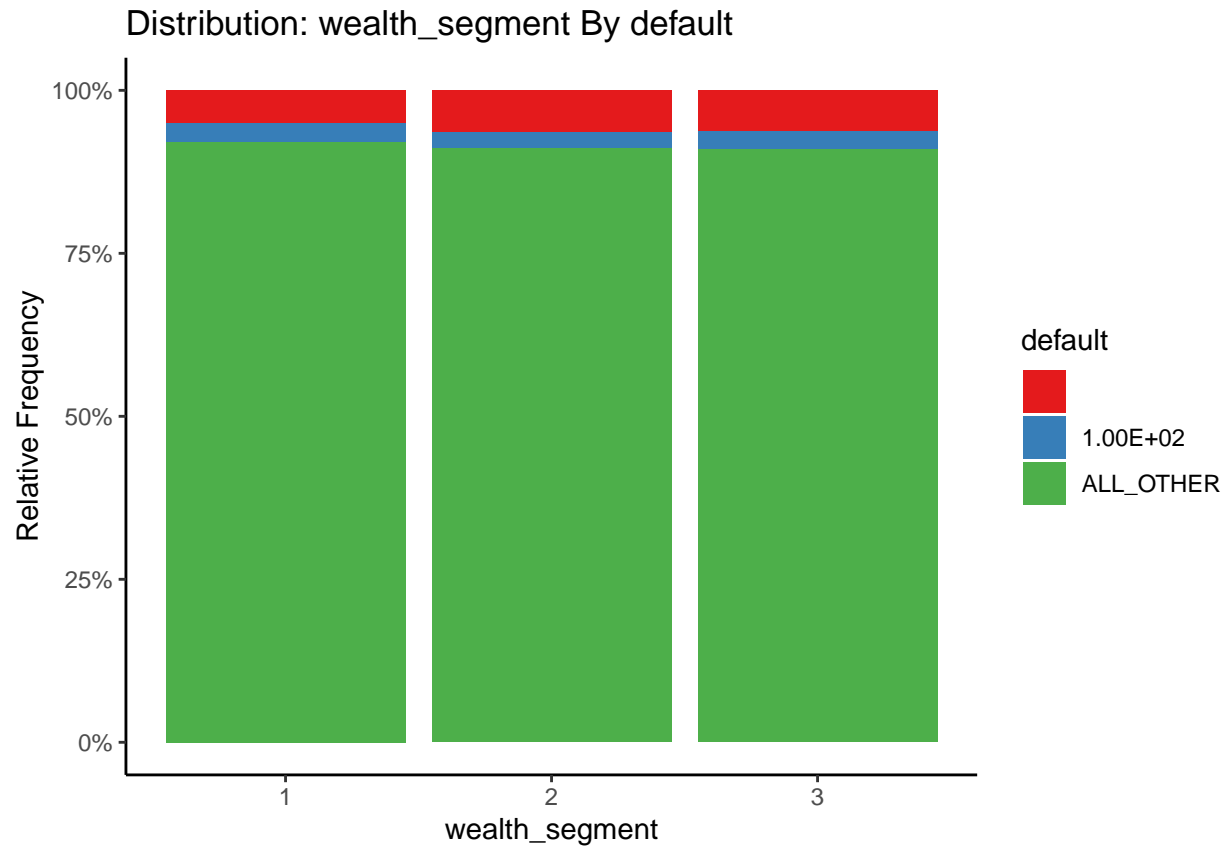


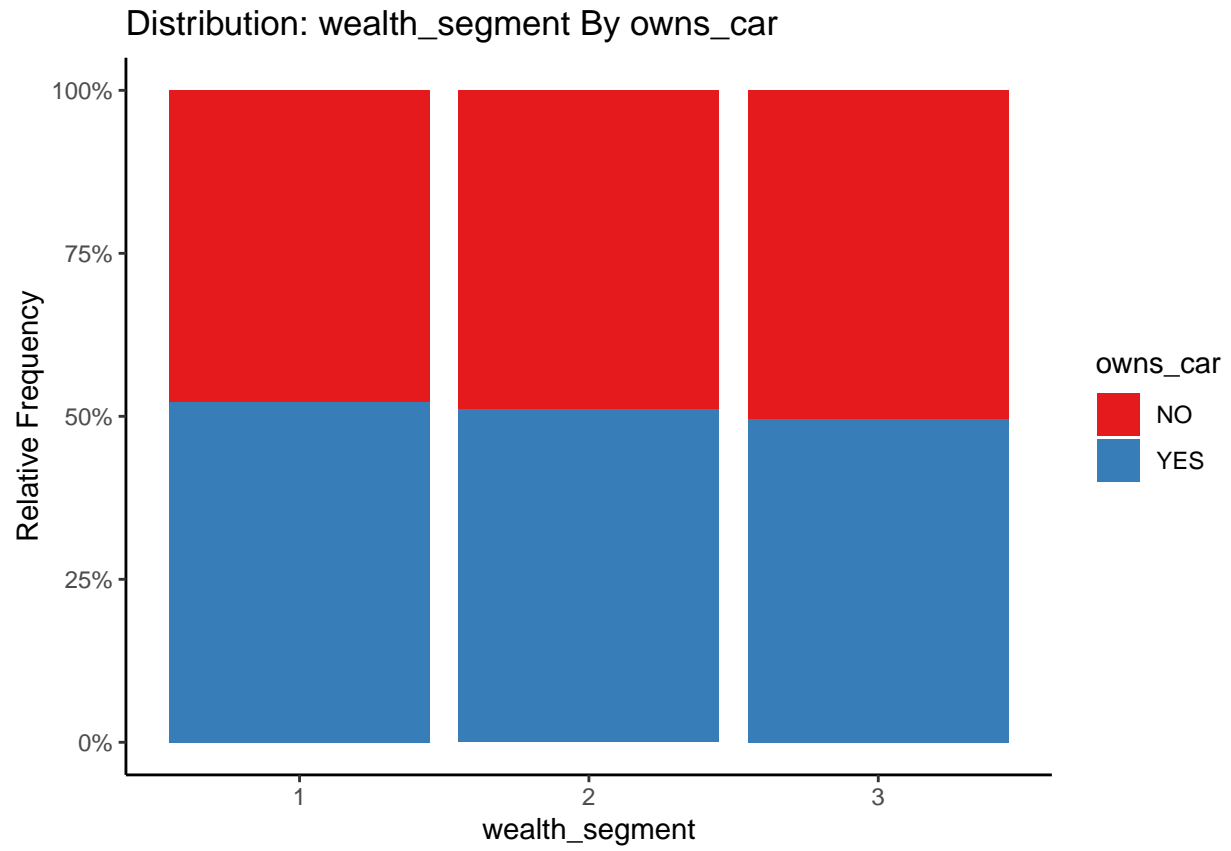


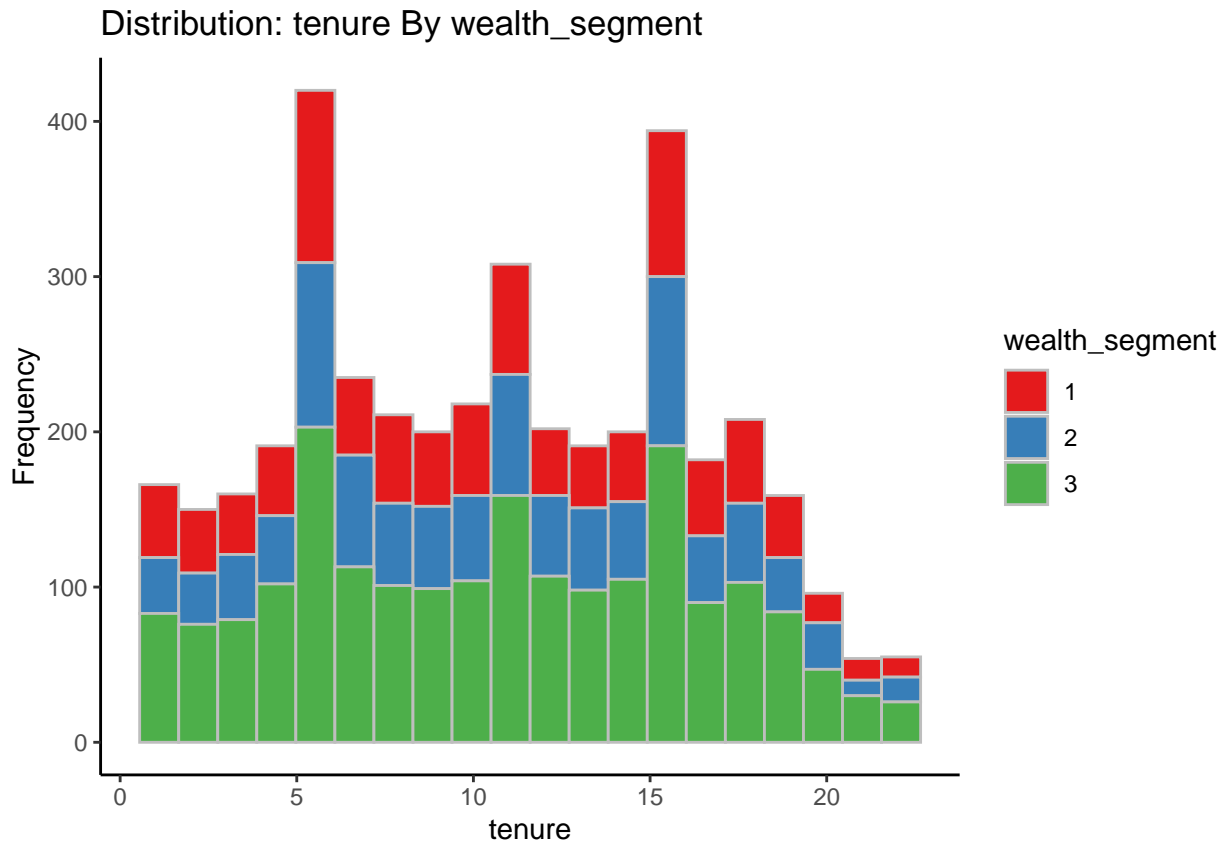


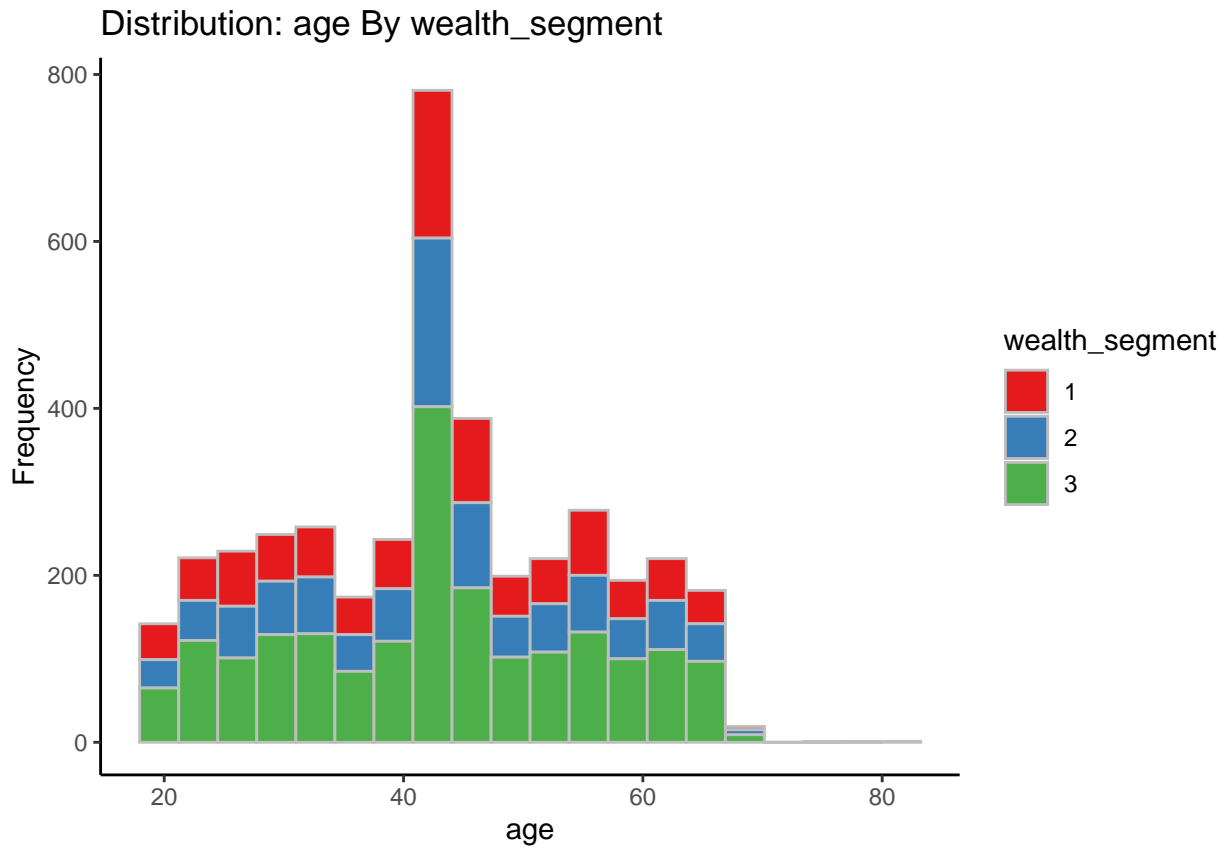


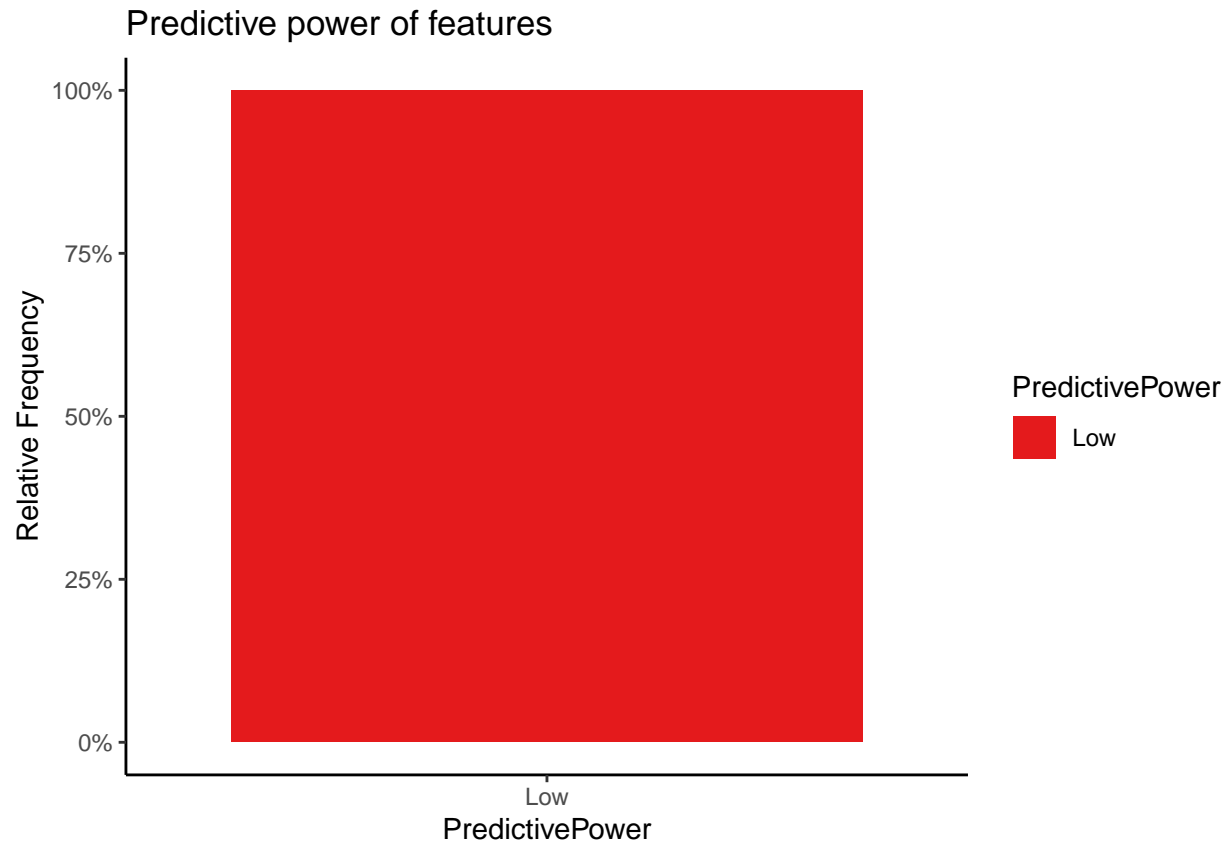












##	Feature	Observations	FeatureClass	FeatureType
## 1	age	4000	numeric	Continuous
## 2	customer_id	4000	numeric	Continuous
## 3	deceased_indicator	4000	character	Categorical
## 4	default	4000	character	Categorical
## 5	DOB	4000	Date	Continuous
## 6	first_name	4000	character	Categorical
## 7	gender	4000	character	Categorical
## 8	job_industry_category	4000	character	Categorical
## 9	job_title	4000	character	Categorical
## 10	last_name	4000	character	Categorical
## 11	owns_car	4000	character	Categorical
## 12	past_3_years_bike_related_purchases	4000	numeric	Continuous
## 13	tenure	4000	numeric	Continuous
## 14	wealth_segment	4000	character	Categorical
##	PercentageMissing	PercentageUnique	ConstantFeature	ZeroSpreadFeature
## 1	2.20	1.40	No	No
## 2	0.00	100.00	No	No
## 3	0.00	0.05	No	No
## 4	0.00	2.55	No	No
## 5	2.20	86.20	No	No
## 6	0.00	78.47	No	No
## 7	0.00	0.08	No	No
## 8	0.00	0.25	No	No
## 9	0.00	4.90	No	No
## 10	0.00	93.15	No	No

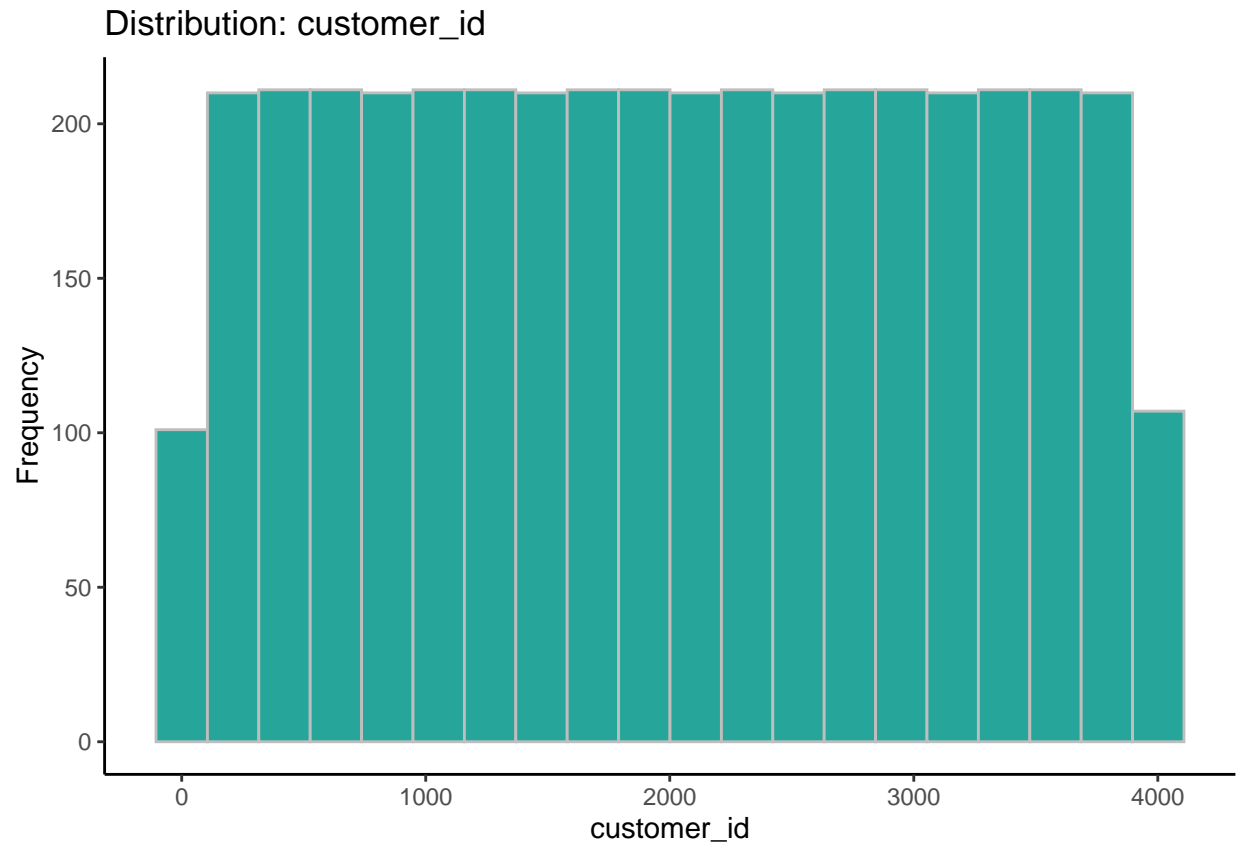
```

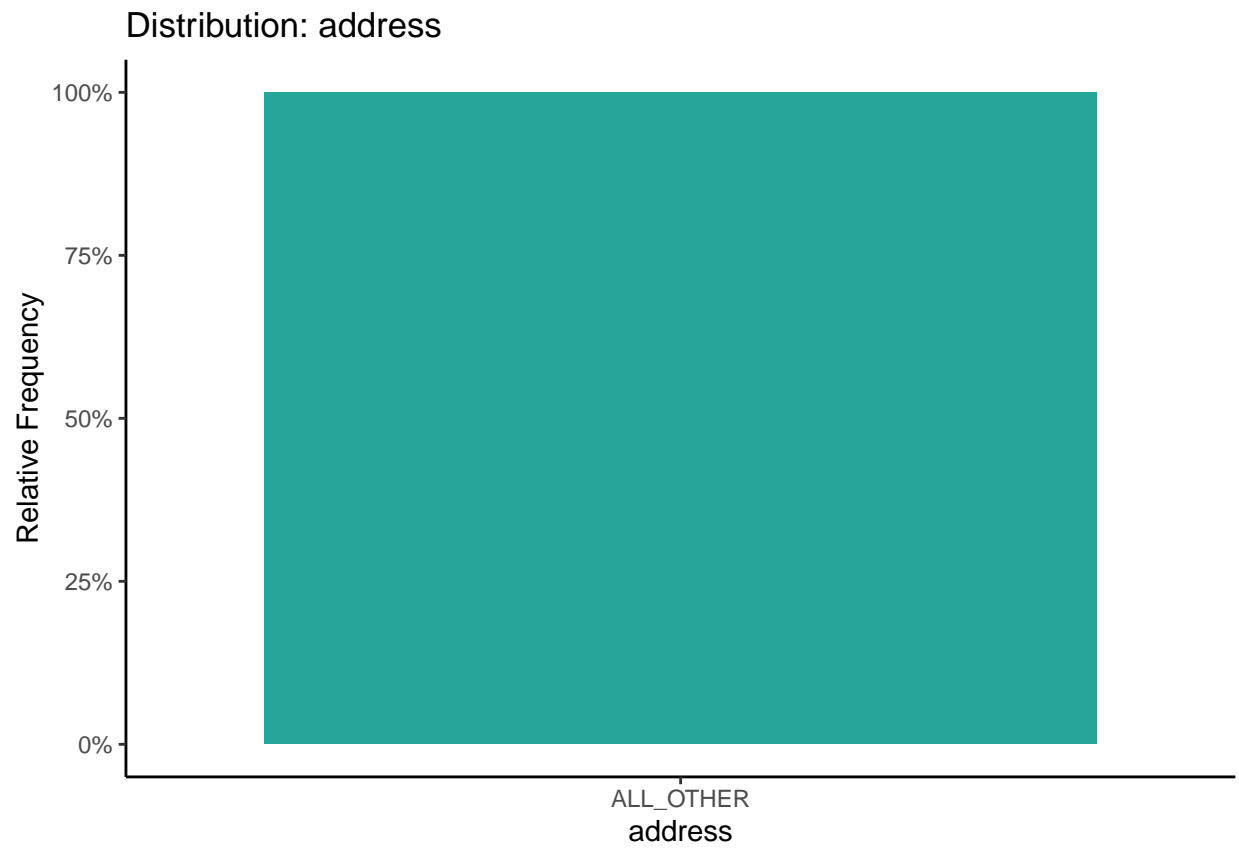
## 11          0.00          0.05          No          No
## 12          0.00          2.50          No          No
## 13          2.17          0.58          No          No
## 14          0.00          0.08          No          No
## LowerOutliers UpperOutliers ImputationValue MinValue FirstQuartile Median
## 1           0           2           43           18           33.00  43.0
## 2           0           0          2000.5           1          1000.75 2000.5
## 3           0           0           N           0           0.00   0.0
## 4           0           0          ALL_OTHER           0           0.00   0.0
## 5           0           0           0           0           0.00   0.0
## 6           0           0          ALL_OTHER           0           0.00   0.0
## 7           0           0          FEMALE           0           0.00   0.0
## 8           0           0      MANUFACTURING           0           0.00   0.0
## 9           0           0          ALL_OTHER           0           0.00   0.0
## 10          0           0          ALL_OTHER           0           0.00   0.0
## 11          0           0           YES           0           0.00   0.0
## 12          0           0           48           0           24.00  48.0
## 13          0           0           11           1           6.00  11.0
## 14          0           0      MASS CUSTOMER           0           0.00   0.0
## Mean          Mode ThirdQuartile MaxValue LowerOutlierValue
## 1      42.94          42          52.00          89           4.5
## 2 2000.50           1      3000.25      4000          -1998.5
## 3      0.00           N           0.00           0           0.0
## 4      0.00           0           0.00           0           0.0
## 5      0.00      1978-01-30          0.00           0           0.0
## 6      0.00          MAX           0.00           0           0.0
## 7      0.00          FEMALE           0.00           0           0.0
## 8      0.00      MANUFACTURING           0.00           0           0.0
## 9      0.00           0           0.00           0           0.0
## 10     0.00           0           0.00           0           0.0
## 11     0.00          YES           0.00           0           0.0
## 12     48.89          16          73.00          99          -49.5
## 13     10.66           7          15.00          22          -7.5
## 14     0.00      MASS CUSTOMER           0.00           0           0.0
## UpperOutlierValue PredictivePowerPercentage PredictivePower
## 1           80.5           1           Low
## 2          5999.5           4           Low
## 3           0.0           0           Low
## 4           0.0           0           Low
## 5           0.0           0           Low
## 6           0.0           0           Low
## 7           0.0           2           Low
## 8           0.0           2           Low
## 9           0.0           0           Low
## 10          0.0           1           Low
## 11          0.0           1           Low
## 12          146.5           5           Low
## 13          28.5           2           Low
## 14           0.0           0           Low

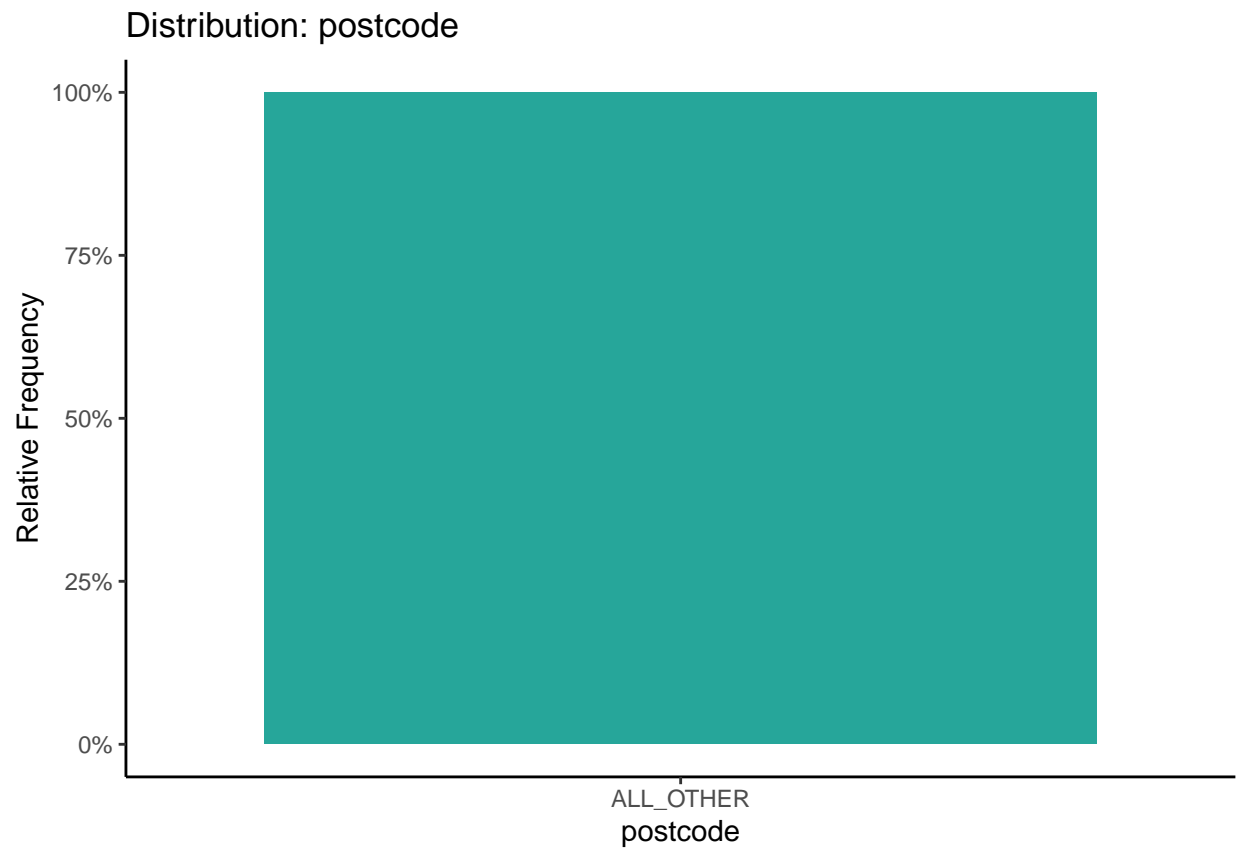
## autoEDA | Setting color theme
## autoEDA | Removing constant features
## autoEDA | 1 constant feature removed
## autoEDA | 0 zero spread features removed

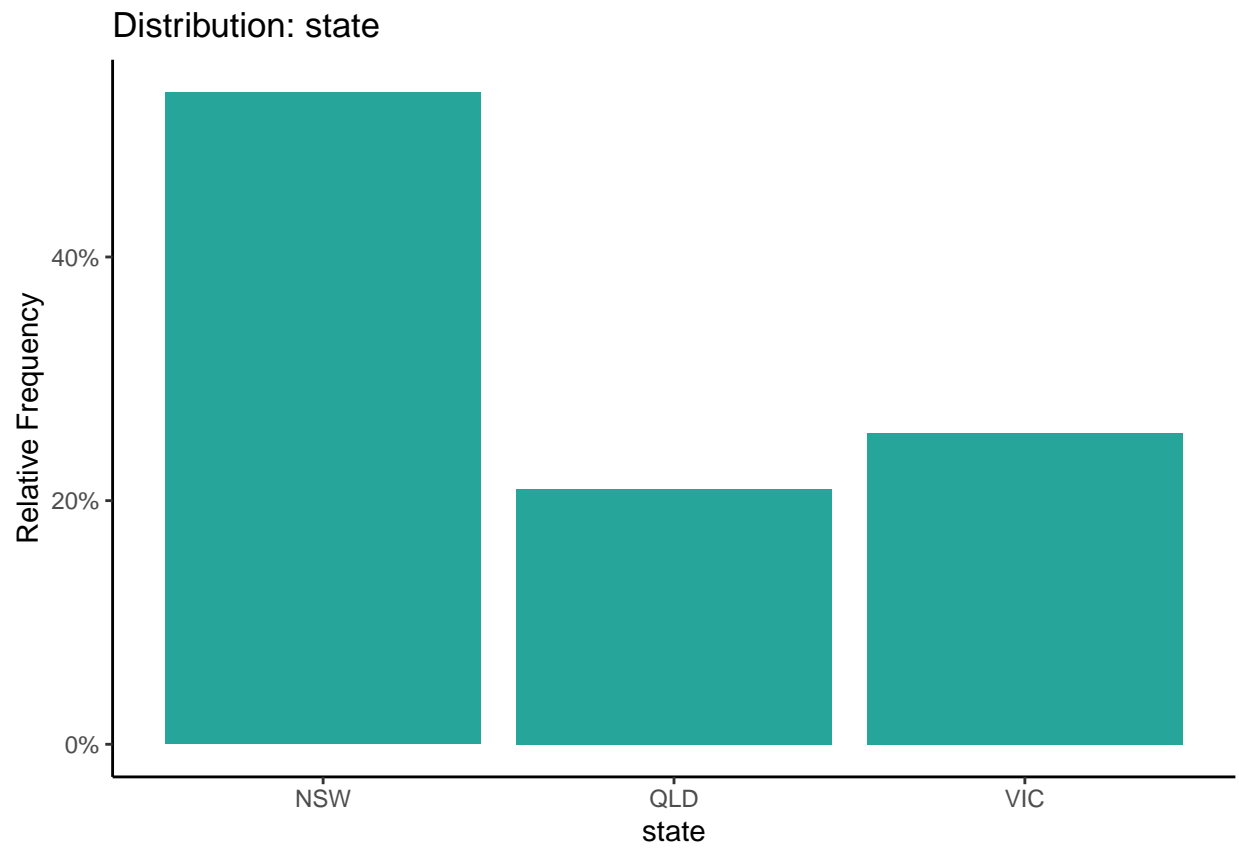
```

```
## autoEDA | Removing features containing majority missing values
## autoEDA | 0 majority missing features removed
## autoEDA | Cleaning data
## autoEDA | Correcting sparse categorical feature levels
## autoEDA | Performing univariate analysis
## autoEDA | Visualizing data
```

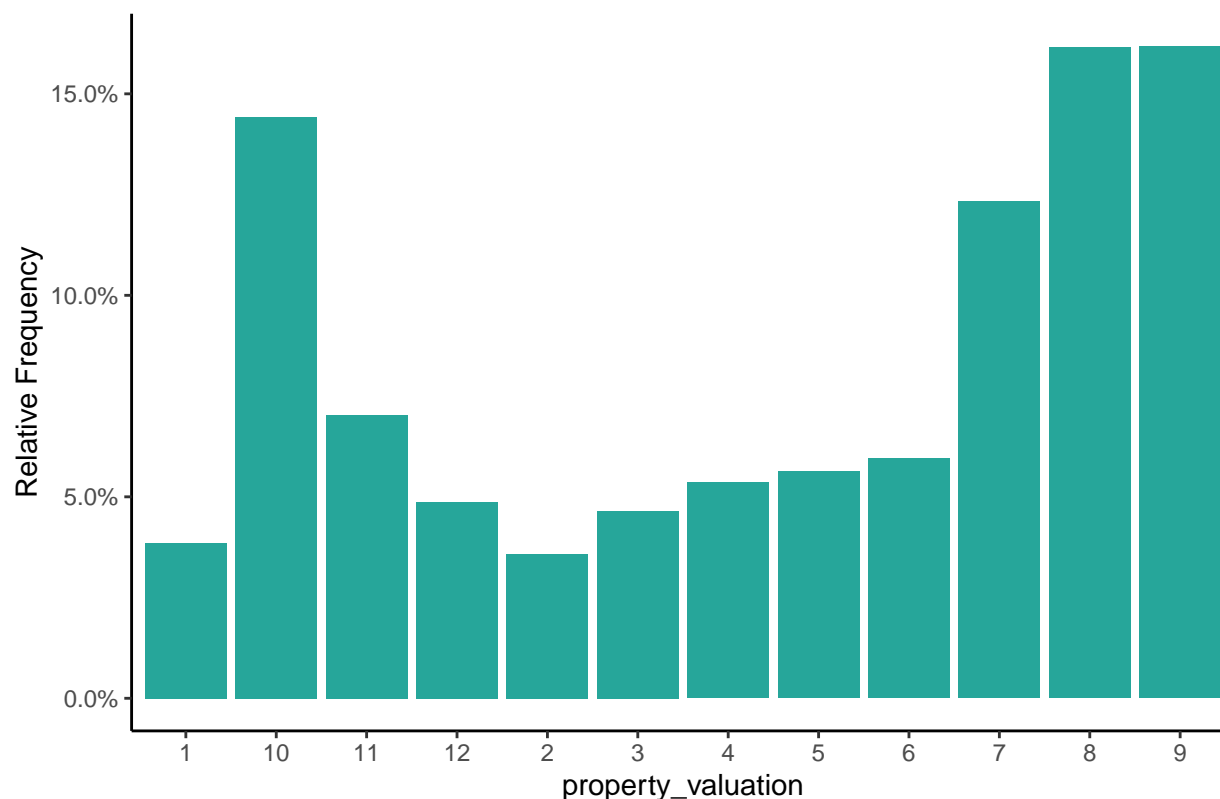








Distribution: property_valuation



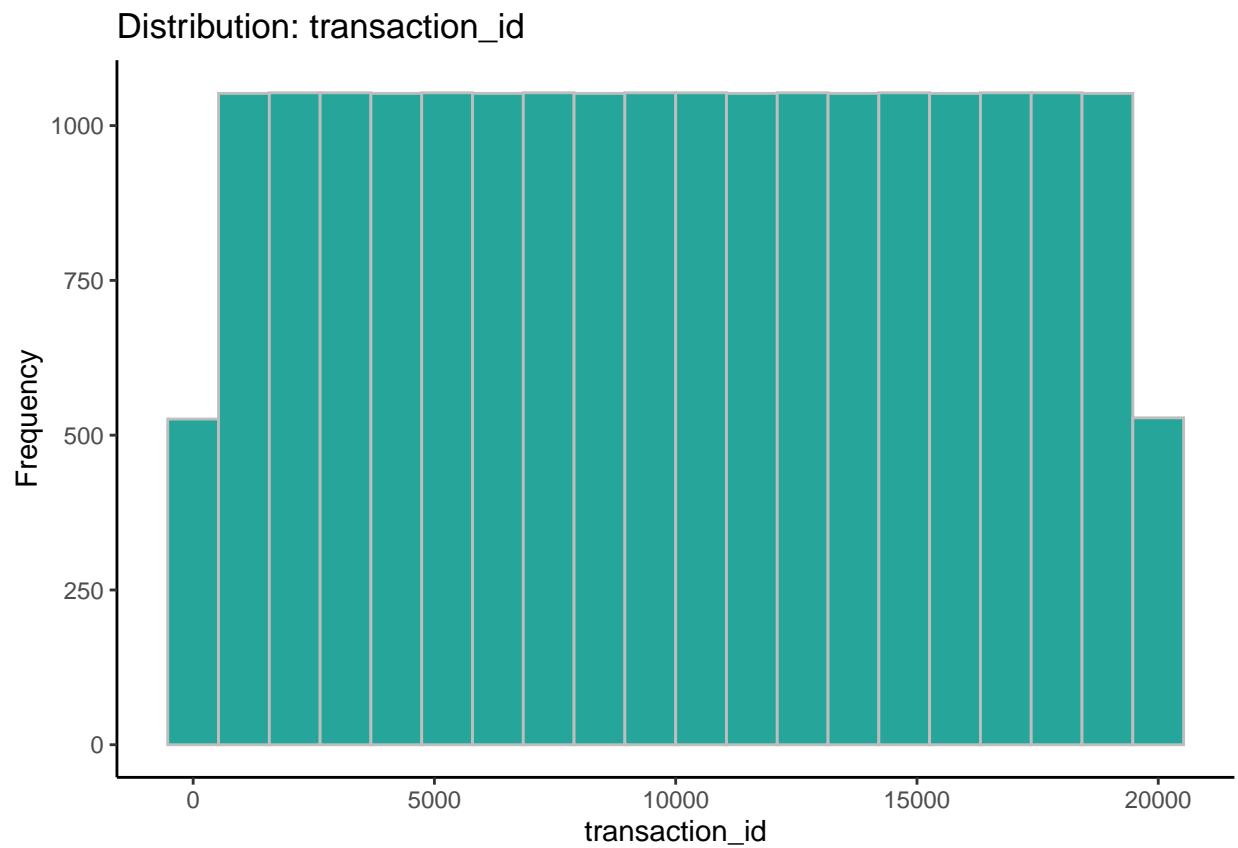
```
##           Feature Observations FeatureClass FeatureType PercentageMissing
## 1      customer_id      3999      numeric Continuous              0
## 2         address      3999    character Categorical              0
## 3        postcode      3999    character Categorical              0
## 4          state      3999    character Categorical              0
## 5 property_valuation      3999    character Categorical              0
## PercentageUnique ConstantFeature ZeroSpreadFeature LowerOutliers
## 1          100.00              No              No              0
## 2           99.92              No              No              0
## 3           21.83              No              No              0
## 4            0.08              No              No              0
## 5            0.30              No              No              0
## UpperOutliers ImputationValue MinValue FirstQuartile Median      Mean
## 1            0          2004          1      1004.5    2004 2003.99
## 2            0      ALL_OTHER          0          0.0      0    0.00
## 3            0      ALL_OTHER          0          0.0      0    0.00
## 4            0          NSW          0          0.0      0    0.00
## 5            0            9          0          0.0      0    0.00
##           Mode ThirdQuartile MaxValue LowerOutlierValue
## 1            1      3003.5      4003          -1994
## 2 3 MARINERS COVE TERRACE          0.0          0          0
## 3          2170          0.0          0          0
## 4          NSW          0.0          0          0
## 5            9          0.0          0          0
## UpperOutlierValue
## 1          6002
```

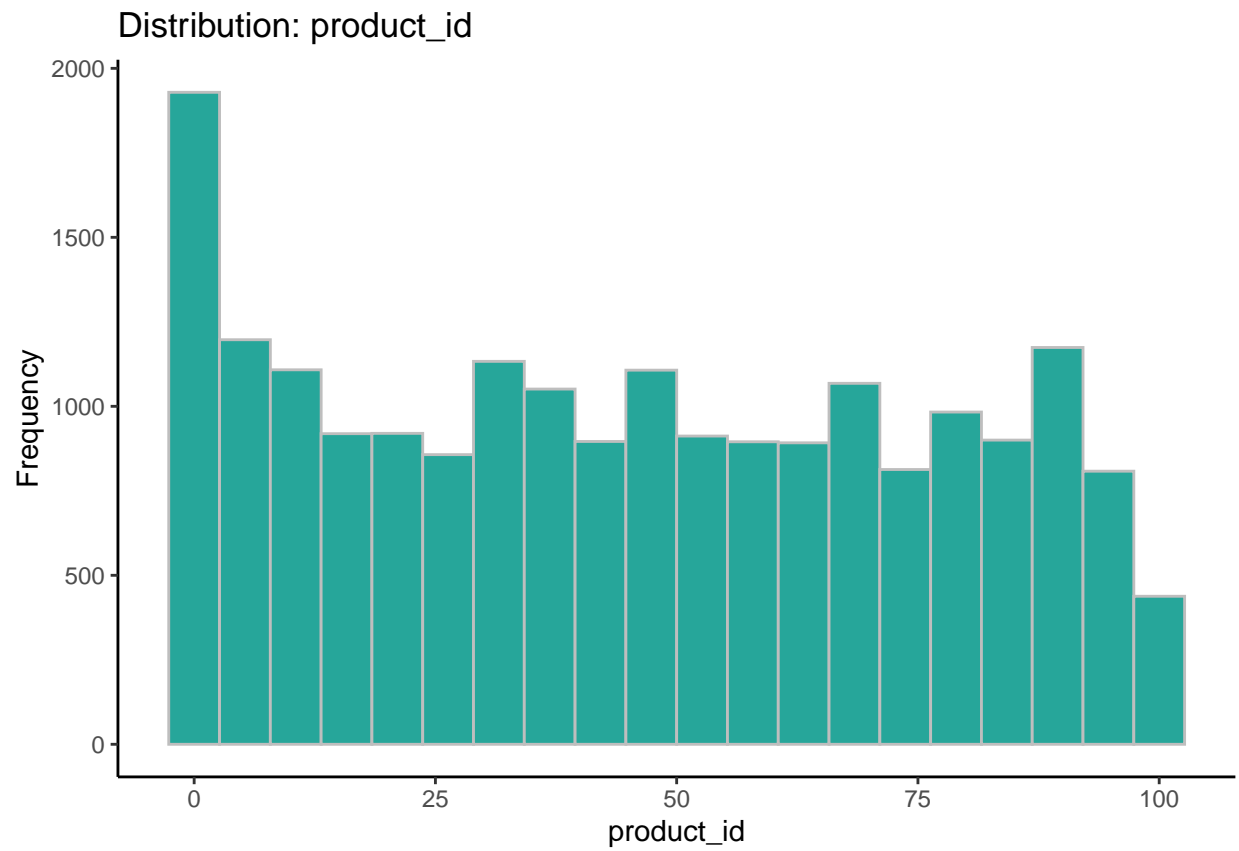
```

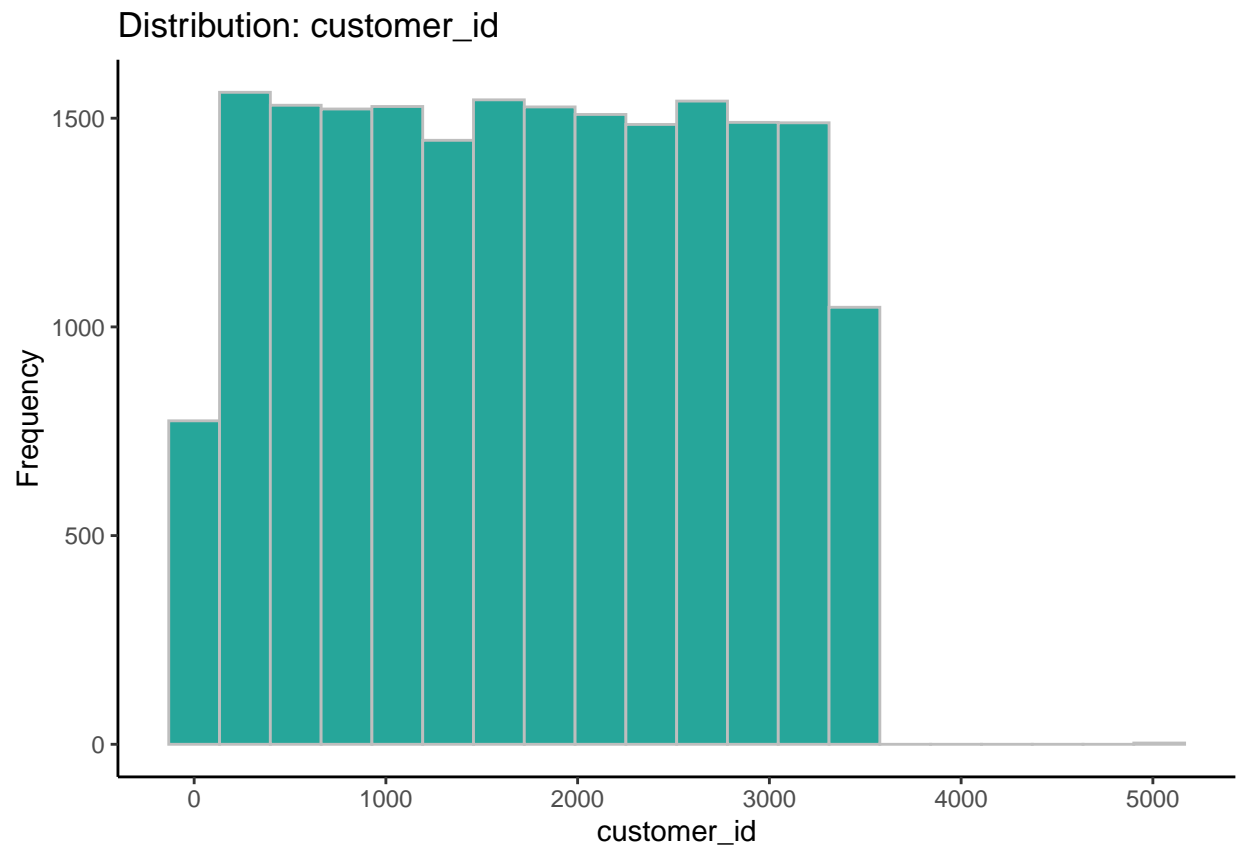
## 2          0
## 3          0
## 4          0
## 5          0

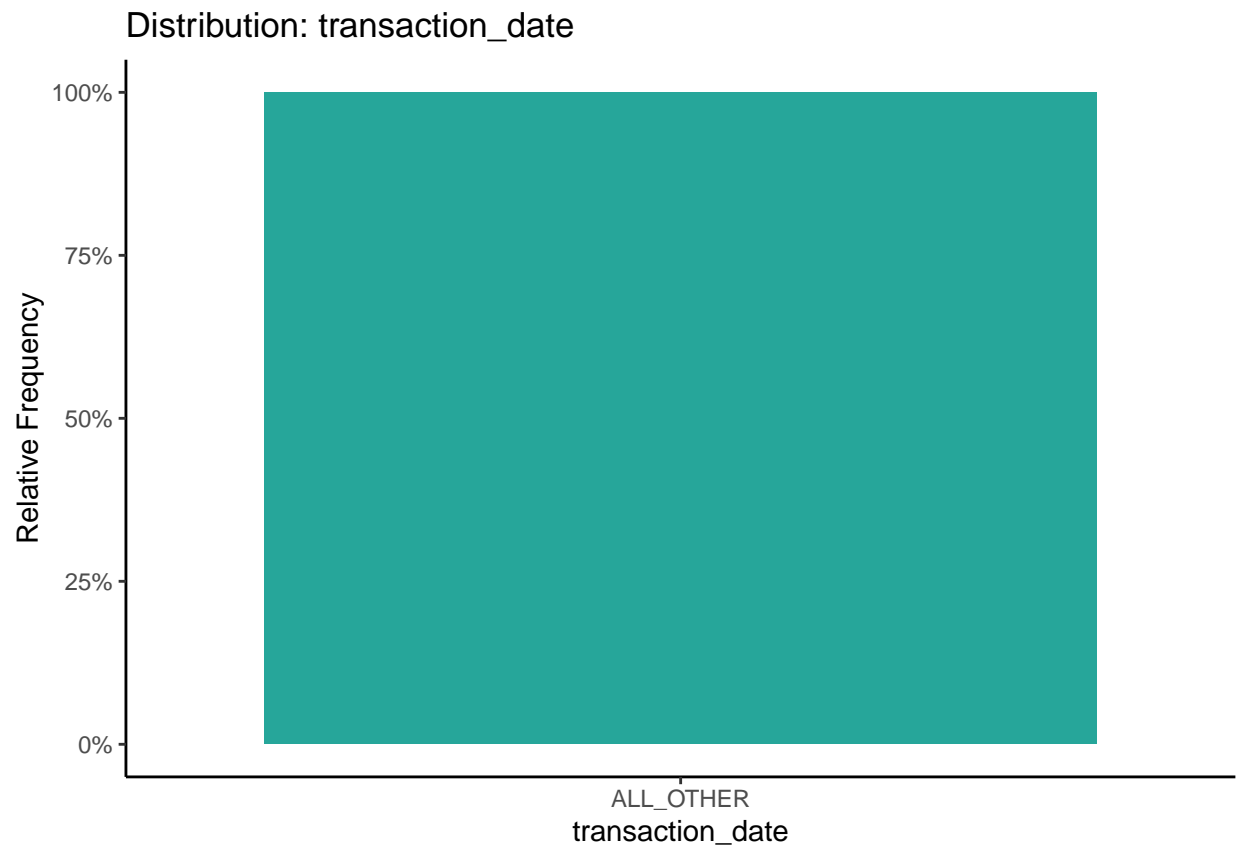
## autoEDA | Setting color theme
## autoEDA | Removing constant features
## autoEDA | 0 constant features removed
## autoEDA | 0 zero spread features removed
## autoEDA | Removing features containing majority missing values
## autoEDA | 0 majority missing features removed
## autoEDA | Cleaning data
## autoEDA | Correcting sparse categorical feature levels
## autoEDA | Performing univariate analysis
## autoEDA | Visualizing data

```

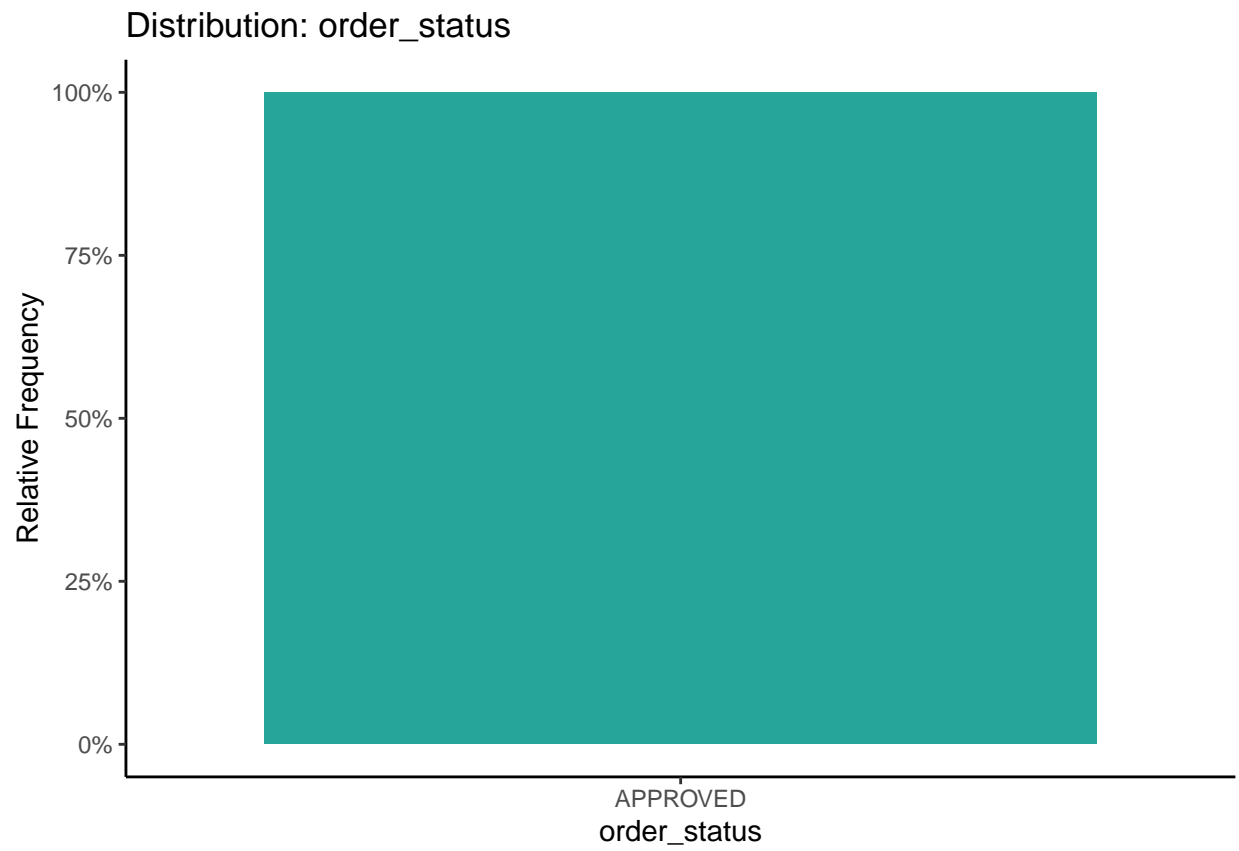


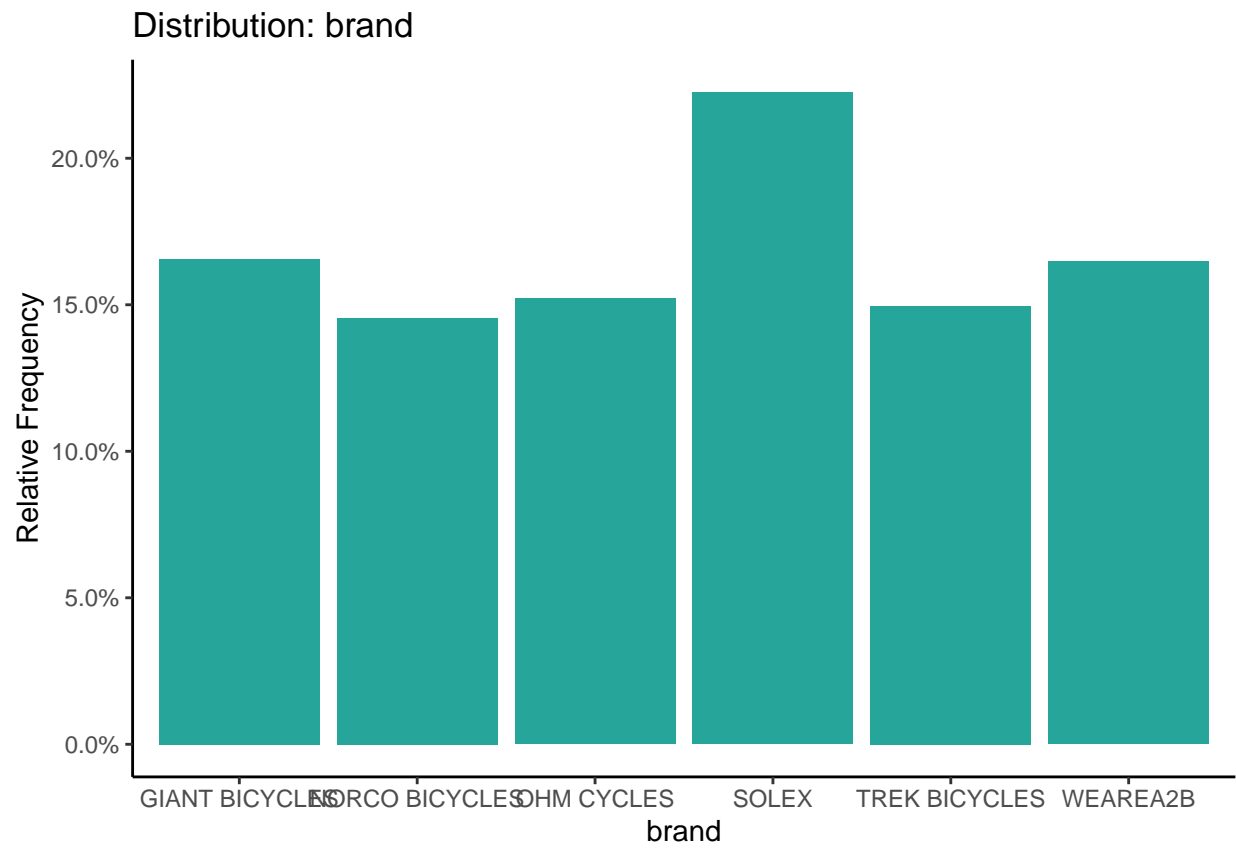


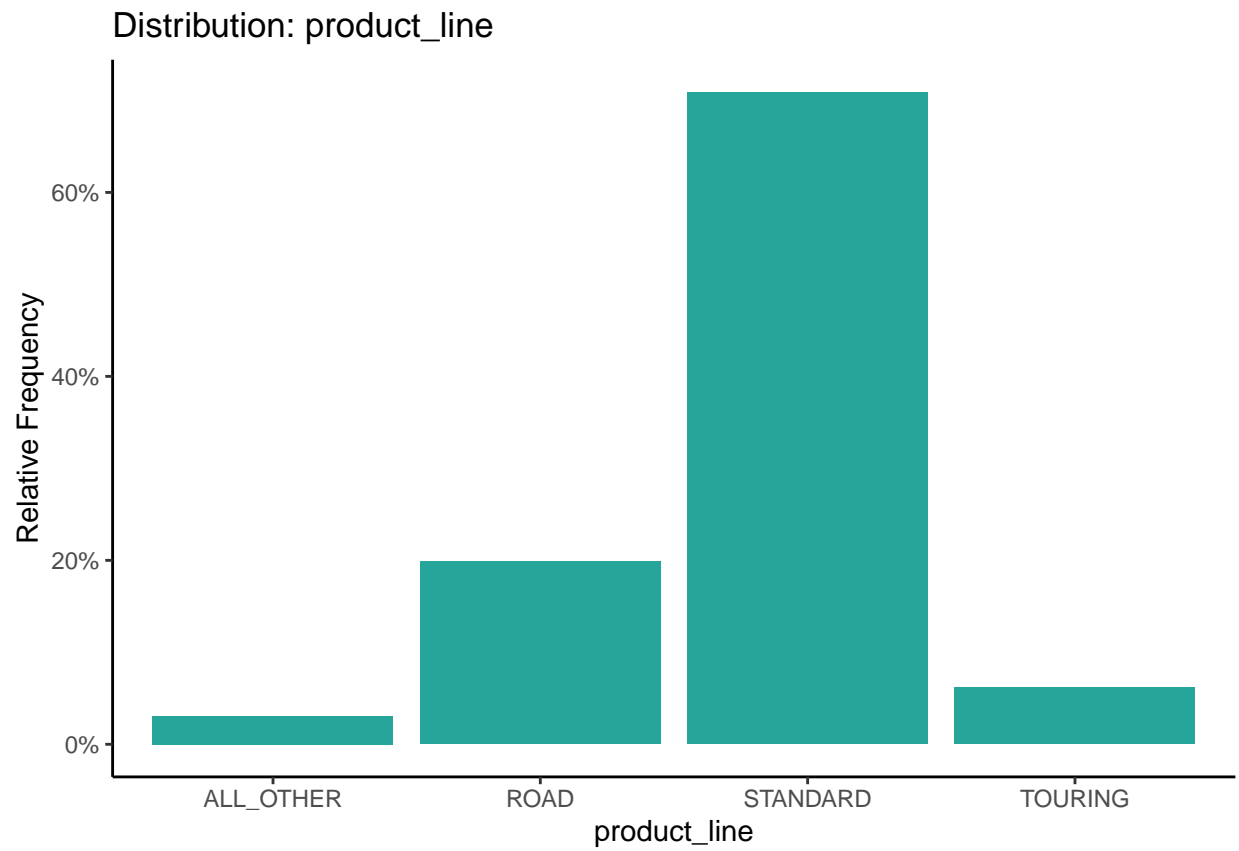


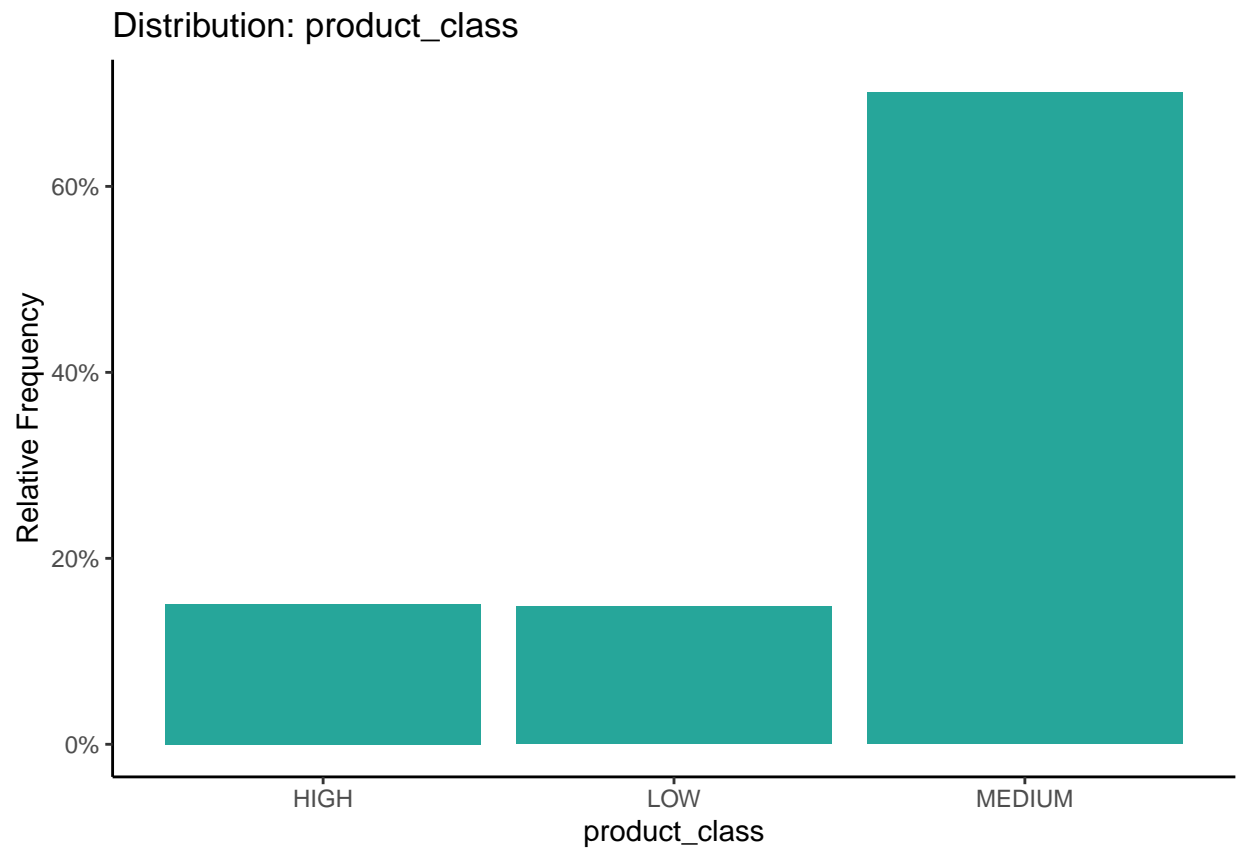


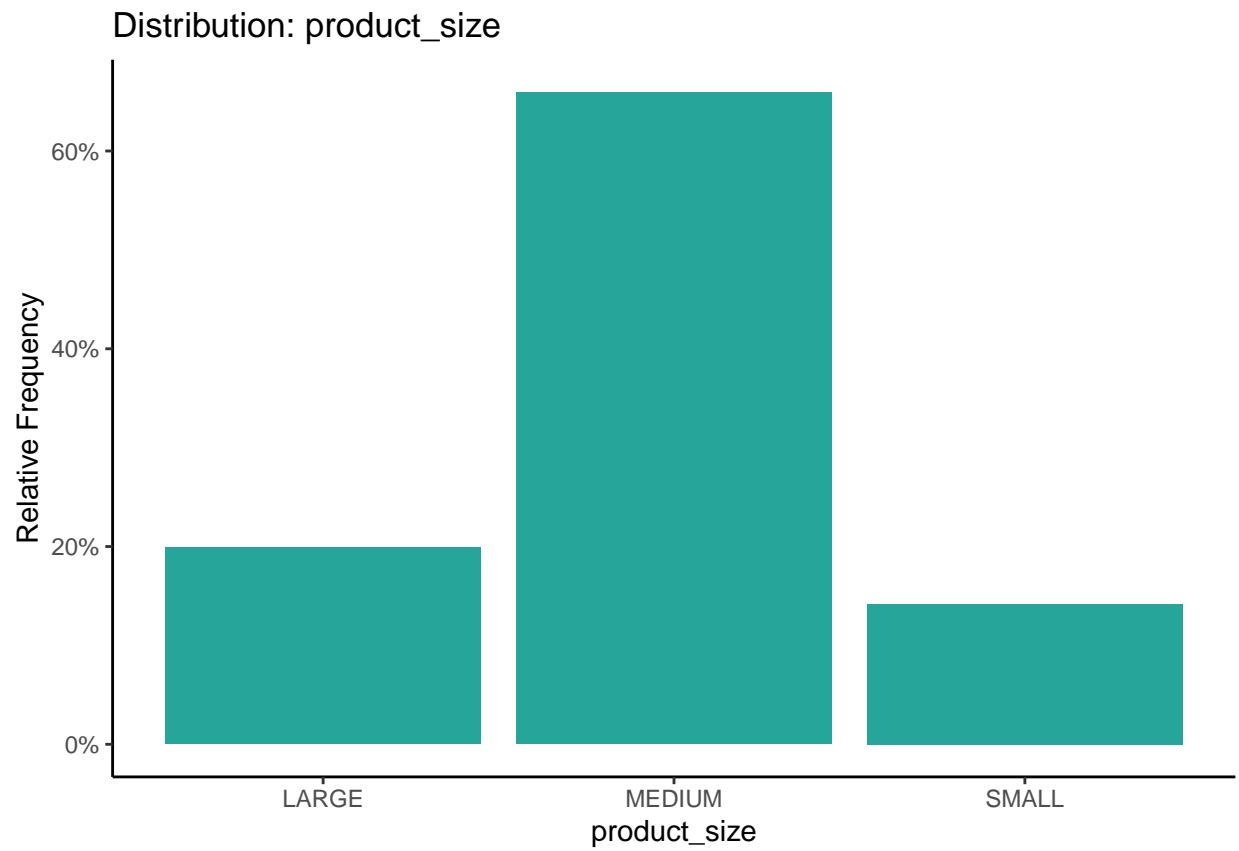


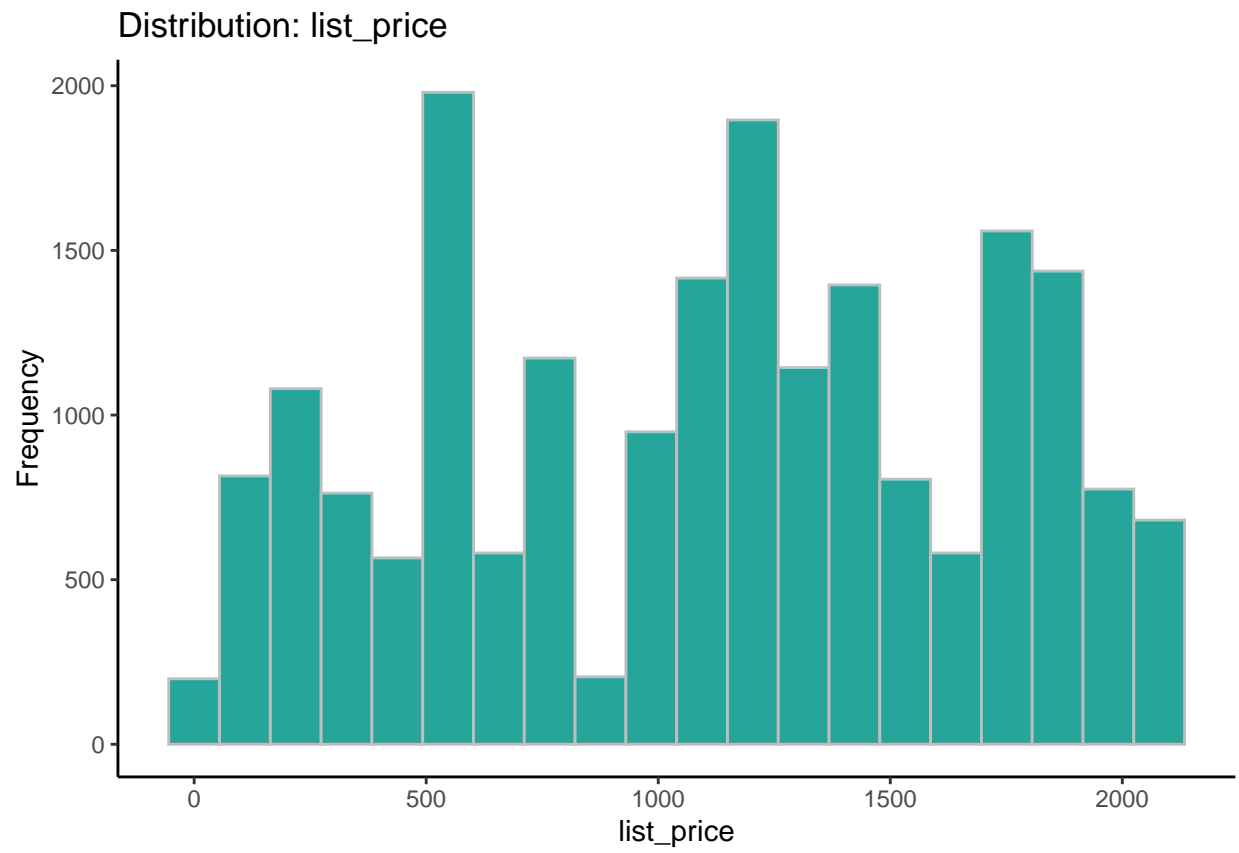


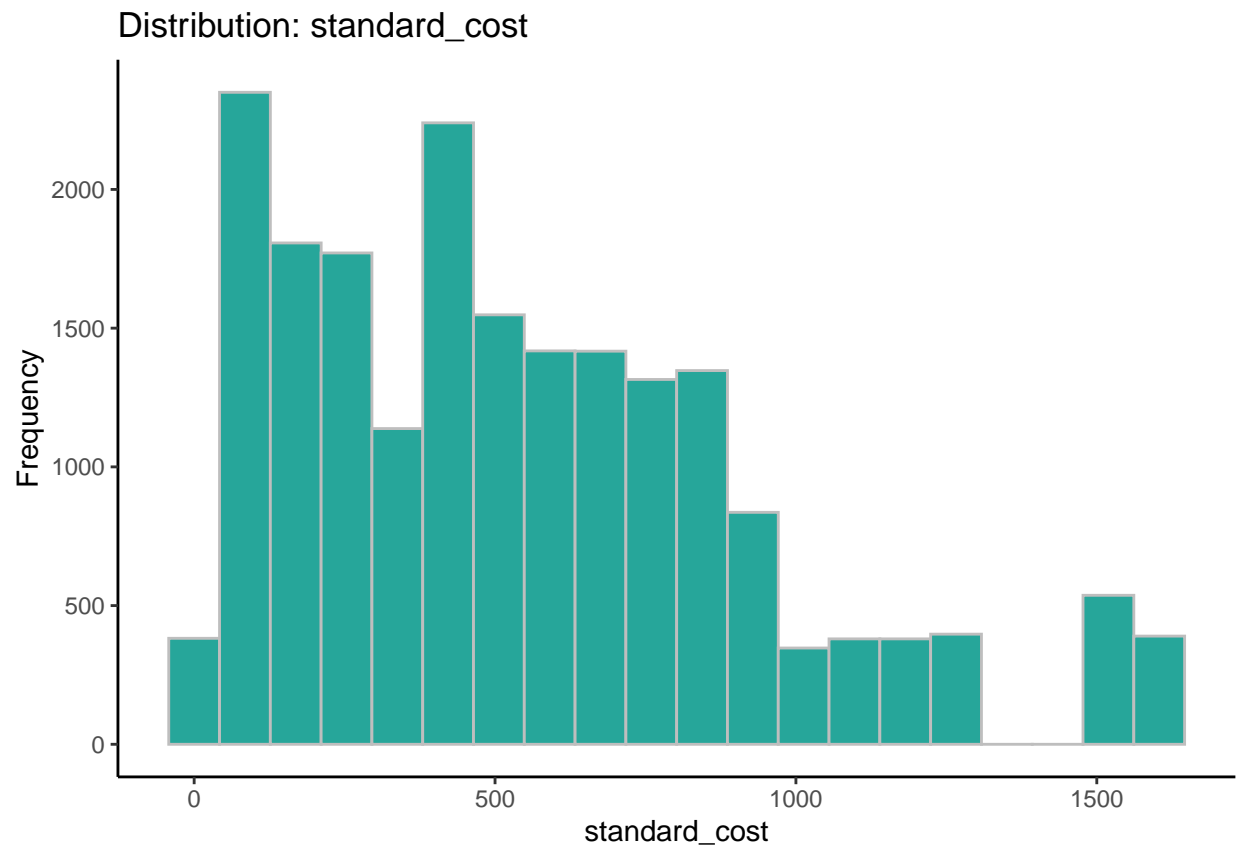




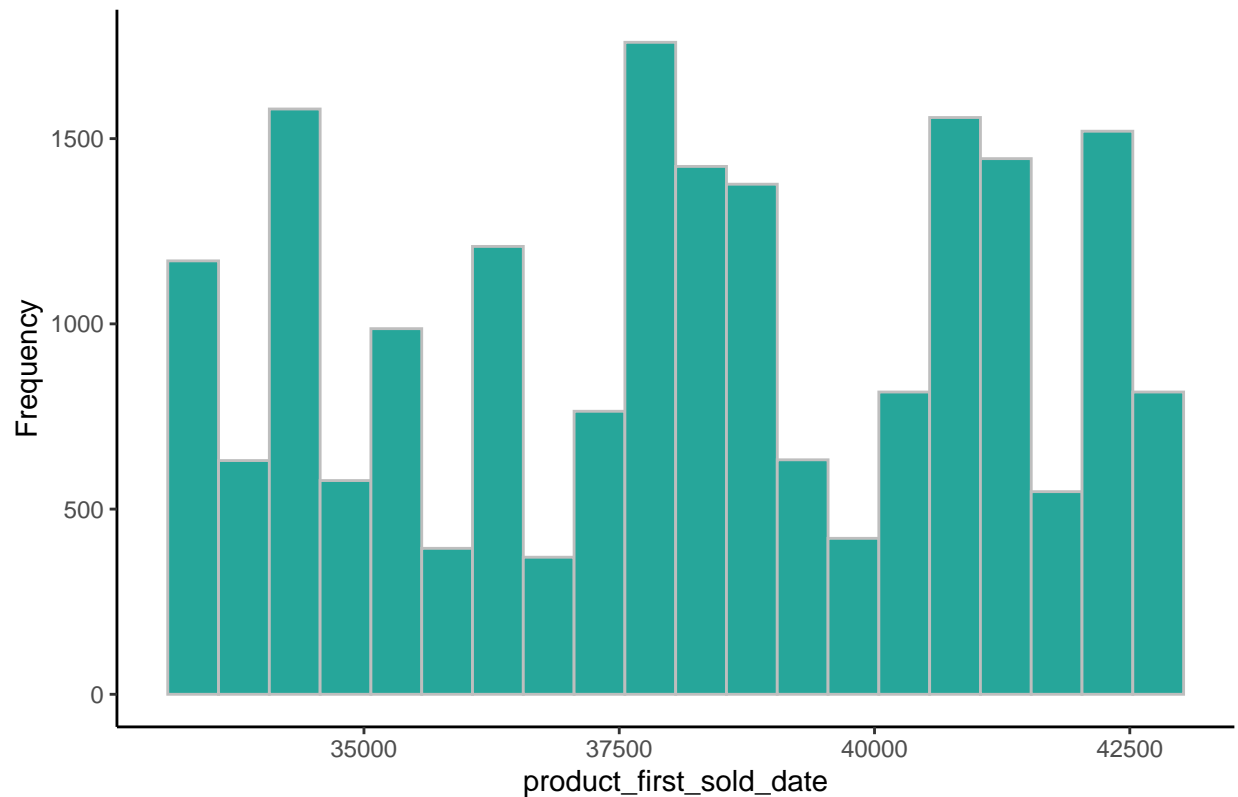








Distribution: product_first_sold_date



##	Feature	Observations	FeatureClass	FeatureType
## 1	transaction_id	20000	numeric	Continuous
## 2	product_id	20000	numeric	Continuous
## 3	customer_id	20000	numeric	Continuous
## 4	transaction_date	20000	character	Categorical
## 5	online_order	20000	character	Categorical
## 6	order_status	20000	character	Categorical
## 7	brand	20000	character	Categorical
## 8	product_line	20000	character	Categorical
## 9	product_class	20000	character	Categorical
## 10	product_size	20000	character	Categorical
## 11	list_price	20000	numeric	Continuous
## 12	standard_cost	20000	numeric	Continuous
## 13	product_first_sold_date	20000	numeric	Continuous
##	PercentageMissing	PercentageUnique	ConstantFeature	ZeroSpreadFeature
## 1	0.00	100.00	No	No
## 2	0.00	0.50	No	No
## 3	0.00	17.47	No	No
## 4	0.00	1.82	No	No
## 5	1.80	0.01	No	No
## 6	0.00	0.01	No	No
## 7	0.00	0.04	No	No
## 8	0.00	0.03	No	No
## 9	0.00	0.02	No	No
## 10	0.00	0.02	No	No
## 11	0.00	1.48	No	No

```

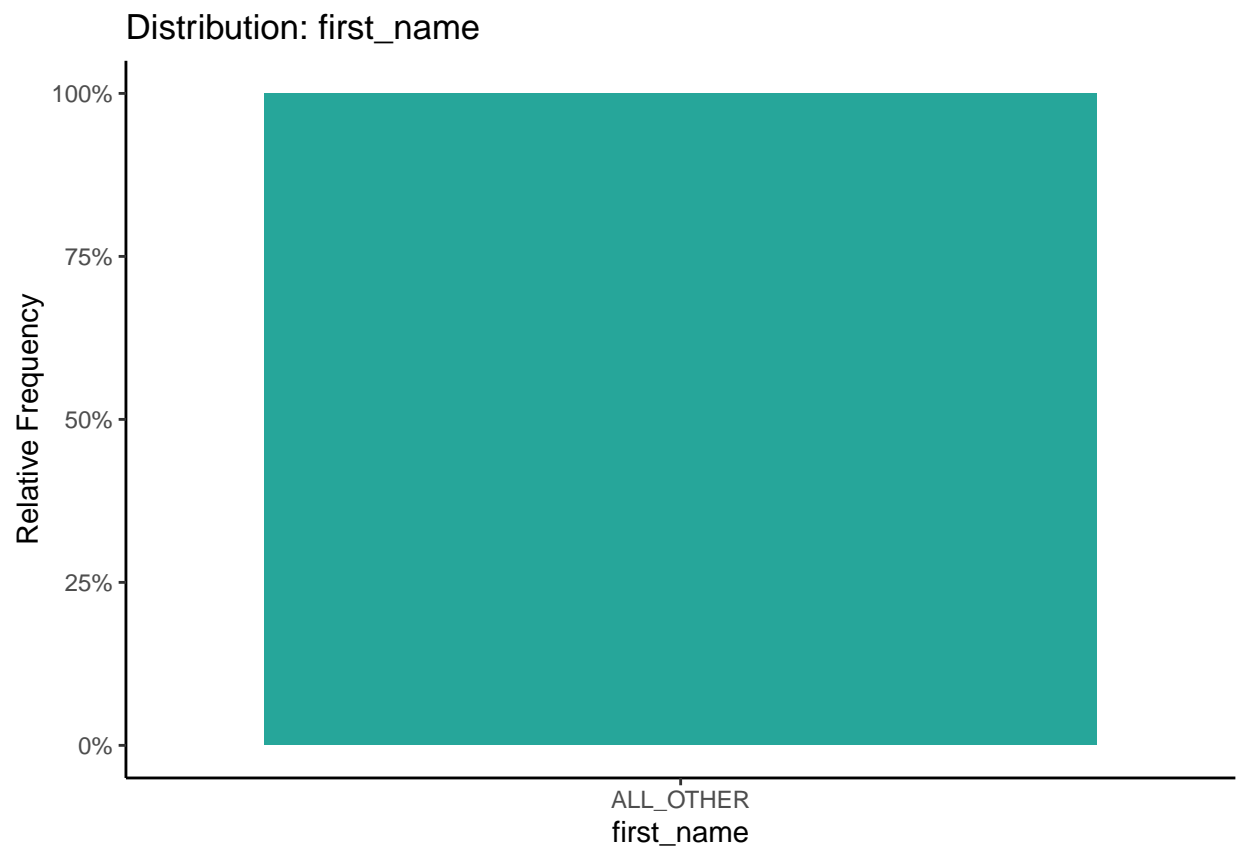
## 12          0.98          0.52          No          No
## 13          0.98          0.50          No          No
## LowerOutliers UpperOutliers ImputationValue MinValue FirstQuartile Median
## 1          0          0          10000.5          1.00          5000.75 10000.50
## 2          0          0           44          0.00          18.00   44.00
## 3          0          0          1736          1.00          857.75 1736.00
## 4          0          0          ALL_OTHER          0.00          0.00   0.00
## 5          0          0          MISSING          0.00          0.00   0.00
## 6          0          0          APPROVED          0.00          0.00   0.00
## 7          0          0          SOLEX          0.00          0.00   0.00
## 8          0          0          ALL_OTHER          0.00          0.00   0.00
## 9          0          0          MEDIUM          0.00          0.00   0.00
## 10         0          0          MEDIUM          0.00          0.00   0.00
## 11         0          0          1163.89          12.01          575.27 1163.89
## 12         0          195          507.58          7.21          215.14 507.58
## 13         0          0          38216 33259.00          35667.00 38216.00
## Mean          Mode ThirdQuartile MaxValue LowerOutlierValue
## 1 10000.50          1          15000.25 20000.00          -9998.500
## 2   45.36          0           72.00   100.00          -63.000
## 3 1738.25        1068          2613.00 5034.00          -1775.125
## 4   0.00 2017-02-14           0.00   0.00           0.000
## 5   0.00      TRUE           0.00   0.00           0.000
## 6   0.00  APPROVED           0.00   0.00           0.000
## 7   0.00   SOLEX           0.00   0.00           0.000
## 8   0.00  STANDARD           0.00   0.00           0.000
## 9   0.00   MEDIUM           0.00   0.00           0.000
## 10  0.00   MEDIUM           0.00   0.00           0.000
## 11 1107.83      2091.47          1635.30 2091.47          -1014.775
## 12  556.05      388.92           795.10 1759.85          -654.800
## 13 38199.78      33879          40672.00 42710.00          28159.500
## UpperOutlierValue
## 1          29999.500
## 2           153.000
## 3          5245.875
## 4           0.000
## 5           0.000
## 6           0.000
## 7           0.000
## 8           0.000
## 9           0.000
## 10          0.000
## 11          3225.345
## 12          1665.040
## 13          48179.500

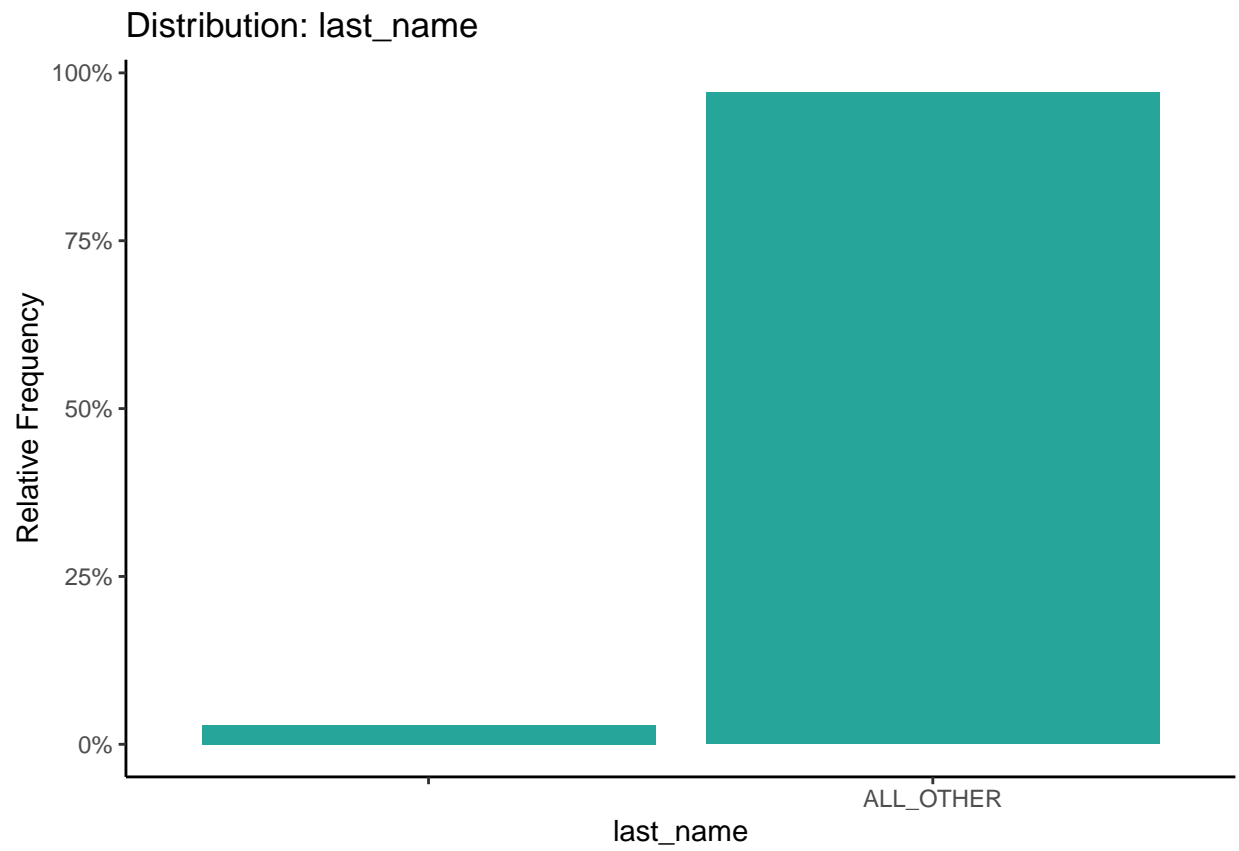
## autoEDA | Setting color theme
## autoEDA | Removing constant features
## autoEDA | 2 constant features removed
## autoEDA | 0 zero spread features removed
## autoEDA | Removing features containing majority missing values
## autoEDA | 0 majority missing features removed
## autoEDA | Cleaning data
## autoEDA | Correcting sparse categorical feature levels
## autoEDA | Performing univariate analysis

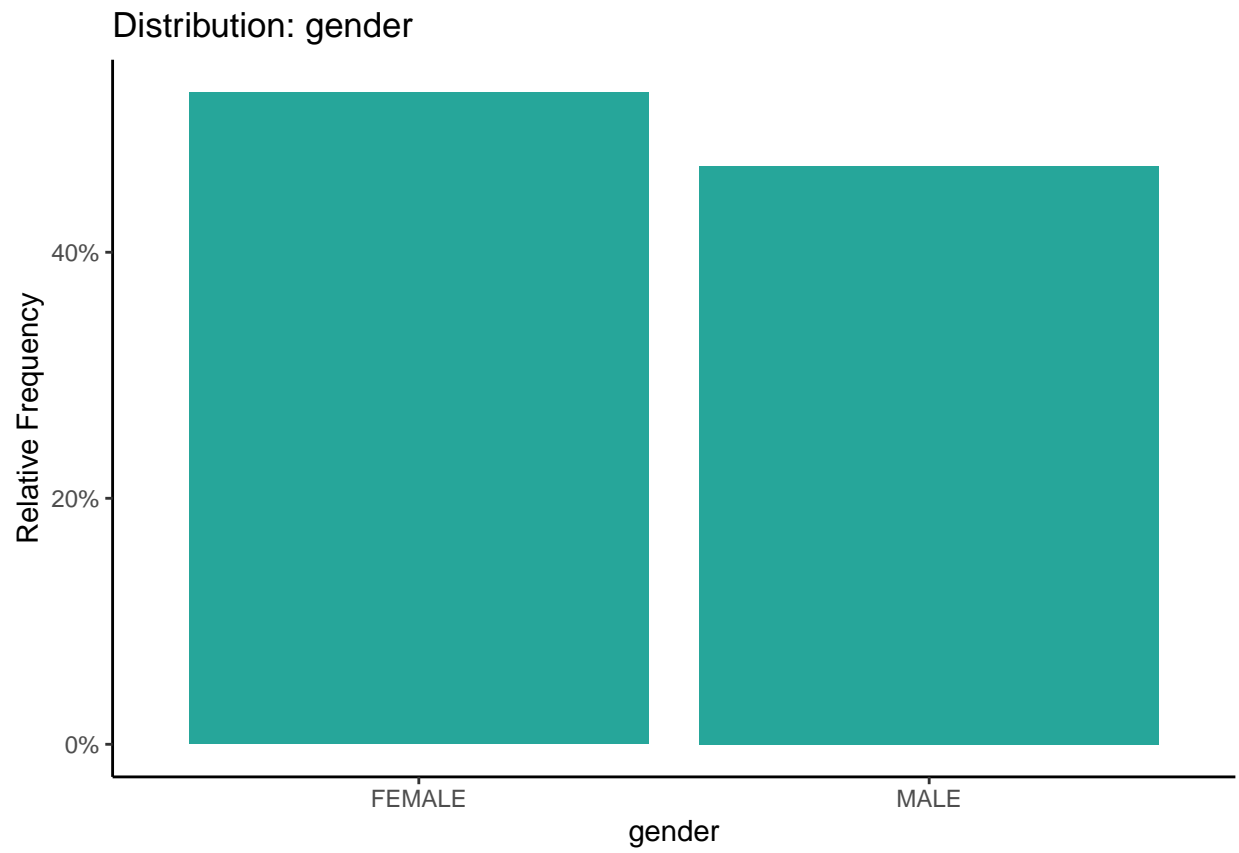
```

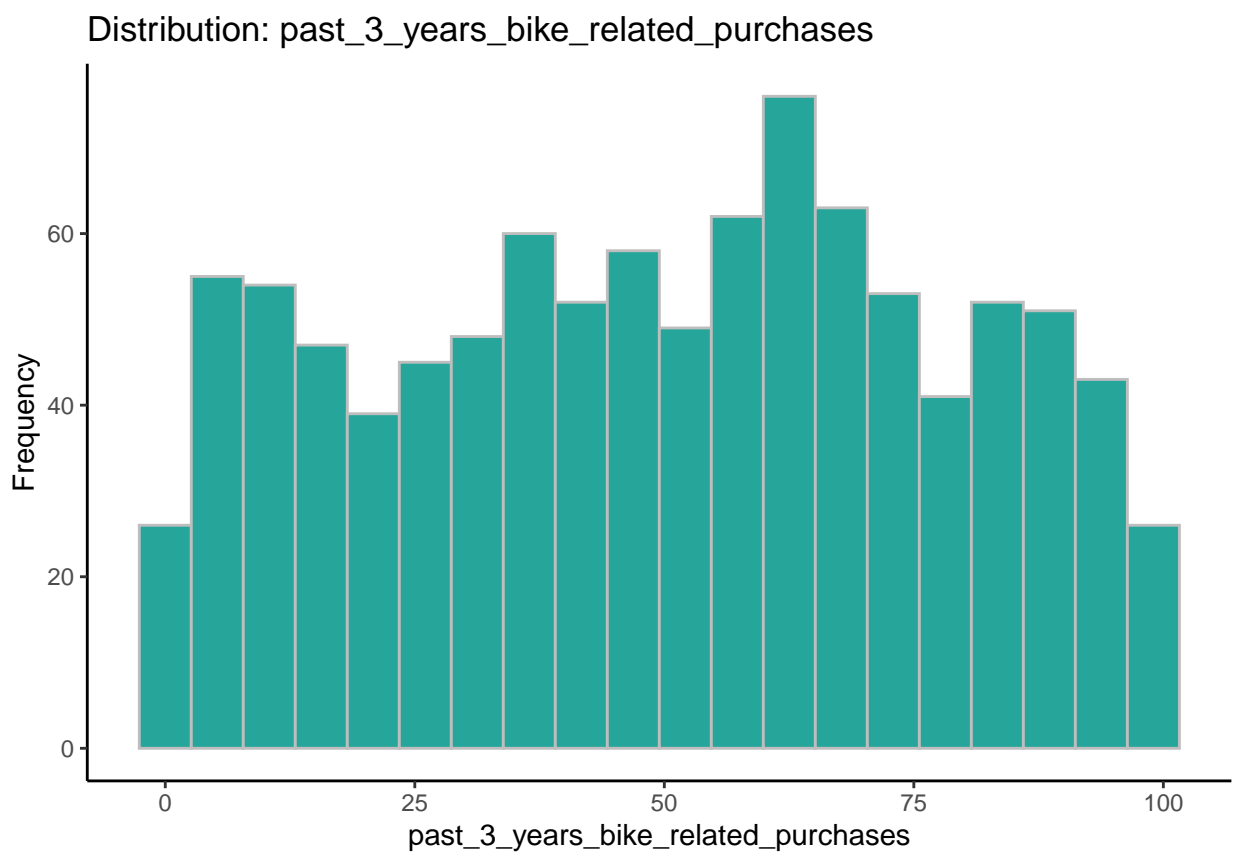


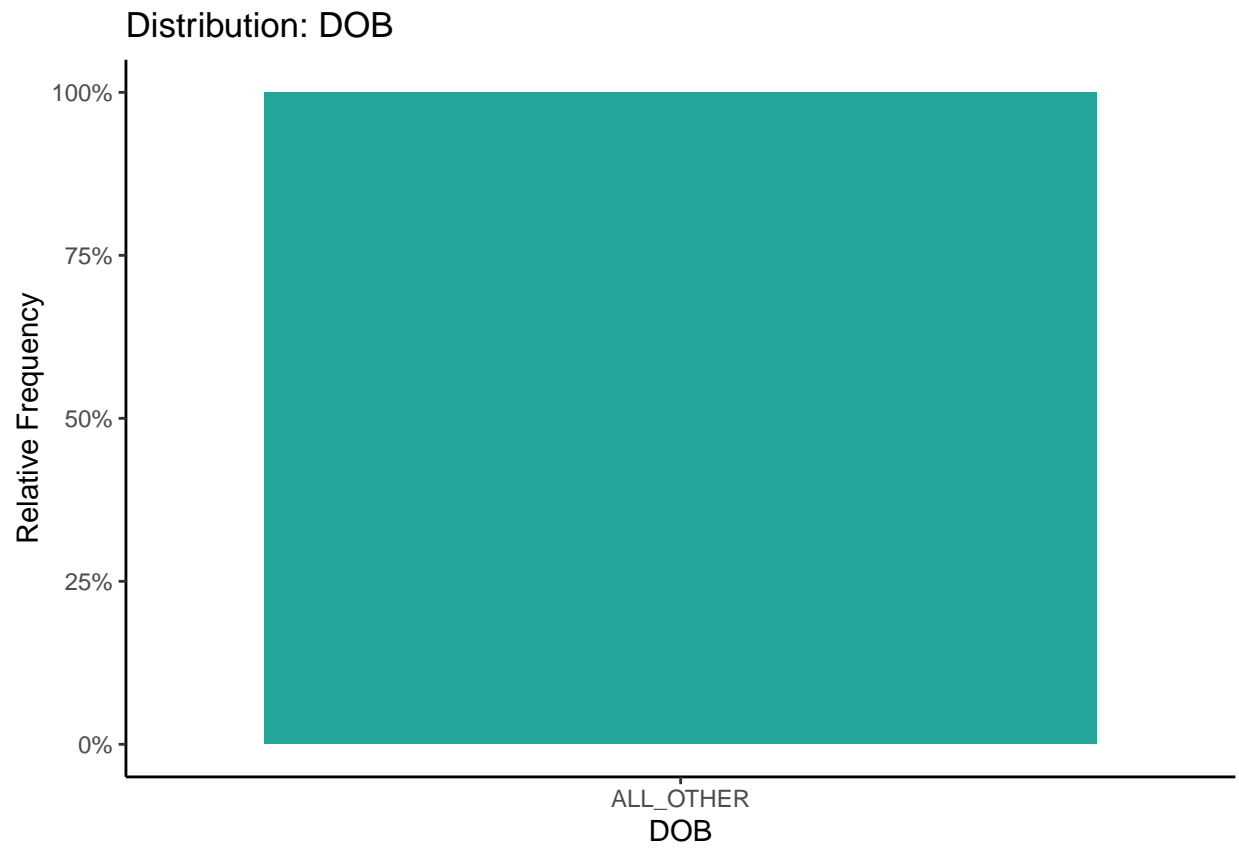
```
## autoEDA | Visualizing data
```

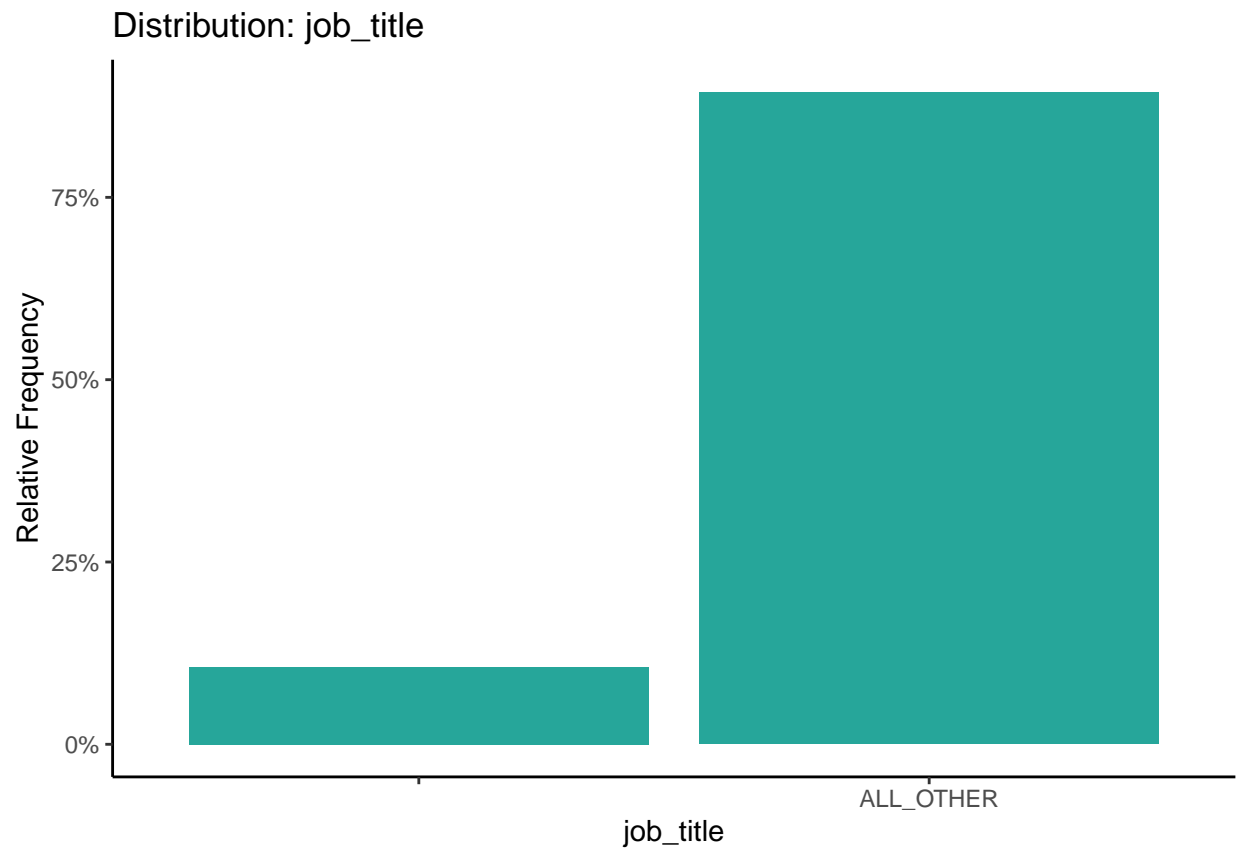


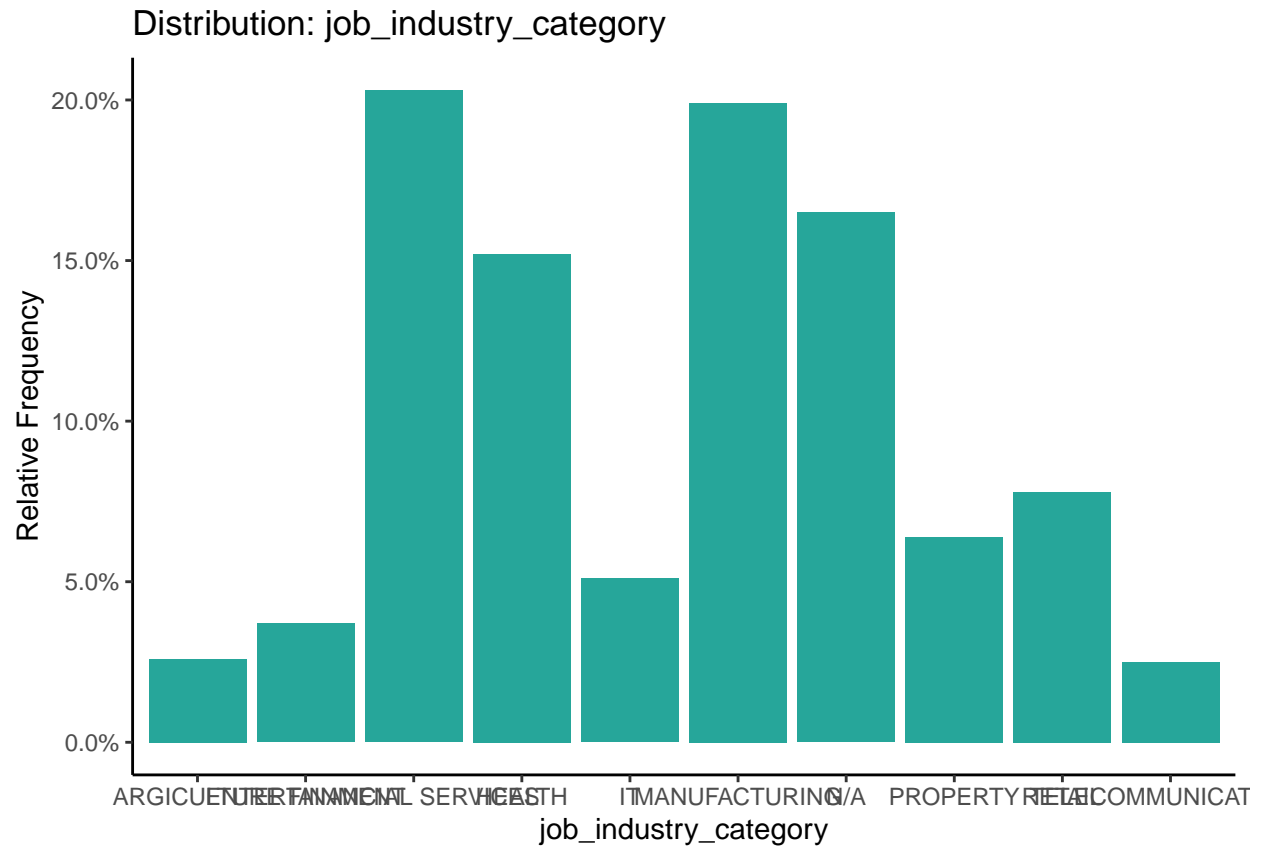


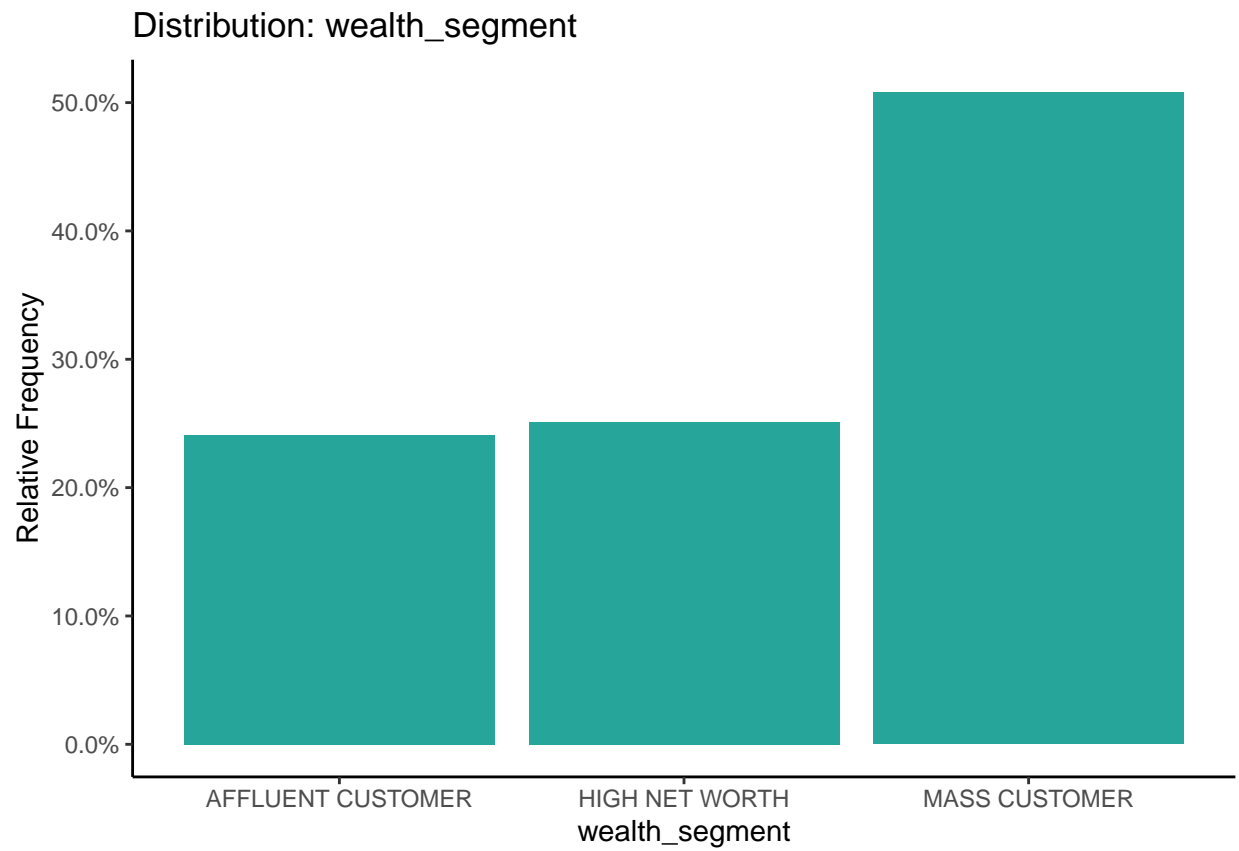


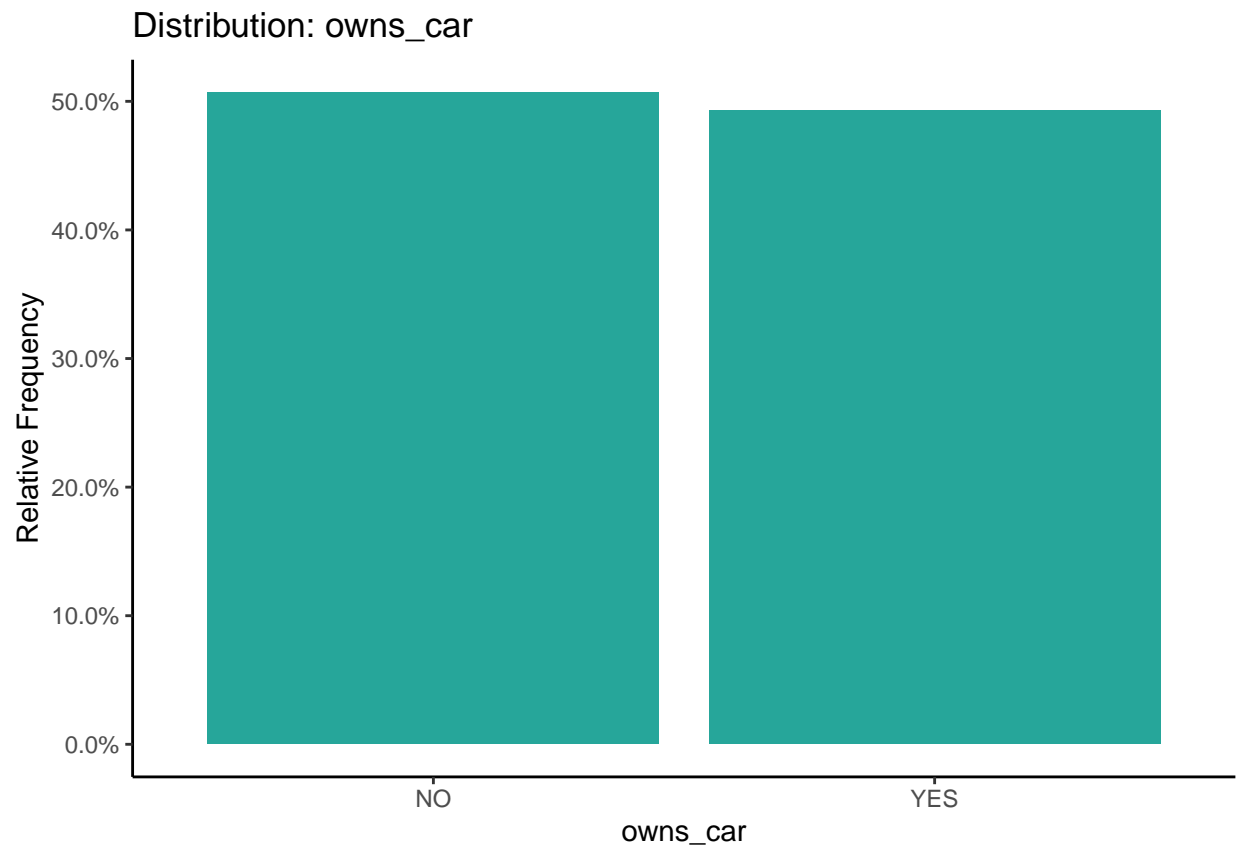


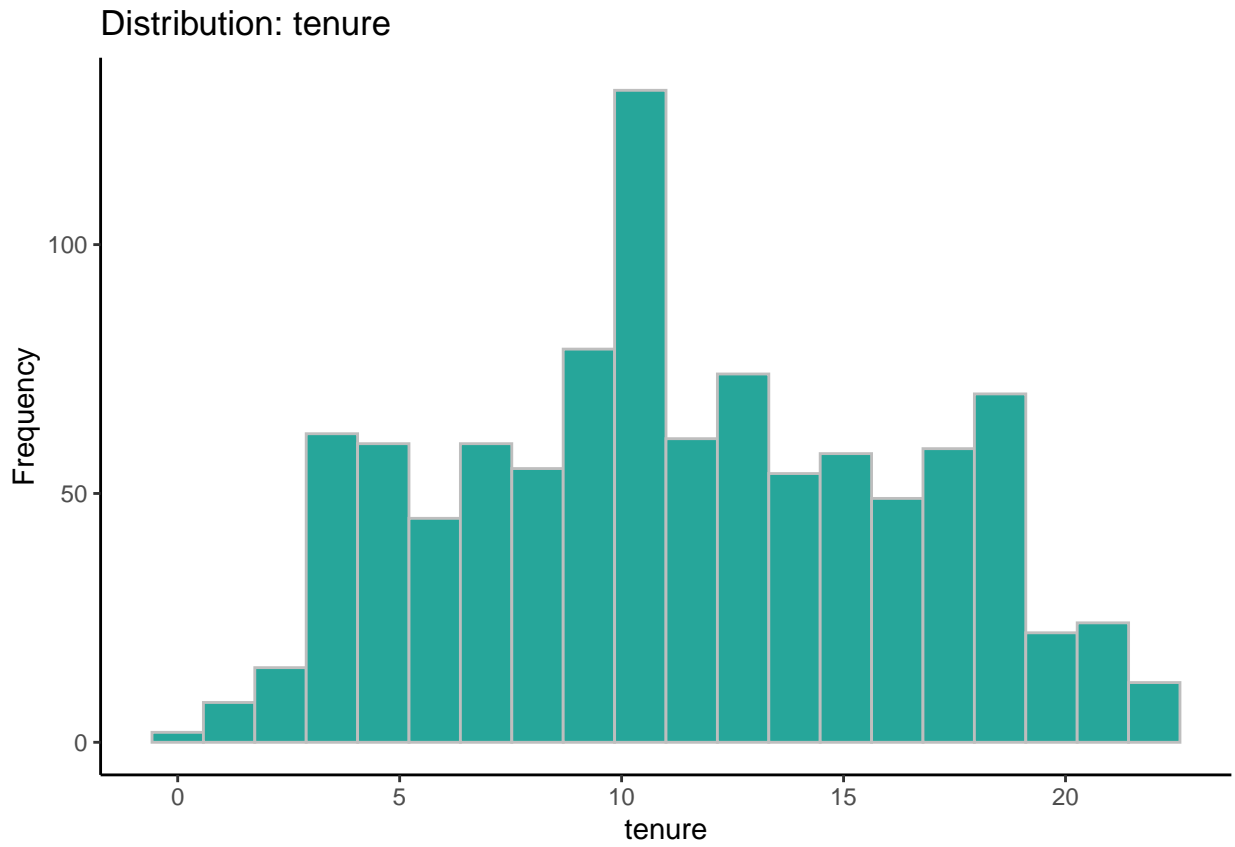


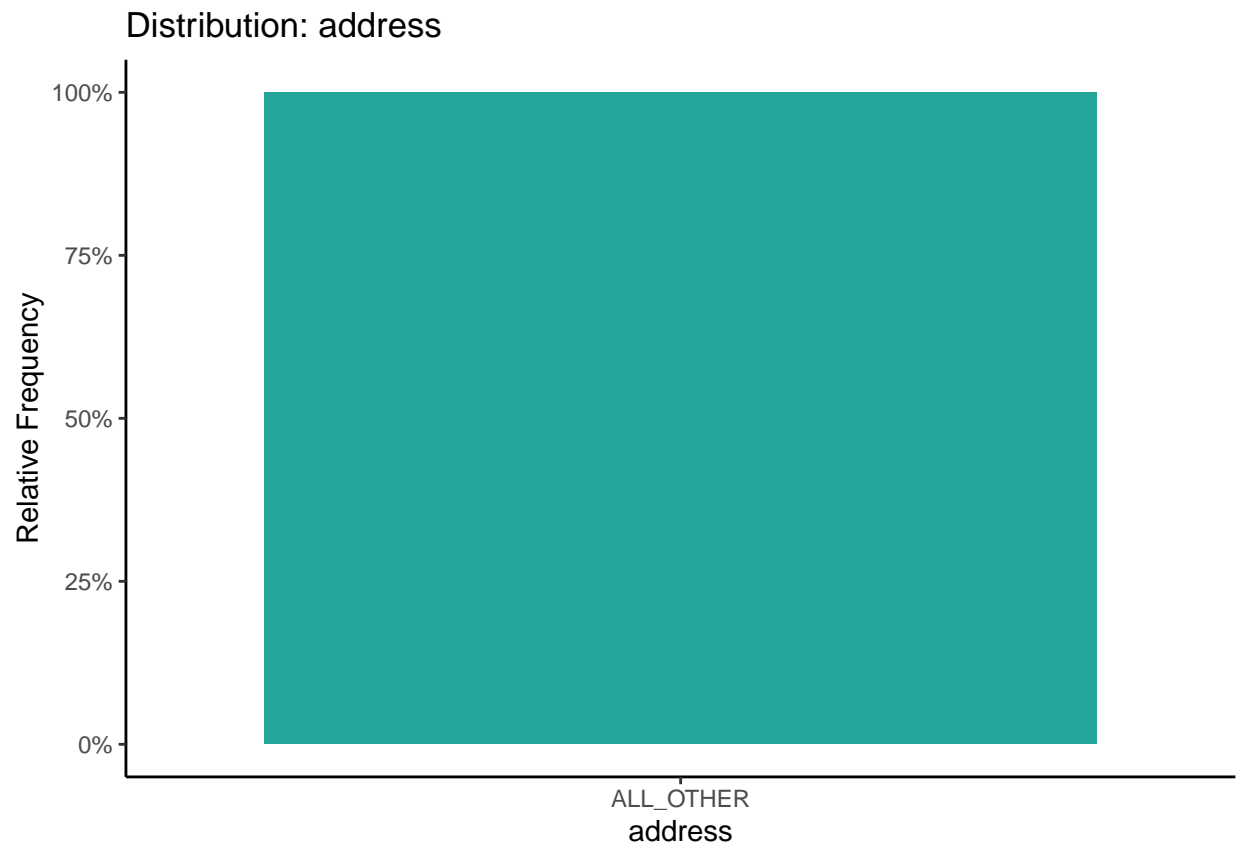


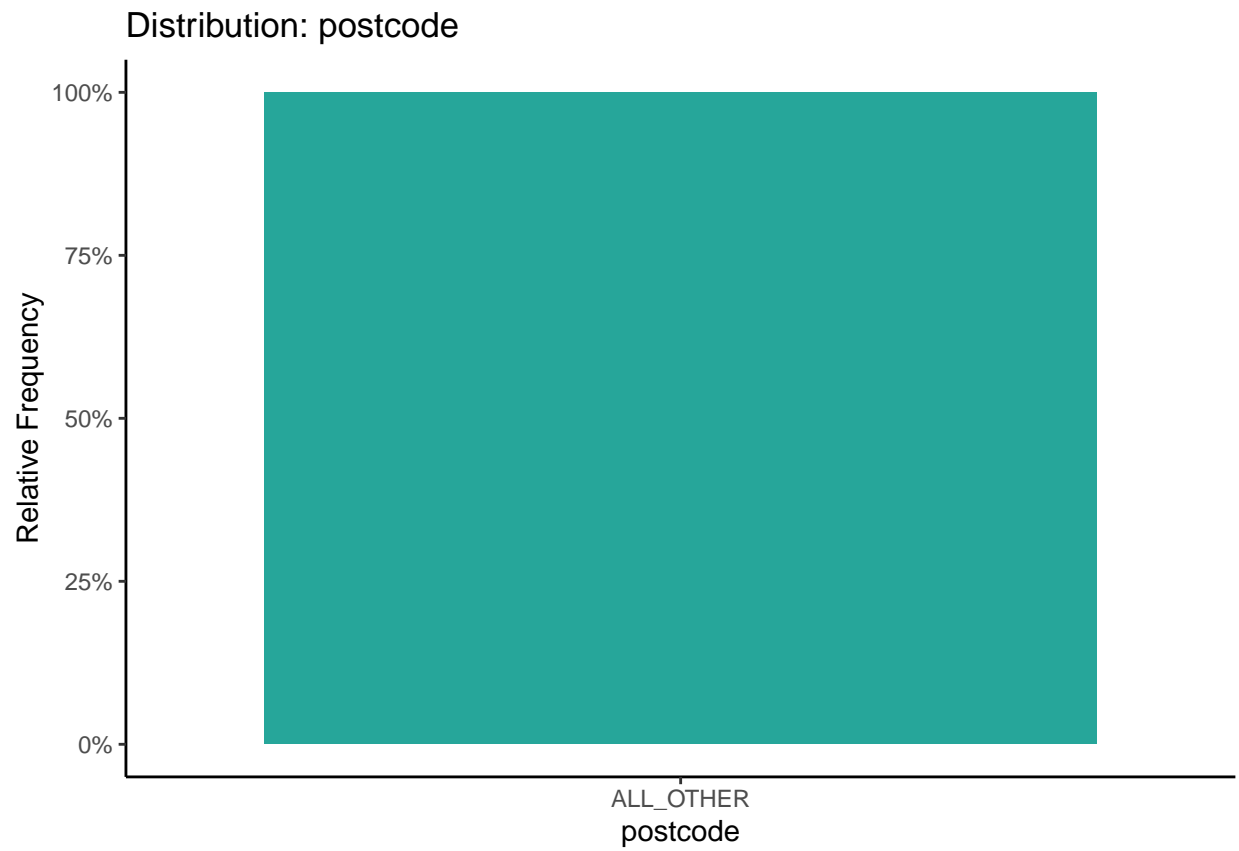


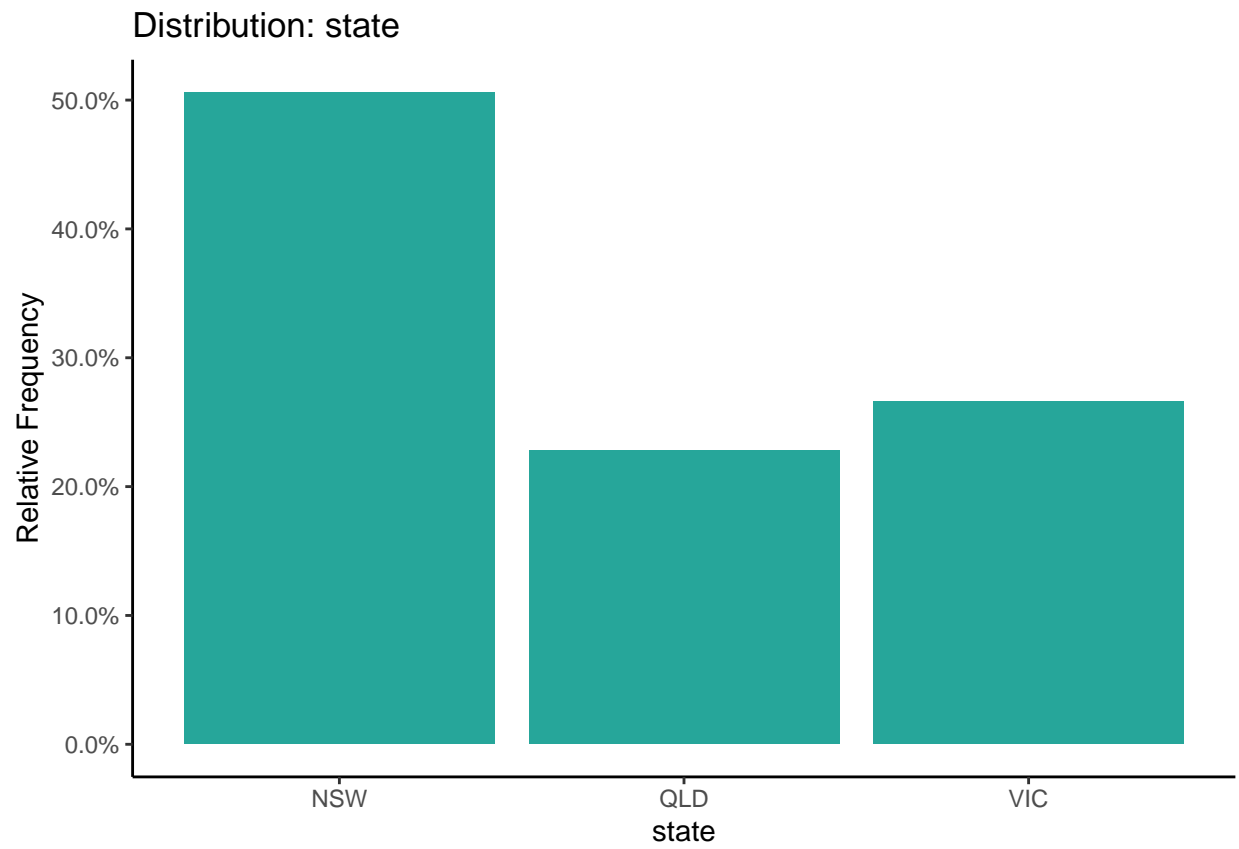


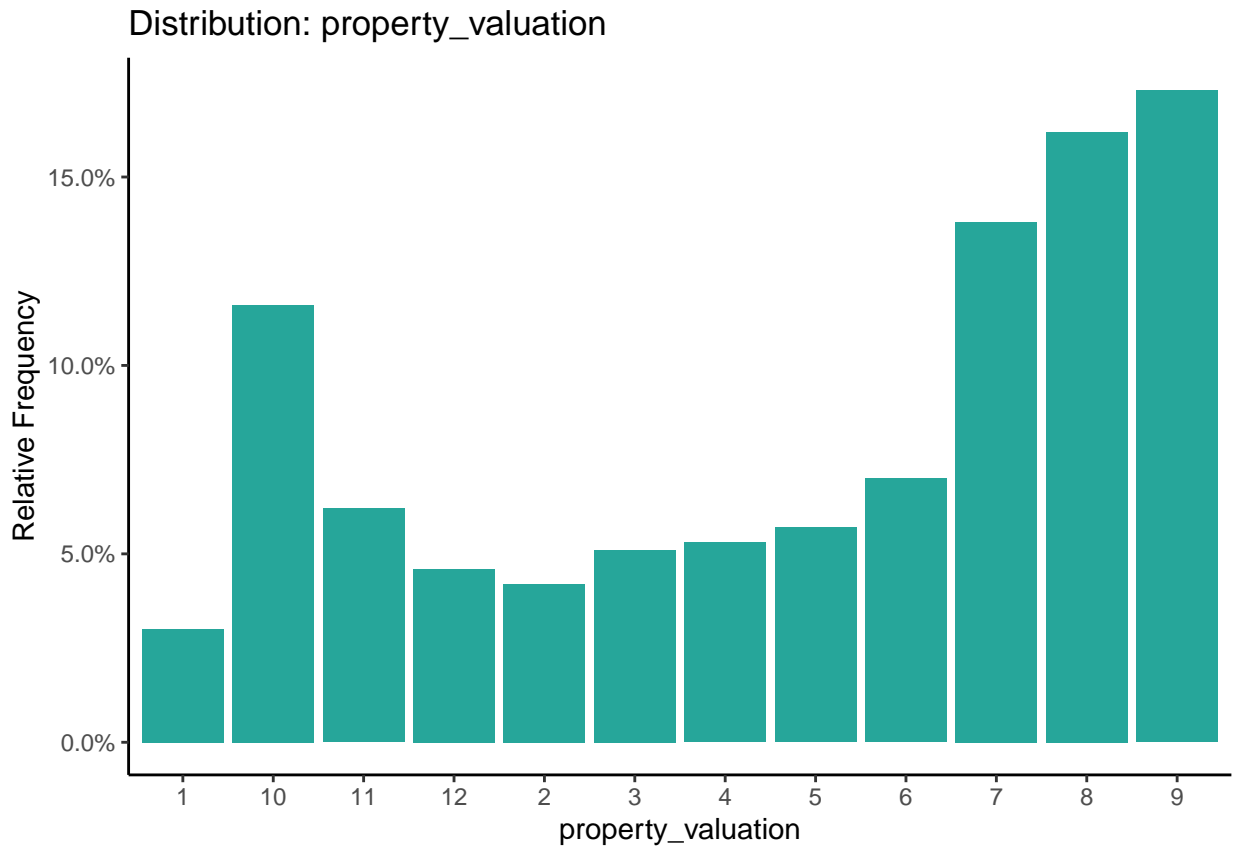


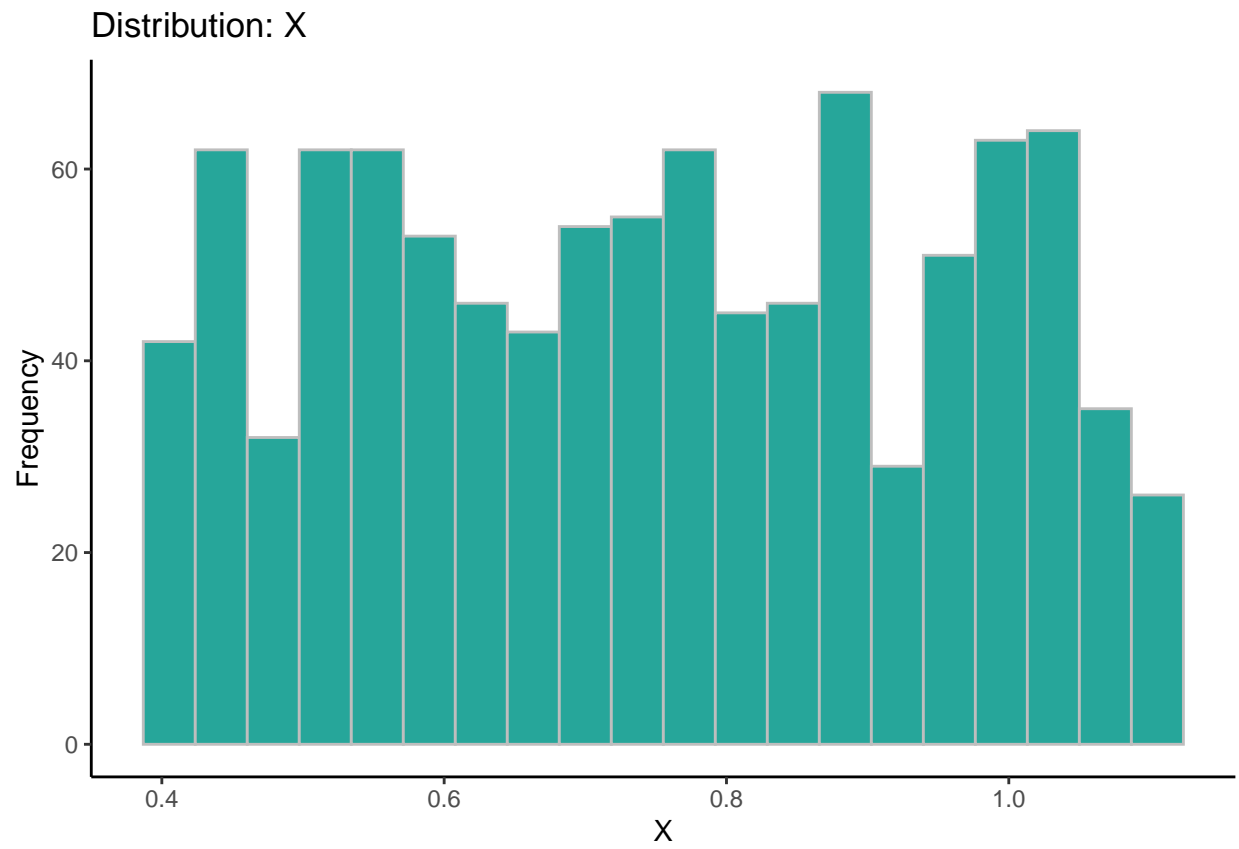


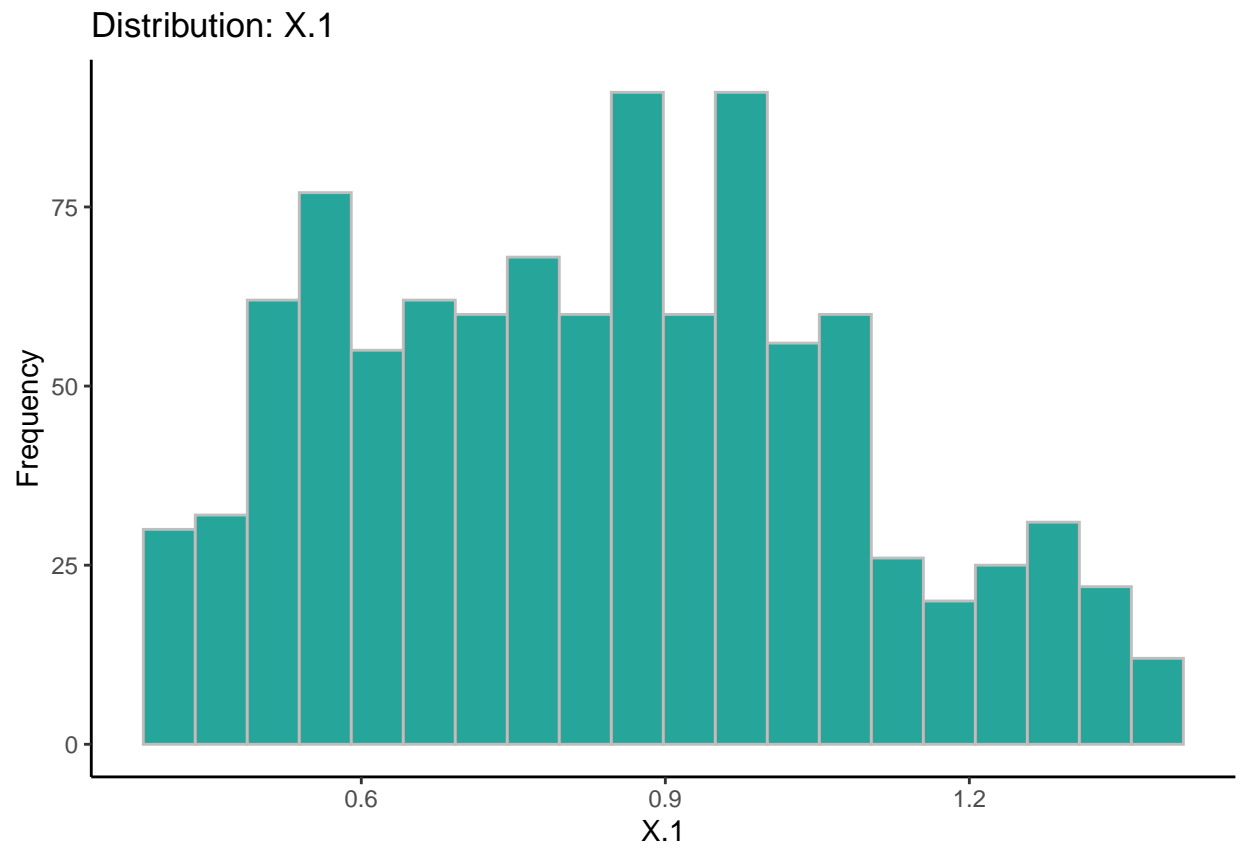


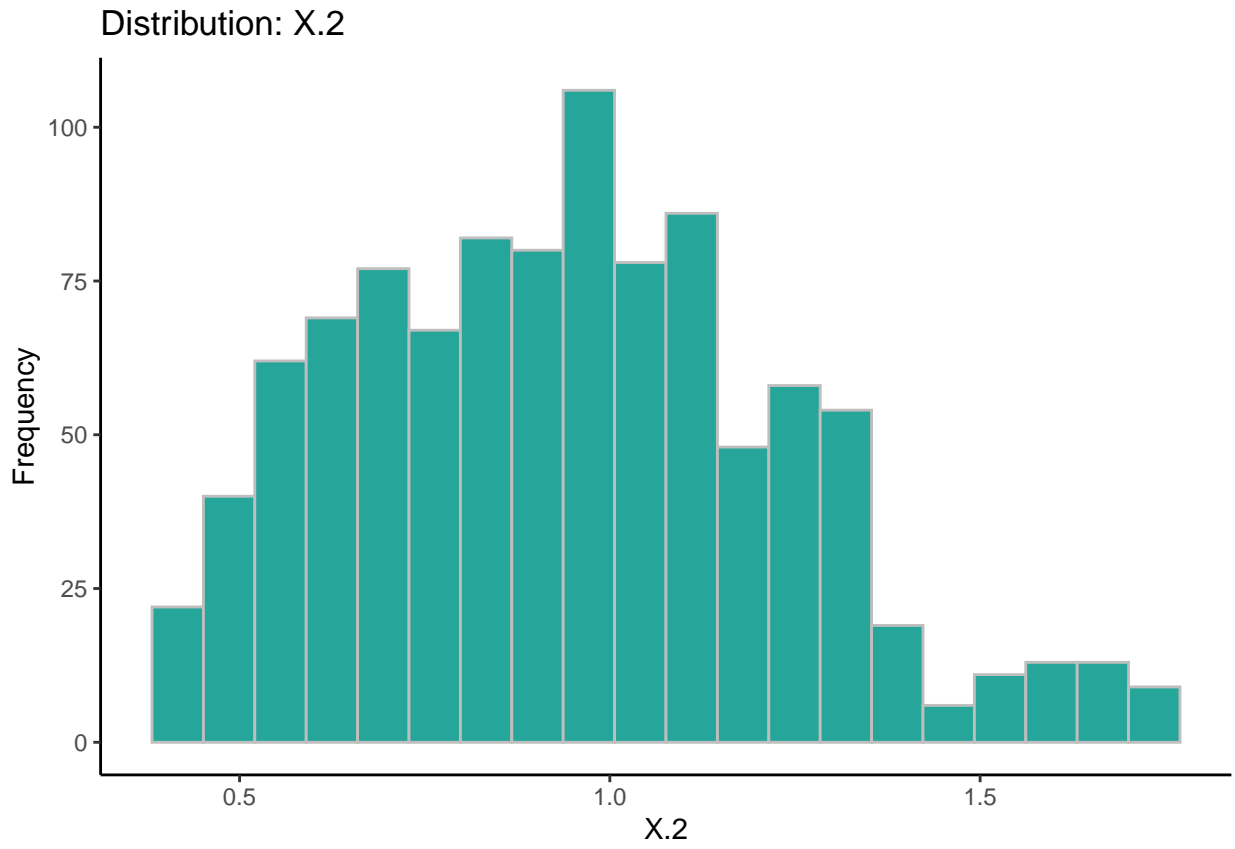


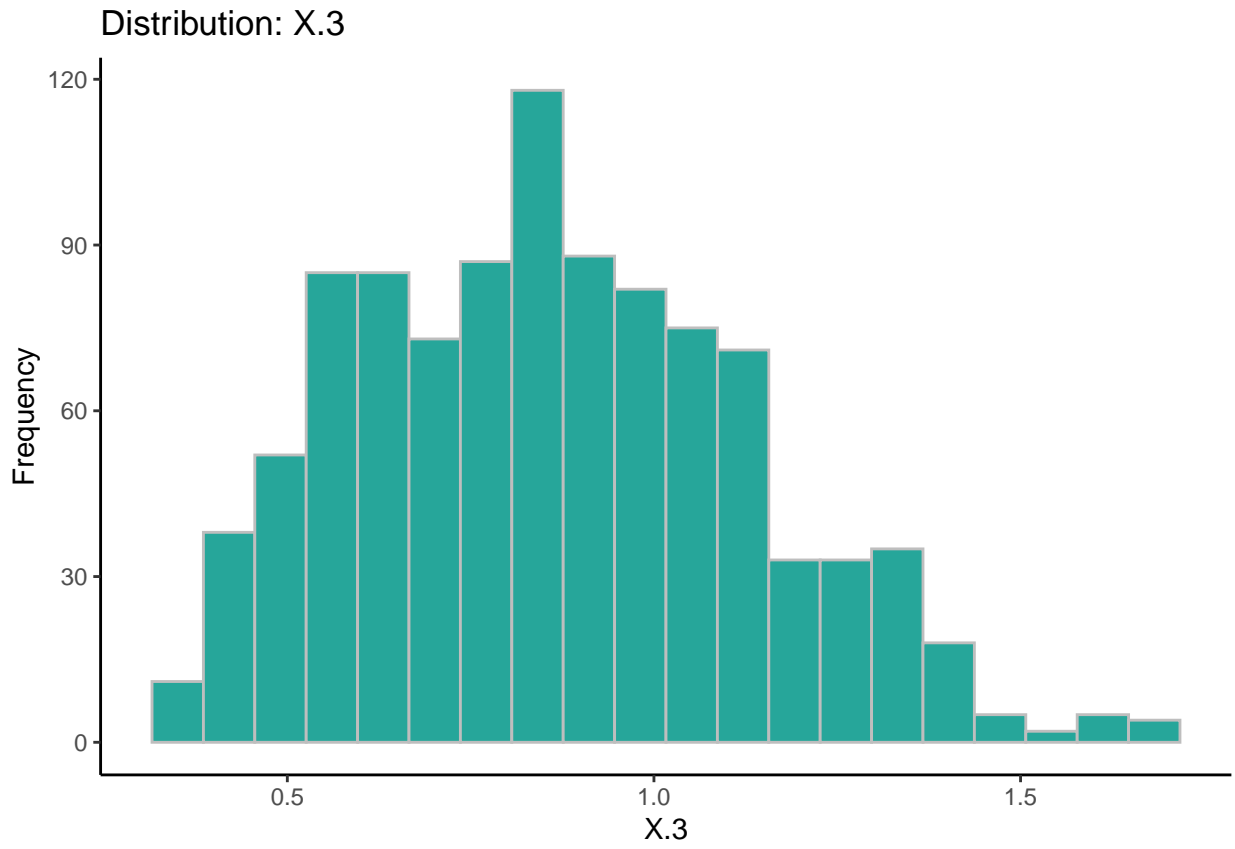


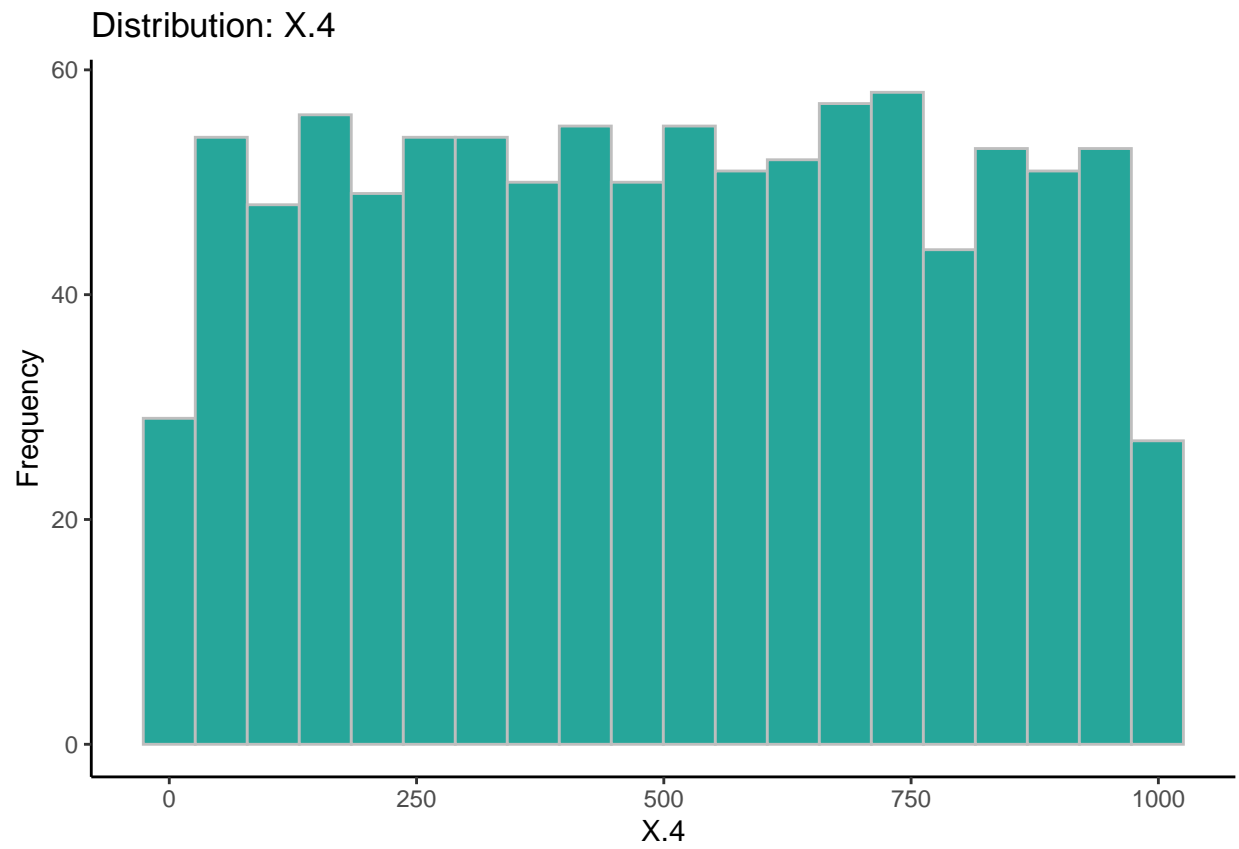


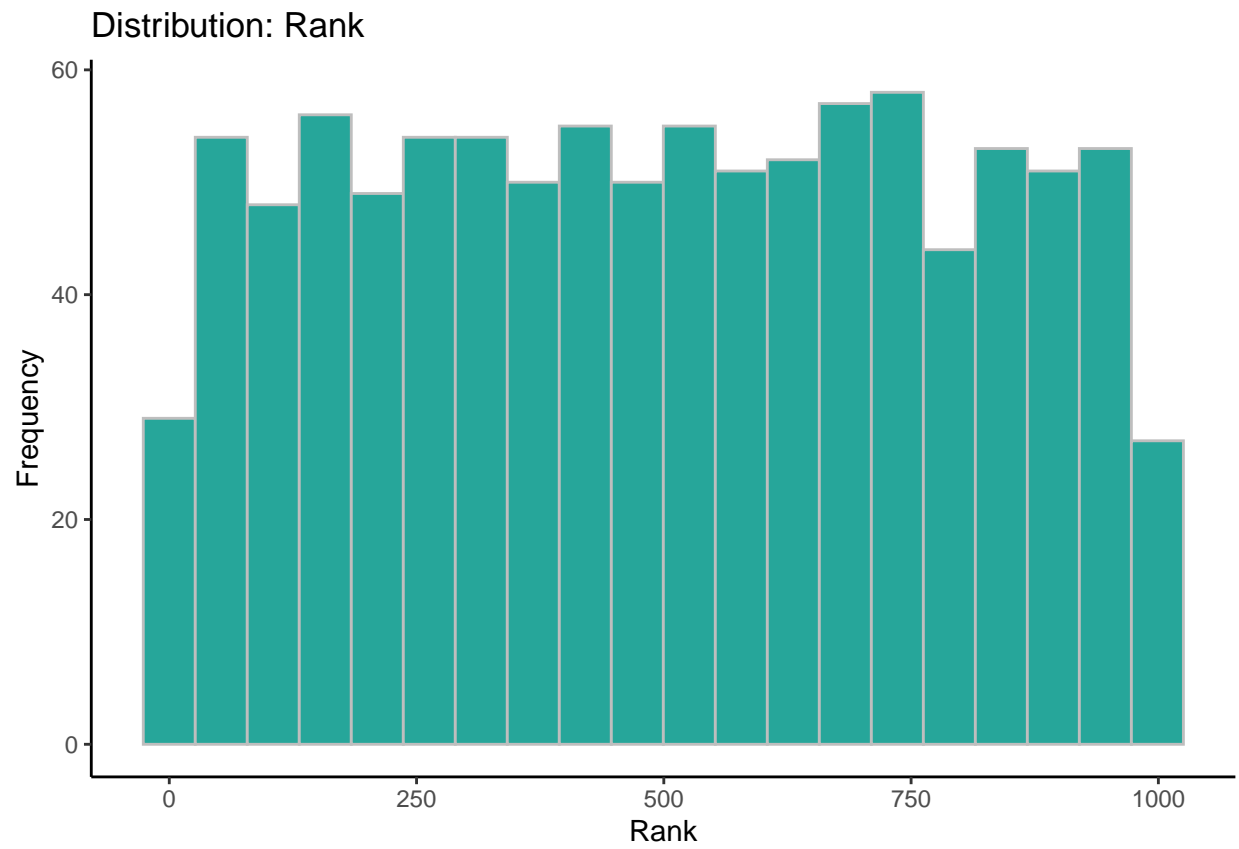


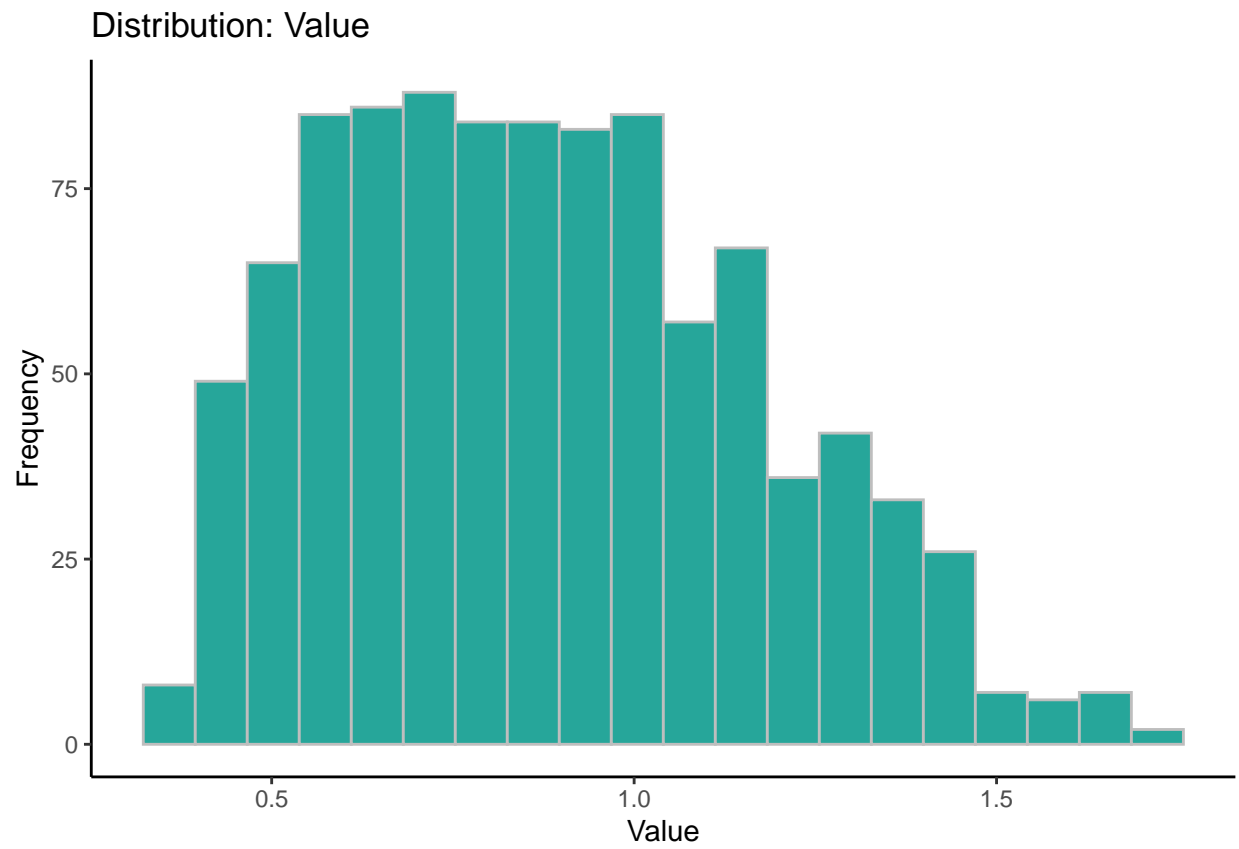


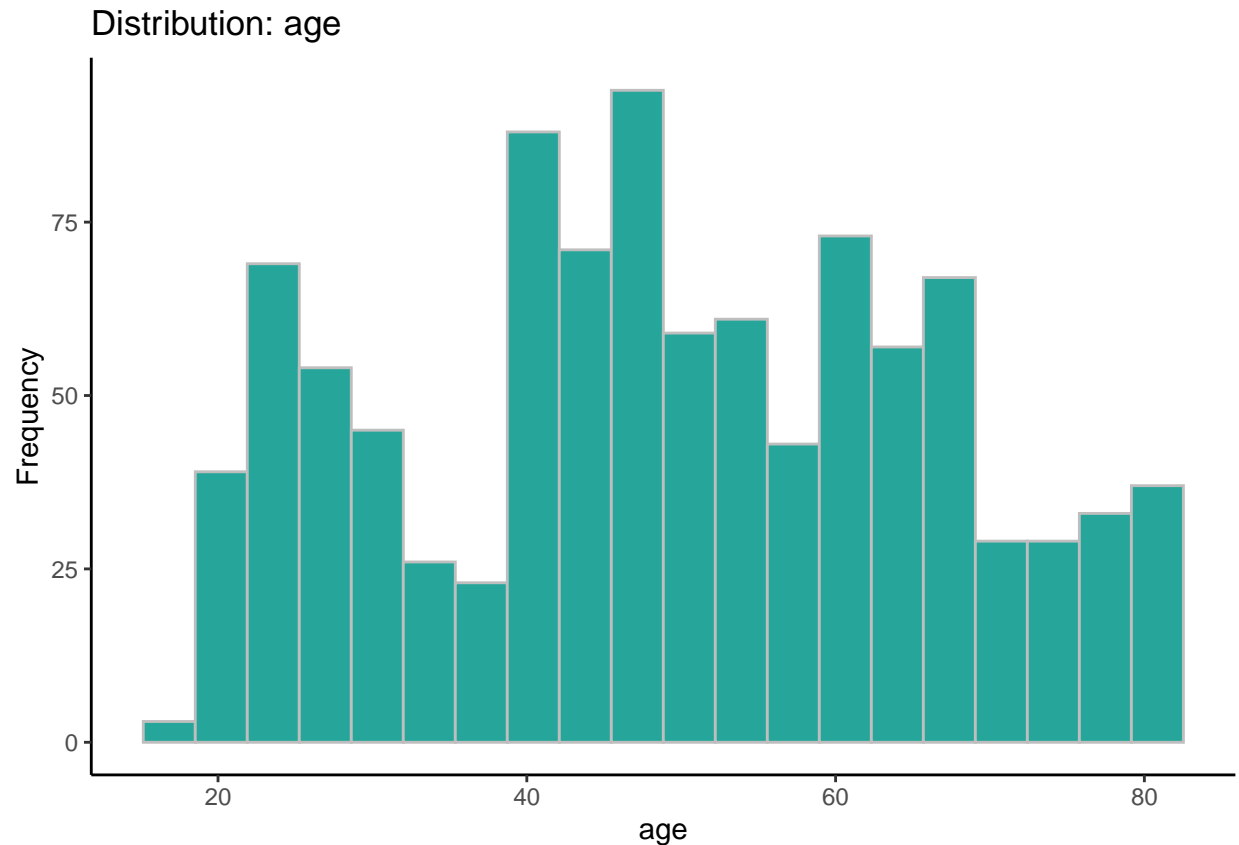












##	Feature	Observations	FeatureClass	FeatureType
## 1	first_name	1000	character	Categorical
## 2	last_name	1000	character	Categorical
## 3	gender	1000	character	Categorical
## 4	past_3_years_bike_related_purchases	1000	numeric	Continuous
## 5	DOB	1000	character	Categorical
## 6	job_title	1000	character	Categorical
## 7	job_industry_category	1000	character	Categorical
## 8	wealth_segment	1000	character	Categorical
## 9	owns_car	1000	character	Categorical
## 10	tenure	1000	numeric	Continuous
## 11	address	1000	character	Categorical
## 12	postcode	1000	character	Categorical
## 13	state	1000	character	Categorical
## 14	property_valuation	1000	character	Categorical
## 15	X	1000	numeric	Continuous
## 16	X.1	1000	numeric	Continuous
## 17	X.2	1000	numeric	Continuous
## 18	X.3	1000	numeric	Continuous
## 19	X.4	1000	numeric	Continuous
## 20	Rank	1000	numeric	Continuous
## 21	Value	1000	numeric	Continuous
## 22	age	1000	numeric	Continuous
##	PercentageMissing	PercentageUnique	ConstantFeature	ZeroSpreadFeature
## 1	0.0	94.0	No	No
## 2	0.0	96.2	No	No

## 3	0.0	0.3	No	No		
## 4	0.0	10.0	No	No		
## 5	1.7	95.9	No	No		
## 6	0.0	18.5	No	No		
## 7	0.0	1.0	No	No		
## 8	0.0	0.3	No	No		
## 9	0.0	0.2	No	No		
## 10	0.0	2.3	No	No		
## 11	0.0	100.0	No	No		
## 12	0.0	52.2	No	No		
## 13	0.0	0.3	No	No		
## 14	0.0	1.2	No	No		
## 15	0.0	7.1	No	No		
## 16	0.0	12.9	No	No		
## 17	0.0	18.3	No	No		
## 18	0.0	31.7	No	No		
## 19	0.0	32.4	No	No		
## 20	0.0	32.4	No	No		
## 21	0.0	31.9	No	No		
## 22	1.7	6.6	No	No		
##	LowerOutliers	UpperOutliers	ImputationValue	MinValue	FirstQuartile	Median
## 1	0	0	ALL_OTHER	0.00	0.0000000	0.00
## 2	0	0	ALL_OTHER	0.00	0.0000000	0.00
## 3	0	0	FEMALE	0.00	0.0000000	0.00
## 4	0	0	51	0.00	26.7500000	51.00
## 5	0	0	MISSING	0.00	0.0000000	0.00
## 6	0	0	ALL_OTHER	0.00	0.0000000	0.00
## 7	0	0	FINANCIAL SERVICES	0.00	0.0000000	0.00
## 8	0	0	MASS CUSTOMER	0.00	0.0000000	0.00
## 9	0	0	NO	0.00	0.0000000	0.00
## 10	0	0	11	0.00	7.0000000	11.00
## 11	0	0	ALL_OTHER	0.00	0.0000000	0.00
## 12	0	0	ALL_OTHER	0.00	0.0000000	0.00
## 13	0	0	NSW	0.00	0.0000000	0.00
## 14	0	0	9	0.00	0.0000000	0.00
## 15	0	0	0.75	0.40	0.5700000	0.75
## 16	0	0	0.8375	0.40	0.6400000	0.84
## 17	0	0	0.9375	0.40	0.7082812	0.94
## 18	0	7	0.85	0.34	0.6500000	0.85
## 19	0	0	500	1.00	250.0000000	500.00
## 20	0	0	500	1.00	250.0000000	500.00
## 21	0	3	0.86	0.34	0.6495313	0.86
## 22	0	0	48	18.00	37.0000000	48.00
##	Mean	Mode	ThirdQuartile	MaxValue	LowerOutlierValue	
## 1	0.00	DORIAN	0.000	0.00000	0.00000000	
## 2	0.00		0.000	0.00000	0.00000000	
## 3	0.00	FEMALE	0.000	0.00000	0.00000000	
## 4	49.84	60	72.000	99.00000	-41.12500000	
## 5	0.00	1941-07-21	0.000	0.00000	0.00000000	
## 6	0.00		0.000	0.00000	0.00000000	
## 7	0.00	FINANCIAL SERVICES	0.000	0.00000	0.00000000	
## 8	0.00	MASS CUSTOMER	0.000	0.00000	0.00000000	
## 9	0.00	NO	0.000	0.00000	0.00000000	
## 10	11.39	9	15.000	22.00000	-5.00000000	

```

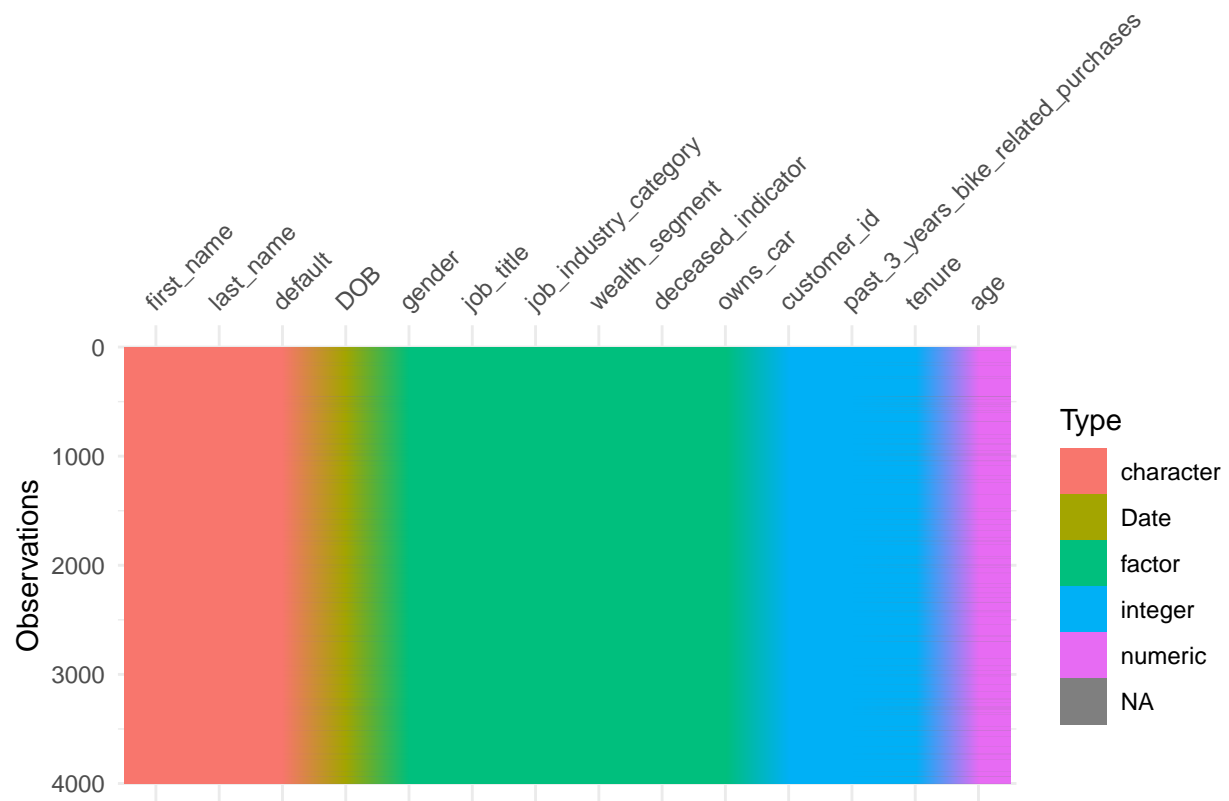
## 11  0.00      0 BAY DRIVE      0.000  0.00000  0.00000000
## 12  0.00      2145            0.000  0.00000  0.00000000
## 13  0.00      NSW             0.000  0.00000  0.00000000
## 14  0.00      9               0.000  0.00000  0.00000000
## 15  0.75      0.6             0.920  1.10000  0.04500000
## 16  0.84      0.75            1.010  1.37500  0.08500000
## 17  0.94      0.8625          1.125  1.71875  0.08320312
## 18  0.87      0.85            1.060  1.71875  0.03500000
## 19 498.82     760             750.250 1000.00000 -500.37500000
## 20 498.82     760             750.250 1000.00000 -500.37500000
## 21  0.88      0.6375          1.075  1.71875  0.01132813
## 22 49.21     46              63.000  82.00000 -2.00000000
##      UpperOutlierValue
## 1      0.000000
## 2      0.000000
## 3      0.000000
## 4     139.875000
## 5      0.000000
## 6      0.000000
## 7      0.000000
## 8      0.000000
## 9      0.000000
## 10     27.000000
## 11     0.000000
## 12     0.000000
## 13     0.000000
## 14     0.000000
## 15     1.445000
## 16     1.565000
## 17     1.750078
## 18     1.675000
## 19    1500.625000
## 20    1500.625000
## 21     1.713203
## 22    102.000000

```

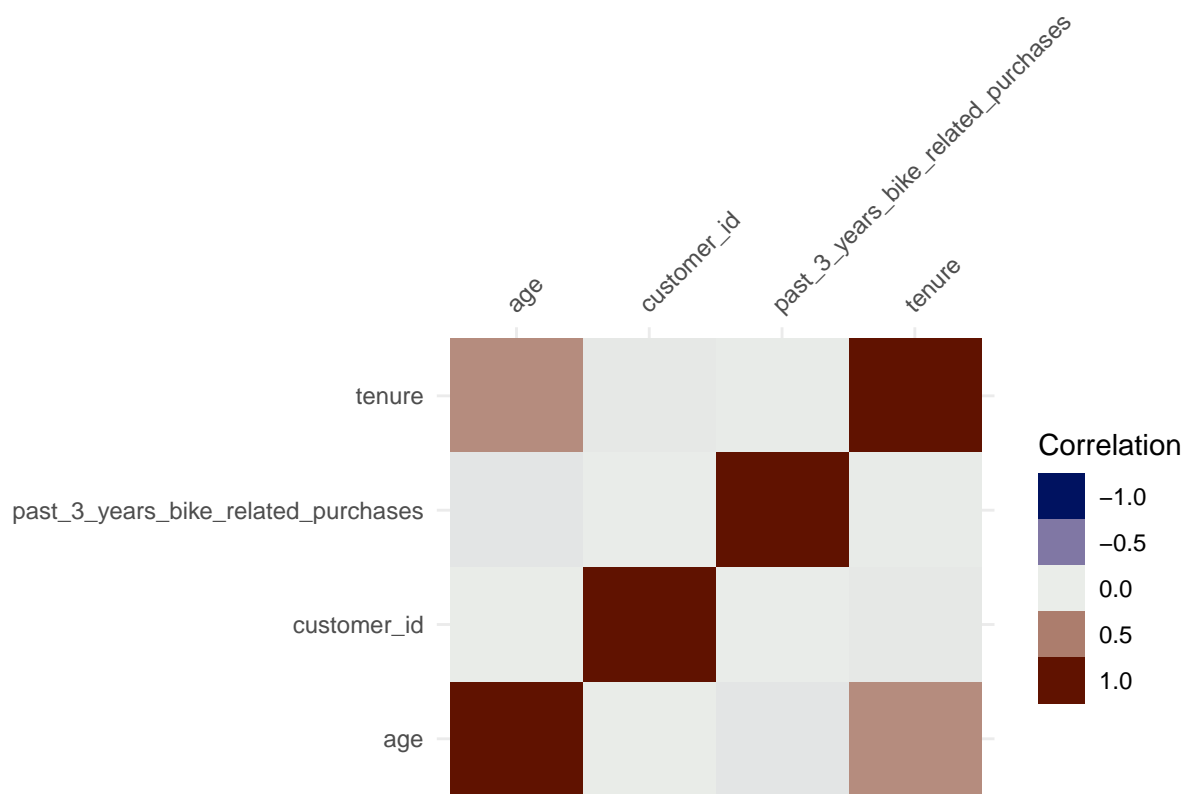
visdat

We can see that age(relatedly DOB) and tenure are missing for some customers. They are somewhat correlated also, we can see this from correlation plot. X columns which are nameless columns on newcustomer table are strongly correlated each other but we don't know about what they are measuring and also we don't have a similar past data about these features.

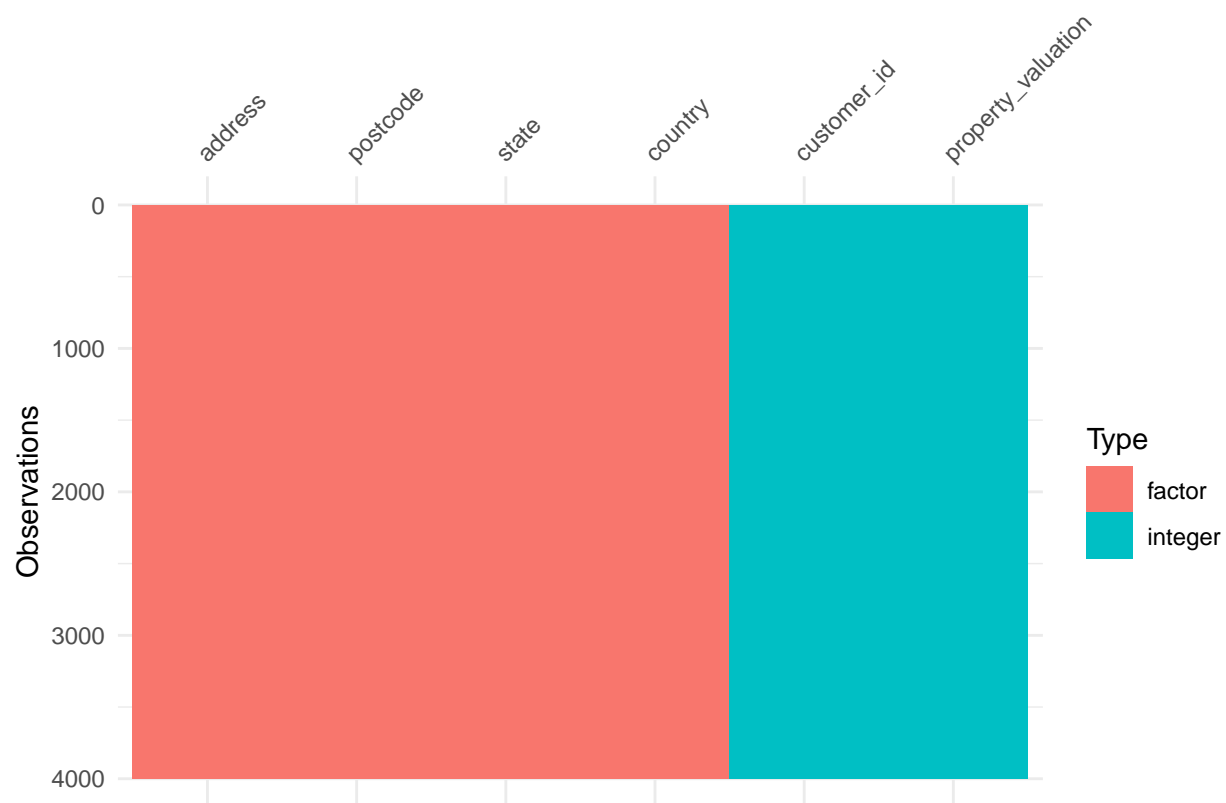
```
vis_dat(cdemographics)
```

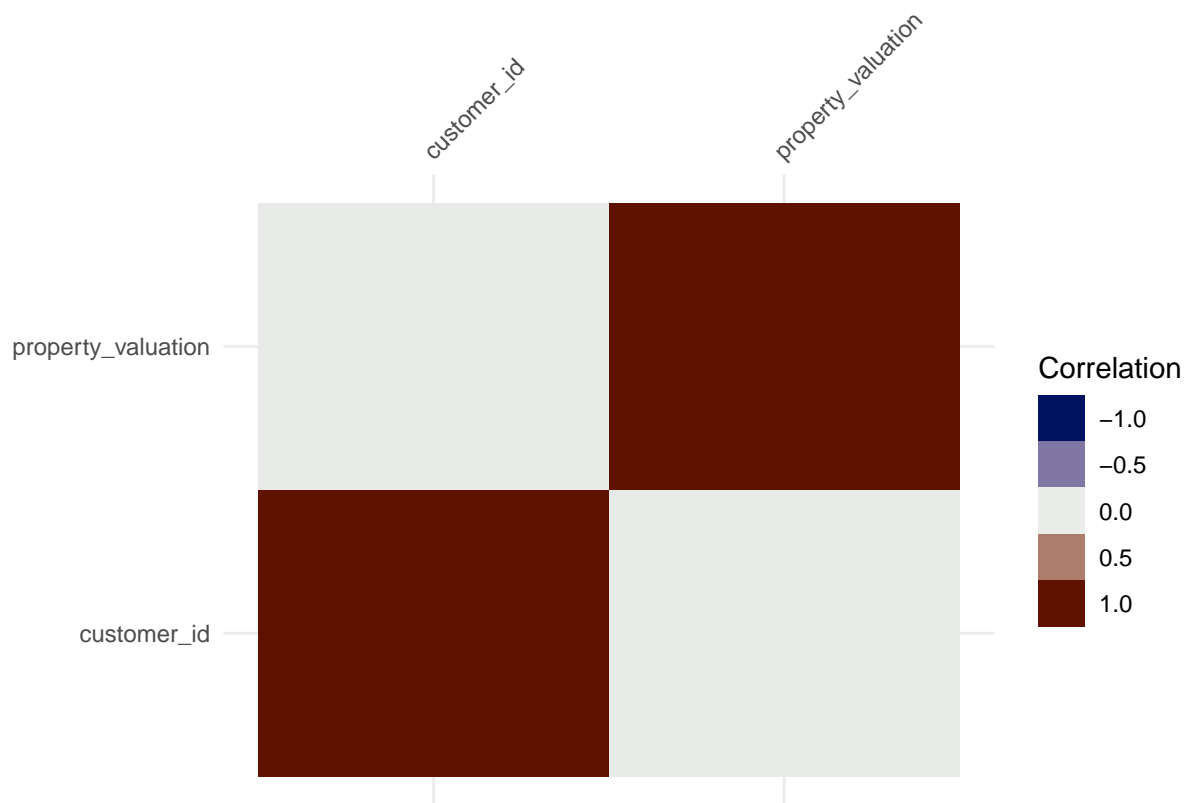
```
cdemographics %>% select_if(is.numeric) %>% vis_cor()
```



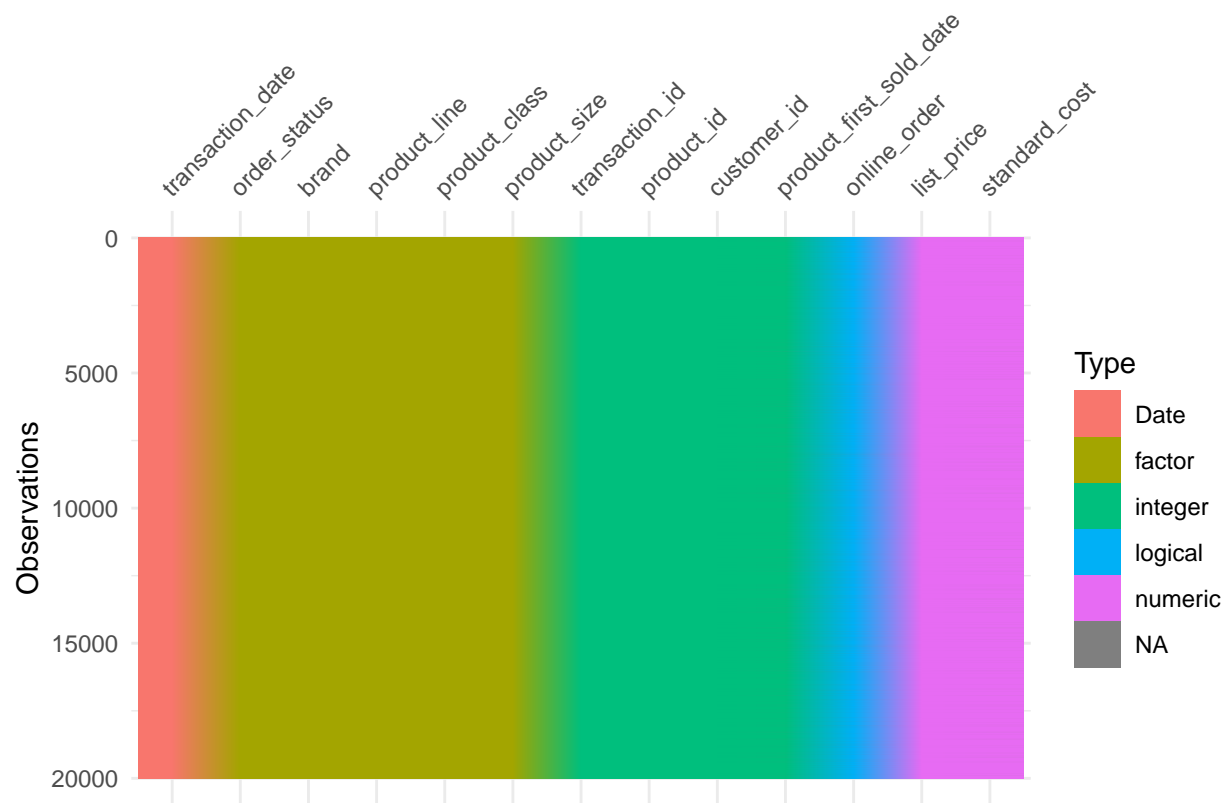
```
vis_dat(caddress)
```



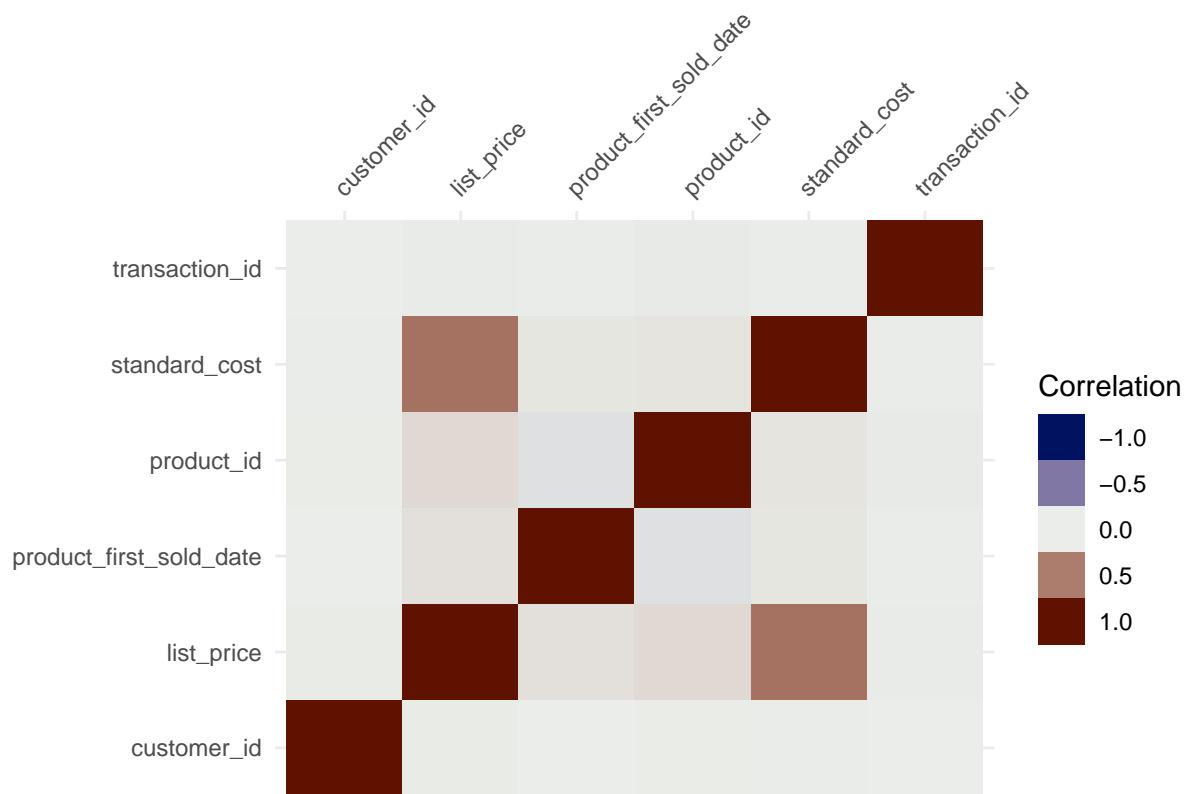
```
address %>% select_if(is.numeric) %>% vis_cor()
```



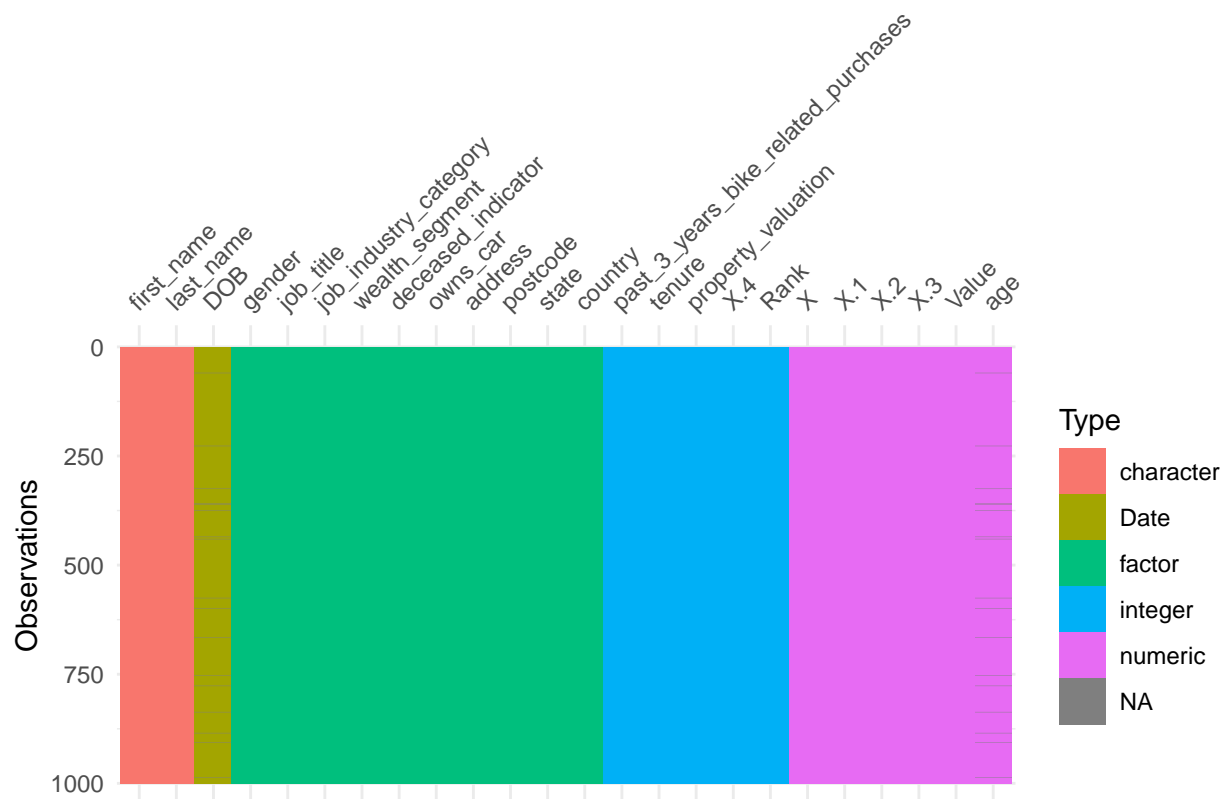
```
vis_dat(transactions)
```



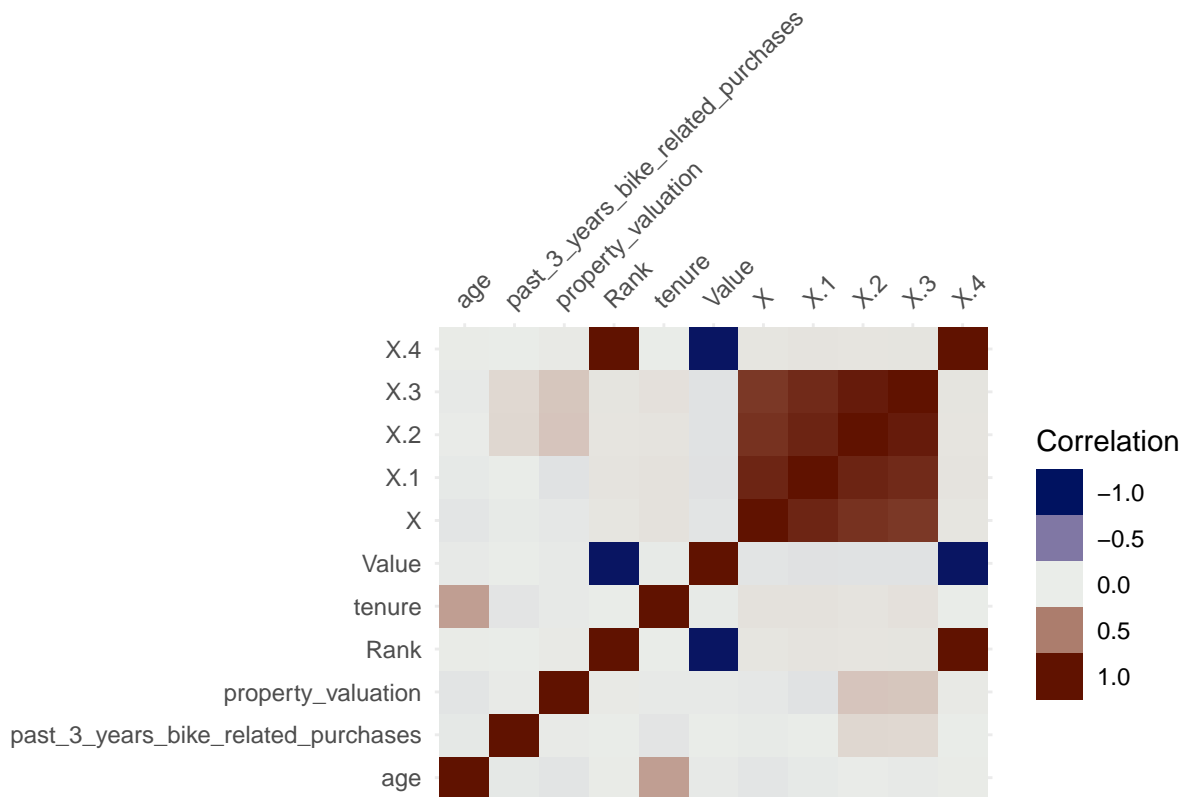
```
transactions %>% select_if(is.numeric) %>% vis_cor()
```



```
vis_dat(newcustomer)
```



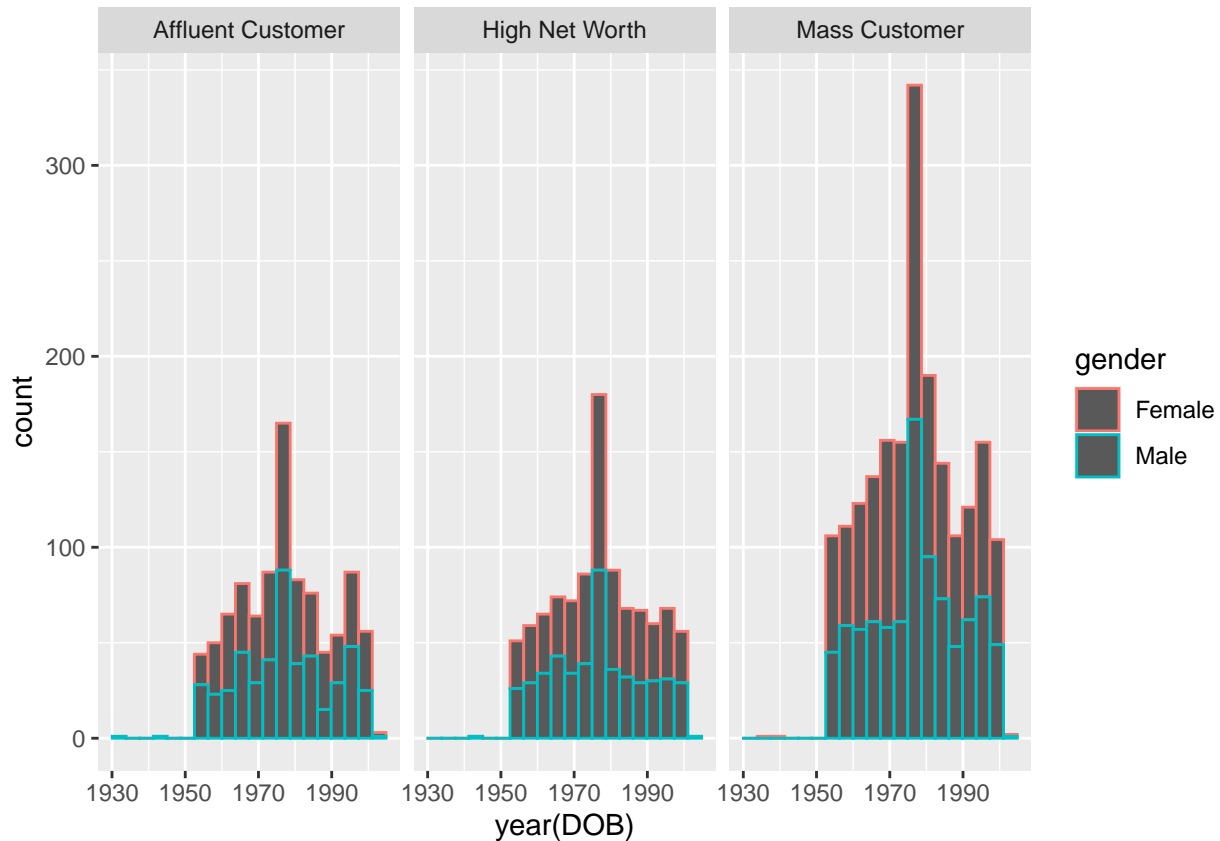
```
newcustomer %>% select_if(is.numeric) %>% vis_cor()
```



Selected Graphs and Tables

This graphic shows date of birth of customers accordingly their sexes. Customers are grouped by their wealth segments. Spreads look normally distributed.

```
cdemographics %>%
  filter(!is.na(DOB)) %>%
  ggplot(aes(year(DOB), color=gender)) +
  geom_histogram(bins=20) +
  facet_wrap(~wealth_segment)
```

I observed that 88 customers gender is marked as U while they do not have a determined date of birth(DOB). Also, only one of them have tenure information.

```
cdemographics %>%
  filter(is.na(DOB) | is.na(tenure)) %>%
  group_by(wealth_segment) %>%
  summarise(total = n(),
            proportion = total / 88)
```

```
## # A tibble: 3 x 3
##   wealth_segment    total proportion
##   <fct>            <int>     <dbl>
## 1 Affluent Customer    17     0.193
## 2 High Net Worth      25     0.284
## 3 Mass Customer       46     0.523
```

We can see that different brands are obtained for the 0th product and their prices are varied. Product_id variable is not consistent results to analyse.

```
transactions %>%
  group_by(product_id, brand) %>%
  summarise(total = n(), avg=mean(list_price), min=min(list_price), max=max(list_price)) %>%
  arrange(product_id) %>%
  head()
```

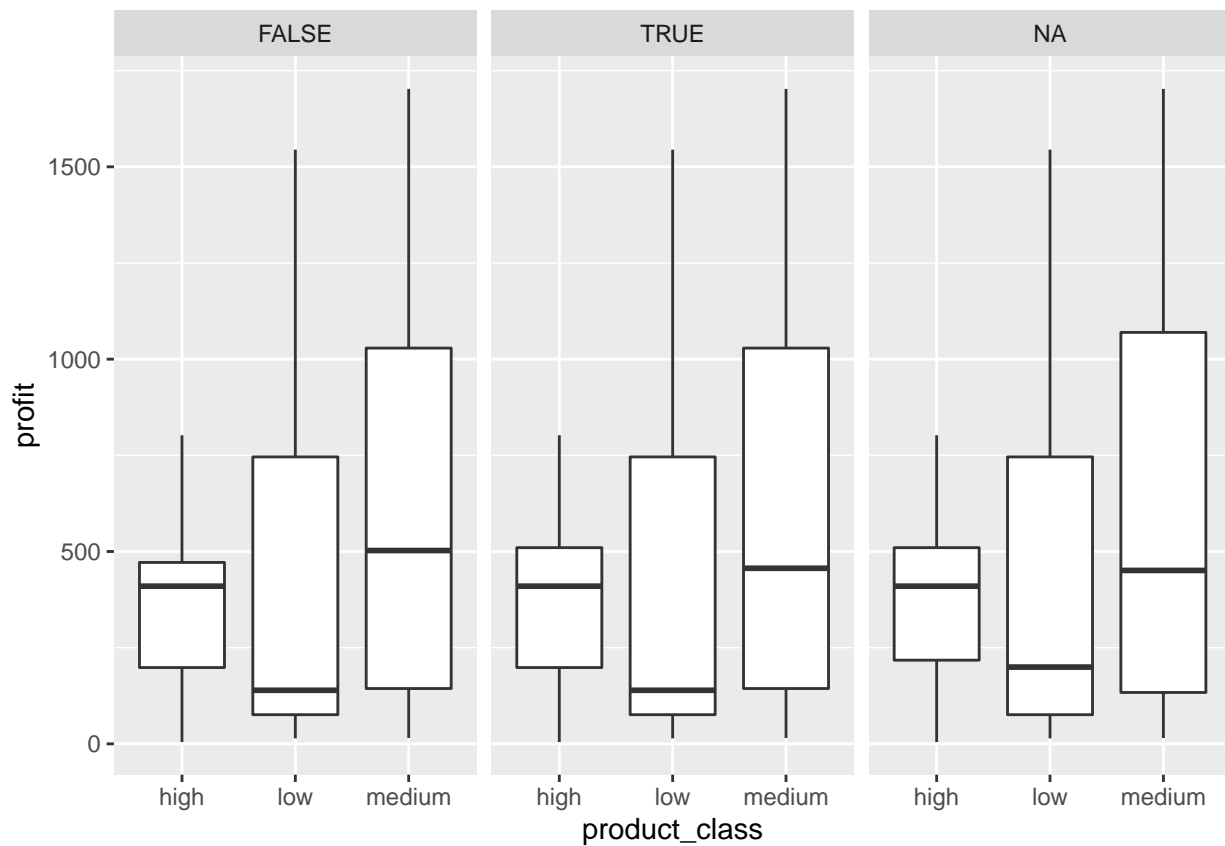
```
## # A tibble: 6 x 6
## # Groups:   product_id [1]
##   product_id brand          total  avg  min  max
```

```
##      <int> <fct>                <int> <dbl> <dbl> <dbl>
## 1         0 ""                  197 1091.  16.1 2086.
## 2         0 "Giant Bicycles"    105  382.  231.  570.
## 3         0 "Norco Bicycles"   241  448.  360.  544.
## 4         0 "OHM Cycles"       242  152.  12.0  743.
## 5         0 "Solex"            276  255.  71.5  478.
## 6         0 "Trek Bicycles"    221  440.  291.  534.
```

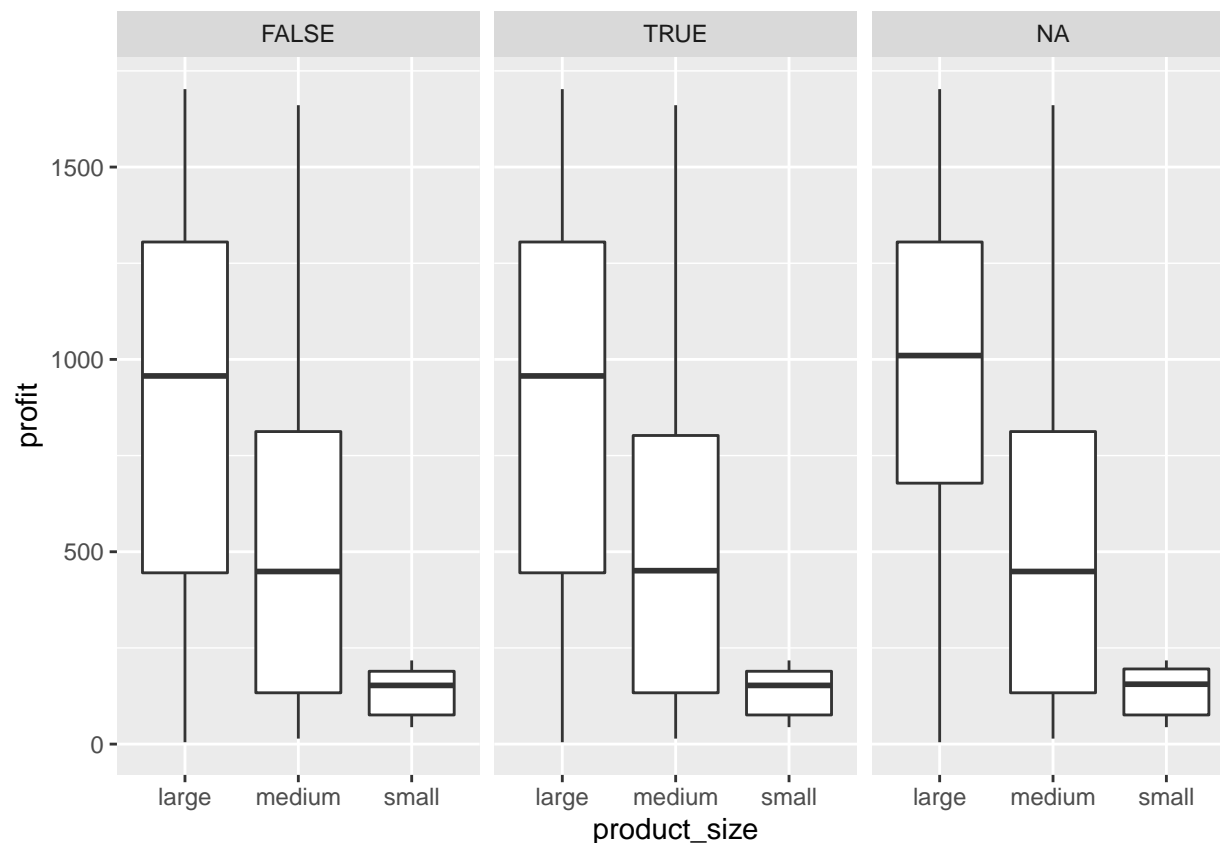
Profit variable has been added to Transactions table. Profit is calculated by difference between list_price and standard_cost.

```
transactions <- transactions %>% mutate(profit = list_price - standard_cost)

transactions %>% filter(!is.na(profit)) %>% ggplot(aes(product_class, profit)) +
  geom_boxplot() +
  facet_wrap(~online_order)
```



```
transactions %>% filter(!is.na(profit)) %>% ggplot(aes(product_size, profit)) +
  geom_boxplot() +
  facet_wrap(~online_order)
```



Joining transactions and cdemographics table made possible to observe wealth_segment spread.

```
transactions %>%
  summarize(total_active_customers = n_distinct(customer_id)
            )
```

```
## total_active_customers
## 1 3494
```

```
transactions %>% filter(!is.na(profit)) %>%
  group_by(customer_id) %>%
  summarise(total_order= n(),
            total_profit=sum(profit),
            avg_profit = sum(profit) / n()) %>%
  arrange(desc(total_order)) %>%
  head()
```

```
## # A tibble: 6 x 4
##   customer_id total_order total_profit avg_profit
##       <int>      <int>      <dbl>      <dbl>
## 1      1068         14      4842.       346.
## 2      2183         14      6513.       465.
## 3      2476         14      7493.       535.
## 4       637         13      5402.       416.
## 5      1129         13      6791.       522.
## 6      1140         13      8533.       656.
```

```

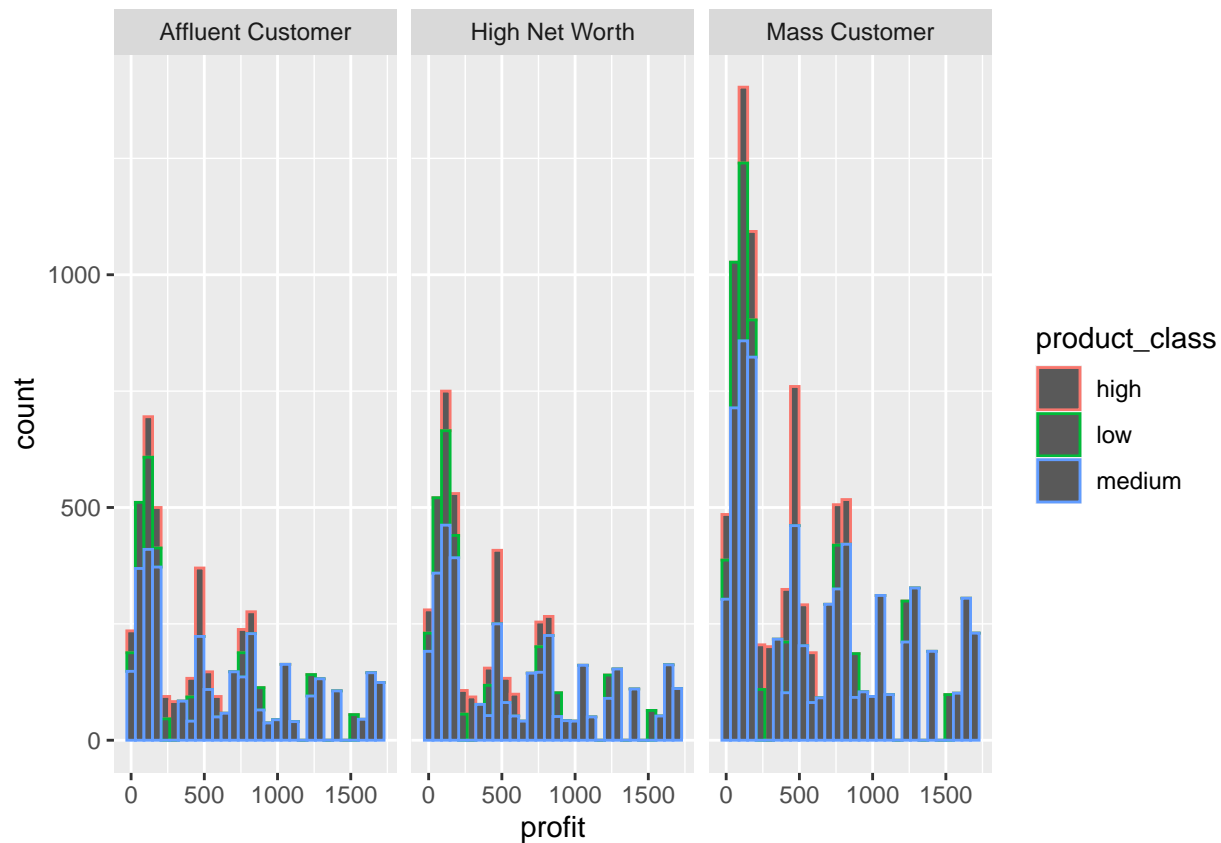
# wealth segment statistics
transactions %>%
  left_join(cdemographics, by="customer_id") %>%
  filter(!is.na(profit)) %>%
  filter(!is.na(wealth_segment)) %>%
  group_by(wealth_segment) %>%
  summarise(total_customer = n_distinct(customer_id),
            total_order= n(),
            order_per_customer = n() / n_distinct(customer_id),
            total_profit = sum(profit),
            avg_profit = sum(profit)/n()
            )

## # A tibble: 3 x 6
##   wealth_segment total_customer total_order order_per_cust~ total_profit
##   <fct>          <int>          <int>          <dbl>          <dbl>
## 1 Affluent Cust~      851          4810          5.65         2678011.
## 2 High Net Worth      895          5046          5.64         2770520.
## 3 Mass Customer     1747          9944          5.69         5481484.
## # ... with 1 more variable: avg_profit <dbl>

transactions %>% filter(!is.na(profit)) %>%
  left_join(cdemographics, by="customer_id") %>%
  filter(!is.na(wealth_segment)) %>%
  ggplot(aes(profit, color = product_class)) +
  geom_histogram() +
  facet_wrap(~ wealth_segment)

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

```



```
transactions_grouped <- transactions %>%
  group_by(customer_id) %>%
  summarise(total_order= n(),
            total_profit = sum(profit),
            avg_profit = sum(profit)/n()
  )
transactions_grouped %>% group_by(total_order) %>% summarise(n = n())
```

```
## # A tibble: 14 x 2
##   total_order    n
##   <int> <int>
## 1         1    49
## 2         2   202
## 3         3   361
## 4         4   499
## 5         5   601
## 6         6   569
## 7         7   476
## 8         8   311
## 9         9   207
## 10        10  112
## 11        11   60
## 12        12   28
## 13        13   16
## 14        14    3
```

3

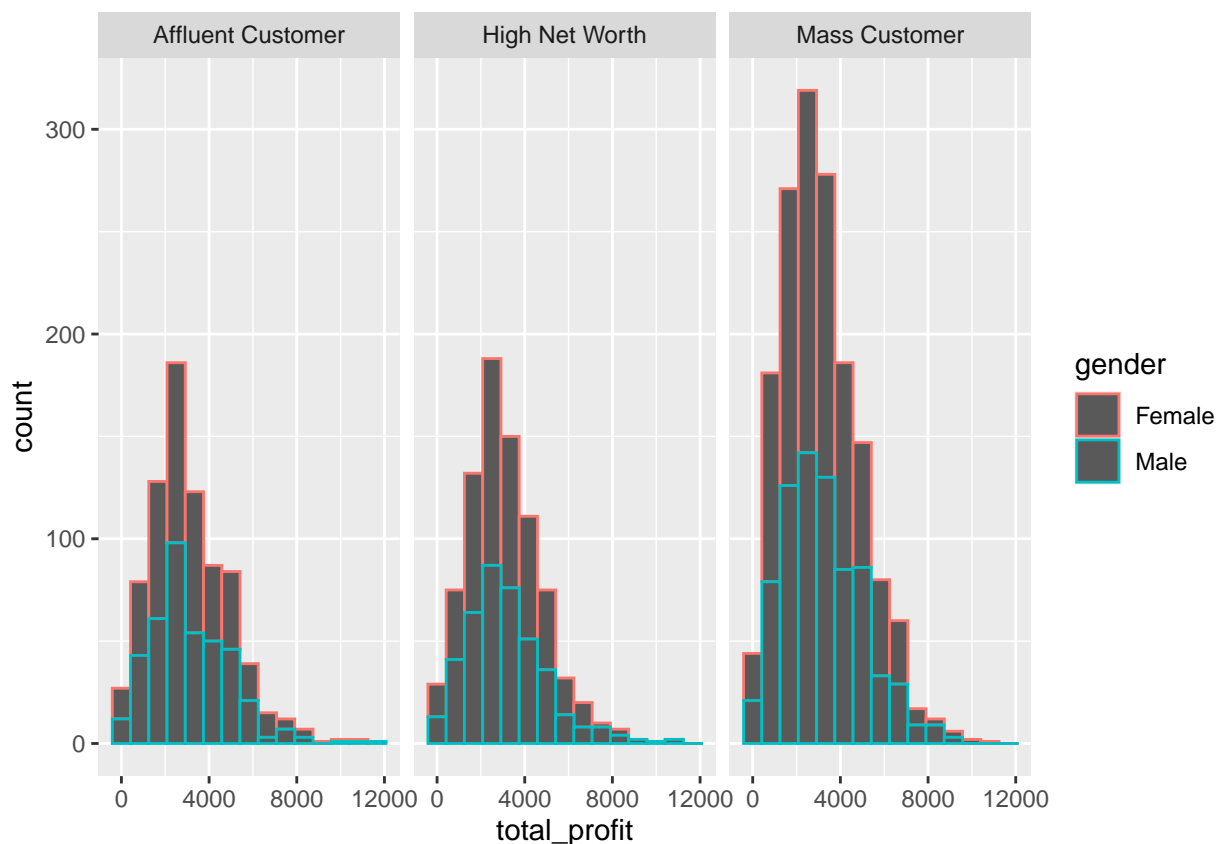
New customers should be categorized subject to given customer demographics data and related datasets. We can join tables to add new features to explore on cdemographics dataset. Firstly, I am going to focus decision tree models.

Preparing the data

I left-joined cdemographics and caddress tables and selected all columns that we can make predictions. I started to learn the data with sampling. 3126 of 3908 observation are attended as train and remainings are test.

```
# Join all the tables to be able to reach more features
training_set <- cdemographics %>%
  left_join(caddress, by="customer_id") %>%
  left_join(transactions_grouped, by="customer_id") %>%
  # job_title and job_industry_category
  select(total_profit, total_order, wealth_segment, gender, past_3_years_bike_related_purchases,
         owns_car, tenure, age, property_valuation) %>%
  drop_na()

training_set %>% ggplot(aes(total_profit, color=gender)) + geom_histogram(bins=15) + facet_wrap(~wealth,
```



```
#set.seed(123)
train_sample <- sample(nrow(training_set), round(nrow(training_set)*0.8))

train <- training_set[train_sample, ]
```

```
test <- training_set[-train_sample, ]
```

We can see below that training and test datasets have similar proportion of wealth_segments

```
prop.table(table(train$wealth_segment))
```

```
##
## Affluent Customer      High Net Worth      Mass Customer
##      0.2491296      0.2618956      0.4889749
```

```
prop.table(table(test$wealth_segment))
```

```
##
## Affluent Customer      High Net Worth      Mass Customer
##      0.2306502      0.2430341      0.5263158
```

```
lm1 <- lm(total_profit ~ ., train)
```

```
summary(lm1)
```

```
##
## Call:
## lm(formula = total_profit ~ ., data = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3823.3  -814.0  -100.1   722.7  6232.1
##
## Coefficients:
##              Estimate Std. Error t value
## (Intercept)    -118.6573    141.7325  -0.837
## total_order      548.4341     10.5823  51.826
## wealth_segmentHigh Net Worth    -59.3131     68.1626  -0.870
## wealth_segmentMass Customer    -56.2541     59.9718  -0.938
## genderMale       30.2904     48.8043   0.621
## past_3_years_bike_related_purchases    2.9735     0.8514   3.493
## owns_carYes      70.9106     48.7495   1.455
## tenure          3.8717     4.7614   0.813
## age             0.3760     2.1454   0.175
## property_valuation    -10.2422     8.6834  -1.180
##
##              Pr(>|t|)
## (Intercept)      0.402562
## total_order      < 0.0000000000000002 ***
## wealth_segmentHigh Net Worth      0.384288
## wealth_segmentMass Customer      0.348328
## genderMale      0.534885
## past_3_years_bike_related_purchases 0.000487 ***
## owns_carYes     0.145905
## tenure          0.416211
## age             0.860891
## property_valuation 0.238300
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1237 on 2575 degrees of freedom
## Multiple R-squared:  0.5127, Adjusted R-squared:  0.511
```

F-statistic: 301 on 9 and 2575 DF, p-value: < 0.00000000000000022