dlookr

Overview

Diagnose, explore and transform data with `dlookr`.
Features:

- Diagnose data quality.
- Find appropriate scenarios to pursuit the follow-up analysis through data exploration and understanding.
- Derive new variables or perform variable transformations.
- Automatically generate reports for the above three tasks.
- Supports quality diagnosis and EDA of table of DBMS.
  - version (≥ 0.3.2)

The name `dlookr` comes from `looking at the data` in the data analysis process.

Install dlookr

The released version is available on CRAN

```
install.packages("dlookr")
```

Or you can get the development version without vignettes from GitHub:

```
devtools::install_github("choonghyunryu/dlookr")
```

Or you can get the development version with vignettes from GitHub:

```
install.packages(c("nycflights13", "ISLR", "DBI", "RSQLite"))
devtools::install_github("choonghyunryu/dlookr", build_vignettes = TRUE)
```

Usage

dlookr includes several vignette files, which we use throughout the documentation.

Provided vignettes is as follows.

- Data quality diagnosis for data.frame, tbl_df, and table of DBMS
- Exploratory Data Analysis for data.frame, tbl_df, and table of DBMS
- Data Transformation
- Data diagnosis and EDA for table of DBMS

```
browseVignettes(package = "dlookr")
```

Data quality diagnosis

Data: nycflights13

To illustrate basic use of the dlookr package, use the `flights` data from the `nycflights13` package. Once loading `nycflights13` library, the `flights` data frame is available. The `flights` dataframe contains departure and arrival information on all flights departing from NYC in 2013.

```
library(nycflights13)
#> Warning: package 'nycflights13' was built under R version 3.4.4
dim(flights)
#> [1] 336776     19
flights
#> # A tibble: 336,776 x 19
#>     year month   day dep_time sched_dep_time dep_delay arr_time
#>    <int> <int> <int>    <int>          <int>     <dbl>    <int>
#>  1  2013     1     1      517            515      2.00      830
#>  2  2013     1     1      533            529      4.00      850
#>  3  2013     1     1      542            540      2.00      923
#>  4  2013     1     1      544            545     -1.00     1004
#>  5  2013     1     1      554            600     -6.00      812
#>  6  2013     1     1      554            558     -4.00      740
#>  7  2013     1     1      555            600     -5.00      913
#>  8  2013     1     1      557            600     -3.00      709
#>  9  2013     1     1      557            600     -3.00      838
#> 10  2013     1     1      558            600     -2.00      753
#> # ... with 336,766 more rows, and 12 more variables: sched_arr_time <int>,
#> #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#> #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#> #   minute <dbl>, time_hour <dttm>
```

General diagnosis of all variables with `diagnose()`

`diagnose()` allows you to diagnose variables on a data frame. Like any other `dplyr` functions, the first argument is the tibble (or data frame). The second and subsequent arguments refer to variables within the data frame.
The variables of the `tbl_df` object returned by `diagnose ()` are as follows.

- `variables` : variable name
- `types` : the data type of the variable

- `missing_count` : number of missing values
- `missing_percent` : percentage of missing values
- `unique_count` : number of unique values
- `unique_rate` : rate of unique value. unique_count / number of observation

For example, we can diagnose all variables in `flights`:

```
library(dlookr)
library(dplyr)

diagnose(flights)
#> # A tibble: 19 x 6
#>    variables  types missing_count missing_percent unique_count unique_rate
#>    <chr>      <chr>         <int>           <dbl>        <int>       <dbl>
#>  1 year       inte…             0           0                1  0.00000297
#>  2 month      inte…             0           0               12  0.0000356
#>  3 day        inte…             0           0               31  0.0000920
#>  4 dep_time   inte…          8255           2.45          1319  0.00392
#>  5 sched_dep… inte…             0           0             1021  0.00303
#>  6 dep_delay  nume…          8255           2.45           528  0.00157
#>  7 arr_time   inte…          8713           2.59          1412  0.00419
#>  8 sched_arr… inte…             0           0             1163  0.00345
#>  9 arr_delay  nume…          9430           2.80           578  0.00172
#> 10 carrier    char…             0           0               16  0.0000475
#> 11 flight     inte…             0           0             3844  0.0114
#> 12 tailnum    char…          2512           0.746         4044  0.0120
#> 13 origin     char…             0           0                3  0.00000891
#> 14 dest       char…             0           0              105  0.000312
#> 15 air_time   nume…          9430           2.80           510  0.00151
#> 16 distance   nume…             0           0              214  0.000635
#> 17 hour       nume…             0           0               20  0.0000594
#> 18 minute     nume…             0           0               60  0.000178
#> 19 time_hour  POSI…             0           0             6936  0.0206
```

- `Missing Value(NA)` : Variables with very large missing values, i.e. those with a `missing_percent` close to 100, should be excluded from the analysis.
- `Unique value` : Variables with a unique value (`unique_count` = 1) are considered to be excluded from data analysis. And if the data type is not numeric (integer, numeric) and the number of unique values is equal to the number of observations (unique_rate = 1), then the variable is likely to be an identifier. Therefore, this variable is also not suitable for the analysis model.

`year` can be considered not to be used in the analysis model since `unique_count` is 1. However, you do not have to remove it if you configure `date` as a combination of `year`, `month`, and `day`.
For example, we can diagnose only a few selected variables:

```
# Select columns by name
diagnose(flights, year, month, day)
```

```
#> # A tibble: 3 x 6
#>   variables types   missing_count missing_percent unique_count unique_rate
#>   <chr>     <chr>           <int>           <dbl>        <int>       <dbl>
#> 1 year      integer             0               0            1  0.00000297
#> 2 month     integer             0               0           12  0.0000356
#> 3 day       integer             0               0           31  0.0000920
# Select all columns between year and day (inclusive)
diagnose(flights, year:day)
#> # A tibble: 3 x 6
#>   variables types   missing_count missing_percent unique_count unique_rate
#>   <chr>     <chr>           <int>           <dbl>        <int>       <dbl>
#> 1 year      integer             0               0            1  0.00000297
#> 2 month     integer             0               0           12  0.0000356
#> 3 day       integer             0               0           31  0.0000920
# Select all columns except those from year to day (inclusive)
diagnose(flights, -(year:day))
#> # A tibble: 16 x 6
#>    variables  types missing_count missing_percent unique_count unique_rate
#>    <chr>      <chr>         <int>           <dbl>        <int>       <dbl>
#>  1 dep_time   inte…          8255           2.45          1319  0.00392
#>  2 sched_dep… inte…             0           0             1021  0.00303
#>  3 dep_delay  nume…          8255           2.45           528  0.00157
#>  4 arr_time   inte…          8713           2.59          1412  0.00419
#>  5 sched_arr… inte…             0           0             1163  0.00345
#>  6 arr_delay  nume…          9430           2.80           578  0.00172
#>  7 carrier    char…             0           0               16  0.0000475
#>  8 flight     inte…             0           0             3844  0.0114
#>  9 tailnum    char…          2512           0.746         4044  0.0120
#> 10 origin     char…             0           0                3  0.00000891
#> 11 dest       char…             0           0              105  0.000312
#> 12 air_time   nume…          9430           2.80           510  0.00151
#> 13 distance   nume…             0           0              214  0.000635
#> 14 hour       nume…             0           0               20  0.0000594
#> 15 minute     nume…             0           0               60  0.000178
#> 16 time_hour  POSI…             0           0             6936  0.0206
```

By using dplyr, variables including missing values can be sorted by the weight of missing values.:

```
flights %>%
  diagnose() %>%
  select(-unique_count, -unique_rate) %>%
  filter(missing_count > 0) %>%
  arrange(desc(missing_count))
#> Warning: package 'bindrcpp' was built under R version 3.4.4
#> # A tibble: 6 x 4
#>   variables types     missing_count missing_percent
#>   <chr>     <chr>             <int>           <dbl>
#> 1 arr_delay numeric            9430           2.80
#> 2 air_time  numeric            9430           2.80
#> 3 arr_time  integer            8713           2.59
#> 4 dep_time  integer            8255           2.45
#> 5 dep_delay numeric            8255           2.45
#> 6 tailnum   character          2512           0.746
```

Diagnosis of numeric variables with `diagnose_numeric()`

`diagnose_numeric()` diagnoses numeric(continuous and discrete) variables in a data frame. Usage is the same as `diagnose()`but returns more diagnostic information. However, if you specify a non-numeric variable in the second and subsequent argument list, the variable is automatically ignored.
The variables of the `tbl_df` object returned by `diagnose_numeric()` are as follows.

- `min` : minimum value
- `Q1` : 1/4 quartile, 25th percentile
- `mean` : arithmetic mean
- `median` : median, 50th percentile
- `Q3` : 3/4 quartile, 75th percentile
- `max` : maximum value
- `zero` : number of observations with a value of 0
- `minus` : number of observations with negative numbers
- `outlier` : number of outliers

Applying the summary () function to a data frame can help you figure out the distribution of data by printing `min`, `Q1`, `mean`, `median`, `Q3`, and `max` give. However, the result is that analysts can only look at it with eyes. However, returning such information as a data frame structure like `tbl_df` widens the scope of utilization.
`zero`, `minus`, and `outlier` are useful for diagnosing the integrity of data. For example, numerical data in some cases may not have 0 or a negative number.
`diagnose_numeric()` can diagnose all numeric variables of `flights` as follows.:

```
diagnose_numeric(flights)
#> # A tibble: 14 x 10
#>    variables      min       Q1    mean   median     Q3    max  zero  minus
#>    <chr>        <dbl>    <dbl>   <dbl>    <dbl>  <dbl>  <dbl> <int>  <int>
#>  1 year       2013     2013    2013     2013    2013   2013       0      0
#>  2 month         1.00     4.00    6.55     7.00   10.0   12.0     0      0
#>  3 day           1.00     8.00   15.7     16.0    23.0   31.0     0      0
#>  4 dep_time      1.00   907    1349     1401    1744   2400       0      0
#>  5 sched_de…   106      906    1344     1359    1729   2359       0      0
#>  6 dep_delay -  43.0  -   5.00   12.6  -   2.00   11.0 1301   16514 183575
#>  7 arr_time      1.00  1104    1502     1535    1940   2400       0      0
#>  8 sched_ar…     1.00  1124    1536     1556    1945   2359       0      0
#>  9 arr_delay -  86.0  -  17.0     6.90 -   5.00   14.0 1272    5409 188933
#> 10 flight        1.00   553    1972     1496    3465   8500       0      0
#> 11 air_time     20.0     82.0   151      129     192    695       0      0
#> 12 distance     17.0    502    1040      872    1389   4983       0      0
#> 13 hour          1.00     9.00   13.2     13.0    17.0   23.0     0      0
#> 14 minute        0        8.00   26.2     29.0    44.0   59.0 60696      0
#> # ... with 1 more variable: outlier <int>
```

If a numeric variable can not logically have a negative or zero value, it can be used with `filter()` to easily find a variable that does not logically match:

```
diagnose_numeric(flights) %>%
  filter(minus > 0 | zero > 0)
#> # A tibble: 3 x 10
#>   variables   min     Q1  mean median    Q3    max  zero  minus outlier
#>   <chr>     <dbl>  <dbl> <dbl>  <dbl> <dbl>  <dbl> <int>  <int>   <int>
#> 1 dep_delay -43.0 - 5.00 12.6   - 2.00  11.0 1301    16514 183575   43216
#> 2 arr_delay -86.0 -17.0   6.90 - 5.00  14.0 1272     5409 188933   27880
#> 3 minute      0     8.00 26.2   29.0   44.0   59.0 60696      0       0
```

Diagnosis of categorical variables with `diagnose_category()`

`diagnose_category()` diagnoses the categorical(factor, ordered, character) variables of a data frame. The usage is similar to `diagnose ()` but returns more diagnostic information. If you specify a non-categorical variable in the second and subsequent argument list, the variable is automatically ignored. The top argument specifies the number of levels to return per variable. The default value is 10, which returns the top 10 level. Of course, if the number of levels is less than 10, all levels are returned.
The variables of the `tbl_df` object returned by `diagnose_category()` are as follows.

- `variables` : variable names
- `levels`: level names
- `N` : Number of observation
- `freq` : Number of observation at the levles
- `ratio` : Percentage of observation at the levles
- `rank` : Rank of occupancy ratio of levels

`` ` ``diagnose_category()` can diagnose all categorical variables of `flights` as follows.:

```
diagnose_category(flights)
#> # A tibble: 33 x 6
#>    variables levels      N  freq ratio  rank
#>    <chr>     <chr>   <int> <int> <dbl> <int>
#>  1 carrier   UA     336776 58665 17.4      1
#>  2 carrier   B6     336776 54635 16.2      2
#>  3 carrier   EV     336776 54173 16.1      3
#>  4 carrier   DL     336776 48110 14.3      4
#>  5 carrier   AA     336776 32729  9.72     5
#>  6 carrier   MQ     336776 26397  7.84     6
#>  7 carrier   US     336776 20536  6.10     7
#>  8 carrier   9E     336776 18460  5.48     8
#>  9 carrier   WN     336776 12275  3.64     9
#> 10 carrier   VX     336776  5162  1.53    10
#> # ... with 23 more rows
```

In collaboration with `filter()` in the `dplyr` package, we can see that the `tailnum` variable is ranked in top 1 with 2,512 missing values in the case where the missing value is included in the top 10:

```
diagnose_category(flights) %>%
  filter(is.na(levels))
#> # A tibble: 1 x 6
#>   variables levels      N  freq ratio  rank
```

```
#>   <chr>     <chr>    <int> <int> <dbl> <int>
#> 1 tailnum   <NA>    336776  2512 0.746     1
```

The following returns a list of levels less than or equal to 0.01%. It should be noted that the top argument has a generous specification of 500. If you use the default value of 10, values below 0.01% would not be included in the list:

```
flights %>%
  diagnose_category(top = 500)  %>%
  filter(ratio <= 0.01)
#> # A tibble: 10 x 6
#>    variables levels      N  freq    ratio  rank
#>    <chr>     <chr>   <int> <int>    <dbl> <int>
#>  1 carrier   OO     336776    32 0.00950     16
#>  2 dest      JAC    336776    25 0.00742     97
#>  3 dest      PSP    336776    19 0.00564     98
#>  4 dest      EYW    336776    17 0.00505     99
#>  5 dest      HDN    336776    15 0.00445    100
#>  6 dest      MTJ    336776    15 0.00445    101
#>  7 dest      SBN    336776    10 0.00297    102
#>  8 dest      ANC    336776     8 0.00238    103
#>  9 dest      LEX    336776     1 0.000297   104
#> 10 dest      LGA    336776     1 0.000297   105
```

In the analytical model, it is also possible to consider removing the small percentage of observations in the observations or joining them together.

Diagnosing outliers with `diagnose_outlier()`

`diagnose_outlier()` diagnoses the outliers of the numeric (continuous and discrete) variables of the data frame. The usage is the same as `diagnose()`.
The variables of the `tbl_df` object returned by `diagnose_outlier()` are as follows.

- `outliers_cnt` : Count of outliers
- `outliers_ratio` : Percent of outliers
- `outliers_mean` : Arithmetic Average of outliers
- `with_mean` : Arithmetic Average of with outliers
- `without_mean` : Arithmetic Average of without outliers

`diagnose_outlier()` can diagnose anomalies of all numeric variables of `flights` as follows:

```
diagnose_outlier(flights)
#> # A tibble: 14 x 6
#>    variables      outliers_cnt outliers_ratio outliers_mean with_mean
#>    <chr>                 <int>          <dbl>         <dbl>     <dbl>
#>  1 year                      0       0              NaN     2013
#>  2 month                     0       0              NaN        6.55
#>  3 day                       0       0              NaN       15.7
#>  4 dep_time                  0       0              NaN     1349
#>  5 sched_dep_time            0       0              NaN     1344
#>  6 dep_delay             43216      12.8             93.1     12.6
#>  7 arr_time                  0       0              NaN     1502
```

```
#>  8 sched_arr_time            0        0                NaN      1536
#>  9 arr_delay             27880        8.28             121         6.90
#> 10 flight                    1        0.000297        8500      1972
#> 11 air_time               5448        1.62             400       151
#> 12 distance                715        0.212           4955      1040
#> 13 hour                      0        0                NaN        13.2
#> 14 minute                    0        0                NaN        26.2
#> # ... with 1 more variable: without_mean <dbl>
```

The following is a list of numeric variables with anomalies greater than 5%.:

```
diagnose_outlier(flights) %>%
  filter(outliers_ratio > 5) %>%
  mutate(rate = outliers_mean / with_mean) %>%
  arrange(desc(rate)) %>%
  select(-outliers_cnt)
#> # A tibble: 2 x 6
#>   variables outliers_ratio outliers_mean with_mean without_mean  rate
#>   <chr>              <dbl>         <dbl>     <dbl>        <dbl> <dbl>
#> 1 arr_delay           8.28         121        6.90       -3.69  17.5
#> 2 dep_delay          12.8           93.1     12.6         0.444  7.37
```

If the outlier is larger than the average of all observations, it may be desirable to replace or remove the outlier in the data analysis process.

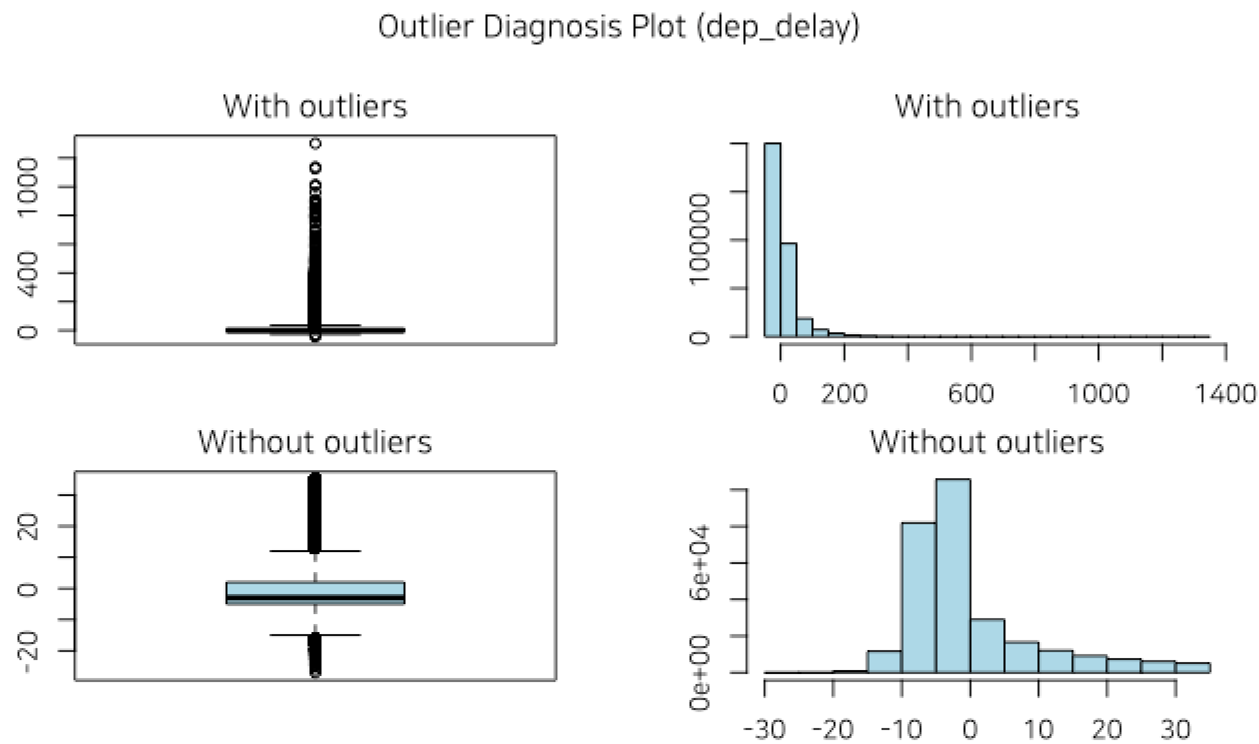
Visualization of outliers using `plot_outlier()`

`plot_outlier()` visualizes outliers of numarical variables(continious and discrete) of data.frame. Usage is the same `diagnose()`.
The plot derived from the numerical data diagnosis is as follows.

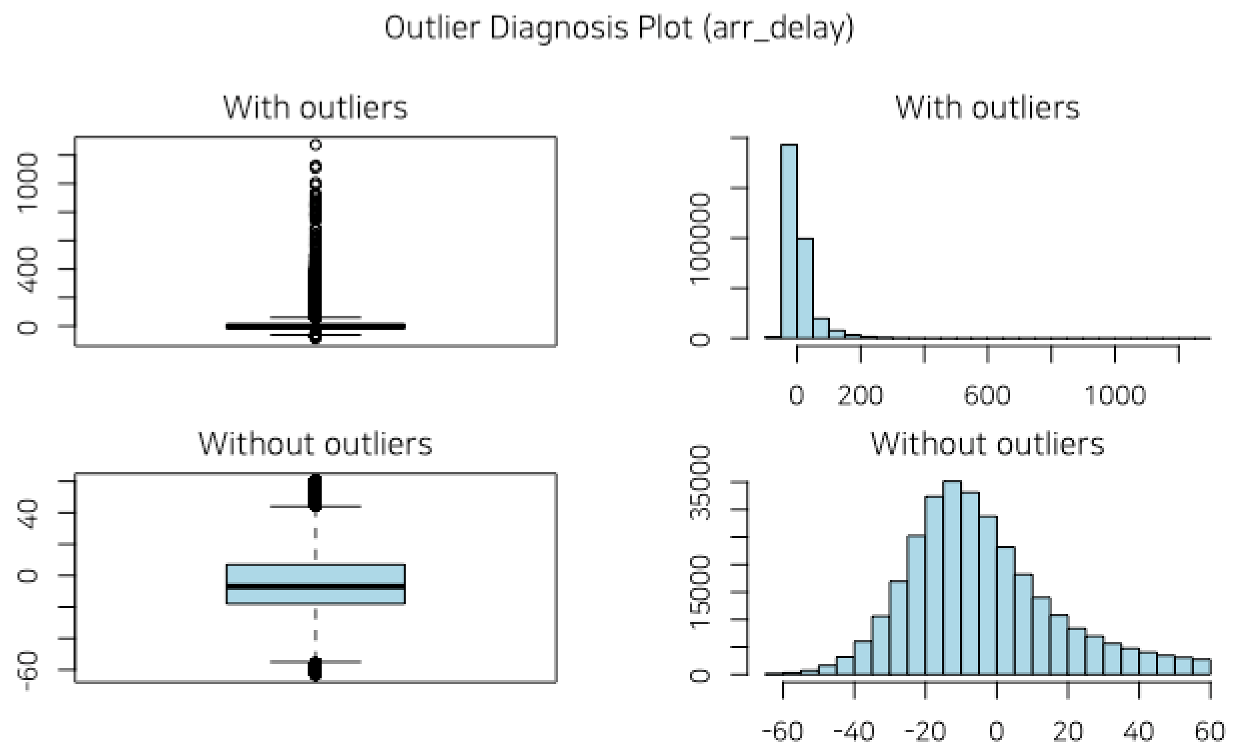
- With outliers box plot
- Without outliers box plot
- With outliers histogram
- Without outliers histogram

Use the function of the dplyr package and `plot_outlier()` and `diagnose_outlier()` to visualize anomaly values of all numeric variables with an outlier ratio of 0.5% or more.:

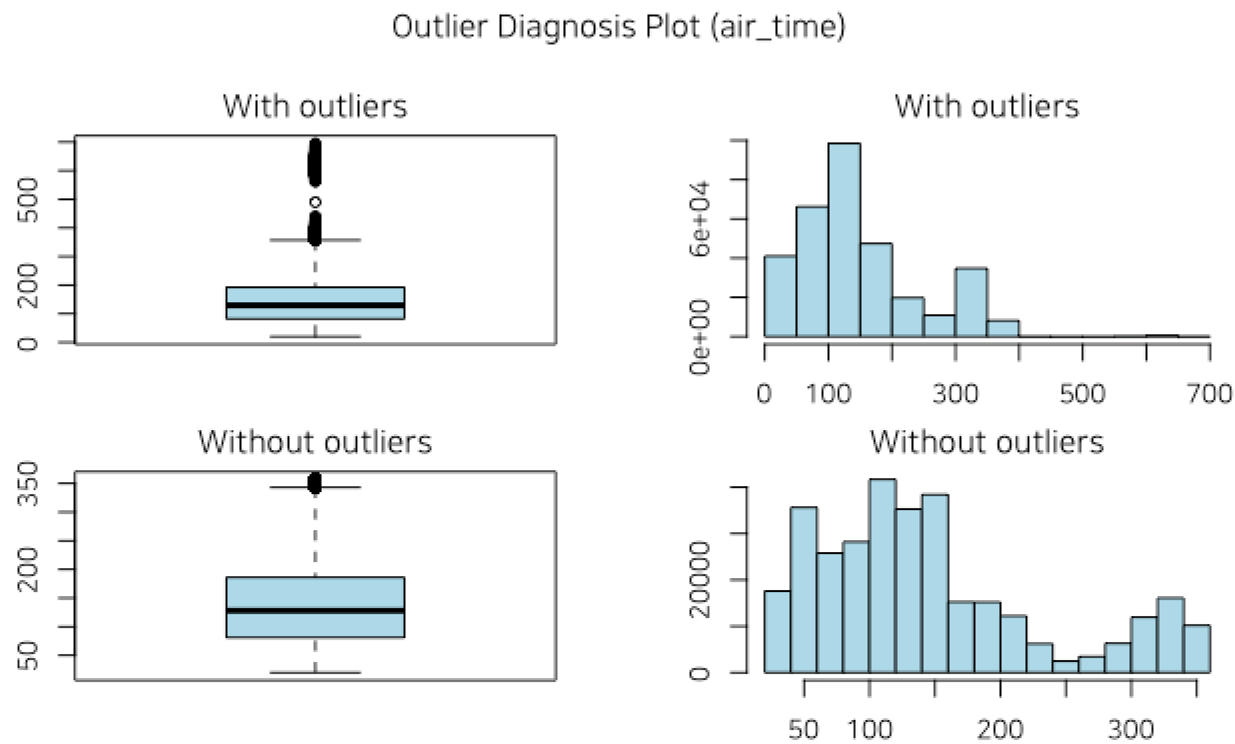
```
flights %>%
  plot_outlier(diagnose_outlier(flights) %>%
               filter(outliers_ratio >= 0.5) %>%
               select(variables) %>%
               unlist())
```



Outlier Diagnosis Plot (dep_delay)
With outliers
0
400
1000
With outliers
0
100000
0
200
600
1000
1400
Without outliers
-20
0
20
Without outliers
0e+00
6e+04
-30
-20
-10
0
10
20
30



Outlier Diagnosis Plot (arr_delay)
With outliers
0
400
1000
With outliers
0
100000
0
200
600
1000
Without outliers
-60
0
40
Without outliers
0
15000
35000
-60
-40
-20
0
20
40
60



You should look at the visualization results and decide whether to remove or replace the outliers. In some cases, it is important to consider removing the variables that contain anomalies from the data analysis model.

In the visualization results, `arr_delay` has similar distributions to the normal distribution of the observed values. In the case of linear models, we can also consider removing or replacing anomalies. And `air_time` shows a roughly similar distribution before and after removing anomalies.

Exploratory Data Analysis

datasets

To illustrate the basic use of EDA in the dlookr package, I use a `Carseats` datasets. `Carseats` in the `ISLR` package is simulation dataset that sells children's car seats at 400 stores. This data is a data.frame created for the purpose of predicting sales volume.

```
library(ISLR)
str(Carseats)
#> 'data.frame':    400 obs. of  11 variables:
#>  $ Sales      : num  9.5 11.22 10.06 7.4 4.15 ...
#>  $ CompPrice  : num  138 111 113 117 141 124 115 136 132 132 ...
#>  $ Income     : num  73 48 35 100 64 113 105 81 110 113 ...
```

```
#>  $ Advertising: num  11 16 10 4 3 13 0 15 0 0 ...
#>  $ Population : num  276 260 269 466 340 501 45 425 108 131 ...
#>  $ Price      : num  120 83 80 97 128 72 108 120 124 124 ...
#>  $ ShelveLoc  : Factor w/ 3 levels "Bad","Good","Medium": 1 2 3 3 1 1 3 2 3 3 ...
#>  $ Age        : num  42 65 59 55 38 78 71 67 76 76 ...
#>  $ Education  : num  17 10 12 14 13 16 15 10 10 17 ...
#>  $ Urban      : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 1 2 2 1 1 ...
#>  $ US         : Factor w/ 2 levels "No","Yes": 2 2 2 2 1 2 1 2 1 2 ...
```

The contents of individual variables are as follows. (Refer to ISLR::Carseats Man page)

- Sales
  - Unit sales (in thousands) at each location
- CompPrice
  - Price charged by competitor at each location
- Income
  - Community income level (in thousands of dollars)
- Advertising
  - Local advertising budget for company at each location (in thousands of dollars)
- Population
  - Population size in region (in thousands)
- Price
  - Price company charges for car seats at each site
- ShelveLoc
  - A factor with levels Bad, Good and Medium indicating the quality of the shelving location for the car seats at each site
- Age
  - Average age of the local population
- Education
  - Education level at each location
- Urban
  - A factor with levels No and Yes to indicate whether the store is in an urban or rural location
- US
  - A factor with levels No and Yes to indicate whether the store is in the US or not

When data analysis is performed, data containing missing values is often encountered. However, Carseats is complete data without missing. Therefore, the missing values are generated as follows. And I created a data.frame object named carseats.

```r
carseats <- ISLR::Carseats

set.seed(123)
carseats[sample(seq(NROW(carseats)), 20), "Income"] <- NA

set.seed(456)
carseats[sample(seq(NROW(carseats)), 10), "Urban"] <- NA
```

Univariate data EDA

Calculating descriptive statistics using `describe()`

`describe()` computes descriptive statistics for numerical data. The descriptive statistics help determine the distribution of numerical variables. Like function of dplyr, the first argument is the tibble (or data frame). The second and subsequent arguments refer to variables within that data frame.

The variables of the `tbl_df` object returned by `describe()` are as follows.

- `n` : number of observations excluding missing values
- `na` : number of missing values
- `mean` : arithmetic average
- `sd` : standard devation
- `se_mean` : standrd error mean. sd/sqrt(n)
- `IQR` : interquartile range (Q3-Q1)
- `skewness` : skewness
- `kurtosis` : kurtosis
- `p25` : Q1. 25% percentile
- `p50` : median. 50% percentile
- `p75` : Q3. 75% percentile
- `p01`, `p05`, `p10`, `p20`, `p30` : 1%, 5%, 20%, 30% percentiles
- `p40`, `p60`, `p70`, `p80` : 40%, 60%, 70%, 80% percentiles
- `p90`, `p95`, `p99`, `p100` : 90%, 95%, 99%, 100% percentiles

For example, we can computes the statistics of all numerical variables in `carseats`:

```r
describe(carseats)
#> # A tibble: 8 x 26
#>   variable        n    na   mean     sd se_mean    IQR skewness kurtosis
#>   <chr>       <dbl> <dbl>  <dbl>  <dbl>   <dbl>  <dbl>    <dbl>    <dbl>
#> 1 Sales         400   0     7.50   2.82   0.141   3.93   0.186   -0.0809
#> 2 CompPrice     400   0   125     15.3    0.767  20.0   -0.0428   0.0417
#> 3 Income        380  20.0  68.9   28.1    1.44   48.2    0.0449  -1.09
#> 4 Advertising   400   0     6.64   6.65   0.333  12.0    0.640   -0.545
#> 5 Population    400   0   265    147      7.37  260     -0.0512  -1.20
#> 6 Price         400   0   116     23.7    1.18   31.0   -0.125    0.452
#> 7 Age           400   0    53.3   16.2    0.810  26.2   -0.0772  -1.13
#> 8 Education     400   0    13.9    2.62   0.131   4.00   0.0440  -1.30
#> # ... with 17 more variables: p00 <dbl>, p01 <dbl>, p05 <dbl>, p10 <dbl>,
```

```
#> #   p20 <dbl>, p25 <dbl>, p30 <dbl>, p40 <dbl>, p50 <dbl>, p60 <dbl>,
#> #   p70 <dbl>, p75 <dbl>, p80 <dbl>, p90 <dbl>, p95 <dbl>, p99 <dbl>,
#> #   p100 <dbl>
```

- `skewness` : The left-skewed distribution data, that is, the variables with large positive skewness should consider the log or sqrt transformations to follow the normal distribution. The variables `Advertising` seem to need to consider variable transformations.
- `mean` and `sd`, `se_mean` : The`Population` with a large `standard error of the mean`(se_mean) has low representativeness of the `arithmetic mean`(mean). The `standard deviation`(sd) is much larger than the arithmetic average.

By using dplyr, You can sort by `left or right skewed size`(skewness).:

```
carseats %>%
  describe() %>%
  select(variable, skewness, mean, p25, p50, p75) %>%
  filter(!is.na(skewness)) %>%
  arrange(desc(abs(skewness)))
#> # A tibble: 8 x 6
#>   variable    skewness   mean    p25    p50    p75
#>   <chr>          <dbl>  <dbl>  <dbl>  <dbl>  <dbl>
#> 1 Advertising   0.640    6.64   0      5.00  12.0
#> 2 Sales         0.186    7.50   5.39   7.49   9.32
#> 3 Price        -0.125  116    100    117    131
#> 4 Age          -0.0772  53.3   39.8   54.5   66.0
#> 5 Population   -0.0512 265    139    272    398
#> 6 Income        0.0449  68.9   42.8   69.0   91.0
#> 7 Education     0.0440  13.9   12.0   14.0   16.0
#> 8 CompPrice    -0.0428 125    115    125    135
```

The `describe()` function supports the `group_by()` function syntax of `dplyr`.

```
carseats %>%
  group_by(US, Urban) %>%
  describe(Sales, Income)
#> # A tibble: 12 x 28
#>    variable US    Urban     n    na  mean    sd se_mean    IQR skewness
#>    <chr>    <fct> <fct> <dbl> <dbl> <dbl> <dbl>   <dbl>  <dbl>    <dbl>
#>  1 Sales    No    No     46.0  0     6.46  2.72   0.402  3.15   0.0889
#>  2 Sales    No    Yes    92.0  0     7.00  2.58   0.269  3.49   0.492
#>  3 Sales    No    <NA>    4.00 0     6.99  1.28   0.639  0.827  1.69
#>  4 Sales    Yes   No     69.0  0     8.23  2.65   0.319  4.10  -0.0212
#>  5 Sales    Yes   Yes   183    0     7.74  2.97   0.219  4.11   0.123
#>  6 Sales    Yes   <NA>    6.00 0     7.61  2.61   1.06   3.25   0.489
#>  7 Income   No    No     42.0  4.00 60.2  29.1    4.49  45.2    0.408
#>  8 Income   No    Yes    84.0  8.00 69.5  27.4    2.99  47.0   -0.0497
#>  9 Income   No    <NA>    4.00 0    48.2  24.7   12.3   40.8   -0.0496
#> 10 Income   Yes   No     65.0  4.00 70.5  29.9    3.70  48.0    0.0736
#> 11 Income   Yes   Yes   179    4.00 70.3  27.2    2.03  46.5    0.00490
#> 12 Income   Yes   <NA>    6.00 0    75.3  34.3   14.0   47.2   -0.412
#> # ... with 18 more variables: kurtosis <dbl>, p00 <dbl>, p01 <dbl>,
#> #   p05 <dbl>, p10 <dbl>, p20 <dbl>, p25 <dbl>, p30 <dbl>, p40 <dbl>,
```

```
#> #   p50 <dbl>, p60 <dbl>, p70 <dbl>, p75 <dbl>, p80 <dbl>, p90 <dbl>,
#> #   p95 <dbl>, p99 <dbl>, p100 <dbl>
```

Test of normality on numeric variables using `normality()`

`normality()` performs a normality test on numerical data. `Shapiro-Wilk normality test` is performed. If the number of observations is larger than 5000, 5000 observations are extracted by random simple sampling and then tested.

The variables of `tbl_df` object returned by `normality()` are as follows.

- `statistic` : Statistics of the Shapiro-Wilk test
- `p_value` : p-value of the Shapiro-Wilk test
- `sample` : Number of sample observations performed Shapiro-Wilk test

`normality()` performs the normality test for all numerical variables of `carseats` as follows.:

```
normality(carseats)
#> # A tibble: 8 x 4
#>   vars        statistic              p_value sample
#>   <chr>           <dbl>                <dbl>  <dbl>
#> 1 Sales           0.995 0.254                   400
#> 2 CompPrice       0.998 0.977                   400
#> 3 Income          0.961 0.0000000152            400
#> 4 Advertising     0.874 0.0000000000000000149   400
#> 5 Population      0.952 0.000000000408          400
#> 6 Price           0.996 0.390                   400
#> 7 Age             0.957 0.00000000186           400
#> 8 Education       0.924 0.000000000000243       400
```

You can use dplyr to sort non-normal distribution variables by p_value.:

```
carseats %>%
  normality() %>%
  filter(p_value <= 0.01) %>%
  arrange(abs(p_value))
#> # A tibble: 5 x 4
#>   vars        statistic              p_value sample
#>   <chr>           <dbl>                <dbl>  <dbl>
#> 1 Advertising     0.874 0.0000000000000000149   400
#> 2 Education       0.924 0.000000000000243       400
#> 3 Population      0.952 0.000000000408          400
#> 4 Age             0.957 0.00000000186           400
#> 5 Income          0.961 0.0000000152            400
```

In particular, the `Advertising` variable is considered to be the most out of the normal distribution.

The `normality()` function supports the `group_by()` function syntax in the `dplyr` package.

```
carseats %>%
  group_by(ShelveLoc, US) %>%
  normality(Income) %>%
  arrange(desc(p_value))
```

```
#> # A tibble: 6 x 6
#>   variable ShelveLoc US    statistic  p_value sample
#>   <chr>    <fct>     <fct>     <dbl>    <dbl>  <dbl>
#> 1 Income   Bad       No        0.969 0.470      34.0
#> 2 Income   Bad       Yes       0.958 0.0343     62.0
#> 3 Income   Good      No        0.902 0.0328     24.0
#> 4 Income   Good      Yes       0.955 0.0296     61.0
#> 5 Income   Medium    No        0.947 0.00319    84.0
#> 6 Income   Medium    Yes       0.961 0.000948  135
```

The `Income` variable does not follow the normal distribution. However, if the `US` is `No` and the `ShelveLoc` is `Good` or `Bad` at the significance level of 0.01, it follows the normal distribution.

In the following, we perform `normality test of log(Income)` for each combination of `ShelveLoc` and `US` variables to inquire about normal distribution cases.

```
carseats %>%
  mutate(log_income = log(Income)) %>%
  group_by(ShelveLoc, US) %>%
  normality(log_income) %>%
  filter(p_value > 0.01)
#> # A tibble: 1 x 6
#>   variable   ShelveLoc US    statistic p_value sample
#>   <chr>      <fct>     <fct>     <dbl>   <dbl>  <dbl>
#> 1 log_income Bad       No        0.940  0.0737   34.0
```

Normalization visualization of numerical variables using `plot_normality()`

`plot_normality()` visualizes the normality of numeric data.

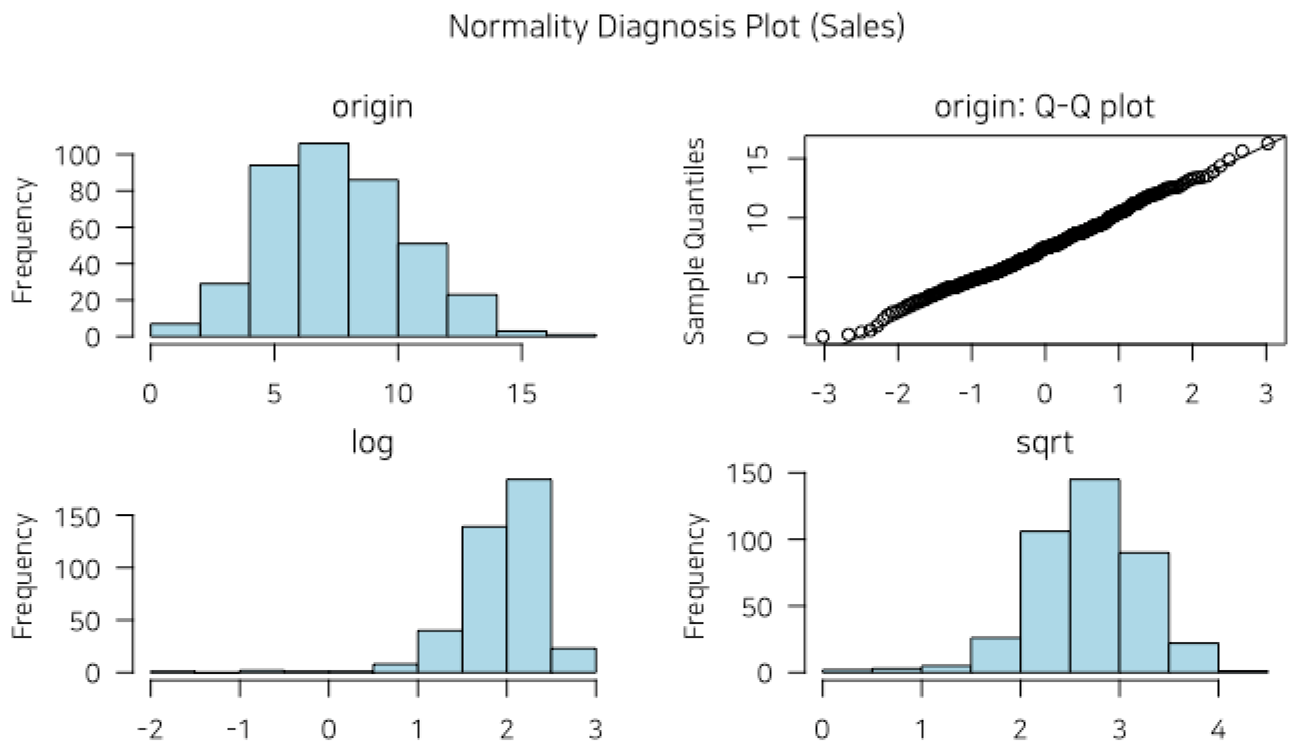
The information that `plot_normality()` visualizes is as follows.

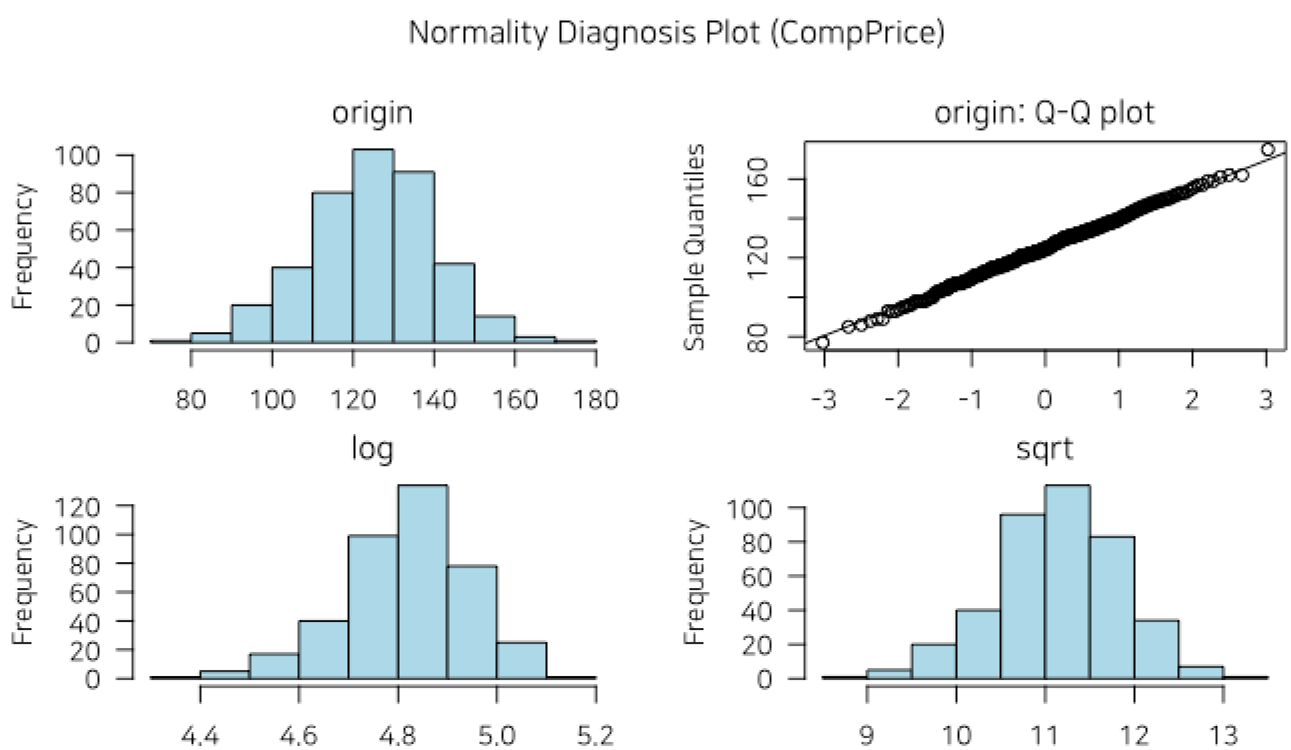
- `Histogram of original data`
- `Q-Q plot of original data`
- `histogram of log transformed data`
- `Histogram of square root transformed data`

Numerical data following a `power-law distribution` are often encountered in data analysis. Since the numerical data following the power distribution is transformed into the normal distribution by performing the log and sqrt transform, the histogram of the data for the log and sqrt transform is drawn.

`plot_normality()` can also specify several variables like `normality()` function.

```
# Select columns by name
plot_normality(carseats, Sales, CompPrice)
```

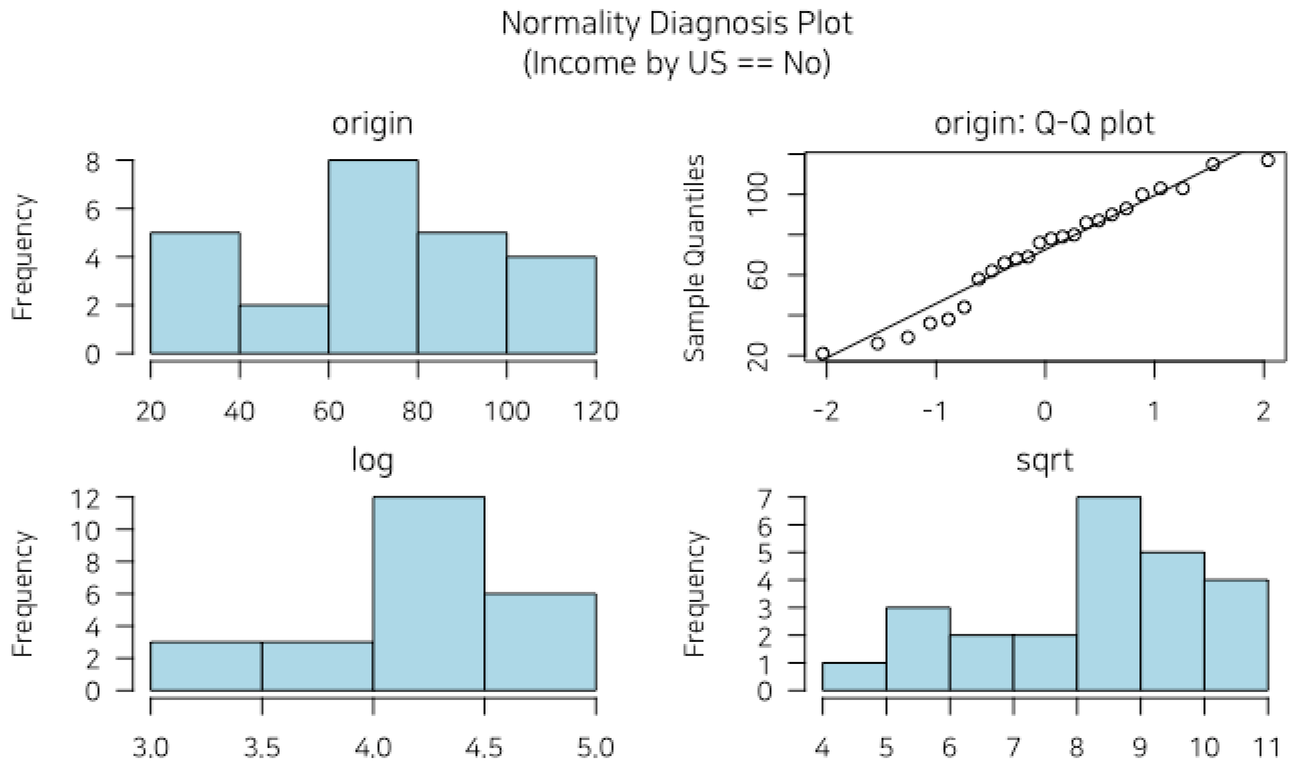


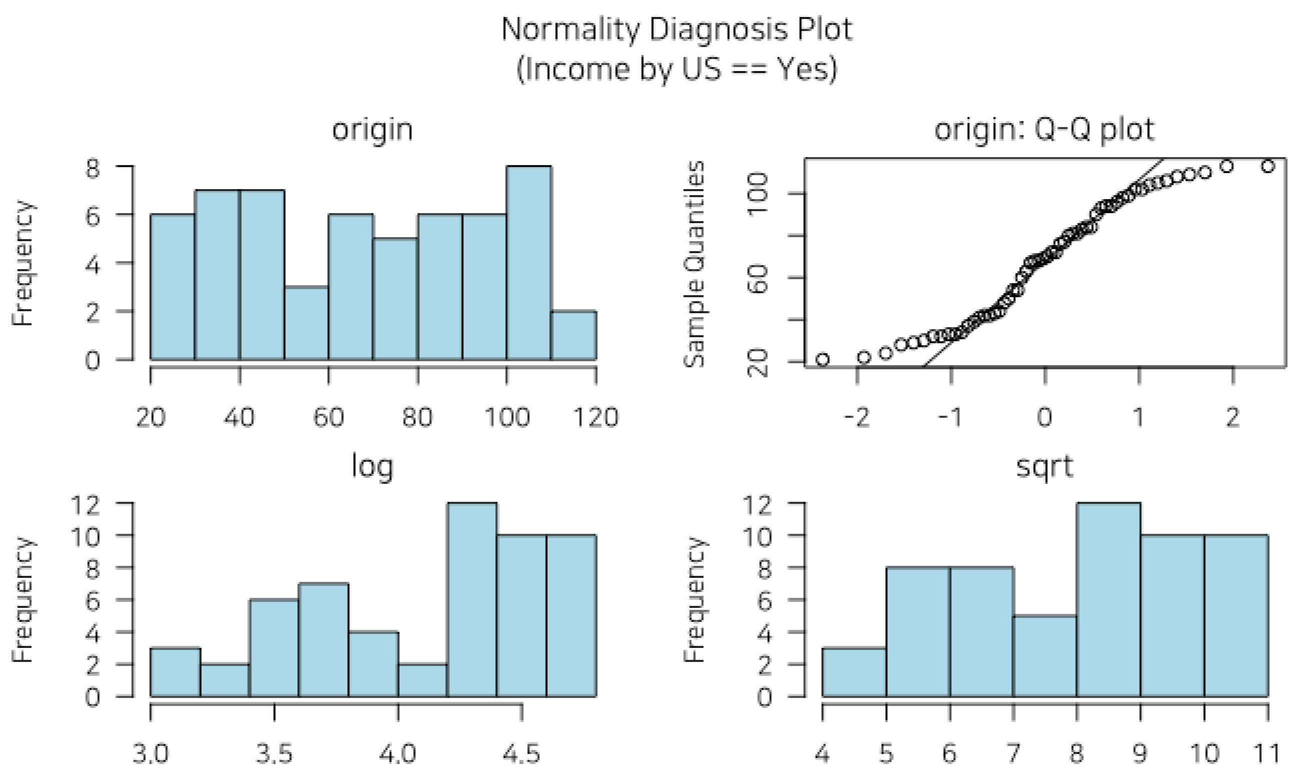


The `plot_normality()` function also supports the `group_by()` function syntax in the `dplyr` package.

```
carseats %>%
  filter(ShelveLoc == "Good") %>%
```

```
group_by(US) %>%
plot_normality(Income)
```





Bivariate data EDA

Calculation of `correlation coefficient` using `correlate()`

`Correlate()` finds the correlation coefficient of all combinations of `carseats` numerical variables as follows:

```
correlate(carseats)
#> # A tibble: 56 x 3
#>    var1        var2      coef_corr
#>    <fct>       <fct>         <dbl>
#>  1 CompPrice   Sales        0.0641
#>  2 Income      Sales        0.151
#>  3 Advertising Sales        0.270
#>  4 Population  Sales        0.0505
#>  5 Price       Sales       -0.445
#>  6 Age         Sales       -0.232
#>  7 Education   Sales       -0.0520
#>  8 Sales       CompPrice    0.0641
#>  9 Income      CompPrice   -0.0761
#> 10 Advertising CompPrice   -0.0242
#> # ... with 46 more rows
```

The following example performs a normality test only on combinations that include several selected variables.

```
# Select columns by name
correlate(carseats, Sales, CompPrice, Income)
#> # A tibble: 21 x 3
#>    var1      var2        coef_corr
#>    <fct>     <fct>           <dbl>
#>  1 CompPrice Sales          0.0641
#>  2 Income    Sales          0.151
#>  3 Sales     CompPrice      0.0641
#>  4 Income    CompPrice     -0.0761
#>  5 Sales     Income         0.151
#>  6 CompPrice Income        -0.0761
#>  7 Sales     Advertising    0.270
#>  8 CompPrice Advertising   -0.0242
#>  9 Income    Advertising    0.0435
#> 10 Sales     Population     0.0505
#> # ... with 11 more rows
```

`correlate()` produces `two pairs of variable` combinations. So you can use the following `filter()` function to get the correlation coefficient for `a pair of variable` combinations:

```
carseats %>%
  correlate(Sales:Income) %>%
  filter(as.integer(var1) > as.integer(var2))
#> # A tibble: 3 x 3
#>   var1      var2      coef_corr
#>   <fct>     <fct>         <dbl>
#> 1 CompPrice Sales        0.0641
#> 2 Income    Sales        0.151
#> 3 Income    CompPrice   -0.0761
```

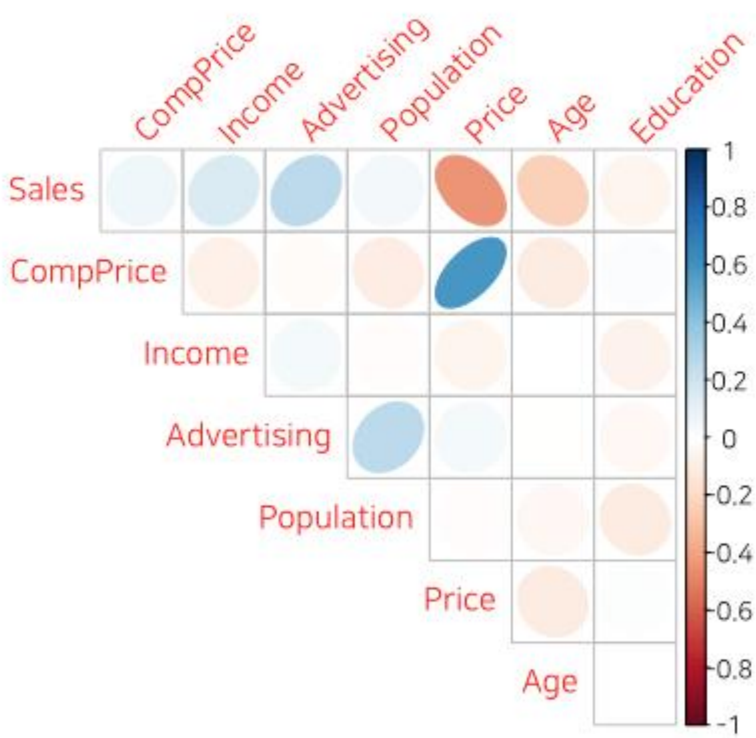
The `correlate()` function also supports the `group_by()` function syntax in the `dplyr` package.

```
carseats %>%
  filter(ShelveLoc == "Good") %>%
  group_by(Urban, US) %>%
  correlate(Sales) %>%
  filter(abs(coef_corr) > 0.5)
#> # A tibble: 12 x 5
#>    Urban US    var1  var2       coef_corr
#>    <fct> <fct> <fct> <fct>          <dbl>
#>  1 No    No    Sales Income        -0.540
#>  2 No    No    Sales Price         -0.943
#>  3 No    No    Sales Age           -0.722
#>  4 No    Yes   Sales Price         -0.791
#>  5 Yes   No    Sales Price         -0.595
#>  6 Yes   Yes   Sales Price         -0.509
#>  7 <NA>  Yes   Sales CompPrice     -0.874
#>  8 <NA>  Yes   Sales Income         0.996
#>  9 <NA>  Yes   Sales Population     0.539
#> 10 <NA>  Yes   Sales Price         -0.623
#> 11 <NA>  Yes   Sales Age           -0.975
#> 12 <NA>  Yes   Sales Education     -0.767
```

Visualization of the correlation matrix using `plot_correlate()`

`plot_correlate()` visualizes the correlation matrix.

```
plot_correlate(carseats)
```



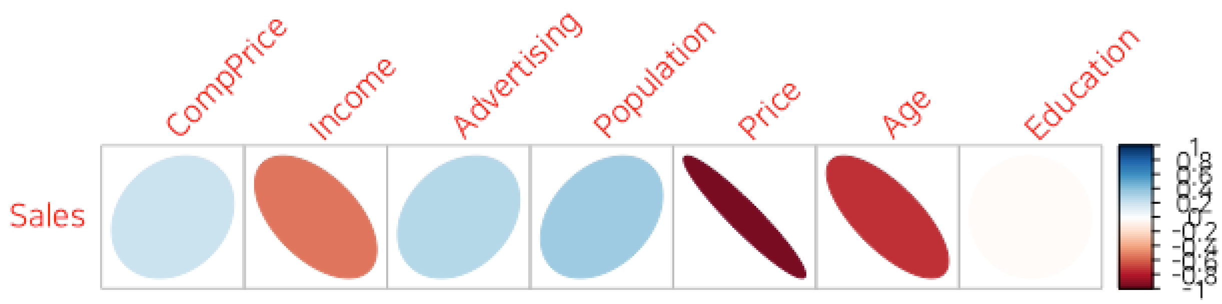
`plot_correlate()` can also specify multiple variables, like the `correlate()` function. The following is a visualization of the correlation matrix including several selected variables.

```
# Select columns by name
plot_correlate(carseats, Sales, Price)
```

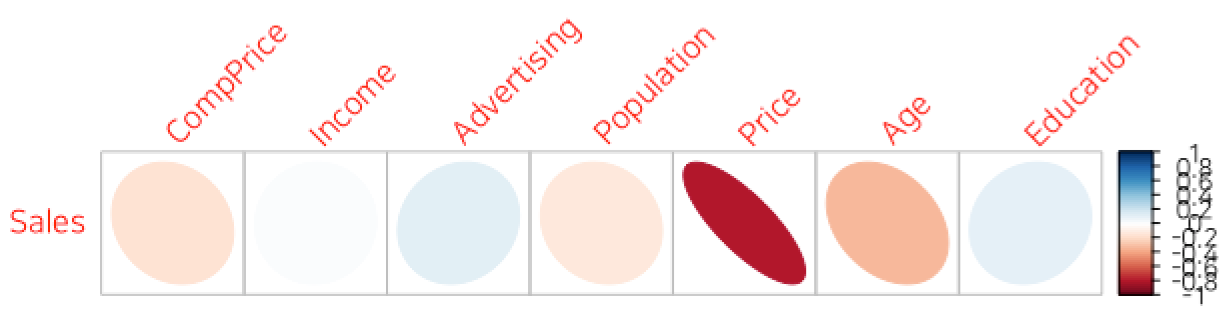
The `plot_correlate()` function also supports the `group_by()` function syntax in the `dplyr` package.

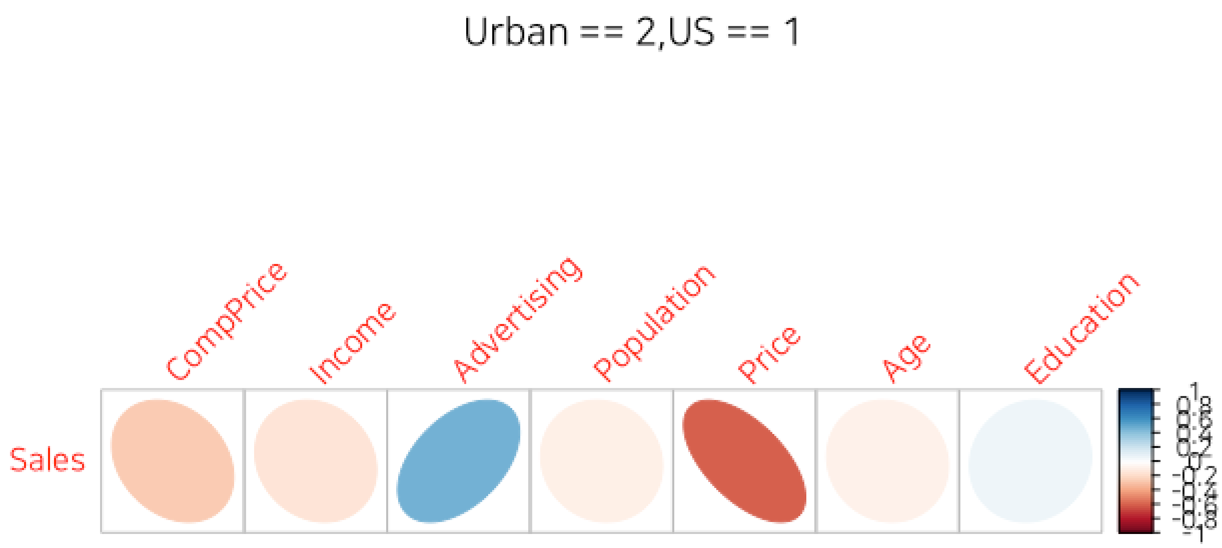
```
carseats %>%
  filter(ShelveLoc == "Good") %>%
  group_by(Urban, US) %>%
  plot_correlate(Sales)
```

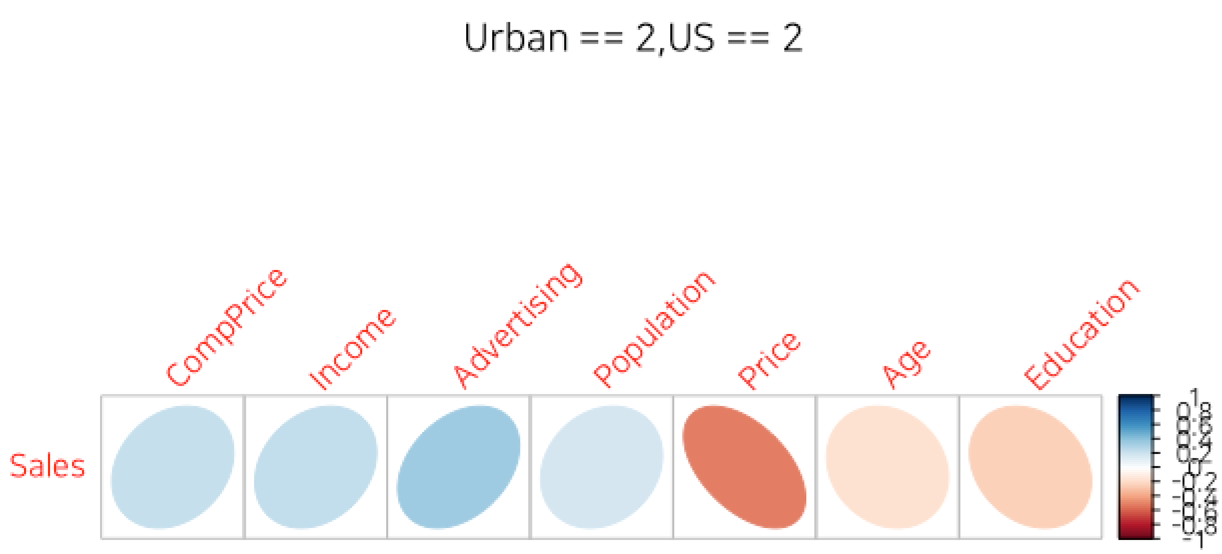
Urban == 1,US == 1



Urban == 1,US == 2







EDA based on target variable

Definition of target variable

To perform EDA based on `target variable`, you need to create a`target_by class` object. `target_by()` creates a target_by class with an object inheriting data.frame or data.frame. `target_by()` is similar to `group_by()` in `dplyr` which creates`grouped_df`. The difference is that you specify only one variable.
The following is an example of specifying US as target variable in carseats data.frame.:

```
categ <- target_by(carseats, US)
```

EDA when target variable is categorical variable

Let's do the EDA when the target variable is categorical. When the categorical variable US is the target variable, the relationship between the target variable and the predictor is examined.

Cases where predictors are numeric variable:

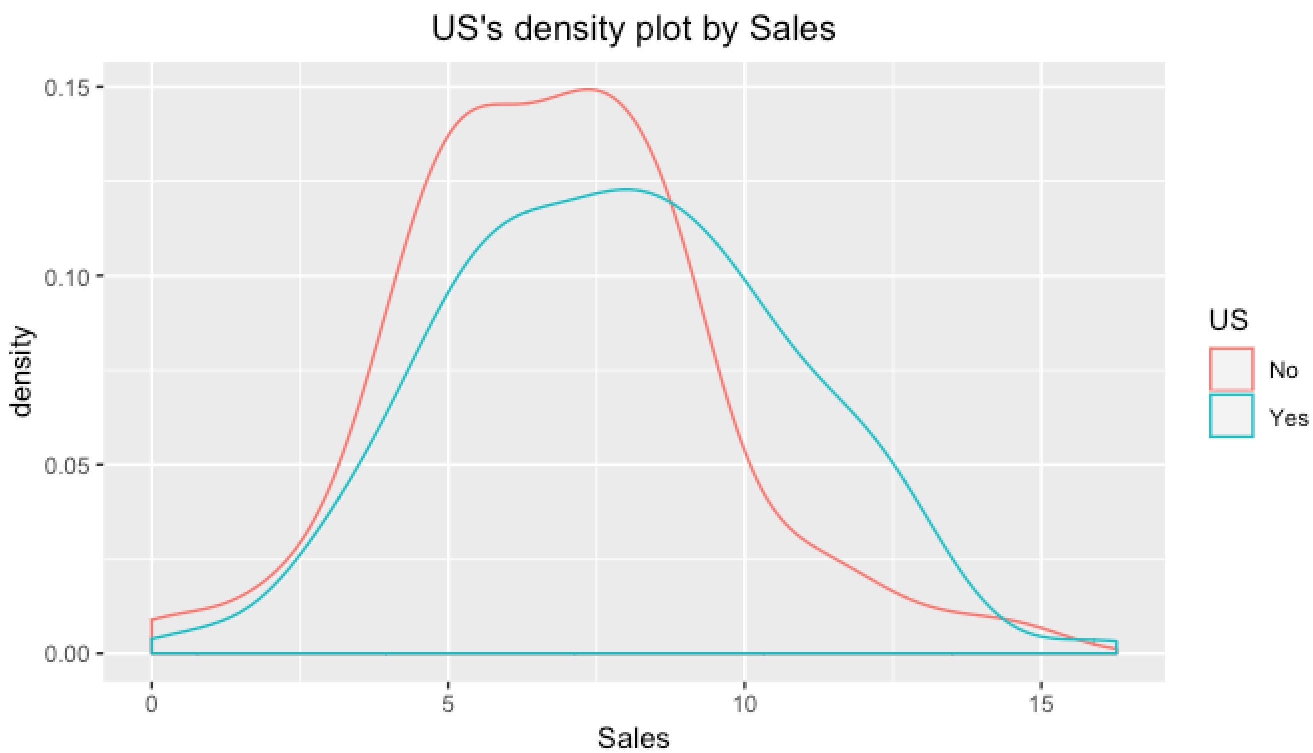
`relate()` shows the relationship between the target variable and the predictor. The following example shows the relationship between Sales and the target variable US. The predictor Sales is a numeric variable. In this case, the descriptive statistics are shown for each level of the target variable.

```
# If the variable of interest is a numarical variable
cat_num <- relate(categ, Sales)
cat_num
#> # A tibble: 3 x 27
#>   variable US        n    na  mean    sd se_mean   IQR skewness kurtosis
#>   <chr>    <fct> <dbl> <dbl> <dbl> <dbl>   <dbl> <dbl>    <dbl>    <dbl>
#> 1 Sales    No      142     0  6.82  2.60   0.218  3.44   0.323    0.808
#> 2 Sales    Yes     258     0  7.87  2.88   0.179  4.23   0.0760  -0.326
#> 3 Sales    total   400     0  7.50  2.82   0.141  3.93   0.186   -0.0809
#> # ... with 17 more variables: p00 <dbl>, p01 <dbl>, p05 <dbl>, p10 <dbl>,
#> #   p20 <dbl>, p25 <dbl>, p30 <dbl>, p40 <dbl>, p50 <dbl>, p60 <dbl>,
#> #   p70 <dbl>, p75 <dbl>, p80 <dbl>, p90 <dbl>, p95 <dbl>, p99 <dbl>,
#> #   p100 <dbl>
summary(cat_num)
#>    variable             US          n                na         mean
#>  Length:3           No   :1   Min.   :142.0   Min.   :0   Min.   :6.823
#>  Class :character   Yes  :1   1st Qu.:200.0   1st Qu.:0   1st Qu.:7.160
#>  Mode  :character   total:1   Median :258.0   Median :0   Median :7.496
#>                               Mean   :266.7   Mean   :0   Mean   :7.395
#>                               3rd Qu.:329.0   3rd Qu.:0   3rd Qu.:7.682
#>                               Max.   :400.0   Max.   :0   Max.   :7.867
#>        sd           se_mean             IQR           skewness
#>  Min.   :2.603   Min.   :0.1412   Min.   :3.442   Min.   :0.07603
#>  1st Qu.:2.713   1st Qu.:0.1602   1st Qu.:3.686   1st Qu.:0.13080
#>  Median :2.824   Median :0.1791   Median :3.930   Median :0.18556
#>  Mean   :2.768   Mean   :0.1796   Mean   :3.866   Mean   :0.19489
#>  3rd Qu.:2.851   3rd Qu.:0.1988   3rd Qu.:4.077   3rd Qu.:0.25432
#>  Max.   :2.877   Max.   :0.2184   Max.   :4.225   Max.   :0.32308
#>     kurtosis             p00              p01              p05
```

```
#>  Min.   :-0.32638   Min.   :0.0000   Min.   :0.4675   Min.   :3.147
#>  1st Qu.:-0.20363   1st Qu.:0.0000   1st Qu.:0.6868   1st Qu.:3.148
#>  Median :-0.08088   Median :0.0000   Median :0.9062   Median :3.149
#>  Mean   : 0.13350   Mean   :0.1233   Mean   :1.0072   Mean   :3.183
#>  3rd Qu.: 0.36344   3rd Qu.:0.1850   3rd Qu.:1.2771   3rd Qu.:3.200
#>  Max.   : 0.80776   Max.   :0.3700   Max.   :1.6480   Max.   :3.252
#>       p10              p20              p25              p30
#>  Min.   :3.917   Min.   :4.754   Min.   :5.080   Min.   :5.306
#>  1st Qu.:4.018   1st Qu.:4.910   1st Qu.:5.235   1st Qu.:5.587
#>  Median :4.119   Median :5.066   Median :5.390   Median :5.867
#>  Mean   :4.073   Mean   :5.051   Mean   :5.411   Mean   :5.775
#>  3rd Qu.:4.152   3rd Qu.:5.199   3rd Qu.:5.576   3rd Qu.:6.010
#>  Max.   :4.184   Max.   :5.332   Max.   :5.763   Max.   :6.153
#>       p40              p50              p60              p70
#>  Min.   :5.994   Min.   :6.660   Min.   :7.496   Min.   :7.957
#>  1st Qu.:6.301   1st Qu.:7.075   1st Qu.:7.787   1st Qu.:8.386
#>  Median :6.608   Median :7.490   Median :8.078   Median :8.815
#>  Mean   :6.506   Mean   :7.313   Mean   :8.076   Mean   :8.740
#>  3rd Qu.:6.762   3rd Qu.:7.640   3rd Qu.:8.366   3rd Qu.:9.132
#>  Max.   :6.916   Max.   :7.790   Max.   :8.654   Max.   :9.449
#>       p75              p80               p90               p95
#>  Min.   :8.523   Min.   : 8.772   Min.   : 9.349   Min.   :11.28
#>  1st Qu.:8.921   1st Qu.: 9.265   1st Qu.:10.325   1st Qu.:11.86
#>  Median :9.320   Median : 9.758   Median :11.300   Median :12.44
#>  Mean   :9.277   Mean   : 9.665   Mean   :10.795   Mean   :12.08
#>  3rd Qu.:9.654   3rd Qu.:10.111   3rd Qu.:11.518   3rd Qu.:12.49
#>  Max.   :9.988   Max.   :10.464   Max.   :11.736   Max.   :12.54
#>       p99              p100
#>  Min.   :13.64   Min.   :14.90
#>  1st Qu.:13.78   1st Qu.:15.59
#>  Median :13.91   Median :16.27
#>  Mean   :13.86   Mean   :15.81
#>  3rd Qu.:13.97   3rd Qu.:16.27
#>  Max.   :14.03   Max.   :16.27
```

The `relate class` object created with`relate()` visualizes the relationship between the target variable and the predictor with `plot()`. The relationship between US and Sales is represented by a density plot.

```
plot(cat_num)
```



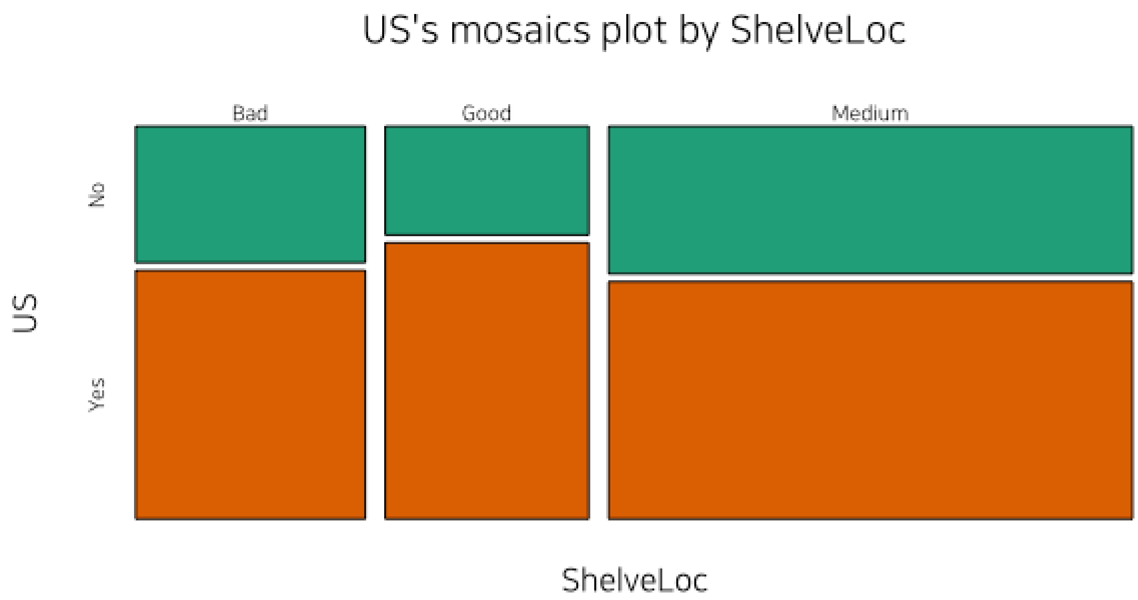
Cases where predictors are categorical variable:

The following example shows the relationship between `ShelveLoc` and the target variable `US`. The predictor, ShelveLoc, is a categorical variable. In this case, we show the `contigency table` of two variables. The `summary()` function also performs an `independence test` on the contigency table.

```
# If the variable of interest is a categorical variable
cat_cat <- relate(categ, ShelveLoc)
cat_cat
#>      ShelveLoc
#> US     Bad Good Medium
#>   No    34   24     84
#>   Yes   62   61    135
summary(cat_cat)
#> Call: xtabs(formula = formula_str, data = data, addNA = TRUE)
#> Number of cases in table: 400
#> Number of factors: 2
#> Test for independence of all factors:
#>  Chisq = 2.7397, df = 2, p-value = 0.2541
```

`plot()` visualizes the relationship between the target variable and the predictor. The relationship between `US` and `ShelveLoc`is represented by a `mosaics plot`.

```
plot(cat_cat)
```



EDA when target variable is numerical variable

Let's do the EDA when the target variable is numeric. When the numeric variable Sales is the target variable, the relationship between the target variable and the predictor is examined.

```
# If the variable of interest is a numarical variable
num <- target_by(carseats, Sales)
```

Cases where predictors are numeric variable:

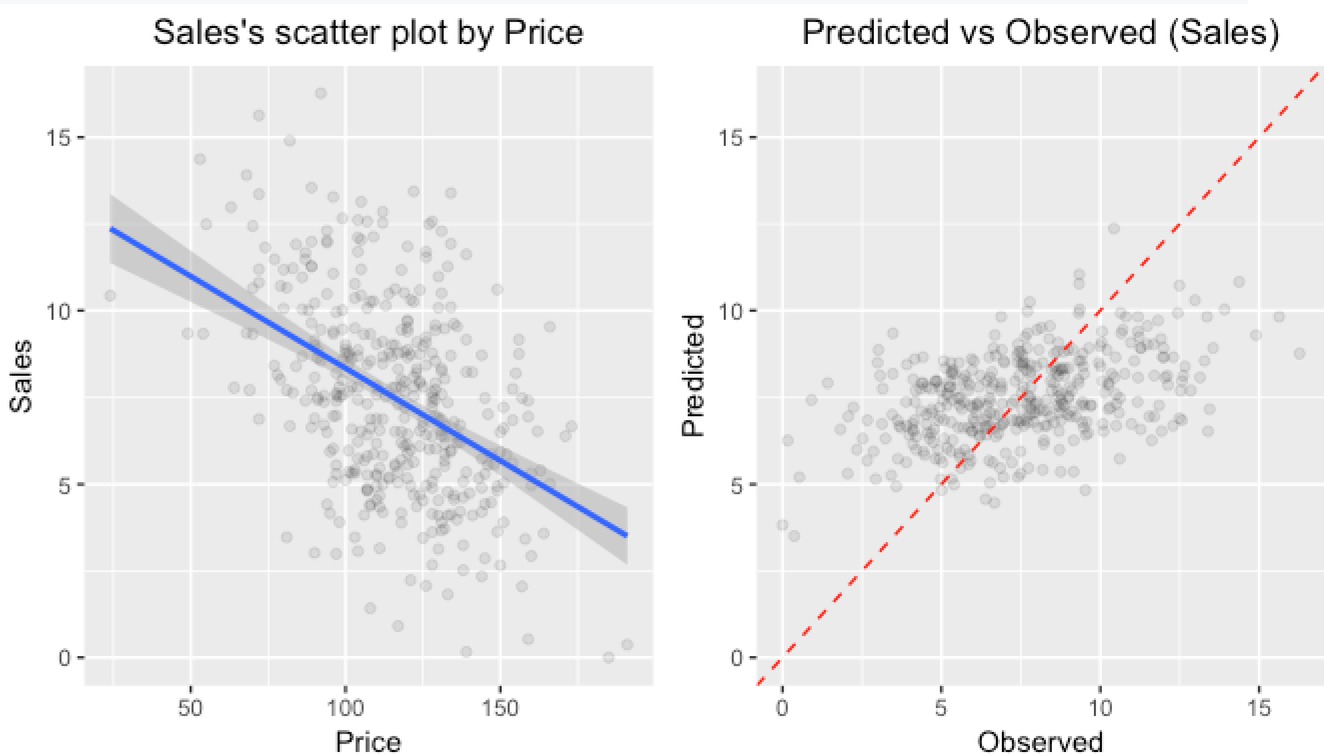
The following example shows the relationship between `Price` and the target variable `Sales`. Price, a predictor, is a numeric variable. In this case, we show the result of `simple regression model` of `target ~ predictor` relation. The `summary()` function represents the details of the model.

```
# If the variable of interest is a numarical variable
num_num <- relate(num, Price)
num_num
#> 
#> Call:
#> lm(formula = formula_str, data = data)
#> 
#> Coefficients:
#> (Intercept)        Price  
#>    13.64192     -0.05307  
summary(num_num)
```

```
#> 
#> Call:
#> lm(formula = formula_str, data = data)
#> 
#> Residuals:
#>     Min      1Q  Median      3Q     Max 
#> -6.5224 -1.8442 -0.1459  1.6503  7.5108 
#> 
#> Coefficients:
#>              Estimate Std. Error t value Pr(>|t|)    
#> (Intercept) 13.641915   0.632812  21.558   <2e-16 ***
#> Price       -0.053073   0.005354  -9.912   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> 
#> Residual standard error: 2.532 on 398 degrees of freedom
#> Multiple R-squared:  0.198,  Adjusted R-squared:  0.196 
#> F-statistic: 98.25 on 1 and 398 DF,  p-value: < 2.2e-16
```

`plot()` visualizes the relationship between the target variable and the predictor. The relationship between Sales and Price is repersented as a scatter plot. The plot on the left represents the scatter plot of Sales and Price and the confidence interval of the regression line and the regression line. The plot on the right represents the relationship between the original data and the predicted value of the linear model as a scatter plot. If there is a linear relationship between the two variables, the observations will converge on the red diagonal in the scatter plot.

```
plot(num_num)
```



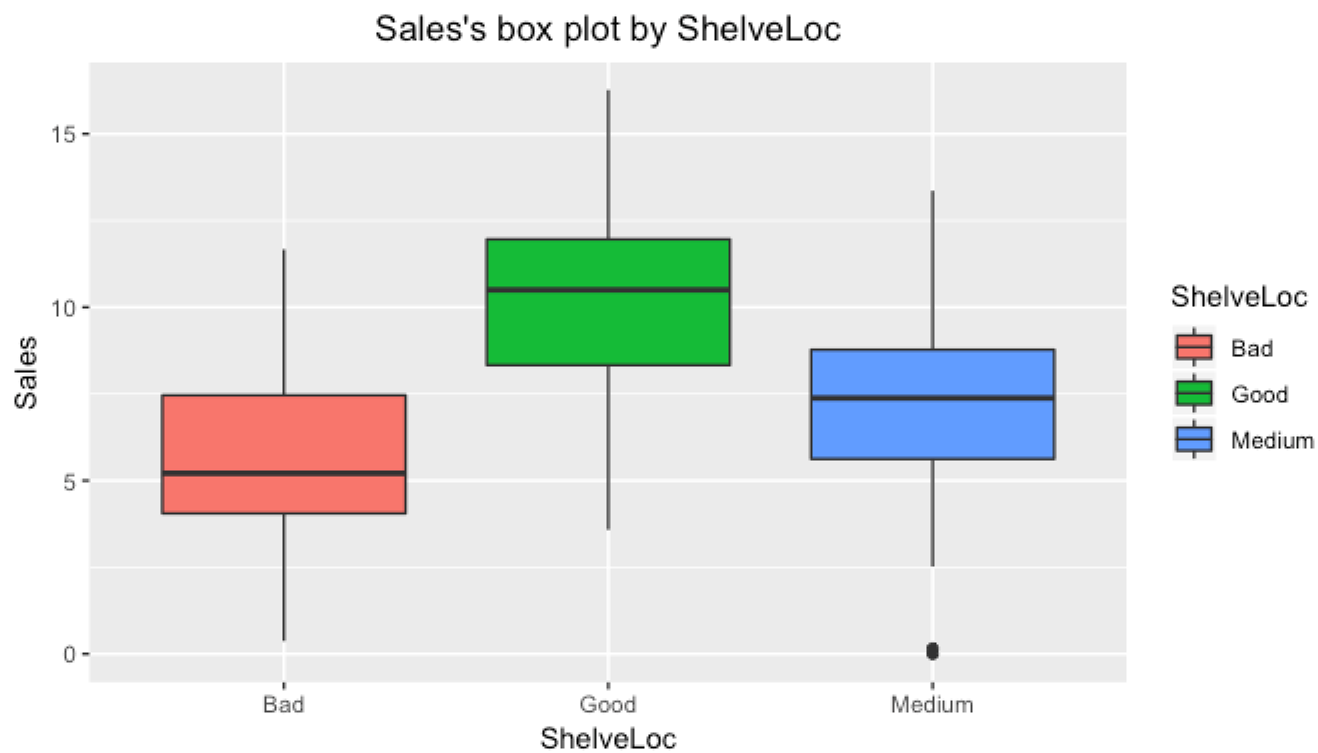
Cases where predictors are categorical variable:

The following example shows the relationship between `ShelveLoc` and the target variable `Sales`. The predictor, ShelveLoc, is a categorical variable. It shows the result of performing `one-way ANOVA` of `target ~ predictor` relation. The results are represented in terms of an analysis of variance. The `summary()` function also shows the `regression coefficients` for each level of the predictor. In other words, it shows detailed information of `simple regression analysis` of `target ~ predictor`relation.

```
# If the variable of interest is a categorical variable
num_cat <- relate(num, ShelveLoc)
num_cat
#> Analysis of Variance Table
#>
#> Response: Sales
#>            Df Sum Sq Mean Sq F value    Pr(>F)
#> ShelveLoc   2 1009.5  504.77   92.23 < 2.2e-16 ***
#> Residuals 397 2172.7    5.47
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
summary(num_cat)
#>
#> Call:
#> lm(formula = formula(formula_str), data = data)
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -7.3066 -1.6282 -0.0416  1.5666  6.1471
#>
#> Coefficients:
#>                 Estimate Std. Error t value Pr(>|t|)
#> (Intercept)       5.5229     0.2388  23.131  < 2e-16 ***
#> ShelveLocGood     4.6911     0.3484  13.464  < 2e-16 ***
#> ShelveLocMedium   1.7837     0.2864   6.229  1.2e-09 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 2.339 on 397 degrees of freedom
#> Multiple R-squared:  0.3172, Adjusted R-squared:  0.3138
#> F-statistic: 92.23 on 2 and 397 DF,  p-value: < 2.2e-16
```

`plot()` visualizes the relationship between the target variable and the predictor. The relationship between `Sales` and `ShelveLoc` is represented by a `box plot`.

```
plot(num_cat)
```



Data Transformation

dlookr imputates missing values and outliers and resolves skewed data. It also provides the ability to bin continuous variables as categorical variables.

Here is a list of the data conversion functions and functions provided by dlookr:

- `find_na()` finds a variable that contains the missing values variable, and `imputate_na()` imputates the missing values.
- `find_outliers()` finds a variable that contains the outliers, and `imputate_outlier()` imputates the outlier.
- `summary.imputation()` and `plot.imputation()` provide information and visualization of the imputated variables.
- `find_skewness()` finds the variables of the skewed data, and `transform()` performs the resolving of the skewed data.
- `transform()` also performs standardization of numeric variables.
- `summary.transform()` and `plot.transform()` provide information and visualization of transformed variables.
- `binning()` and `binning_by()` convert binational data into categorical data.
- `print.bins()` and `summary.bins()` show and summarize the binning results.
- `plot.bins()` and `plot.optimal_bins()` provide visualization of the binning result.

- `transformation_report()` performs the data transform and reports the result.

Imputation of missing values

Imputates the missing value with `imputate_na()`

`imputate_na()` imputates the missing value in the variable. The predictor with missing values supports both numeric and categorical variables and supports the following methods.

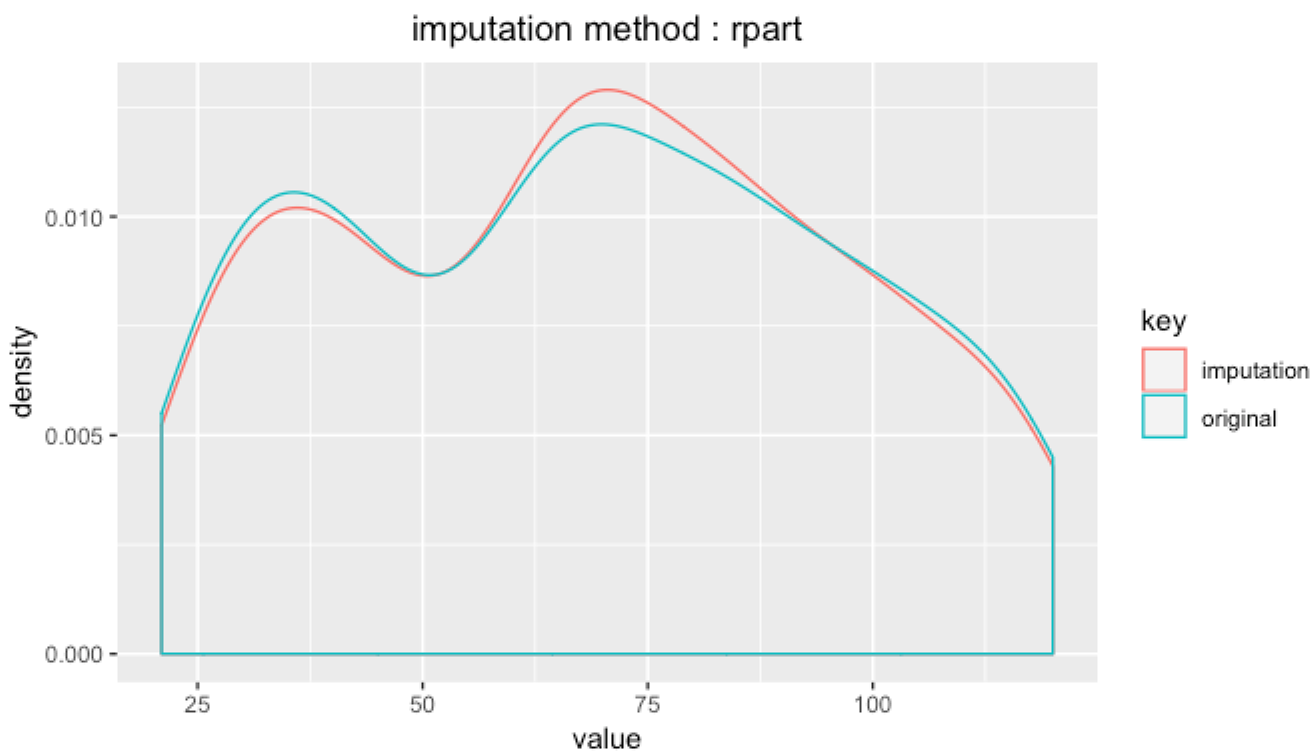
- predictor is numerical variable
  - "mean" : arithmetic mean
  - "median" : median
  - "mode" : mode
  - "knn" : K-nearest neighbors
    - target variable must be specified
  - "rpart" : Recursive Partitioning and Regression Trees
    - target variable must be specified
  - "mice" : Multivariate Imputation by Chained Equations
    - target variable must be specified
    - random seed must be set
- predictor is categorical variable
  - "mode" : mode
  - "rpart" : Recursive Partitioning and Regression Trees
    - target variable must be specified
  - "mice" : Multivariate Imputation by Chained Equations
    - target variable must be specified
    - random seed must be set

`imputate_na()` imputates the missing value with "rpart" for the numeric variable, `Income`. `summary()` summarizes missing value imputation information, and `plot()` visualizes imputation information.

```
income <- imputate_na(carseats, Income, US, method = "rpart")

# result of imputate
income
#>   [1]  73.00000  48.00000  35.00000 100.00000  64.00000 113.00000 105.00000
#>   [8]  81.00000 110.00000 113.00000  78.00000  94.00000  35.00000  28.00000
#>  [15] 117.00000  95.00000  76.75000  68.70968 110.00000  76.00000  90.00000
#>  [22]  29.00000  46.00000  31.00000 119.00000  32.00000 115.00000 118.00000
#>  [29]  74.00000  99.00000  94.00000  58.00000  32.00000  38.00000  54.00000
#>  [36]  84.00000  76.00000  41.00000  73.00000  69.27778  98.00000  53.00000
#>  [43]  69.00000  42.00000  79.00000  63.00000  90.00000  98.00000  52.00000
```

```
#>  [50]  93.00000  32.00000  90.00000  40.00000  64.00000 103.00000  81.00000
#>  [57]  82.00000  91.00000  93.00000  71.00000 102.00000  32.00000  45.00000
#>  [64]  88.00000  67.00000  26.00000  92.00000  61.00000  69.00000  59.00000
#>  [71]  81.00000  51.00000  45.00000  90.00000  68.00000 111.00000  87.00000
#>  [78]  71.00000  48.00000  67.00000 100.00000  72.00000  83.00000  36.00000
#>  [85]  25.00000 103.00000  84.00000  67.00000  42.00000  66.00000  22.00000
#>  [92]  46.00000 113.00000  30.00000  88.93750  25.00000  42.00000  82.00000
#>  [99]  77.00000  47.00000  69.00000  93.00000  22.00000  91.00000  96.00000
#> [106] 100.00000  33.00000 107.00000  79.00000  65.00000  62.00000 118.00000
#> [113]  99.00000  29.00000  87.00000  68.70968  75.00000  53.00000  88.00000
#> [120]  94.00000 105.00000  89.00000 100.00000 103.00000 113.00000  98.33333
#> [127]  68.00000  48.00000 100.00000 120.00000  84.00000  69.00000  87.00000
#> [134]  98.00000  31.00000  94.00000  75.00000  42.00000 103.00000  62.00000
#> [141]  60.00000  42.00000  84.00000  88.00000  68.00000  63.00000  83.00000
#> [148]  54.00000 119.00000 120.00000  84.00000  58.00000  78.00000  36.00000
#> [155]  69.00000  72.00000  34.00000  58.00000  90.00000  60.00000  28.00000
#> [162]  21.00000  83.53846  64.00000  64.00000  58.00000  67.00000  73.00000
#> [169]  89.00000  41.00000  39.00000 106.00000 102.00000  91.00000  24.00000
#> [176]  89.00000  69.27778  72.00000  85.00000  25.00000 112.00000  83.00000
#> [183]  60.00000  74.00000  33.00000 100.00000  51.00000  32.00000  37.00000
#> [190] 117.00000  37.00000  42.00000  26.00000  70.00000  98.00000  93.00000
#> [197]  28.00000  61.00000  80.00000  88.00000  92.00000  83.00000  78.00000
#> [204]  82.00000  80.00000  22.00000  67.00000 105.00000  98.33333  21.00000
#> [211]  41.00000 118.00000  69.00000  84.00000 115.00000  83.00000  43.75000
#> [218]  44.00000  61.00000  79.00000 120.00000  73.47368 119.00000  45.00000
#> [225]  82.00000  25.00000  33.00000  64.00000  73.00000 104.00000  60.00000
#> [232]  69.00000  80.00000  76.00000  62.00000  32.00000  34.00000  28.00000
#> [239]  24.00000 105.00000  80.00000  63.00000  46.00000  25.00000  30.00000
#> [246]  43.00000  56.00000 114.00000  52.00000  67.00000 105.00000 111.00000
#> [253]  97.00000  24.00000 104.00000  81.00000  40.00000  62.00000  38.00000
#> [260]  36.00000 117.00000  42.00000  73.47368  26.00000  29.00000  35.00000
#> [267]  93.00000  82.00000  57.00000  69.00000  26.00000  56.00000  33.00000
#> [274] 106.00000  93.00000 119.00000  69.00000  48.00000 113.00000  57.00000
#> [281]  86.00000  69.00000  96.00000 110.00000  46.00000  26.00000 118.00000
#> [288]  44.00000  40.00000  77.00000 111.00000  70.00000  66.00000  84.00000
#> [295]  76.00000  35.00000  44.00000  83.00000  63.00000  40.00000  78.00000
#> [302]  93.00000  77.00000  52.00000  98.00000  29.00000  32.00000  92.00000
#> [309]  80.00000 111.00000  65.00000  68.00000 117.00000  81.00000  56.57895
#> [316]  21.00000  36.00000  30.00000  72.00000  45.00000  70.00000  39.00000
#> [323]  50.00000 105.00000  65.00000  69.00000  30.00000  38.00000  66.00000
#> [330]  54.00000  59.00000  63.00000  33.00000  60.00000 117.00000  70.00000
#> [337]  35.00000  38.00000  24.00000  44.00000  29.00000 120.00000 102.00000
#> [344]  42.00000  80.00000  68.00000  76.75000  39.00000 102.00000  27.00000
#> [351]  51.83333 115.00000 103.00000  67.00000  31.00000 100.00000 109.00000
#> [358]  73.00000  96.00000  62.00000  86.00000  25.00000  55.00000  51.83333
#> [365]  21.00000  30.00000  56.00000 106.00000  22.00000 100.00000  41.00000
#> [372]  81.00000  68.66667  68.88889  47.00000  46.00000  60.00000  61.00000
#> [379]  88.00000 111.00000  64.00000  65.00000  28.00000 117.00000  37.00000
#> [386]  73.00000 116.00000  73.00000  89.00000  42.00000  75.00000  63.00000
#> [393]  42.00000  51.00000  58.00000 108.00000  81.17647  26.00000  79.00000
#> [400]  37.00000
#> attr(,"var_type")
#> [1] "numerical"
#> attr(,"method")
#> [1] "rpart"
```

```
#> attr(,"na_pos")
#>  [1]  17  18  40  95 116 126 163 177 179 209 217 222 263 315 347 351 364
#> [18] 373 374 397
#> attr(,"type")
#> [1] "missing values"
#> attr(,"class")
#> [1] "imputation" "numeric"

# summary of imputate
summary(income)
#> * Impute missing values based on Recursive Partitioning and Regression Trees
#>  - method : rpart
#>
#> * Information of Imputation (before vs after)
#>             Original   Imputation
#> n        380.000000 400.00000000
#> na        20.000000   0.00000000
#> mean      68.860526  69.05073137
#> sd        28.091615  27.57381661
#> se_mean    1.441069   1.37869083
#> IQR       48.250000  46.00000000
#> skewness   0.044906   0.02935732
#> kurtosis  -1.089201  -1.03508622
#> p00       21.000000  21.00000000
#> p01       21.790000  21.99000000
#> p05       26.000000  26.00000000
#> p10       30.000000  30.90000000
#> p20       39.000000  40.00000000
#> p25       42.750000  44.00000000
#> p30       48.000000  51.58333333
#> p40       62.000000  63.00000000
#> p50       69.000000  69.00000000
#> p60       78.000000  77.40000000
#> p70       86.300000  84.30000000
#> p75       91.000000  90.00000000
#> p80       96.200000  96.00000000
#> p90      108.100000 106.10000000
#> p95      115.050000 115.00000000
#> p99      119.210000 119.01000000
#> p100     120.000000 120.00000000

# viz of imputate
plot(income)
```

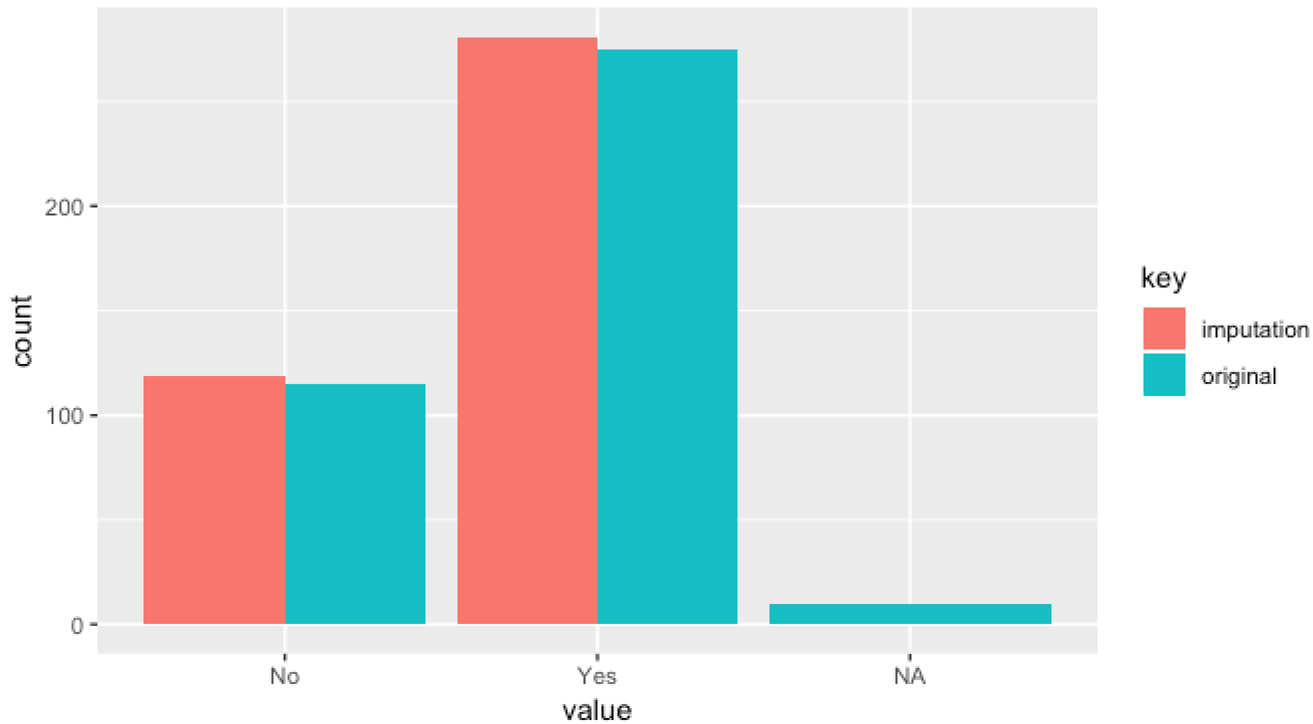


The following imputates the categorical variable `urban` by the "mice" method.

```
library(mice)
#> Warning: package 'mice' was built under R version 3.4.4
#> Loading required package: lattice
#>
#> Attaching package: 'mice'
#> The following objects are masked from 'package:base':
#>
#>     cbind, rbind

urban <- imputate_na(carseats, Urban, US, method = "mice")
#>
#>  iter imp variable
#>   1   1  Income  Urban
#>   1   2  Income  Urban
#>   1   3  Income  Urban
#>   1   4  Income  Urban
#>   1   5  Income  Urban
#>   2   1  Income  Urban
#>   2   2  Income  Urban
#>   2   3  Income  Urban
#>   2   4  Income  Urban
#>   2   5  Income  Urban
#>   3   1  Income  Urban
#>   3   2  Income  Urban
#>   3   3  Income  Urban
#>   3   4  Income  Urban
#>   3   5  Income  Urban
#>   4   1  Income  Urban
```

```
#>   4   2  Income  Urban
#>   4   3  Income  Urban
#>   4   4  Income  Urban
#>   4   5  Income  Urban
#>   5   1  Income  Urban
#>   5   2  Income  Urban
#>   5   3  Income  Urban
#>   5   4  Income  Urban
#>   5   5  Income  Urban

# result of imputate
urban
#>   [1] Yes Yes Yes Yes Yes No  Yes Yes No  No  No  Yes Yes Yes Yes No  Yes
#>  [18] Yes No  Yes Yes No  Yes Yes Yes No  No  Yes Yes Yes Yes Yes Yes Yes
#>  [35] Yes Yes No  Yes Yes No  No  Yes Yes Yes Yes Yes No  Yes Yes Yes Yes
#>  [52] Yes Yes Yes No  Yes Yes Yes Yes Yes Yes No  Yes Yes No  No  Yes Yes
#>  [69] Yes Yes Yes No  Yes No  No  No  Yes No  Yes Yes Yes Yes Yes Yes No
#>  [86] No  Yes No  Yes No  No  Yes Yes Yes Yes Yes No  Yes No  No  No  Yes
#> [103] No  Yes Yes Yes No  Yes Yes No  Yes Yes No  Yes Yes Yes No  Yes Yes
#> [120] Yes Yes Yes Yes No  Yes No  Yes Yes Yes No  Yes No  Yes Yes Yes No
#> [137] No  Yes Yes No  Yes Yes Yes Yes No  Yes Yes No  No  Yes No  No  No
#> [154] No  No  Yes Yes No  No  No  No  No  Yes No  No  Yes Yes Yes Yes Yes
#> [171] Yes Yes Yes Yes No  Yes No  Yes No  Yes Yes Yes Yes Yes No  Yes No
#> [188] Yes Yes No  No  Yes No  Yes Yes Yes Yes Yes Yes Yes No  Yes No  Yes
#> [205] Yes Yes Yes No  Yes No  No  Yes Yes Yes Yes Yes Yes No  Yes Yes Yes
#> [222] Yes Yes Yes No  Yes Yes Yes No  No  No  No  Yes No  No  Yes Yes Yes
#> [239] Yes Yes Yes Yes No  Yes Yes No  Yes Yes Yes Yes Yes Yes Yes No  Yes
#> [256] Yes Yes Yes No  No  Yes Yes Yes Yes Yes Yes No  No  Yes Yes Yes Yes
#> [273] Yes Yes Yes Yes Yes Yes No  Yes Yes No  Yes No  No  Yes No  Yes No
#> [290] Yes No  No  Yes Yes Yes No  Yes Yes Yes No  Yes Yes Yes Yes Yes Yes
#> [307] Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes No  No  No  Yes Yes Yes
#> [324] Yes Yes Yes Yes Yes Yes Yes No  Yes Yes Yes Yes Yes Yes Yes Yes Yes
#> [341] Yes No  No  Yes No  Yes No  No  Yes No  No  No  Yes No  Yes Yes Yes
#> [358] Yes Yes Yes No  No  Yes Yes Yes No  No  Yes No  Yes Yes Yes No  Yes
#> [375] Yes Yes Yes No  Yes Yes Yes Yes Yes Yes Yes Yes Yes No  Yes Yes Yes
#> [392] Yes Yes No  Yes Yes No  Yes Yes Yes
#> attr(,"var_type")
#> [1] categorical
#> attr(,"method")
#> [1] mice
#> attr(,"na_pos")
#>  [1]  33  36  84  94 113 132 151 292 313 339
#> attr(,"type")
#> [1] missing values
#> Levels: No Yes

# summary of imputate
summary(urban)
#> Warning in if (attr(list(...)[[1]], "class") == "mids")
#> return(cbind.mids(...)) else return(base::cbind(...)): length > 1 이라는 조
#> 건이 있고, 첫번째 요소만이 사용될 것입니다
#> * Information of Imputation (before vs after)
#>      original imputation original_percent imputation_percent
#> No        115        119            28.75              29.75
```

```
#> Yes        275         281            68.75              70.25
#> <NA>        10           0             2.50               0.00

# viz of imputate
plot(urban)
```



Collaboration with dplyr

The following is an example of calculating the arithmetic mean of `US` variables by using the `Income` variable that imputates the missing value with `dplyr`.

```
# The mean before and after the imputation of the Income variable
carseats %>%
  mutate(Income_imp = imputate_na(carseats, Income, US, method = "knn")) %>%
  group_by(US) %>%
  summarise(orig = mean(Income, na.rm = TRUE),
    imputation = mean(Income_imp))
#> # A tibble: 2 x 3
#>   US     orig imputation
#>   <fct> <dbl>      <dbl>
#> 1 No     65.8       66.1
#> 2 Yes    70.4       70.5
```

Imputation of outliers

Imputates thr outliers with `imputate_outlier()`

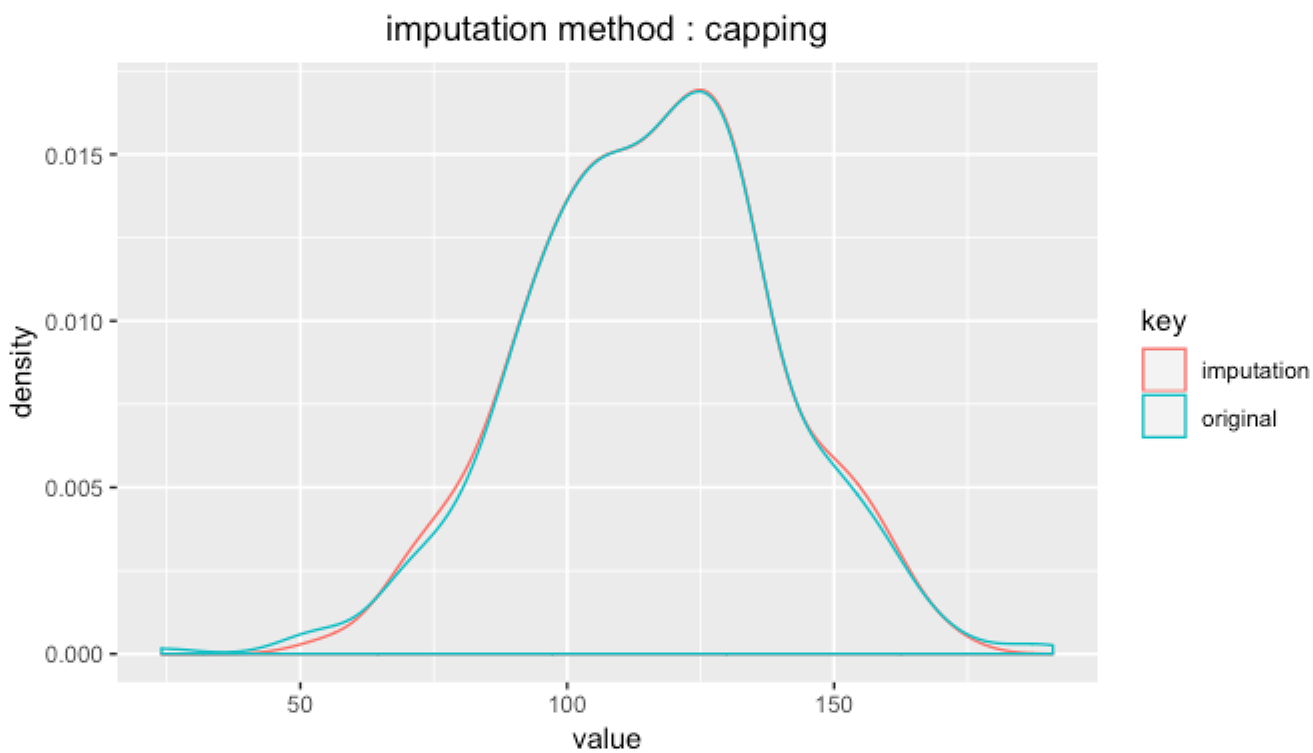
`imputate_outlier()` imputates the outliers value. The predictor with outliers supports only numeric variables and supports the following methods.

- predictor is numerical variable
    - "mean" : arithmetic mean
    - "median" : median
    - "mode" : mode
    - "capping" : Imputate the upper outliers with 95 percentile, and Imputate the bottom outliers with 5 percentile.

`imputate_outlier()` imputates the outliers with the numeric variable `Price` as the "capping" method, as follows. `summary()`summarizes outliers imputation information, and `plot()` visualizes imputation information.

```
price <- imputate_outlier(carseats, Price, method = "capping")

# result of imputate
price
#>   [1] 120.00  83.00  80.00  97.00 128.00  72.00 108.00 120.00 124.00 124.00
#>  [11] 100.00  94.00 136.00  86.00 118.00 144.00 110.00 131.00  68.00 121.00
#>  [21] 131.00 109.00 138.00 109.00 113.00  82.00 131.00 107.00  97.00 102.00
#>  [31]  89.00 131.00 137.00 128.00 128.00  96.00 100.00 110.00 102.00 138.00
#>  [41] 126.00 124.00  77.00 134.00  95.00 135.00  70.00 108.00  98.00 149.00
#>  [51] 108.00 108.00 129.00 119.00 144.00 154.00  84.00 117.00 103.00 114.00
#>  [61] 123.00 107.00 133.00 101.00 104.00 128.00  91.00 115.00 134.00  99.00
#>  [71]  99.00 150.00 116.00 104.00 136.00  92.00  70.00  89.00 145.00  90.00
#>  [81]  79.00 128.00 139.00  94.00 121.00 112.00 134.00 126.00 111.00 119.00
#>  [91] 103.00 107.00 125.00 104.00  84.00 148.00 132.00 129.00 127.00 107.00
#> [101] 106.00 118.00  97.00  96.00 138.00  97.00 139.00 108.00 103.00  90.00
#> [111] 116.00 151.00 125.00 127.00 106.00 129.00 128.00 119.00  99.00 128.00
#> [121] 131.00  87.00 108.00 155.00 120.00  77.00 133.00 116.00 126.00 147.00
#> [131]  77.00  94.00 136.00  97.00 131.00 120.00 120.00 118.00 109.00  94.00
#> [141] 129.00 131.00 104.00 159.00 123.00 117.00 131.00 119.00  97.00  87.00
#> [151] 114.00 103.00 128.00 150.00 110.00  69.00 157.00  90.00 112.00  70.00
#> [161] 111.00 160.00 149.00 106.00 141.00 155.05 137.00  93.00 117.00  77.00
#> [171] 118.00  55.00 110.00 128.00 155.05 122.00 154.00  94.00  81.00 116.00
#> [181] 149.00  91.00 140.00 102.00  97.00 107.00  86.00  96.00  90.00 104.00
#> [191] 101.00 173.00  93.00  96.00 128.00 112.00 133.00 138.00 128.00 126.00
#> [201] 146.00 134.00 130.00 157.00 124.00 132.00 160.00  97.00  64.00  90.00
#> [211] 123.00 120.00 105.00 139.00 107.00 144.00 144.00 111.00 120.00 116.00
#> [221] 124.00 107.00 145.00 125.00 141.00  82.00 122.00 101.00 163.00  72.00
#> [231] 114.00 122.00 105.00 120.00 129.00 132.00 108.00 135.00 133.00 118.00
#> [241] 121.00  94.00 135.00 110.00 100.00  88.00  90.00 151.00 101.00 117.00
#> [251] 156.00 132.00 117.00 122.00 129.00  81.00 144.00 112.00  81.00 100.00
#> [261] 101.00 118.00 132.00 115.00 159.00 129.00 112.00 112.00 105.00 166.00
#> [271]  89.00 110.00  63.00  86.00 119.00 132.00 130.00 125.00 151.00 158.00
#> [281] 145.00 105.00 154.00 117.00  96.00 131.00 113.00  72.00  97.00 156.00
#> [291] 103.00  89.00  74.00  89.00  99.00 137.00 123.00 104.00 130.00  96.00
#> [301]  99.00  87.00 110.00  99.00 134.00 132.00 133.00 120.00 126.00  80.00
#> [311] 166.00 132.00 135.00  54.00 129.00 171.00  72.00 136.00 130.00 129.00
#> [321] 152.00  98.00 139.00 103.00 150.00 104.00 122.00 104.00 111.00  89.00
```

```
#> [331] 112.00 134.00 104.00 147.00  83.00 110.00 143.00 102.00 101.00 126.00
#> [341]  91.00  93.00 118.00 121.00 126.00 149.00 125.00 112.00 107.00  96.00
#> [351]  91.00 105.00 122.00  92.00 145.00 146.00 164.00  72.00 118.00 130.00
#> [361] 114.00 104.00 110.00 108.00 131.00 162.00 134.00  77.00  79.00 122.00
#> [371] 119.00 126.00  98.00 116.00 118.00 124.00  92.00 125.00 119.00 107.00
#> [381]  89.00 151.00 121.00  68.00 112.00 132.00 160.00 115.00  78.00 107.00
#> [391] 111.00 124.00 130.00 120.00 139.00 128.00 120.00 159.00  95.00 120.00
#> attr(,"method")
#> [1] "capping"
#> attr(,"var_type")
#> [1] "numerical"
#> attr(,"outlier_pos")
#> [1]  43 126 166 175 368
#> attr(,"outliers")
#> [1]  24  49 191 185  53
#> attr(,"type")
#> [1] "outliers"
#> attr(,"class")
#> [1] "imputation" "numeric"

# summary of imputate
summary(price)
#> Impute outliers with capping
#>
#> * Information of Imputation (before vs after)
#>             Original  Imputation
#> n        400.0000000 400.0000000
#> na         0.0000000   0.0000000
#> mean     115.7950000 115.8927500
#> sd        23.6766644  22.6109187
#> se_mean    1.1838332   1.1305459
#> IQR       31.0000000  31.0000000
#> skewness  -0.1252862  -0.0461621
#> kurtosis   0.4518850  -0.3030578
#> p00       24.0000000  54.0000000
#> p01       54.9900000  67.9600000
#> p05       77.0000000  77.0000000
#> p10       87.0000000  87.0000000
#> p20       96.8000000  96.8000000
#> p25      100.0000000 100.0000000
#> p30      104.0000000 104.0000000
#> p40      110.0000000 110.0000000
#> p50      117.0000000 117.0000000
#> p60      122.0000000 122.0000000
#> p70      128.3000000 128.3000000
#> p75      131.0000000 131.0000000
#> p80      134.0000000 134.0000000
#> p90      146.0000000 146.0000000
#> p95      155.0500000 155.0025000
#> p99      166.0500000 164.0200000
#> p100     191.0000000 173.0000000

# viz of imputate
plot(price)
```



Collaboration with dplyr

The following is an example of calculating the arithmetic mean of `US` variables by using the `Price` variable that imputates the outlier with `dplyr`.

```
# The mean before and after the imputation of the Price variable
carseats %>%
  mutate(Price_imp = imputate_outlier(carseats, Price, method = "capping")) %>%
  group_by(US) %>%
  summarise(orig = mean(Price, na.rm = TRUE),
    imputation = mean(Price_imp, na.rm = TRUE))
#> # A tibble: 2 x 3
#>   US     orig imputation
#>   <fct> <dbl>      <dbl>
#> 1 No      114        114
#> 2 Yes     117        117
```

Standardization and Resolving Skewness

Introduction to the use of `transform()`

`transform()` performs data transformation. Only numeric variables are supported, and the following methods are provided.

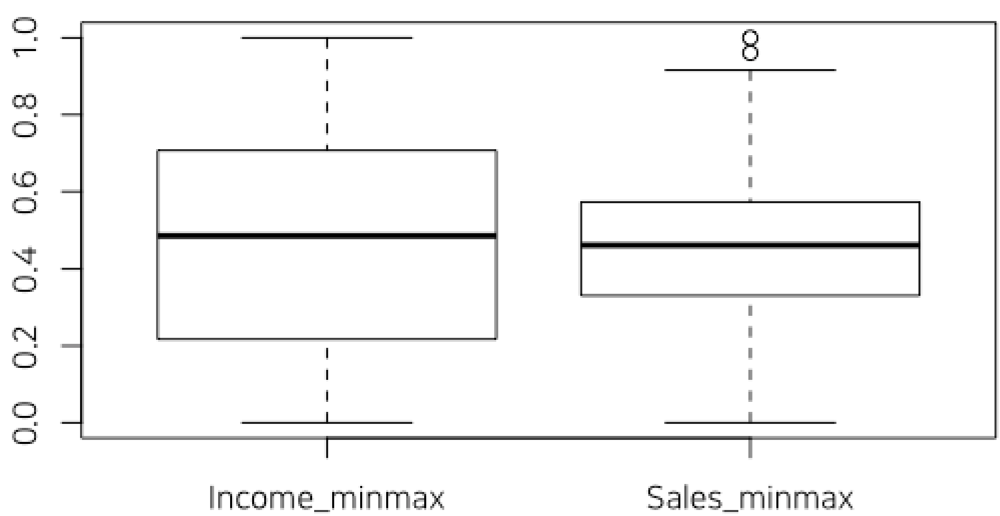
- Standardization
    - "zscore" : z-score transformation. (x - mu) / sigma

    - "minmax" : minmax transformation. (x - min) / (max - min)
- Resolving Skewness
    - "log" : log transformation. log(x)
    - "log+1" : log transformation. log(x + 1). Used for values that contain 0.
    - "sqrt" : square root transformation.
    - "1/x" : 1 / x transformation
    - "x^2" : x square transformation
    - "x^3" : x^3 square transformation

Standardization with `transform()`

Use the methods "zscore" and "minmax" to perform standardization.

```
carseats %>%
  mutate(Income_minmax = transform(carseats$Income, method = "minmax"),
    Sales_minmax = transform(carseats$Sales, method = "minmax")) %>%
  select(Income_minmax, Sales_minmax) %>%
  boxplot()
```



Resolving Skewness data with `transform()`

`find_skewness()` calculates the skewness and finds the skewed data.

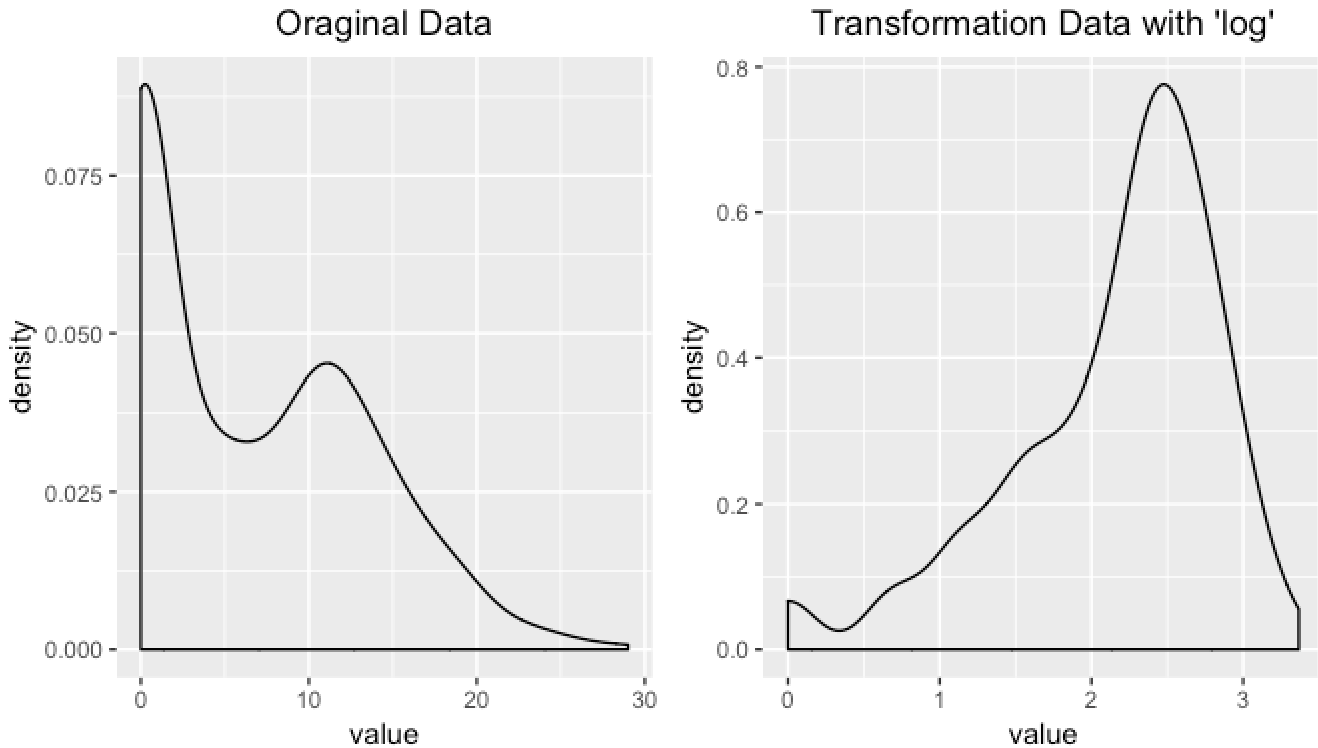
```
# find index of skewed variables
find_skewness(carseats)
#> [1] 4
```

```r
# find names of skewed variables
find_skewness(carseats, index = FALSE)
#> [1] "Advertising"

# compute the skewness
find_skewness(carseats, value = TRUE)
#>       Sales   CompPrice      Income Advertising  Population       Price
#>       0.185      -0.043          NA       0.637      -0.051      -0.125
#>         Age   Education
#>      -0.077       0.044

# compute the skewness & filtering with threshold
find_skewness(carseats, value = TRUE, thres = 0.1)
#>       Sales Advertising       Price
#>       0.185       0.637      -0.125
```

The skewness of `Advertising` is 0.637, which is a little slanted to the left, so I use `transformation ()` to convert it to `log`. `summary()` summarizes the transformation information, and `plot()` visualizes the transformation information.

```r
Advertising_log = transform(carseats$Advertising, method = "log")

# result of transformation
head(Advertising_log)
#> [1] 2.397895 2.772589 2.302585 1.386294 1.098612 2.564949
# summary of transformation
summary(Advertising_log)
#> * Resolving Skewness with log
#>
#> * Information of Transformation (before vs after)
#>             Original Transformation
#> n        400.0000000    400.0000000
#> na         0.0000000      0.0000000
#> mean       6.6350000           -Inf
#> sd         6.6503642            NaN
#> se_mean    0.3325182            NaN
#> IQR       12.0000000            Inf
#> skewness   0.6395858            NaN
#> kurtosis  -0.5451178            NaN
#> p00        0.0000000           -Inf
#> p01        0.0000000           -Inf
#> p05        0.0000000           -Inf
#> p10        0.0000000           -Inf
#> p20        0.0000000           -Inf
#> p25        0.0000000           -Inf
#> p30        0.0000000           -Inf
#> p40        2.0000000      0.6931472
#> p50        5.0000000      1.6094379
#> p60        8.4000000      2.1265548
#> p70       11.0000000      2.3978953
#> p75       12.0000000      2.4849066
#> p80       13.0000000      2.5649494
#> p90       16.0000000      2.7725887
#> p95       19.0000000      2.9444390
#> p99       23.0100000      3.1359198
```

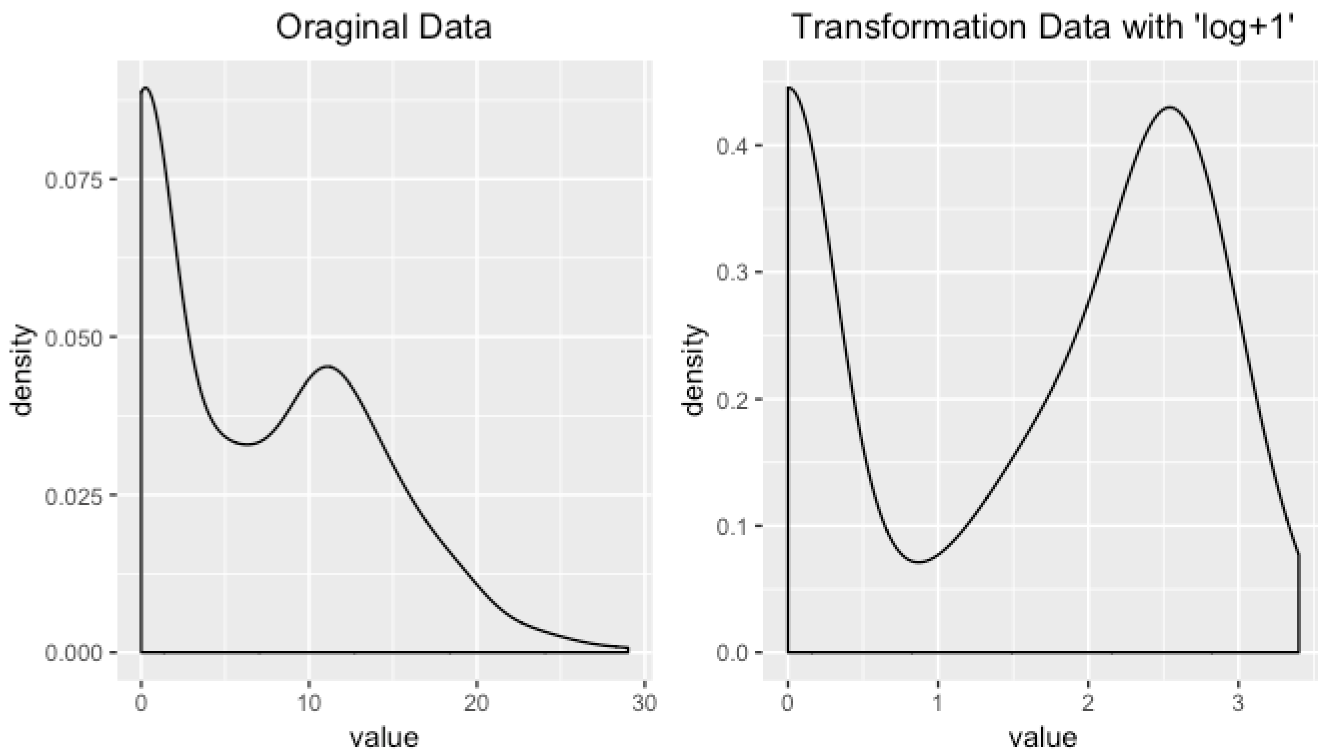
```
#> p100      29.0000000      3.3672958
# viz of transformation
plot(Advertising_log)
```



It seems that the raw data contains 0, as there is a -Inf in the log converted value. So this time we convert it to "log + 1".

```
Advertising_log <- transform(carseats$Advertising, method = "log+1")

# result of transformation
head(Advertising_log)
#> [1] 2.484907 2.833213 2.397895 1.609438 1.386294 2.639057
# summary of transformation
summary(Advertising_log)
#> * Resolving Skewness with log+1
#>
#> * Information of Transformation (before vs after)
#>             Original Transformation
#> n        400.0000000   400.00000000
#> na         0.0000000     0.00000000
#> mean       6.6350000     1.46247709
#> sd         6.6503642     1.19436323
#> se_mean    0.3325182     0.05971816
#> IQR       12.0000000     2.56494936
#> skewness   0.6395858    -0.19852549
#> kurtosis  -0.5451178    -1.66342876
#> p00        0.0000000     0.00000000
#> p01        0.0000000     0.00000000
#> p05        0.0000000     0.00000000
```

```
#> p10         0.0000000     0.00000000
#> p20         0.0000000     0.00000000
#> p25         0.0000000     0.00000000
#> p30         0.0000000     0.00000000
#> p40         2.0000000     1.09861229
#> p50         5.0000000     1.79175947
#> p60         8.4000000     2.23936878
#> p70        11.0000000     2.48490665
#> p75        12.0000000     2.56494936
#> p80        13.0000000     2.63905733
#> p90        16.0000000     2.83321334
#> p95        19.0000000     2.99573227
#> p99        23.0100000     3.17846205
#> p100       29.0000000     3.40119738
# viz of transformation
plot(Advertising_log)
```



Binning

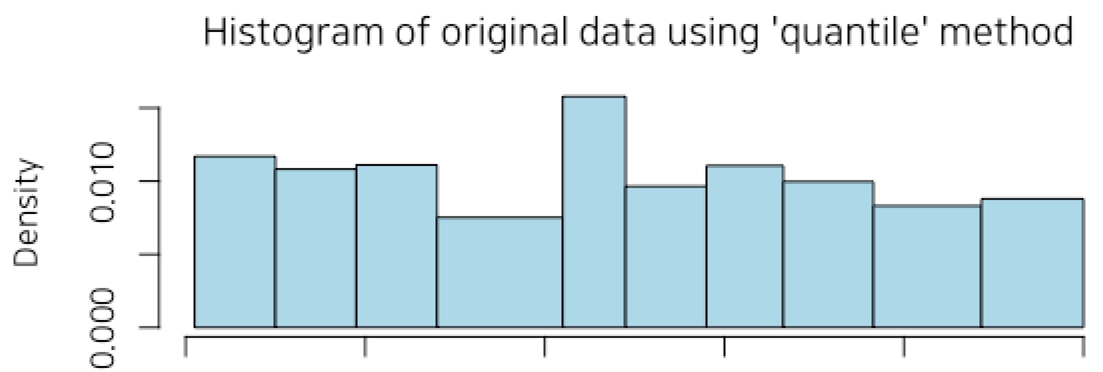
Binning of individual variables using `binning()`
`binning()` transforms a numeric variable into a categorical variable by binning it. The following types of binning are supported.

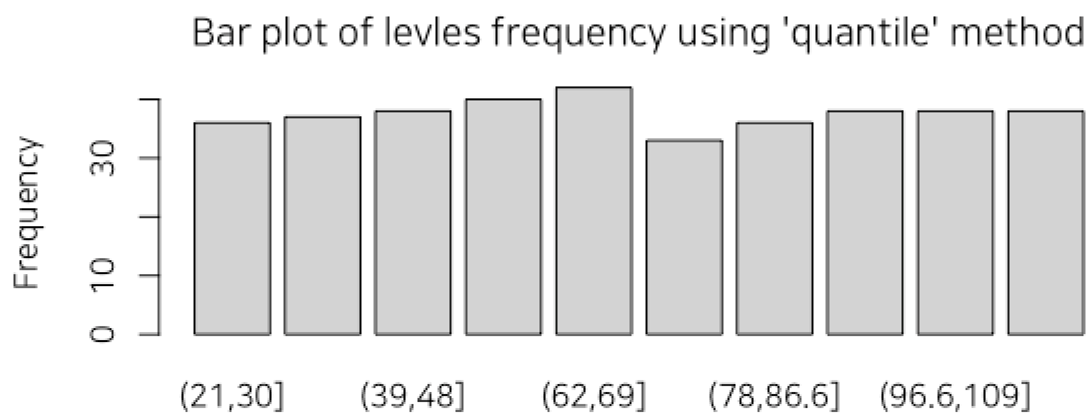
- "quantile" : categorize using quantile to include the same frequencies
- "equal" : categorize to have equal length segments
- "pretty" : categorized into moderately good segments

- "kmeans" : categorization using K-means clustering
- "bclust" : categorization using bagged clustering technique

The following example illustrates some ways to `Income` binning using `binning()`.:

```
# Binning the carat variable. default type argument is "quantile"
bin <- binning(carseats$Income)
# Print bins class object
bin
#> binned type: quantile
#> number of bins: 10
#> x
#>     (21,30]     (30,39]     (39,48]     (48,62]     (62,69]     (69,78]
#>          36          37          38          40          42          33
#>   (78,86.6] (86.6,96.6]  (96.6,109]   (109,120]        <NA>
#>          36          38          38          38          24
# Summarise bins class object
summary(bin)
#>         levels freq   rate
#> 1      (21,30]   36 0.0900
#> 2      (30,39]   37 0.0925
#> 3      (39,48]   38 0.0950
#> 4      (48,62]   40 0.1000
#> 5      (62,69]   42 0.1050
#> 6      (69,78]   33 0.0825
#> 7    (78,86.6]   36 0.0900
#> 8  (86.6,96.6]   38 0.0950
#> 9   (96.6,109]   38 0.0950
#> 10   (109,120]   38 0.0950
#> 11        <NA>   24 0.0600
# Plot bins class object
plot(bin)
```






```
# Using labels argument
bin <- binning(carseats$Income, nbins = 4,
              labels = c("LQ1", "UQ1", "LQ3", "UQ3"))
bin
#> binned type: quantile
#> number of bins: 4
#> x
#>   LQ1  UQ1  LQ3  UQ3 <NA>
#>    91  102   89   94   24
# Using another type argument
binning(carseats$Income, nbins = 5, type = "equal")
#> binned type: equal
#> number of bins: 5
#> x
#>   (21,40.8] (40.8,60.6] (60.6,80.4]  (80.4,100]   (100,120]        <NA>
#>          77          65          94          80          60          24
binning(carseats$Income, nbins = 5, type = "pretty")
#> binned type: pretty
#> number of bins: 5
#> x
#>   (20,40]   (40,60]   (60,80]  (80,100] (100,120]      <NA>
#>        81        65        94        80        60        20
binning(carseats$Income, nbins = 5, type = "kmeans")
```

```
#> binned type: kmeans
#> number of bins: 5
#> x
#>   (21,36.5] (36.5,55.5] (55.5,75.5] (75.5,97.5]  (97.5,120]        <NA>
#>          62          62          91          86          75          24
binning(carseats$Income, nbins = 5, type = "bclust")
#> binned type: bclust
#> number of bins: 5
#> x
#>   (21,34.5] (34.5,55.5] (55.5,77.5] (77.5,96.5]  (96.5,120]        <NA>
#>          53          71          98          78          76          24

# -------------------------
# Using pipes & dplyr
# -------------------------
library(dplyr)

carseats %>%
 mutate(Income_bin = binning(carseats$Income)) %>%
 group_by(ShelveLoc, Income_bin) %>%
 summarise(freq = n()) %>%
 arrange(desc(freq)) %>%
 head(10)
#> # A tibble: 10 x 3
#> # Groups:   ShelveLoc [1]
#>    ShelveLoc Income_bin   freq
#>    <fct>     <ord>       <int>
#>  1 Medium    (21,30]        24
#>  2 Medium    (62,69]        24
#>  3 Medium    (48,62]        23
#>  4 Medium    (39,48]        21
#>  5 Medium    (30,39]        20
#>  6 Medium    (86.6,96.6]    20
#>  7 Medium    (109,120]      20
#>  8 Medium    (69,78]        18
#>  9 Medium    (96.6,109]     18
#> 10 Medium    (78,86.6]      17
```

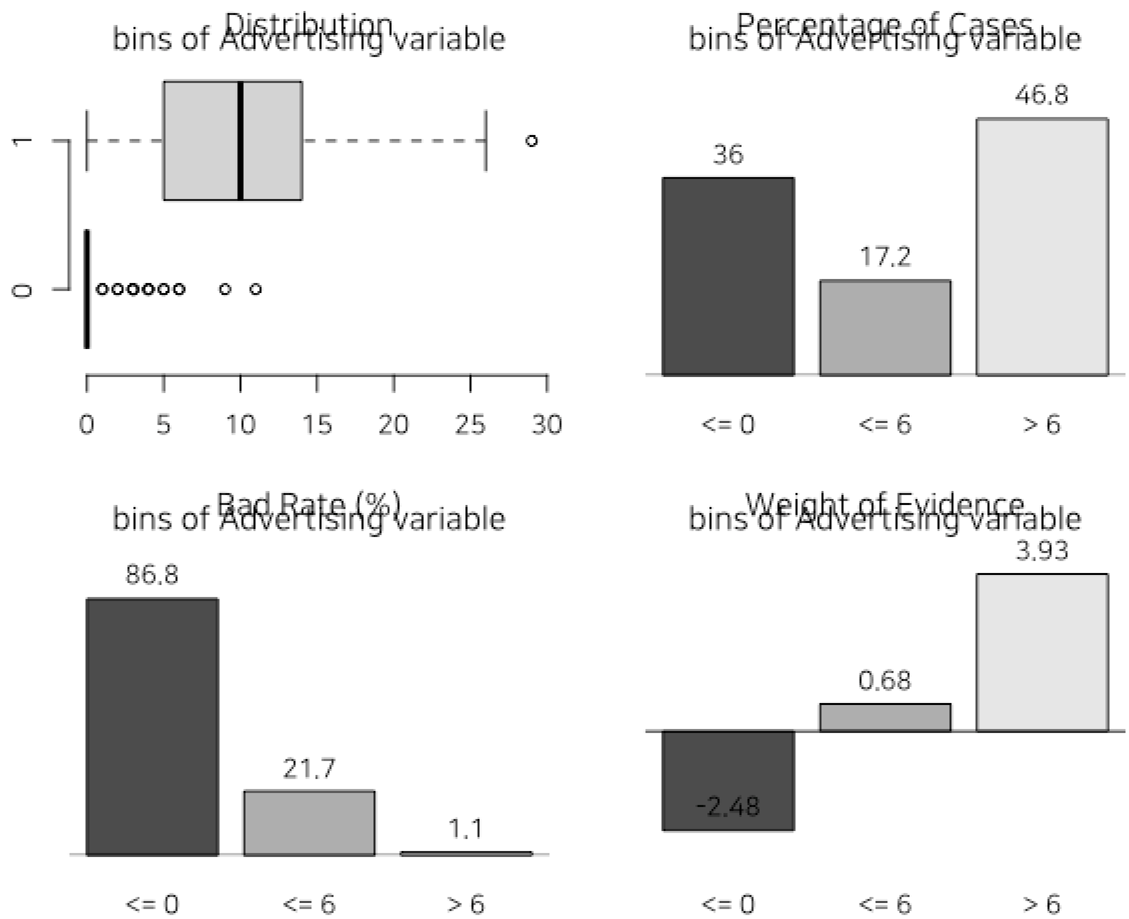
Optimal Binning with `binning_by()`

`binning_by()` converts a numeric variable into a categorical variable by optimal binning. This method is often used when developing a `scorecard model`.

The following `binning_by()` example optimally binning `Advertising` if `US` is a target variable with a binary class.

```
# optimal binning
bin <- binning_by(carseats, "US", "Advertising")
#> Warning in binning_by(carseats, "US", "Advertising"): The factor y has been
#> changed to a numeric vector consisting of 0 and 1.
#> Warning: package 'RSQLite' was built under R version 3.4.4
bin
#> binned type: optimal
#> number of bins: 3
#> x
#> (-1,0]  (0,6] (6,29]
#>    144     69    187
```

```r
# summary optimal_bins class
summary(bin)
#>   levels freq   rate
#> 1 (-1,0]  144 0.3600
#> 2  (0,6]   69 0.1725
#> 3 (6,29]  187 0.4675

# information value
attr(bin, "iv")
#> [1] 4.8349

# information value table
attr(bin, "ivtable")
#>   Cutpoint CntRec CntGood CntBad CntCumRec CntCumGood CntCumBad PctRec
#> 1     <= 0    144      19    125       144         19       125 0.3600
#> 2     <= 6     69      54     15       213         73       140 0.1725
#> 3      > 6    187     185      2       400        258       142 0.4675
#> 4  Missing      0       0      0       400        258       142 0.0000
#> 5    Total    400     258    142        NA         NA        NA 1.0000
#>   GoodRate BadRate    Odds  LnOdds     WoE     IV
#> 1   0.1319  0.8681  0.1520 -1.8839 -2.4810 2.0013
#> 2   0.7826  0.2174  3.6000  1.2809  0.6838 0.0709
#> 3   0.9893  0.0107 92.5000  4.5272  3.9301 2.7627
#> 4      NaN     NaN     NaN     NaN     NaN    NaN
#> 5   0.6450  0.3550  1.8169  0.5971  0.0000 4.8349

# visualize optimal_bins class
plot(bin, sub = "bins of Advertising variable")
```



Reporting

Create a diagnostic report using `diagnose_report()`

`diagnose_report()` performs data diagnosis of all variables of object inherited from data.frame(`tbl_df`, `tbl`, etc) or data.frame.
`diagnose_report() writes the report in two formats:

- Latex based pdf file
- html file

The contents of the report are as follows.:

- Diagnose Data
    - Overview of Diagnosis
        - List of all variables quality
        - Diagnosing Missing Data

        - Diagnosis of unique data(Text and Category)
        - Diagnosis of unique data(Numerical)
    - Detailed data diagnosis
        - Diagnosis of categorical variables
        - Diagnosis of numerical variables
        - List of numerical diagnosis (zero)
        - List of numerical diagnosis (minus)
- Diagnose Outliers
    - Overview of Diagnosis
        - Diagnosis of numerical variable outliers
        - Detailed outliers diagnosis

The follwing creates a quality diagnostic report for flights, a `tbl_df` class object. The file format is pdf and file name is `DataDiagnosis_Report.pdf`.

```
flights %>%
  diagnose_report()
```

The following script creates an html report named `DataDiagnosis_Report.html`.

```
flights %>%
  diagnose_report(output_format = "html")
```

The following generates an HTML report named `Diagn.html`.

```
flights %>%
  diagnose_report(output_format = "html", output_file = "Diagn.html")
```

The `Data Diagnostic Report` is an automated report intended to aid in the data diahnosis process. It judged whether the data is supplemented or reacquired by referring to the report results.

Creating an EDA report using `eda_report()`

`eda_report()` performs EDA on all variables of the data frame or object (`tbl_df`,`tbl`, etc.) that inherits the data frame.

`eda_report()` creates an EDA report in two forms:

- pdf file based on Latex
- html file

The contents of the report are as follows.:

- introduction
    - Information of Dataset
    - Information of Variables
    - Numerical Variables

- Univariate Analysis
    - Descriptive Statistics
    - Normality Test of Numerical Variables
        - Statistics and Visualization of (Sample) Data
- Relationship Between Variables
    - Correlation Coefficient
        - Correlation Coefficient by Variable Combination
        - Correlation Plot of Numerical Variables
- Target based Analysis
    - Gruoped Descriptive Statistics
        - Gruoped Numerical Variables
        - Gruoped Categorical Variables
    - Gruoped Relationship Between Variables
        - Grouped Correlation Coefficient
        - Grouped Correlation Plot of Numerical Variables

The following will create an EDA report for `carseats`. The file format is pdf, and the file name is `EDA_Report.pdf`.

```
carseats %>%
  eda_report(target = Sales)
```

The following generates an HTML-formatted report named `EDA.html`.

```
carseats %>%
  eda_report(target = Sales, output_format = "html", output_file = "EDA.html")
```

The EDA report is an automated report to assist in the EDA process. Design the data analysis scenario with reference to the report results.

Creating a data transformation report using `transformation_report()`

`transformation_report()` creates a data transformation report for all the variables in the data frame or objects that inherit the data frame (`tbl_df`, `tbl`, etc.).
`transformation_report()` creates a data transformation report in two forms:

- pdf file based on Latex
- html file

The contents of the report are as follows.:

- Imputation
    - Missing Values
        - Missing values imputation information

        - (variable names)
    - Outliers
        - Outliers imputation information
        - (variable names)
- Resolving Skewness
    - Skewed variables information
        - (variable names)
- Binning
    - Numerical Variables for Binning
    - Binning
        - (variable names)
    - Optimal Binning
        - (variable names)

The following creates a data transformation report for `carseats`. The file format is pdf, and the file name is `Transformation_Report.pdf`.

```
carseats %>%
  transformation_report(target = US)
```

The following generates a report in html format called `transformation.html`.

```
carseats %>%
  transformation_report(target = US, output_format = "html",
    output_file = "transformation.html")
```

Data transformation reports are automated reports to assist in the data transformation process. Design data conversion scenarios by referring to the report results.

Look at the report

version of pdf file

The cover of the report

The cover of the report is shown in the following figure.:

REPORT SERIES WITH DLOOKR

Exploratory Data Analysis Report

Author:
dlookr package

Version:
0.3.0

April 25, 2018

EDA report cover

The argenda of the report

The report's argenda is shown in the following figure.:

Contents

1 Introduction . . . 3

1.1 Information of Dataset . . . 3

1.2 Information of Variables . . . 3

1.3 About EDA Report . . . 3

2 Univariate Analysis . . . 5

2.1 Descriptive Statistics . . . 5

2.2 Normality Test of Numerical Variables . . . 7

2.2.1 Statistics and Visualization of (Sample) Data . . . 7

3 Relationship Between Variables . . . 15

3.1 Correlation Coefficient . . . 15

3.1.1 Correlation Coefficient by Variable Combination . . . 15

3.1.2 Correlation Plot of Numerical Variables . . . 15

4 Target based Analysis . . . 17

4.1 Grouped Descriptive Statistics . . . 17

4.1.1 Grouped Numerical Variables . . . 17

4.1.2 Grouped Categorical Variables . . . 33

4.2 Grouped Relationship Between Variables . . . 35

4.2.1 Grouped Correlation Coefficient . . . 35

4.2.2 Grouped Correlation Plot of Numerical Variables . . . 35

EDA Report Contents

Appearance of table

Most information is represented in the report as a table. An example of a table is shown in the following figure.:

Chapter 1

Diagnose Data

1.1 Overview of Diagnosis

1.1.1 List of all variables quality

Table 1.1: Data quality overview table

variables	type	missing value(n)	missing value(%)	unique value(n)	unique value(n/N)
year	integer	0	0.0000	1	0.0000
month	integer	0	0.0000	12	0.0000
day	integer	0	0.0000	31	0.0001
dep_time	integer	8,255	2.4512	1,319	0.0039
sched_dep_time	integer	0	0.0000	1,021	0.0030
dep_delay	numeric	8,255	2.4512	528	0.0016
arr_time	integer	8,713	2.5872	1,412	0.0042
sched_arr_time	integer	0	0.0000	1,163	0.0035
arr_delay	numeric	9,430	2.8001	578	0.0017
carrier	character	0	0.0000	16	0.0000
flight	integer	0	0.0000	3,844	0.0114
tailnum	character	2,512	0.7459	4,044	0.0120
origin	character	0	0.0000	3	0.0000
dest	character	0	0.0000	105	0.0003
air_time	numeric	9,430	2.8001	510	0.0015
distance	numeric	0	0.0000	214	0.0006
hour	numeric	0	0.0000	20	0.0001
minute	numeric	0	0.0000	60	0.0002
time_hour	POSIXct	0	0.0000	6,936	0.0206

1.1.2 Diagnosis of missing data

Table 1.2: Variables that include missing values

variables	type	missing value(n)	missing value(%)	unique value(n)	unique value(n/N)
arr_delay	numeric	9,430	2.8001	578	0.0017
air_time	numeric	9,430	2.8001	510	0.0015

Sample data diagnostic report table

Appearance of plot

In EDA reports, information on linear relationships includes tables and visualization results. The result is shown in the following figure.:

Price

1. Simple Linear Model Information

Residual standard error: 3 on 398 degrees of freedom
Multiple R-squared: 0.19798, Adjusted R-squared: 0.19597
F-statistic: 98 on 1 and 398 DF, p-value: 0

Table 4.5: Simple Linear Model coefficients : Price

	Estimate	Std. Error	t value	$Pr(>\|t\|)$
(Intercept)	13.64	0.63	21.56	0
Price	-0.05	0.01	-9.91	0

2. Visualization - Scatterplots

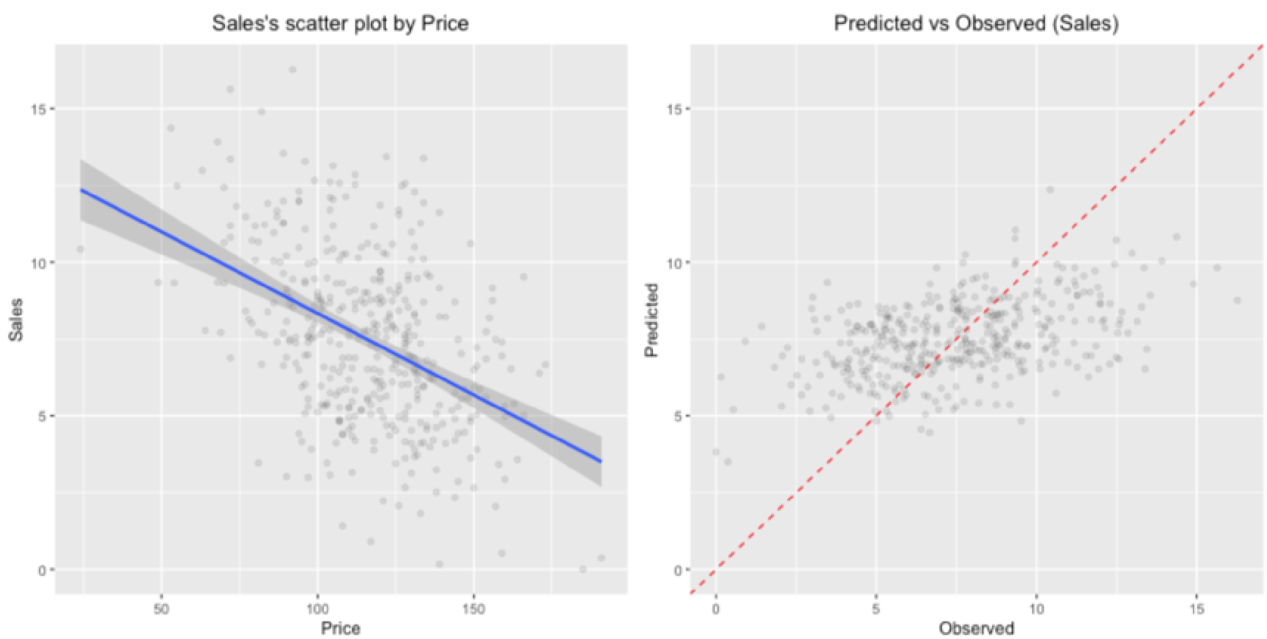


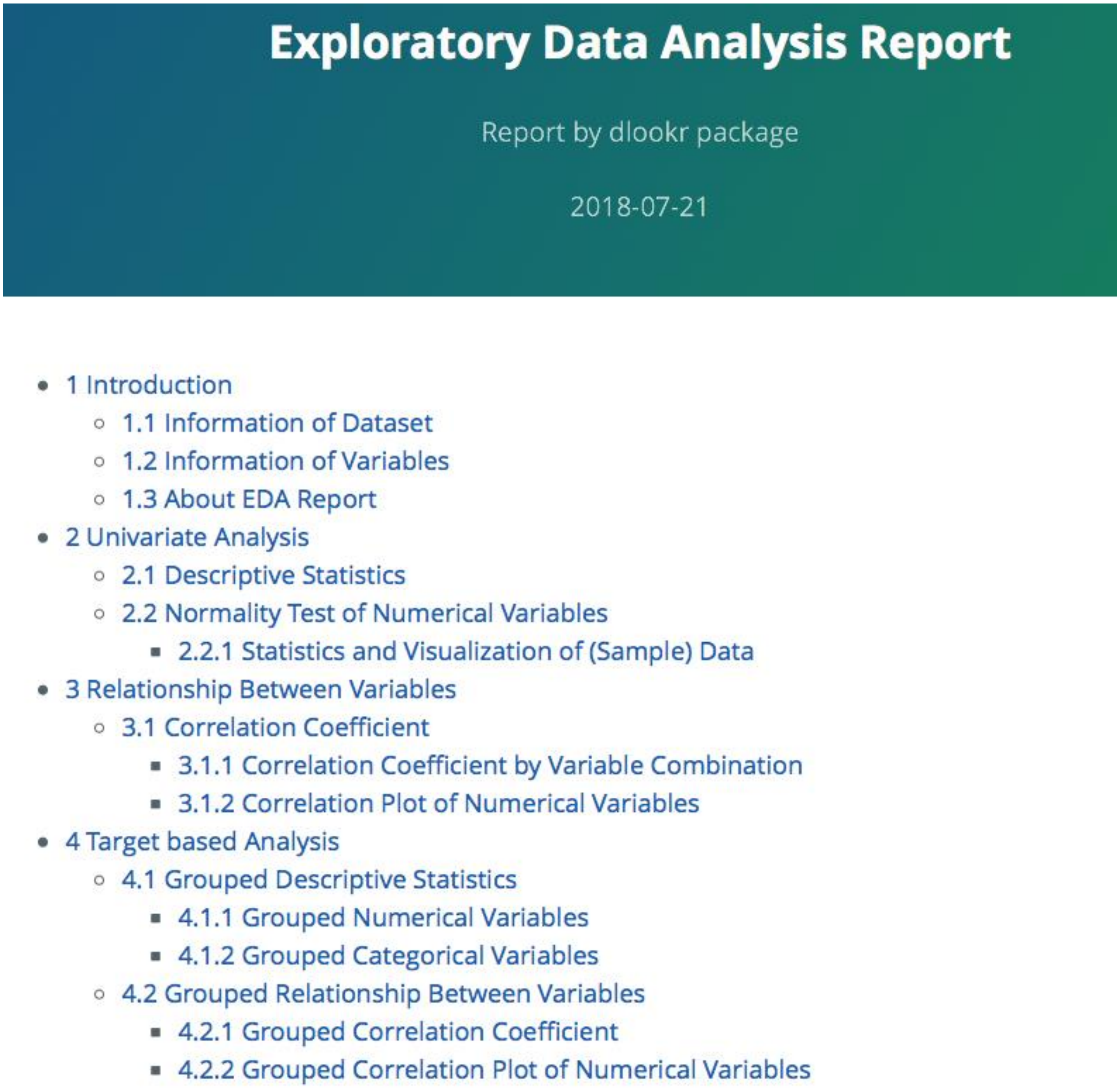
Figure 4.5: Price

Linear relationship information in EDA reports

version of html file

The argenda of the report

The title and contents of the report are shown in the following figure.:



Exploratory Data Analysis Report

Report by dlookr package

2018-07-21

- 1 Introduction
  - 1.1 Information of Dataset
  - 1.2 Information of Variables
  - 1.3 About EDA Report
- 2 Univariate Analysis
  - 2.1 Descriptive Statistics
  - 2.2 Normality Test of Numerical Variables
    - 2.2.1 Statistics and Visualization of (Sample) Data
- 3 Relationship Between Variables
  - 3.1 Correlation Coefficient
    - 3.1.1 Correlation Coefficient by Variable Combination
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- 4 Target based Analysis
  - 4.1 Grouped Descriptive Statistics
    - 4.1.1 Grouped Numerical Variables
    - 4.1.2 Grouped Categorical Variables
  - 4.2 Grouped Relationship Between Variables
    - 4.2.1 Grouped Correlation Coefficient
    - 4.2.2 Grouped Correlation Plot of Numerical Variables

EDA report titles and table of contents

Appearance of table

Much information is represented in tables in the report. An example of a table in an html file is shown in the following figure.:

1.1 Information of Dataset

The dataset that generated the EDA Report is an **'data.frame'** object. It consists of **400 observations** and **11 variables**.

1.2 Information of Variables

The variable information of the data set that generated the EDA Report is shown in the following table.:

Information of Variables

variables	types	missing_count	missing_percent	unique_count	unique_rate
Sales	numeric	0	0.00	336	0.8400
CompPrice	numeric	0	0.00	73	0.1825
Income	numeric	20	5.00	99	0.2475
Advertising	numeric	0	0.00	28	0.0700
Population	numeric	0	0.00	275	0.6875
Price	numeric	0	0.00	101	0.2525
ShelveLoc	factor	0	0.00	3	0.0075
Age	numeric	0	0.00	56	0.1400
Education	numeric	0	0.00	9	0.0225
Urban	factor	5	1.25	3	0.0075
US	factor	0	0.00	2	0.0050

The target variable of the data is **'US'**, and the data type of the variable is **factor**.

EDA report table example (Web)

Appearance of plot

In EDA reports, normality test information includes visualization results. The result of the html file is shown in the following figure.:

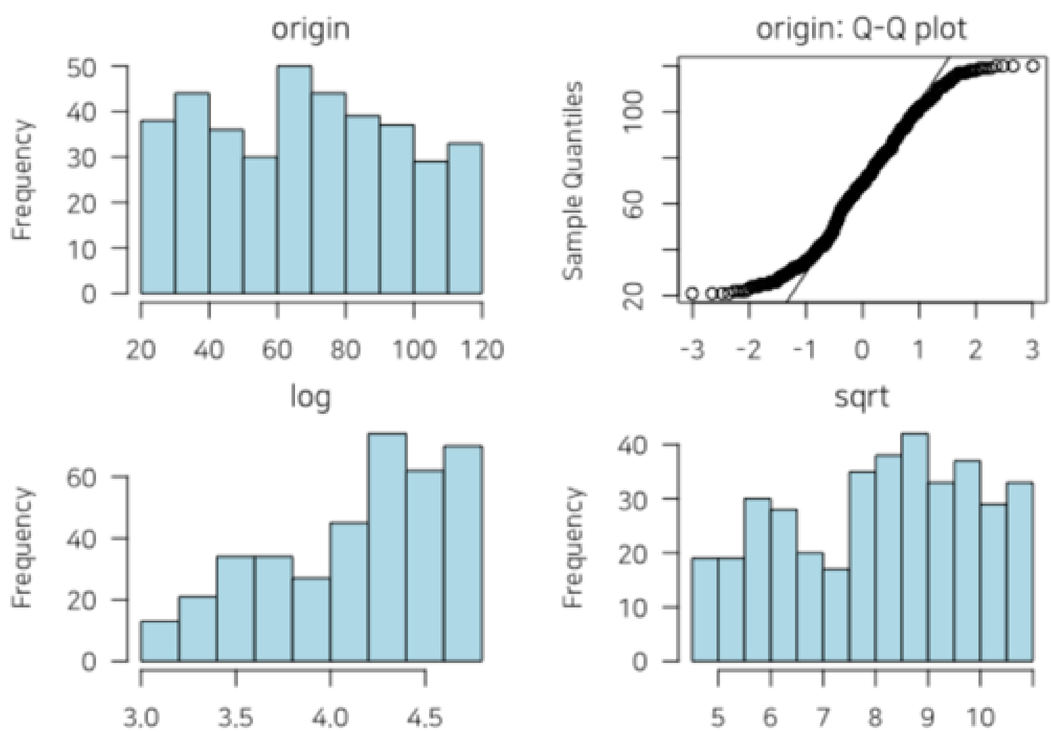
[Income]

normality test : Shapiro-Wilk normality test

```
statistic : 0.95968,  p-value : 1.044E-08
```

skewness and kurtosis

type	skewness	kurtosis
original	0.0501816	1.893236
log transformation	-0.5672675	2.247539
sqrt transformation	-0.2491934	1.955296



EDA Report Normality Test Information (Web)

Supports table of DBMS

Functions that supports tables of DBMS

The DBMS table diagnostic/EDA function supports In-database mode that performs SQL operations on the DBMS side. If the size of the data is large, using In-database mode is faster.

It is difficult to obtain anomaly or to implement the sampling-based algorithm in SQL of DBMS. So some functions do not yet support In-database mode. In this case, it is performed in In-memory mode in which table data is brought to R side and calculated. In this case, if the data size is large, the execution speed may be slow. It supports the collect_size argument, which allows you to import the specified number of samples of data into R.

- In-database support fuctions
  - `diagonse()`
  - `diagnose_category()`
- In-database not support fuctions
  - `diagnose_numeric()`
  - `diagnose_outlier()`
  - `plot_outlier()`
  - `diagnose_report()`
  - `normality()`
  - `plot_normality()`
  - `correlate()`
  - `plot_correlate()`
  - `describe()`
  - `eda_report()`

How to use functions

- Function calls using the In-database mode
  - in_database = TRUE
- Function calls using the In-memory mode
  - in_database = FALSE
- Diagnosis and EDA using sample data from DBMS
  - collect_size =
  - only In-memory mode

Preparing table data

Copy the `carseats` data frame to the SQLite DBMS and create it as a table named `TB_CARSEATS`. Mysql/MariaDB, PostgreSQL, Oracle DBMS, etc. are also available for your environment.

```
if (!require(DBI)) install.packages('DBI')
if (!require(RSQLite)) install.packages('RSQLite')
if (!require(dplyr)) install.packages('dplyr')
if (!require(dbplyr)) install.packages('dbplyr')

library(dbplyr)
library(dplyr)

carseats <- ISLR::Carseats
carseats[sample(seq(NROW(carseats)), 20), "Income"] <- NA
carseats[sample(seq(NROW(carseats)), 5), "Urban"] <- NA

# connect DBMS
con_sqlite <- DBI::dbConnect(RSQLite::SQLite(), ":memory:")

# copy carseats to the DBMS with a table named TB_CARSEATS
copy_to(con_sqlite, carseats, name = "TB_CARSEATS", overwrite = TRUE)
```

Diagonose table of the DBMS

Diagnose data quality of variables in the DBMS

Use `dplyr::tbl()` to create a tbl_dbi object, then use it as a data frame object. That is, the data argument of all diagonose function is specified as tbl_dbi object instead of data frame object.

```
# Diagnosis of all columns
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  diagnose()
#> # A tibble: 11 x 6
#>    variables  types missing_count missing_percent unique_count unique_rate
#>    <chr>      <chr>         <dbl>           <dbl>        <int>       <dbl>
#>  1 Sales      doub…          0               0             336     0.840
#>  2 CompPrice  doub…          0               0              73     0.182
#>  3 Income     doub…         20.0             5.00           99     0.248
#>  4 Advertisi… doub…          0               0              28     0.0700
#>  5 Population doub…          0               0             275     0.688
#>  6 Price      doub…          0               0             101     0.252
#>  7 ShelveLoc  char…          0               0               3     0.00750
#>  8 Age        doub…          0               0              56     0.140
#>  9 Education  doub…          0               0               9     0.0225
#> 10 Urban      char…          5.00            1.25            3     0.00750
#> 11 US         char…          0               0               2     0.00500

# Positions values select columns, and In-memory mode
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
```

```
  diagnose(1, 3, 8, in_database = FALSE)
#> # A tibble: 3 x 6
#>   variables types   missing_count missing_percent unique_count unique_rate
#>   <chr>     <chr>           <int>           <dbl>        <int>       <dbl>
#> 1 Sales     numeric             0            0             336       0.840
#> 2 Income    numeric            20            5.00           99       0.248
#> 3 Age       numeric             0            0              56       0.140
```

Diagnose data quality of categorical variables in the DBMS

```
# Positions values select variables, and In-memory mode and collect size is 200
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  diagnose_category(7, in_database = FALSE, collect_size = 200)
#> # A tibble: 3 x 6
#>   variables levels     N  freq ratio  rank
#> * <chr>     <chr>  <int> <int> <dbl> <int>
#> 1 ShelveLoc Medium   200   113  56.5     1
#> 2 ShelveLoc Bad      200    47  23.5     2
#> 3 ShelveLoc Good     200    40  20.0     3
```

Diagnose data quality of numerical variables in the DBMS

```
# Diagnosis of all numerical variables
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  diagnose_numeric()
#> # A tibble: 8 x 10
#>   variables     min     Q1   mean median     Q3   max  zero minus outlier
#>   <chr>       <dbl>  <dbl>  <dbl>  <dbl>  <dbl> <dbl> <int> <int>   <int>
#> 1 Sales         0     5.39   7.50   7.49   9.32  16.3     1     0       2
#> 2 CompPrice    77.0 115    125    125    135    175       0     0       2
#> 3 Income       21.0  42.0   67.9   68.5   90.0  120       0     0       0
#> 4 Advertising   0     0      6.64   5.00  12.0   29.0   144     0       0
#> 5 Population   10.0 139    265    272    398    509       0     0       0
#> 6 Price        24.0 100    116    117    131    191       0     0       5
#> 7 Age          25.0  39.8   53.3   54.5   66.0   80.0     0     0       0
#> 8 Education    10.0  12.0   13.9   14.0   16.0   18.0     0     0       0
```

Diagnose outlier of numerical variables in the DBMS

```
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  diagnose_outlier()  %>%
  filter(outliers_ratio > 1)
#> # A tibble: 1 x 6
#>   variables outliers_cnt outliers_ratio outliers_mean with_mean
#>   <chr>            <int>          <dbl>         <dbl>     <dbl>
#> 1 Price                5           1.25           100       116
#> # ... with 1 more variable: without_mean <dbl>
```

Plot outlier information of numerical data diagnosis in the DBMS

```
# Visualization of numerical variables with a ratio of
# outliers greater than 1%
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  plot_outlier(con_sqlite %>%
               tbl("TB_CARSEATS") %>%
               diagnose_outlier() %>%
               filter(outliers_ratio > 1) %>%
               select(variables) %>%
               pull())
```

Reporting the information of data diagnosis for table of thr DBMS

The following shows several examples of creating an data diagnosis report for a DBMS table.

Using the `collect_size` argument, you can perform data diagonosis with the corresponding number of sample data. If the number of data is very large, use `collect_size`.

```
# create pdf file. file name is DataDiagnosis_Report.pdf
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  diagnose_report()

# create html file. file name is Diagn.html
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  diagnose_report(output_format = "html", output_file = "Diagn.html")
```

EDA table of the DBMS

Calculating descriptive statistics of numerical column of table in the DBMS

Use `dplyr::tbl()` to create a tbl_dbi object, then use it as a data frame object. That is, the data argument of all EDA function is specified as tbl_dbi object instead of data frame object.

```
# extract only those with 'Urban' variable level is "Yes",
# and find 'Sales' statistics by 'ShelveLoc' and 'US'
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  filter(Urban == "Yes") %>%
  group_by(ShelveLoc, US) %>%
  describe(Sales)
#> # A tibble: 3 x 27
```

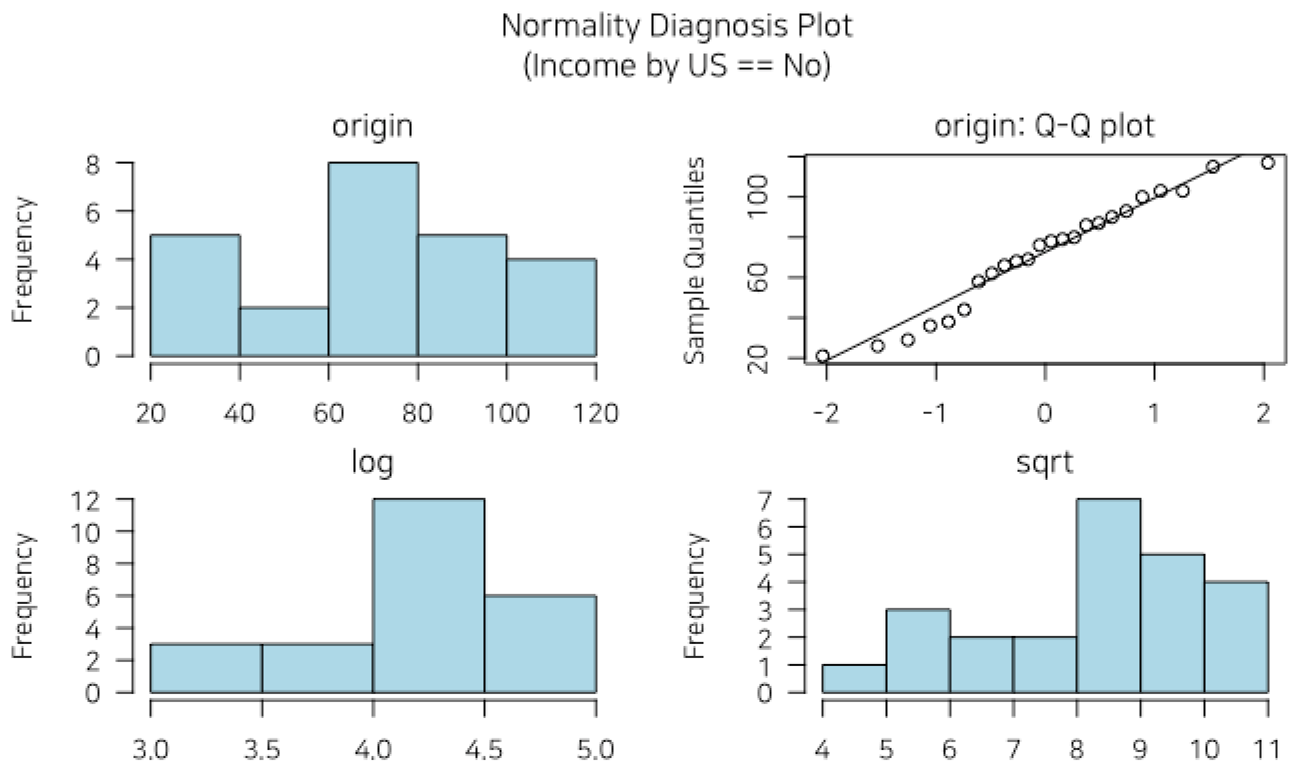
```
#>   variable ShelveLoc     n    na  mean    sd se_mean   IQR skewness
#>   <chr>    <chr>     <dbl> <dbl> <dbl> <dbl>   <dbl> <dbl>    <dbl>
#> 1 Sales    Bad        73.0     0  5.54  2.38   0.279  3.59    0.120
#> 2 Sales    Good       57.0     0 10.4   2.64   0.349  3.78   -0.235
#> 3 Sales    Medium    149       0  7.37  2.15   0.176  3.05    0.229
#> # ... with 18 more variables: kurtosis <dbl>, p00 <dbl>, p01 <dbl>,
#> #   p05 <dbl>, p10 <dbl>, p20 <dbl>, p25 <dbl>, p30 <dbl>, p40 <dbl>,
#> #   p50 <dbl>, p60 <dbl>, p70 <dbl>, p75 <dbl>, p80 <dbl>, p90 <dbl>,
#> #   p95 <dbl>, p99 <dbl>, p100 <dbl>
```

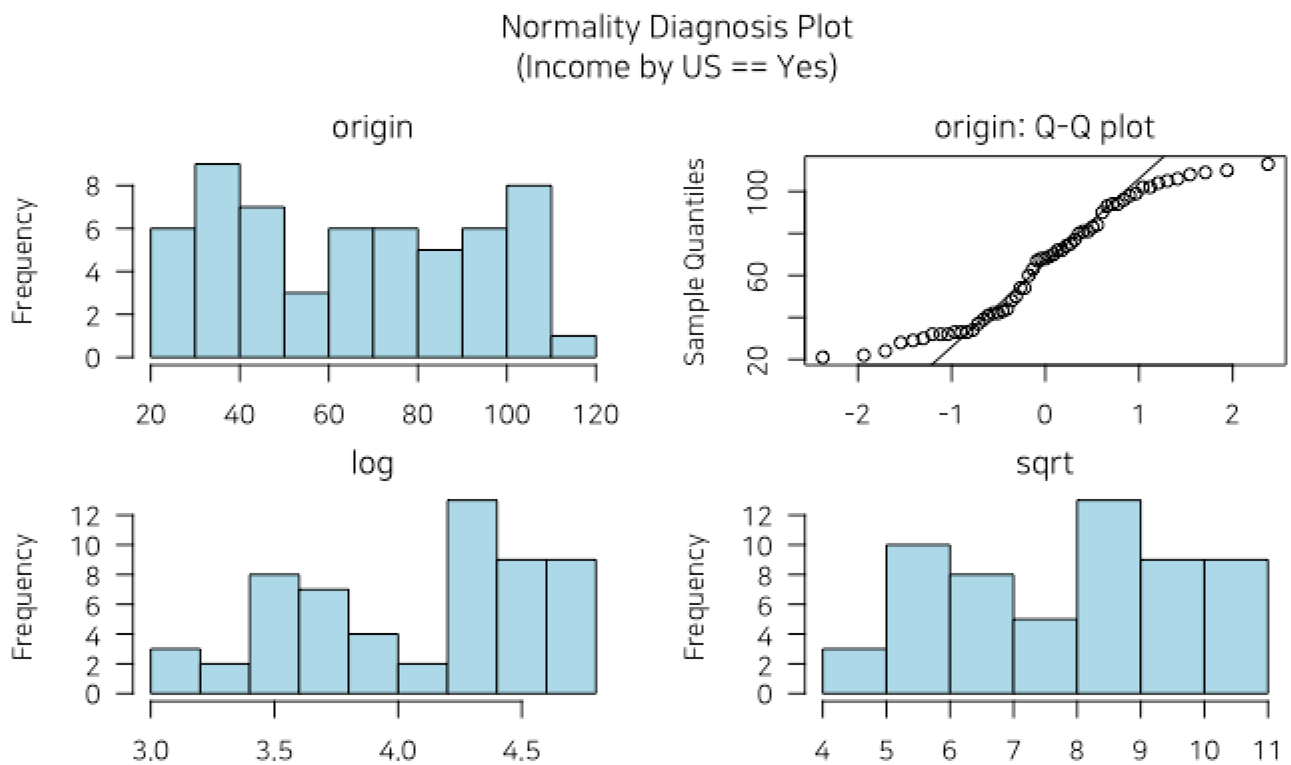
Test of normality on numeric columns using in the DBMS

```
# Test log(Income) variables by 'ShelveLoc' and 'US',
# and extract only p.value greater than 0.01.

# SQLite extension functions for log transformation
RSQLite::initExtension(con_sqlite)

con_sqlite %>%
  tbl("TB_CARSEATS") %>%
 mutate(log_income = log(Income)) %>%
 group_by(ShelveLoc, US) %>%
 normality(log_income) %>%
 filter(p_value > 0.01)
#> # A tibble: 1 x 6
#>   variable   ShelveLoc US    statistic p_value sample
#>   <chr>      <chr>     <chr>     <dbl>   <dbl>  <dbl>
#> 1 log_income Bad       No        0.945   0.103   34.0
```

Normalization visualization of numerical column in the DBMS

```
# extract only those with 'ShelveLoc' variable level is "Good",
# and plot 'Income' by 'US'
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  filter(ShelveLoc == "Good") %>%
  group_by(US) %>%
  plot_normality(Income)
```





Compute the correlation coefficient between two columns of table in DBMS

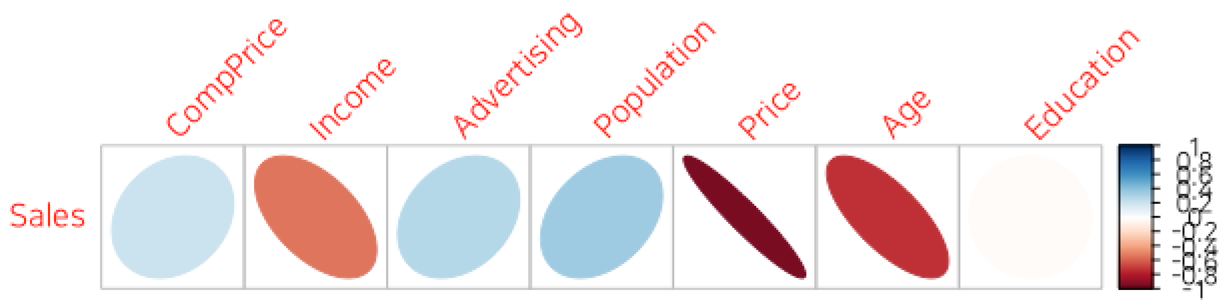
```
# extract only those with 'ShelveLoc' variable level is "Good",
# and compute the correlation coefficient of 'Sales' variable
```

```r
# by 'Urban' and 'US' variables.
# And the correlation coefficient is negative and smaller than 0.5
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  filter(ShelveLoc == "Good") %>%
  group_by(Urban, US) %>%
  correlate(Sales) %>%
  filter(coef_corr < 0) %>%
  filter(abs(coef_corr) > 0.5)
#> # A tibble: 5 x 5
#>   Urban US    var1  var2   coef_corr
#>   <chr> <chr> <fct> <fct>      <dbl>
#> 1 No    No    Sales Income    -0.540
#> 2 No    No    Sales Price     -0.943
#> 3 No    No    Sales Age       -0.722
#> 4 No    Yes   Sales Price     -0.828
#> 5 Yes   No    Sales Price     -0.595
```

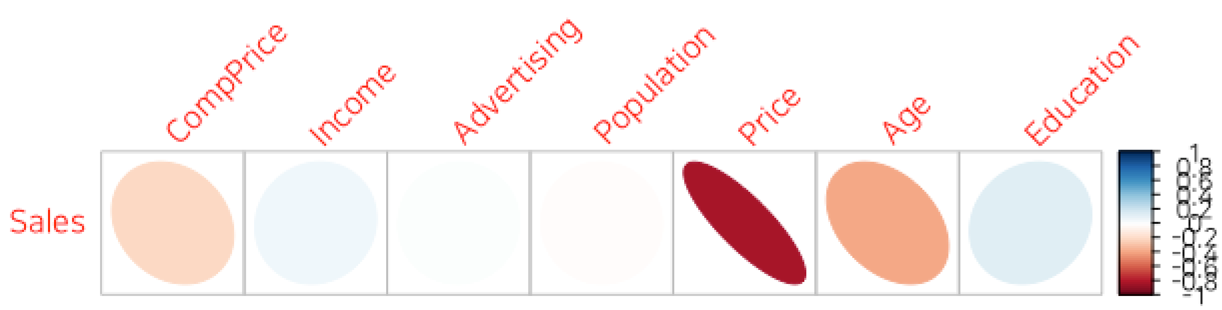
Visualize correlation plot of numerical columns in the DBMS

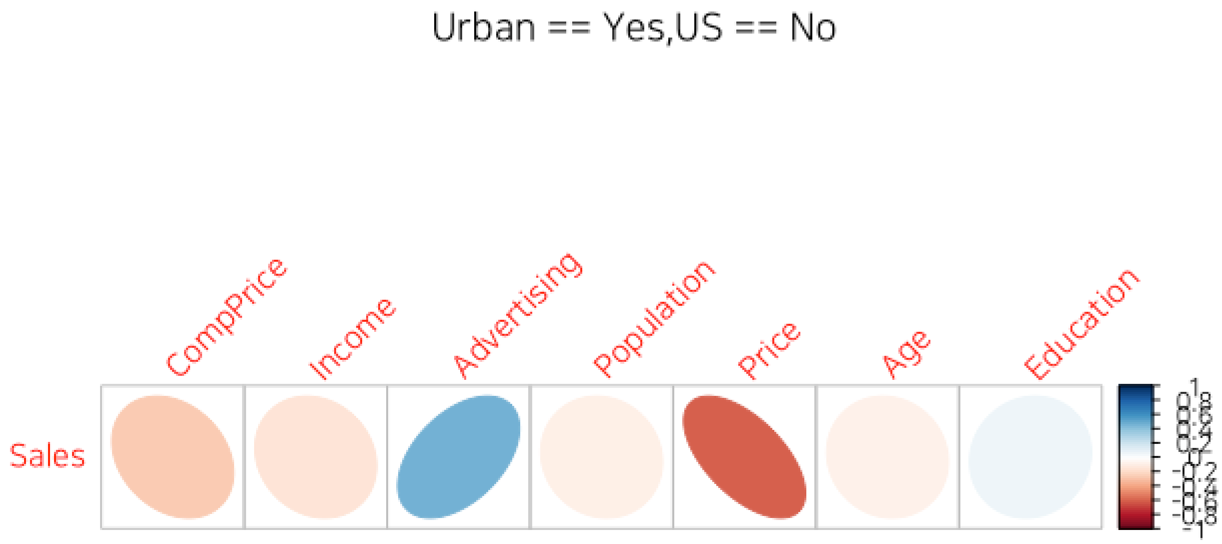
```r
# Extract only those with 'ShelveLoc' variable level is "Good",
# and visualize correlation plot of 'Sales' variable by 'Urban'
# and 'US' variables.
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  filter(ShelveLoc == "Good") %>%
  group_by(Urban, US) %>%
  plot_correlate(Sales)
```

Urban == No,US == No

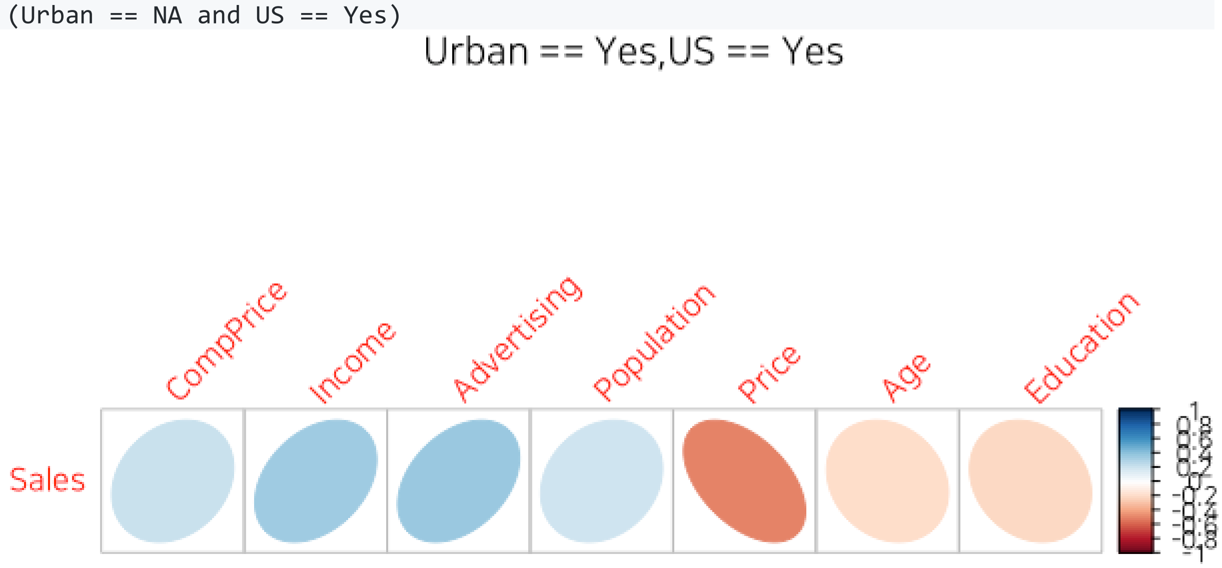


Urban == No,US == Yes






```
#> Warning: Passed a group with no more than five observations.
#> (Urban == NA and US == Yes)
```

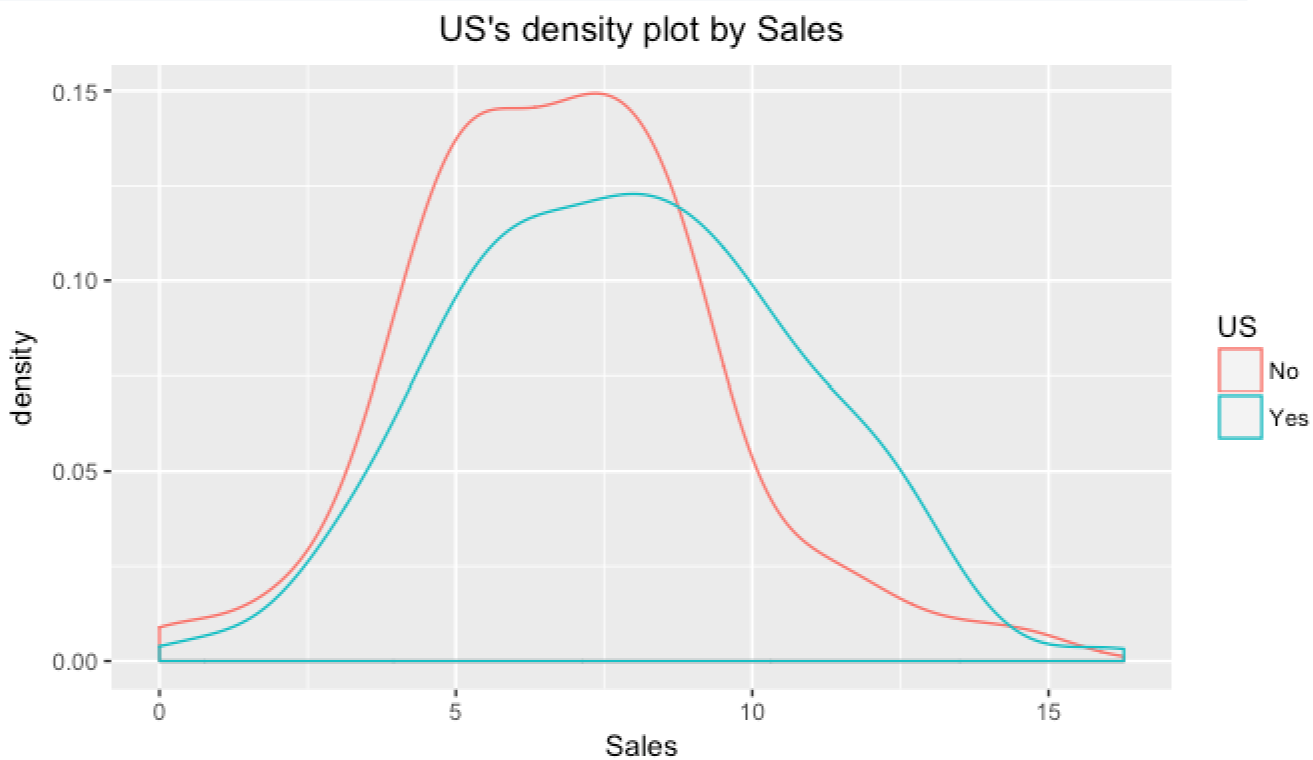


EDA based on target variable

The following is an EDA where the target column is character and the predictor column is a numeric type.

```
# If the target variable is a categorical variable
categ <- target_by(con_sqlite %>% tbl("TB_CARSEATS") , US)

# If the variable of interest is a numarical variable
cat_num <- relate(categ, Sales)
cat_num
#> # A tibble: 3 x 27
#>   variable US        n    na  mean    sd se_mean   IQR skewness kurtosis
#>   <chr>    <fct> <dbl> <dbl> <dbl> <dbl>   <dbl> <dbl>    <dbl>    <dbl>
#> 1 Sales    No      142     0  6.82  2.60   0.218  3.44   0.323     0.808
#> 2 Sales    Yes     258     0  7.87  2.88   0.179  4.23   0.0760   -0.326
#> 3 Sales    total   400     0  7.50  2.82   0.141  3.93   0.186    -0.0809
#> # ... with 17 more variables: p00 <dbl>, p01 <dbl>, p05 <dbl>, p10 <dbl>,
#> #   p20 <dbl>, p25 <dbl>, p30 <dbl>, p40 <dbl>, p50 <dbl>, p60 <dbl>,
#> #   p70 <dbl>, p75 <dbl>, p80 <dbl>, p90 <dbl>, p95 <dbl>, p99 <dbl>,
#> #   p100 <dbl>
summary(cat_num)
#>    variable              US          n                na         mean      
#>  Length:3           No   :1   Min.   :142.0   Min.   :0   Min.   :6.823  
#>  Class :character   Yes  :1   1st Qu.:200.0   1st Qu.:0   1st Qu.:7.160  
#>  Mode  :character   total:1   Median :258.0   Median :0   Median :7.496  
#>                               Mean   :266.7   Mean   :0   Mean   :7.395  
#>                               3rd Qu.:329.0   3rd Qu.:0   3rd Qu.:7.682  
#>                               Max.   :400.0   Max.   :0   Max.   :7.867  
#>        sd           se_mean            IQR           skewness      
#>  Min.   :2.603   Min.   :0.1412   Min.   :3.442   Min.   :0.07603  
#>  1st Qu.:2.713   1st Qu.:0.1602   1st Qu.:3.686   1st Qu.:0.13080  
#>  Median :2.824   Median :0.1791   Median :3.930   Median :0.18556  
#>  Mean   :2.768   Mean   :0.1796   Mean   :3.866   Mean   :0.19489  
#>  3rd Qu.:2.851   3rd Qu.:0.1988   3rd Qu.:4.077   3rd Qu.:0.25432  
#>  Max.   :2.877   Max.   :0.2184   Max.   :4.225   Max.   :0.32308  
#>     kurtosis             p00              p01              p05       
#>  Min.   :-0.32638   Min.   :0.0000   Min.   :0.4675   Min.   :3.147  
#>  1st Qu.:-0.20363   1st Qu.:0.0000   1st Qu.:0.6868   1st Qu.:3.148  
#>  Median :-0.08088   Median :0.0000   Median :0.9062   Median :3.149  
#>  Mean   : 0.13350   Mean   :0.1233   Mean   :1.0072   Mean   :3.183  
#>  3rd Qu.: 0.36344   3rd Qu.:0.1850   3rd Qu.:1.2771   3rd Qu.:3.200  
#>  Max.   : 0.80776   Max.   :0.3700   Max.   :1.6480   Max.   :3.252  
#>       p10             p20             p25             p30       
#>  Min.   :3.917   Min.   :4.754   Min.   :5.080   Min.   :5.306  
#>  1st Qu.:4.018   1st Qu.:4.910   1st Qu.:5.235   1st Qu.:5.587  
#>  Median :4.119   Median :5.066   Median :5.390   Median :5.867  
#>  Mean   :4.073   Mean   :5.051   Mean   :5.411   Mean   :5.775  
#>  3rd Qu.:4.152   3rd Qu.:5.199   3rd Qu.:5.576   3rd Qu.:6.010  
#>  Max.   :4.184   Max.   :5.332   Max.   :5.763   Max.   :6.153  
#>       p40             p50             p60             p70       
#>  Min.   :5.994   Min.   :6.660   Min.   :7.496   Min.   :7.957  
#>  1st Qu.:6.301   1st Qu.:7.075   1st Qu.:7.787   1st Qu.:8.386  
#>  Median :6.608   Median :7.490   Median :8.078   Median :8.815  
#>  Mean   :6.506   Mean   :7.313   Mean   :8.076   Mean   :8.740  
#>  3rd Qu.:6.762   3rd Qu.:7.640   3rd Qu.:8.366   3rd Qu.:9.132  
```

```
#>  Max.   :6.916   Max.   :7.790   Max.   :8.654   Max.   :9.449
#>       p75              p80               p90               p95
#>  Min.   :8.523   Min.   : 8.772   Min.   : 9.349   Min.   :11.28
#>  1st Qu.:8.921   1st Qu.: 9.265   1st Qu.:10.325   1st Qu.:11.86
#>  Median :9.320   Median : 9.758   Median :11.300   Median :12.44
#>  Mean   :9.277   Mean   : 9.665   Mean   :10.795   Mean   :12.08
#>  3rd Qu.:9.654   3rd Qu.:10.111   3rd Qu.:11.518   3rd Qu.:12.49
#>  Max.   :9.988   Max.   :10.464   Max.   :11.736   Max.   :12.54
#>       p99              p100
#>  Min.   :13.64   Min.   :14.90
#>  1st Qu.:13.78   1st Qu.:15.59
#>  Median :13.91   Median :16.27
#>  Mean   :13.86   Mean   :15.81
#>  3rd Qu.:13.97   3rd Qu.:16.27
#>  Max.   :14.03   Max.   :16.27

plot(cat_num)
```



Reporting the information of EDA for table of the DBMS

The following shows several examples of creating an EDA report for a DBMS table.

Using the `collect_size` argument, you can perform EDA with the corresponding number of sample data. If the number of data is very large, use `collect_size`.

```
# create html file. file name is EDA.html
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  eda_report(US, output_format = "html", output_file = "EDA.html")
```

```r
## target variable is numerical variable
# reporting the EDA information, and collect size is 350
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  eda_report(Sales, collect_size = 350)

# create pdf file. file name is EDA2.pdf
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  eda_report("Sales", output_file = "EDA2.pdf")

# create html file. file name is EDA_Report.html
con_sqlite %>%
  tbl("TB_CARSEATS") %>%
  eda_report("Sales", output_format = "html")
```