# MATH2349 Semester 2, 2018, Assignment 3

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```
library(readxl)
library(rvest)
library(dplyr)
library(tidyr)
library(Hmisc)
library(forecast)
library(stringr)
library(outliers)
library(MVN)
library(infotheo)
library(caret)
library(mlr)
library(knitr)
```

# Executive summary:

This data-preprocessing task takes two data sources, Employment/Income of NSW residents and Mortgage repayment/Total dwellings of NsW residents, and merges them together. The merged dataset would be useful to find relationships between interrelated variables. Firstly, I imported open data from xlsx files from the web. These were not in tidy format, so I manipulated and changed data types (eg. character to numeric, character to factors) to be able to get two workable tidy datasets, "Employ_income" and "mort_common_clean" (mortgage repayments). With the combined "full_data" dataframe, I conducted univariate outlier analyses on the jobs, income and total dwellings variables. I then inspected multivariate outliers for the pairs: job-income, income-dwellings, job-dwellings. Finally, the last variable, mortgage repayment frequencies describes how often a repayment amount is selected per region. The distribution of these frequencies was not normal, so I transformed this variable into a normal one.

# Read employment dataset

- The employment data comes from the Australian Bureau of Statistics (ABS) website. The title of the data is "6160.0 Table 1. JOBS and Employment income per job, by selected characteristics and by Regions and by Sex (2011-12 to 2015-16)". The particular set used is the New South Wales data (Statistical area level 3).
- Variables include: number of jobs ('000) and median employment income per job($) in males, females or persons, SA2 region (ID and name) and years.
- The data can be obtained from: http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/6160.02011-12%20to%202015-16?OpenDocument (http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/6160.02011-12%20to%202015-16?OpenDocument)

```
Employment <- read_excel("ABS_Employment.xlsx", sheet = "Table 1.5", range = "A7:Q2305
")
colnames(Employment)
```

```
##  [1] "X__1"    "X__2"    "MALES"   "X__3"    "X__4"    "X__5"    "X__6"
##  [8] "FEMALES" "X__7"    "X__8"    "X__9"    "X__10"   "PERSONS" "X__11"
## [15] "X__12"   "X__13"   "X__14"
```

```
head(Employment)
```

```
## # A tibble: 6 x 17
##   X__1  X__2  MALES X__3  X__4  X__5  X__6  FEMALES X__7  X__8  X__9  X__~
##   <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr>   <chr> <chr> <chr> <ch>
## 1 SA2   SA2 ~ 2011~ 2012~ 2013~ 2014~ 2015~ 2011-12 2012~ 2013~ 2014~ 201~
## 2 Aust~ <NA>  9474~ 9578~ 9539~ 9591~ 9637~ 8532.1  8679~ 8691~ 8769~ 886~
## 3 New ~ <NA>  2916~ 2949~ 2952~ 2977~ 3039~ 2633.9~ 2725~ 2718~ 2726~ 278~
## 4 1010~ Brai~ 1.54~ 1.583 1.56~ 1.55~ 1.52~ 1.3979~ 1.49~ 1.476 1.415 1.5~
## 5 1010~ Kara~ 3.97~ 3.98~ 3.65~ 3.6   3.68~ 3.746   3.68~ 3.415 3.31~ 3.3~
## 6 1010~ Quea~ 5.21~ 5.22~ 4.88  4.78~ 4.92~ 4.5199~ 4.48~ 4.18~ 4.20~ 4.3~
## # ... with 5 more variables: PERSONS <chr>, X__11 <chr>, X__12 <chr>,
## #   X__13 <chr>, X__14 <chr>
```

- Inspect/ understand Employment data structure:
- get class, dimensions, names and classes of columns
- Data is a dataframe of characters: The frequency and income characters are actually numbers and will be converted to numerics. The first column contains characters of SA2 regions, which are suited as characters.

```
class(Employment)
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

```
dim(Employment)
```

```
## [1] 2298   17
```

```
names(Employment)
```

```
##  [1] "X__1"    "X__2"    "MALES"   "X__3"    "X__4"    "X__5"    "X__6"
##  [8] "FEMALES" "X__7"    "X__8"    "X__9"    "X__10"   "PERSONS" "X__11"
## [15] "X__12"   "X__13"   "X__14"
```

```
sapply(Employment,class)
```

```
##         X__1        X__2       MALES        X__3        X__4        X__5
## "character" "character" "character" "character" "character" "character"
##         X__6     FEMALES        X__7        X__8        X__9       X__10
## "character" "character" "character" "character" "character" "character"
##     PERSONS       X__11       X__12       X__13       X__14
## "character" "character" "character" "character" "character"
```

# Read income dataset

```
Income <- read_excel("ABS_Employment.xlsx", sheet = "Table 1.5", range = "R7:AF2305")
colnames(Income)
```

```
##  [1] "MALES"   "X__1"    "X__2"    "X__3"    "X__4"    "FEMALES" "X__5"
##  [8] "X__6"    "X__7"    "X__8"    "PERSONS" "X__9"    "X__10"   "X__11"
## [15] "X__12"
```

```
head(Income)
```

```
## # A tibble: 6 x 15
##   MALES X__1  X__2  X__3  X__4  FEMALES X__5  X__6  X__7  X__8  PERSONS
##   <chr> <chr> <chr> <chr> <chr> <chr>   <chr> <chr> <chr> <chr> <chr>
## 1 2011~ 2012~ 2013~ 2014~ 2015~ 2011-12 2012~ 2013~ 2014~ 2015~ 2011-12
## 2 27769 28799 29537 29963 30410 17247   18000 18735 19676 20538 21918
## 3 28223 28862 29767 30279 30875 18608.5 18517 19627 20672 21645 22938
## 4 17914 17784 19553 21523 2332~ 13103   1223~ 12000 14439 1349~ 15123
## 5 35269 33944 3681~ 38015 34614 23000   26229 27863 28725 3022~ 28614
## 6 3078~ 32952 33250 34091 33009 24030.5 27010 29618 29580 29654 27234.5
## # ... with 4 more variables: X__9 <chr>, X__10 <chr>, X__11 <chr>,
## #   X__12 <chr>
```

- Inspect/ understand Income data structure:
- get class, dimensions and names of columns

```
class(Income)
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

```
dim(Income)
```

```
## [1] 2298   15
```

```
names(Income)
```

```
##  [1] "MALES"   "X__1"    "X__2"    "X__3"    "X__4"    "FEMALES" "X__5"
##  [8] "X__6"    "X__7"    "X__8"    "PERSONS" "X__9"    "X__10"   "X__11"
## [15] "X__12"
```

# Data tidying

- Clean employment data of all persons (male and female) into tidy format.
- First, subset the columns relating to 'persons'
- Second, subset the rows which relate to observations for each region
- Gather the various columns containing year ranges into one long column
- convert into a data frame structure
- Convert "no. of jobs" variable from character to numeric, rounded to 3 digits.

```
#1
all_employment <-Employment[,c(2,13:17)]
colnames(all_employment)[1:6] <- all_employment[1,1:6]
#2
all_employment <- all_employment[4:nrow(all_employment),]
#3
all_emp <- all_employment %>% gather("2011-12", "2012-13", "2013-14", "2014-15", "2015
-16", key = "year", value = "no. of jobs")
#4
all_emp <- as.data.frame(all_emp)
#5
all_emp$`no. of jobs` <- round(as.numeric(all_emp$`no. of jobs`), digits = 3)
```

```
## Warning: NAs introduced by coercion
```

```
#6
head(all_emp)
```

```
##                            SA2 NAME    year no. of jobs
## 1                         Braidwood 2011-12       2.945
## 2                           Karabar 2011-12       7.719
## 3                        Queanbeyan 2011-12       9.732
## 4                 Queanbeyan - East 2011-12       4.516
## 5                 Queanbeyan Region 2011-12      12.794
## 6 Queanbeyan West - Jerrabomberra 2011-12      11.189
```

# Data tidying part2

*As with employment data, tidy into one long data frame with income converted to numeric (3 d.ps)

```
#1
all_Income <- bind_cols(Employment[,2],Income);
colnames(all_Income)
```

```
##  [1] "X__2"    "MALES"   "X__1"    "X__21"   "X__3"    "X__4"    "FEMALES"
##  [8] "X__5"    "X__6"    "X__7"    "X__8"    "PERSONS" "X__9"    "X__10"
## [15] "X__11"   "X__12"
```

```
all_Income <- all_Income[,c(1,12:16)]
colnames(all_Income)[1:6] <- all_Income[1,1:6]
#2
all_Income <- all_Income[4:nrow(all_Income),]
#3
all_Income <- all_Income %>% gather("2011-12", "2012-13", "2013-14", "2014-15", "2015-
16", key = "year", value = "Income")
#4
all_Income <- as.data.frame(all_Income)
#5
all_Income$Income <- round(as.numeric(all_Income$Income), digits = 0)
```

```
## Warning: NAs introduced by coercion
```

```
#6
head(all_Income)
```

```
##                          SA2 NAME    year Income
## 1                       Braidwood 2011-12  15123
## 2                         Karabar 2011-12  28614
## 3                      Queanbeyan 2011-12  27234
## 4               Queanbeyan - East 2011-12  26528
## 5               Queanbeyan Region 2011-12  29999
## 6 Queanbeyan West - Jerrabomberra 2011-12  37290
```

# Merging employment and Income datasets

```
Employ_income <- bind_cols(all_emp, Income = all_Income$Income)
```

# Filtering data and further tidying

- As we only have data from the 2016 census data, the most relevant time period for the employment figures is the 2015-2016 data set. Therefore, we filter the employment data for this time range.
- convert the year range, 2015-2016 into a single year, 2016, in numeric format.
- multiply the “no. of jobs” by 1000 as this data is thousands

```
Employ_income <- Employ_income %>% filter(year == "2015-16")
Employ_income <- Employ_income %>% mutate(year = str_replace(year, "15-", ""))
Employ_income$year = as.numeric(Employ_income$year)
Employ_income$`no. of jobs` <- Employ_income$`no. of jobs` * 1000
head(Employ_income)
```

```
##                          SA2 NAME year no. of jobs Income
## 1                       Braidwood 2016       3063  17882
## 2                         Karabar 2016       7067  31950
## 3                      Queanbeyan 2016       9310  31491
## 4               Queanbeyan - East 2016       4480  29988
## 5               Queanbeyan Region 2016      14061  37092
## 6 Queanbeyan West - Jerrabomberra 2016      11356  39012
```

# Read mortgage dataset

- Read mortgage data from ABS: 2016 Census - Monthly Mortgage Repayments & dwellings location on census night
- The data is ABS census data from the 2016 Australian census. It was downloaded from TableBuilder (https://auth.censusdata.abs.gov.au/webapi/jsf/login.xhtml (https://auth.censusdata.abs.gov.au/webapi/jsf/login.xhtml) ) using a public account.
- The fields selected were: * all SA2s within NSW * monthly mortgage repayments by dwelling
- This data is under a creative commons licence.

```
mortgage <- read_excel("NSW_SA2_MortgageRepayments.xlsx", range = "B9:X587")
head(mortgage)
```

```
## # A tibble: 6 x 23
##   X__1  `Nil repayments` `$1-$149` `$150-$299` `$300-$449` `$450-$599`
##   <chr>            <dbl>     <dbl>       <dbl>       <dbl>       <dbl>
## 1 SA2                 NA        NA          NA          NA          NA
## 2 Avoc~               17         8          12          17          14
## 3 Box ~               49        27          15          29          30
## 4 Calg~               27        12           7           8          12
## 5 Erin~               45        13          11          40          33
## 6 Gosf~               44        17          25          42          52
## # ... with 17 more variables: `$600-$799` <dbl>, `$800-$999` <dbl>,
## #   `$1,000-$1,199` <dbl>, `$1,200-$1,399` <dbl>, `$1,400-$1,599` <dbl>,
## #   `$1,600-$1,799` <dbl>, `$1,800-$1,999` <dbl>, `$2,000-$2,199` <dbl>,
## #   `$2,200-$2,399` <dbl>, `$2,400-$2,599` <dbl>, `$2,600-$2,999` <dbl>,
## #   `$3,000-$3,999` <dbl>, `$4,000-$4,999` <dbl>, `$5000 and over` <dbl>,
## #   `Not stated` <dbl>, `Not applicable` <dbl>, Total <dbl>
```

- Inspect/ understand mortgage data structure:
- The dataframe consists of characters: SA2 regions (matching the employment and income data column, SA2 region), mortgage replayment ranges (more suited to factors) and frequencies (more suited to numerics).

```
class(mortgage)
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

```
dim(mortgage)
```

```
## [1] 578  23
```

```
names(mortgage)
```

```
##  [1] "X__1"            "Nil repayments" "$1-$149"         "$150-$299"
##  [5] "$300-$449"       "$450-$599"      "$600-$799"       "$800-$999"
##  [9] "$1,000-$1,199"  "$1,200-$1,399"  "$1,400-$1,599"  "$1,600-$1,799"
## [13] "$1,800-$1,999"  "$2,000-$2,199"  "$2,200-$2,399"  "$2,400-$2,599"
## [17] "$2,600-$2,999"  "$3,000-$3,999"  "$4,000-$4,999"  "$5000 and over"
## [21] "Not stated"      "Not applicable" "Total"
```

```
sapply(mortgage,class)
```

```
##           X__1 Nil repayments        $1-$149      $150-$299      $300-$449
##    "character"      "numeric"      "numeric"      "numeric"      "numeric"
##      $450-$599      $600-$799      $800-$999  $1,000-$1,199  $1,200-$1,399
##      "numeric"      "numeric"      "numeric"      "numeric"      "numeric"
##  $1,400-$1,599  $1,600-$1,799  $1,800-$1,999  $2,000-$2,199  $2,200-$2,399
##      "numeric"      "numeric"      "numeric"      "numeric"      "numeric"
##  $2,400-$2,599  $2,600-$2,999  $3,000-$3,999  $4,000-$4,999 $5000 and over
##      "numeric"      "numeric"      "numeric"      "numeric"      "numeric"
##     Not stated Not applicable          Total
##      "numeric"      "numeric"      "numeric"
```

# Tidying the mortgage data.

- gather the different columns relating to mortgage repayment bands into one long dataframe.
- tidy the data so that the variable names appear at the top of the columns

```
Repayments <- colnames(mortgage[2:22])
mortgage2 <- mortgage %>% gather(Repayments, key = "Most common mortgage repayments",
value = "Repayment reportings")
mortgage2 <- mortgage2[2:nrow(mortgage2),]
colnames(mortgage2)[1] <- "SA2 NAME"
colnames(mortgage2)[2] <- "Total dwellings in SA2"
head(mortgage2)
```

```
## # A tibble: 6 x 4
##   `SA2 NAME`     `Total dwellings ~ `Most common mortga~ `Repayment repor~
##   <chr>                       <dbl> <chr>                            <dbl>
## 1 Avoca Beach -~               3676 Nil repayments                      17
## 2 Box Head - Ma~               5374 Nil repayments                      49
## 3 Calga - Kulnu~               2205 Nil repayments                      27
## 4 Erina - Green~               5760 Nil repayments                      45
## 5 Gosford - Spr~               9213 Nil repayments                      44
## 6 Kariong                      2183 Nil repayments                      27
```

- Convert the mortgage monthly repayments into an ordered factor
- Take out the fators, “Not applicable” and “Not stated” as we are more interested and concerned about knowing the repayment ranges that were stated in the census.

```
mortgage2$`Most common mortgage repayments` <- factor(mortgage2$`Most common mortgage
repayments`, levels = Repayments)
levels(mortgage2$`Most common mortgage repayments`)
```

```
##  [1] "Nil repayments" "$1-$149"        "$150-$299"      "$300-$449"
##  [5] "$450-$599"      "$600-$799"      "$800-$999"      "$1,000-$1,199"
##  [9] "$1,200-$1,399"  "$1,400-$1,599"  "$1,600-$1,799"  "$1,800-$1,999"
## [13] "$2,000-$2,199"  "$2,200-$2,399"  "$2,400-$2,599"  "$2,600-$2,999"
## [17] "$3,000-$3,999"  "$4,000-$4,999"  "$5000 and over" "Not stated"
## [21] "Not applicable"
```

```
clean_mortgage <- mortgage2 %>% filter(!(`Most common mortgage repayments` %in% c("Not
applicable", "Not stated")))
# table(clean_mortgage$`Most common mortgage repayments`)
head(mortgage2)
```

```
## # A tibble: 6 x 4
##   `SA2 NAME`     `Total dwellings ~ `Most common mortga~ `Repayment repor~
##   <chr>                       <dbl> <fct>                            <dbl>
## 1 Avoca Beach -~               3676 Nil repayments                      17
## 2 Box Head - Ma~               5374 Nil repayments                      49
## 3 Calga - Kulnu~               2205 Nil repayments                      27
## 4 Erina - Green~               5760 Nil repayments                      45
## 5 Gosford - Spr~               9213 Nil repayments                      44
## 6 Kariong                      2183 Nil repayments                      27
```

- Find the most commonly occuring repayment range for each region by filtering for the max number of frequency in each SA2.

```
mortgage_common <- clean_mortgage %>% group_by(`SA2 NAME`) %>% filter(`Repayment repor
tings` == max(`Repayment reportings`))
head(mortgage_common)
```

```
## # A tibble: 6 x 4
## # Groups:   SA2 NAME [6]
##   `SA2 NAME`     `Total dwellings ~ `Most common mortga~ `Repayment repor~
##   <chr>                       <dbl> <fct>                            <dbl>
## 1 Prospect Rese~                  7 Nil repayments                       0
## 2 Banksmeadow                     4 Nil repayments                       0
## 3 Port Botany I~                  6 Nil repayments                       0
## 4 Sydney Airport                  7 Nil repayments                       0
## 5 Centennial Pa~                  0 Nil repayments                       0
## 6 Holsworthy Mi~                  0 Nil repayments                       0
```

- Exclude duplicated regions where all repayment reportings are “0”:

```
mort_common_clean <- mortgage_common[!duplicated(mortgage_common$`SA2 NAME`),]
head(mort_common_clean)
```

```
## # A tibble: 6 x 4
## # Groups:   SA2 NAME [6]
##   `SA2 NAME`     `Total dwellings ~ `Most common mortga~ `Repayment repor~
##   <chr>                       <dbl> <fct>                            <dbl>
## 1 Prospect Rese~                  7 Nil repayments                       0
## 2 Banksmeadow                     4 Nil repayments                       0
## 3 Port Botany I~                  6 Nil repayments                       0
## 4 Sydney Airport                  7 Nil repayments                       0
## 5 Centennial Pa~                  0 Nil repayments                       0
## 6 Holsworthy Mi~                  0 Nil repayments                       0
```

# Merging employment and mortgage datasets

- The mortgage data does not capture as many regions as the employment data (eg. mortgage_cleaned contain 577 observations compared with all_emp_clean with 2295 observations) If we are using the combined dataset for the purpose of records, we can join all these variables. However, if pre-processing is for analysis purposes, we should subset only the regions where we have both mortgage and employment data. The next part does this merge.
- Merge the employment dataset with the mortgage dataset by SA2 name.

```
full_data <- Employ_income %>% inner_join(mort_common_clean, by="SA2 NAME")
head(full_data)
```

```
##                          SA2 NAME year no. of jobs Income
## 1                       Braidwood 2016        3063  17882
## 2                         Karabar 2016        7067  31950
## 3                      Queanbeyan 2016        9310  31491
## 4               Queanbeyan - East 2016        4480  29988
## 5               Queanbeyan Region 2016       14061  37092
## 6 Queanbeyan West - Jerrabomberra 2016       11356  39012
##   Total dwellings in SA2 Most common mortgage repayments
## 1                   2297                   $1,600-$1,799
## 2                   3387                   $2,000-$2,199
## 3                   5652                   $2,000-$2,199
## 4                   2458                   $2,000-$2,199
## 5                   6295                   $3,000-$3,999
## 6                   4616                   $3,000-$3,999
##   Repayment reportings
## 1                   42
## 2                  149
## 3                  161
## 4                   66
## 5                  588
## 6                  351
```

# Treat missing values

- Scan for missing values in SA2 name, no.of jobs and total dwellings by finding the total number of NAs per column.

```
colSums(is.na(full_data))
```

```
##                        SA2 NAME                            year
##                               0                               0
##                     no. of jobs                          Income
##                              13                              13
##          Total dwellings in SA2 Most common mortgage repayments
##                               0                               0
##            Repayment reportings
##                               0
```

- Impute the median number of jobs for missing values here as there are only such cases. The number of missing values is <5% of the data so we can be safe to exclude these observations.

```
imputed_jobs <- Hmisc::impute(full_data$`no. of jobs`, fun=median)
full_data$`no. of jobs` <- imputed_jobs

imputed_income <- Hmisc::impute(full_data$Income, fun=median)
full_data$Income <- imputed_income

colSums(is.na(full_data))
```

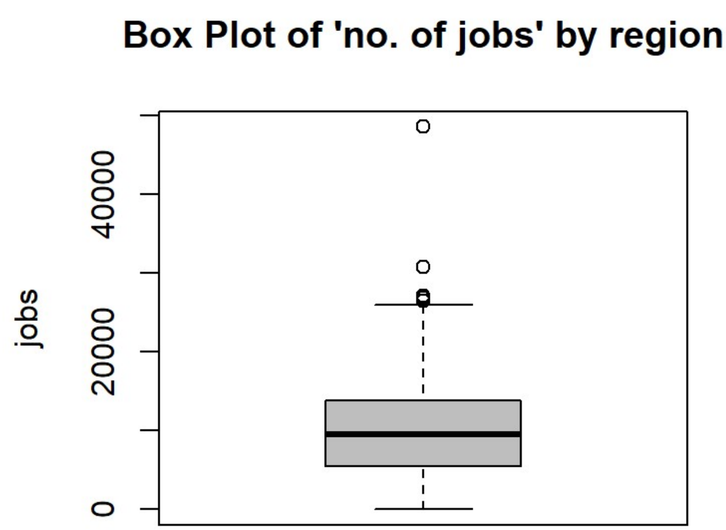
```
##                       SA2 NAME                            year
##                              0                               0
##                    no. of jobs                          Income
##                              0                               0
##          Total dwellings in SA2 Most common mortgage repayments
##                              0                               0
##            Repayment reportings
##                              0
```

# Treating univariate and multivariate outliers.

## Univariate outliers:

- Detect any outliers in either jobs, income or total dwellings by using Tukey's method of detection.

```
job_boxplot <- boxplot(as.numeric(full_data$`no. of jobs`), main = "Box Plot of 'no. o
f jobs' by region", ylab = "jobs", col = "grey")
```




* Find the outlier cases by using the z-score method to find when the z score is greater than 3. These are outliers.

```
z_score_job <- full_data$`no. of jobs` %>% scores(type ="z")
z_score_job %>% summary()
```

```
##
##   13 values imputed to -0.1243648
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.7009 -0.7944 -0.1244  0.0000  0.5899  6.3429
```

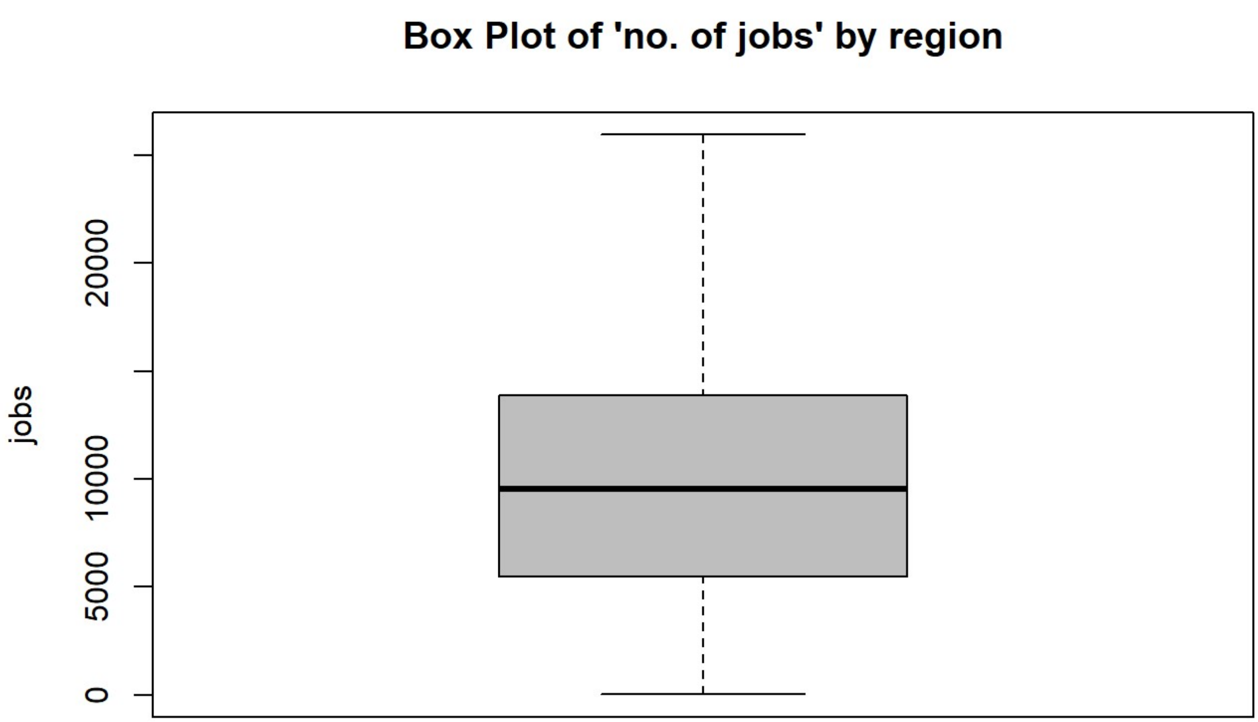
```
which(abs(z_score_job) > 3)
```

```
## [1] 348 349
```

- Handling the outliers by capping

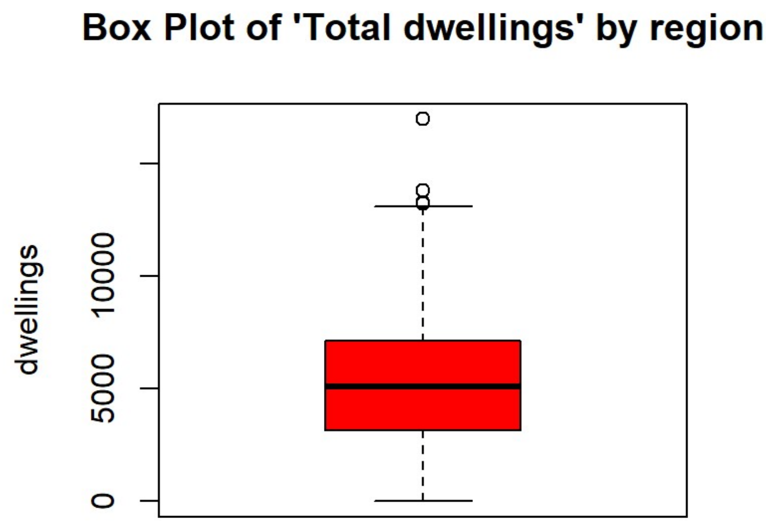
```
cap <- function(x){
    quantiles <- quantile( x, c(.05, 0.25, 0.75, .95 ) )
    x[ x < quantiles[2] - 1.5*IQR(x) ] <- quantiles[1]
    x[ x > quantiles[3] + 1.5*IQR(x) ] <- quantiles[4]
    x
}

jobs_capped <- full_data$`no. of jobs` %>% cap()
boxplot(as.numeric(jobs_capped), main = "Box Plot of 'no. of jobs' by region", ylab =
"jobs", col = "grey")
```



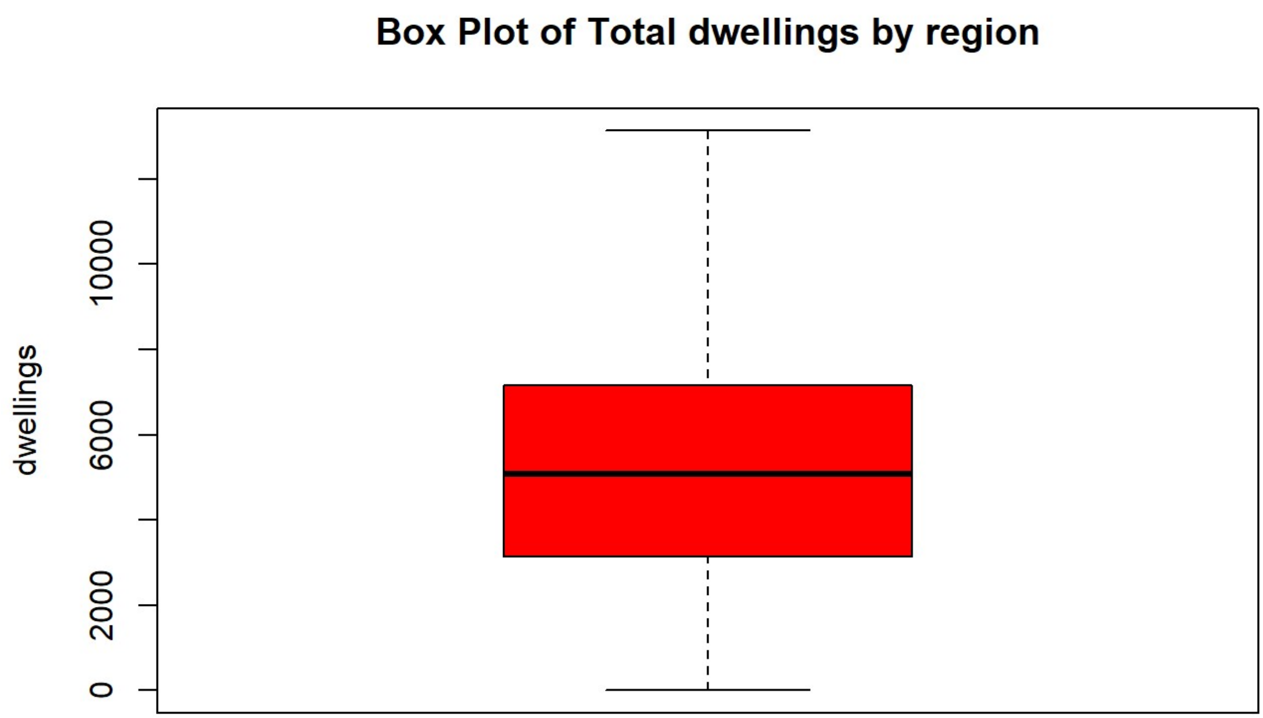

```
full_data$`no. of jobs` <- jobs_capped
```

```
dwellings_boxplot <- boxplot(as.numeric(full_data$`Total dwellings in SA2`), main = "B
ox Plot of 'Total dwellings' by region", ylab = "dwellings", col = "red")
```




- handle the outliers by capping.

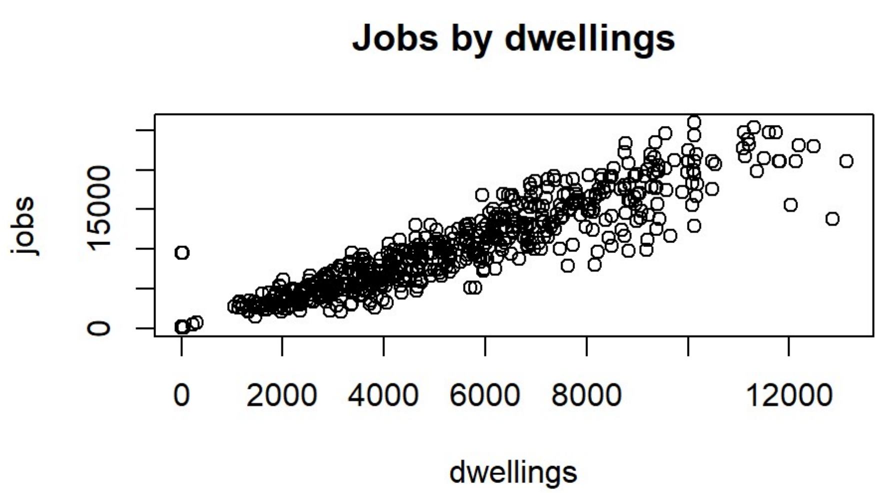
```
dwellings_capped <- full_data$`Total dwellings in SA2` %>% cap()
boxplot(as.numeric(dwellings_capped), main = "Box Plot of Total dwellings by region",
ylab = "dwellings", col = "red")
```




```
full_data$`Total dwellings in SA2` <- dwellings_capped
```

- Look for multivariate outliers by inspection using a scatterplot.

```
scatter1 <- full_data %>% plot(`no. of jobs`~ `Total dwellings in SA2`, data = ., ylab
= "jobs", xlab = "dwellings", main = "Jobs by dwellings")
```




- Look for multivariate outliers with the mvn package which uses the Chi-Square distribution critical value

- Treat by excluding the outliers using “showNewData”
- Jobs vs. total dwellings

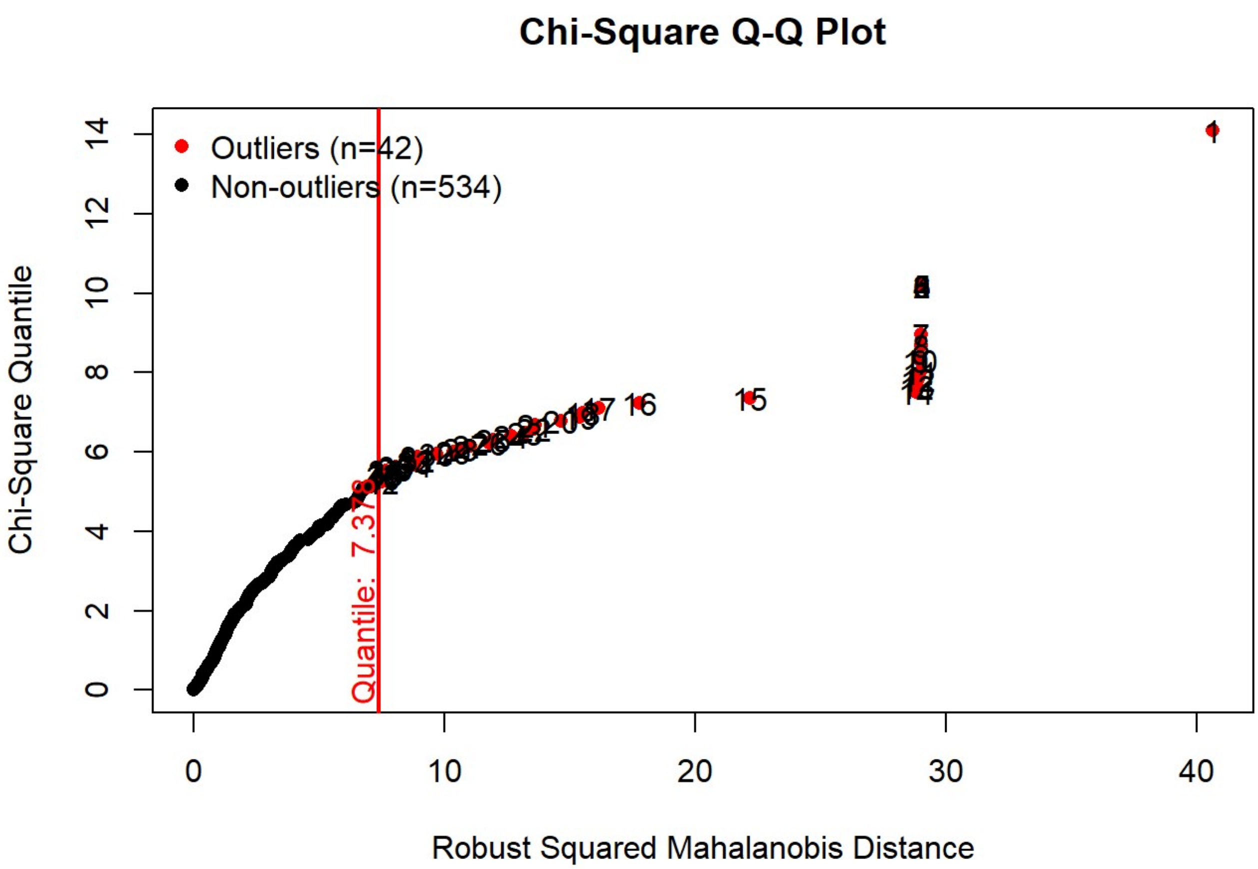
```
class(full_data)
```

```
## [1] "data.frame"
```

```
colnames(full_data)
```

```
## [1] "SA2 NAME"                          "year"
## [3] "no. of jobs"                       "Income"
## [5] "Total dwellings in SA2"            "Most common mortgage repayments"
## [7] "Repayment reportings"
```

```
full_data_sub <- full_data %>% dplyr::select(`no. of jobs`, `Total dwellings in SA2`)
job_dwelling_clean <- mvn(data = full_data_sub, multivariateOutlierMethod = "quan", sh
owOutliers = TRUE, showNewData = TRUE)
```

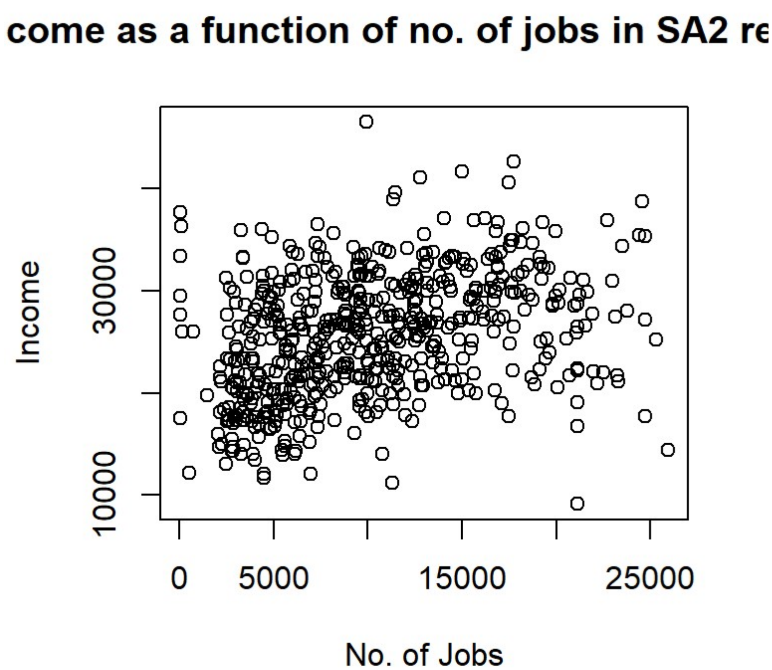



```
full_data2 <- job_dwelling_clean$newData
head(full_data2)
```

```
##     no. of jobs Total dwellings in SA2
## 100        8760                   4208
## 101       13965                   7486
## 102        6784                   3760
## 103        4690                   2166
## 104        3442                   2037
## 105        4978                   2918
```

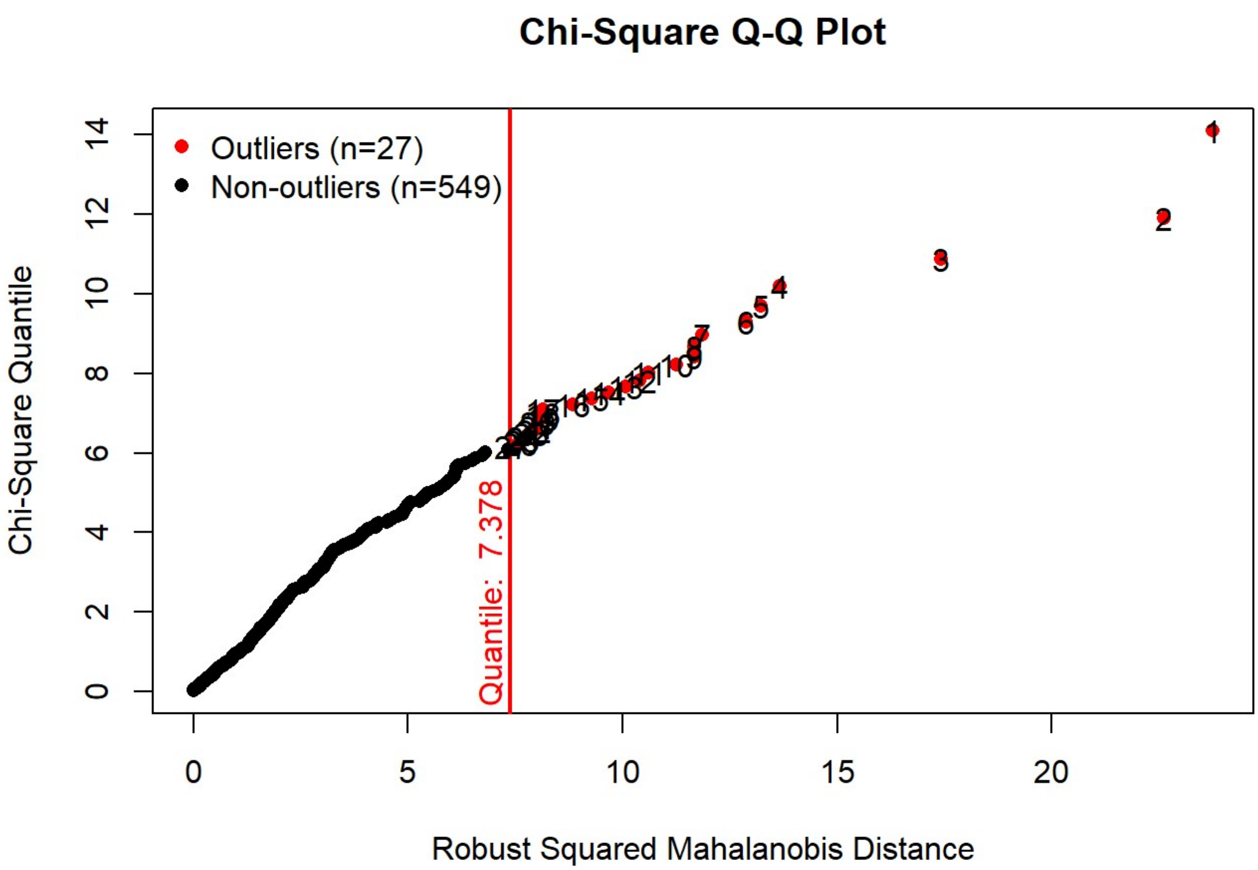
*Multivariate outlier #2* income vs jobs

```
full_data_sub2 <- full_data %>% dplyr::select(`no. of jobs`, Income)
scatplot2 <- full_data %>% plot(Income ~ `no. of jobs`, data = ., ylab = "Income", xla
b = "No. of Jobs", main = "Income as a function of no. of jobs in SA2 regions")
```




- Treat mutlivariate outlier

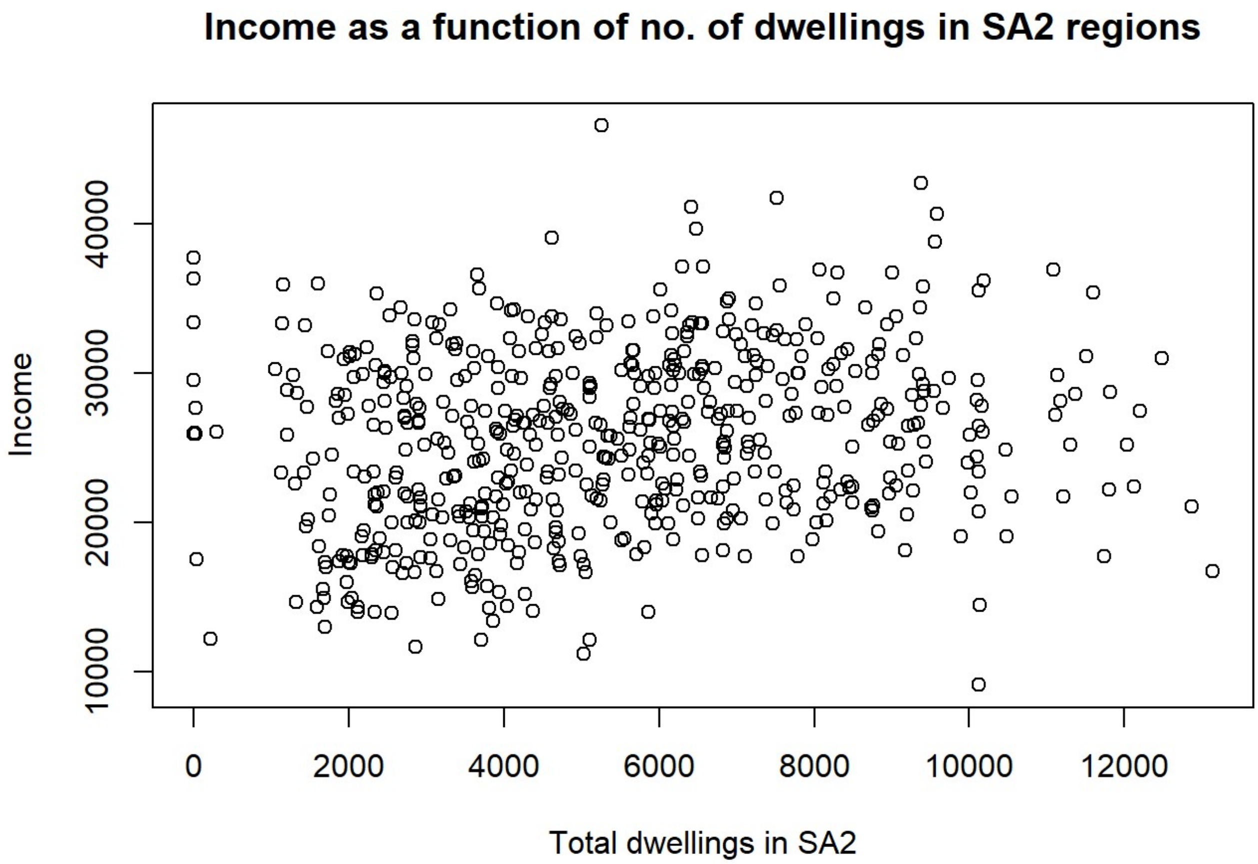
```
Income_job_clean <- mvn(data = full_data_sub2, multivariateOutlierMethod = "quan", sho
wOutliers = TRUE, showNewData = TRUE)
```



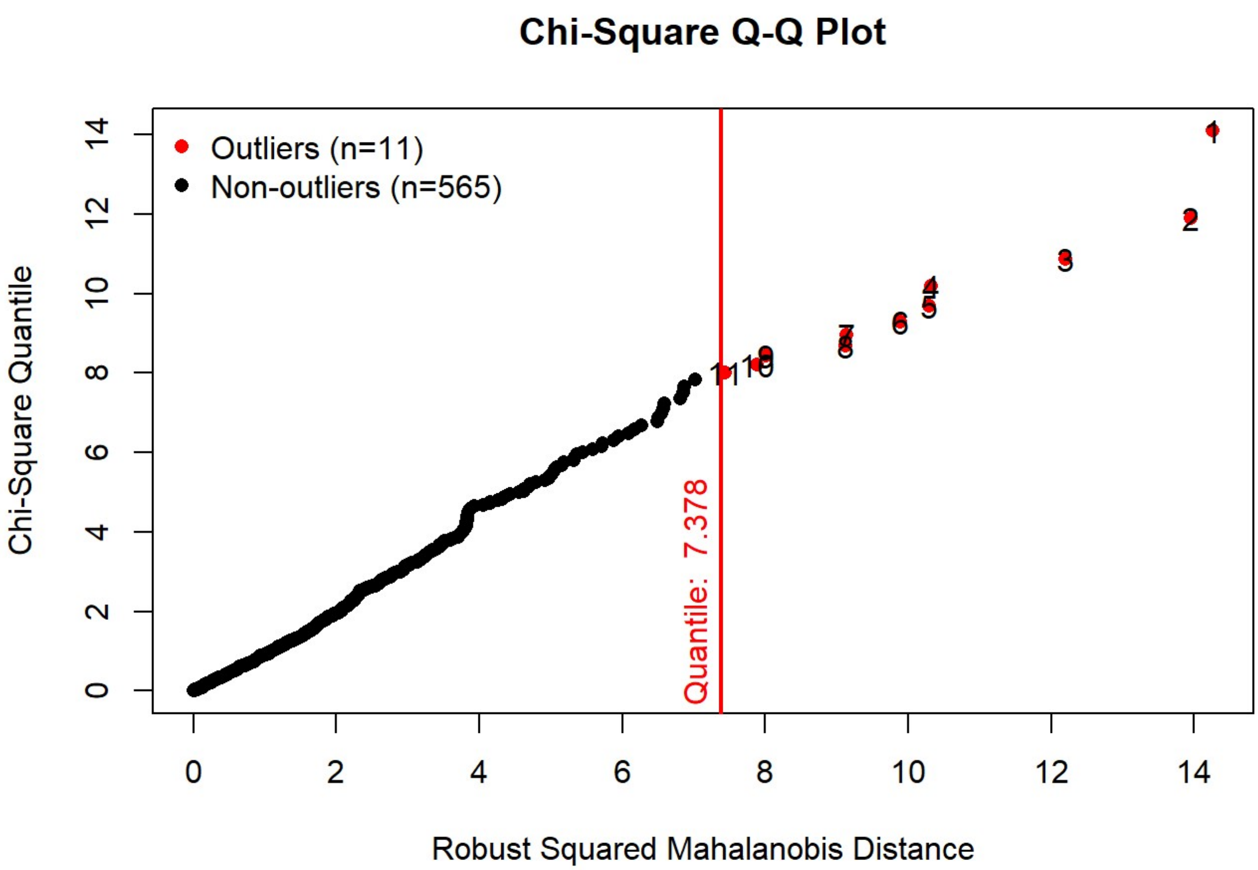

```
full_data3 <- Income_job_clean$newData
## head(full_data3)  #data suppressed in order ot fit within the page limit of the ass
ignment
```

*Multivariate outlier #3* income vs dwellings

```
full_data_sub3 <- full_data %>% dplyr::select(`Total dwellings in SA2`, Income)
full_data %>% plot(Income ~ `Total dwellings in SA2`, data = ., ylab = "Income", xlab
= "Total dwellings in SA2", main = "Income as a function of no. of dwellings in SA2 re
gions")
```




```
Income_dwelling_clean <- mvn(data = full_data_sub3, multivariateOutlierMethod = "quan"
, showOutliers = TRUE, showNewData = TRUE)
```

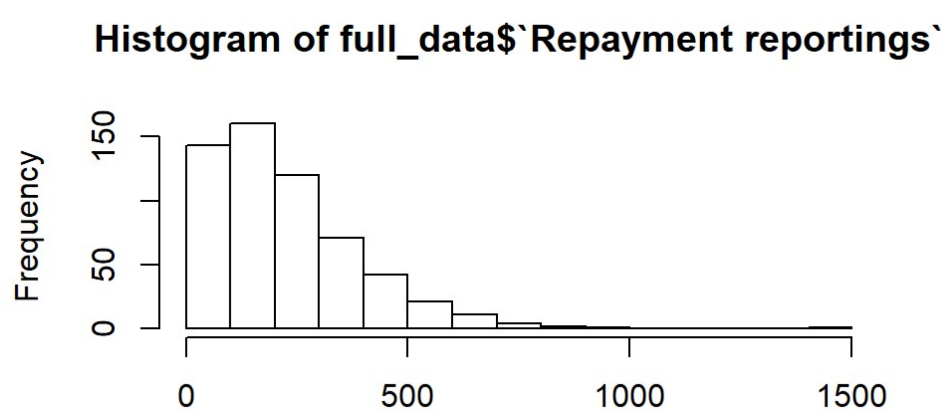



```
full_data4 <- Income_dwelling_clean$newData
## head(full_data3)  #data suppressed in order ot fit within the page limit of the ass
ignment
```

# Data transformations:

*Histogram of Repayment reporting numbers

```
hist <- hist(full_data$`Repayment reportings`, xlab = "Reportings of the most common r
epayment range ")
```



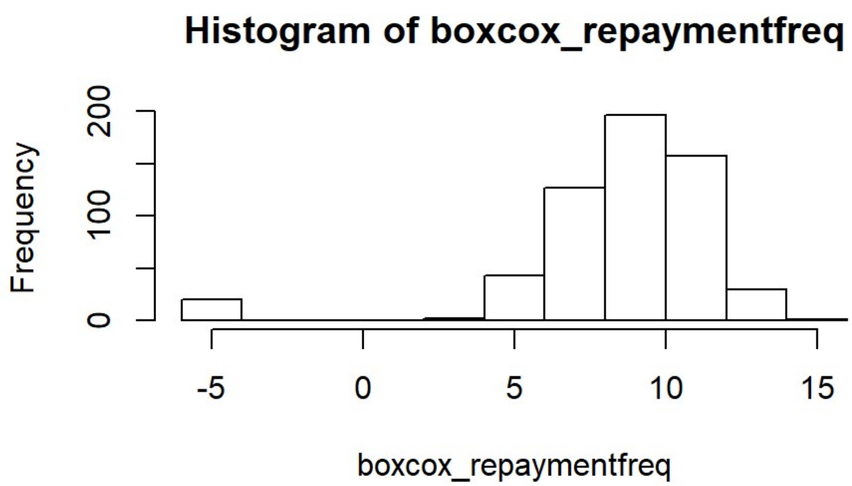
Reportings of the most common repayment range

- The counts of the most common repayment option per region is positively skewed. It would be beneficial to transform the data ,
- BoxCox transformation.
- Use boxcox with lambda set as auto by the package.

```
boxcox_repaymentfreq <- BoxCox(full_data$`Repayment reportings`, lambda = "auto")
head(boxcox_repaymentfreq)
```

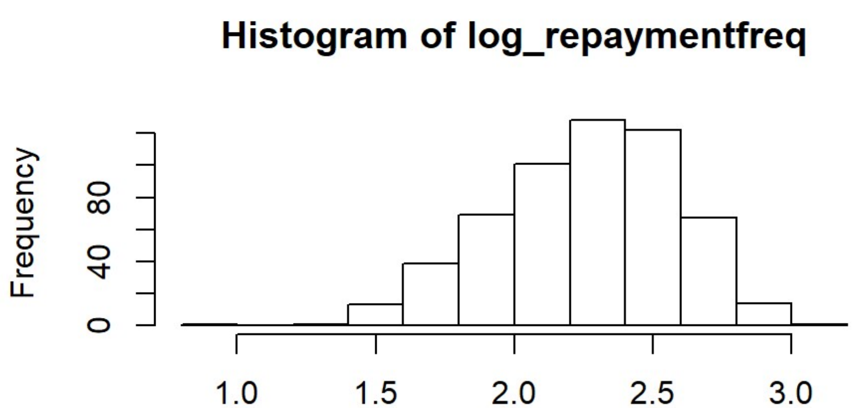
```
## [1]  5.429006  8.324734  8.525332  6.384187 12.353288 10.715659
```

```
hist(boxcox_repaymentfreq)
```




*log10 transformation* Alternatively use log10 as the shape is positively skewed.

```
log_repaymentfreq <- log10(full_data$`Repayment reportings`)
hist(log_repaymentfreq)
```



log_repaymentfreq