APA-L0

September 6, 2018

1 APA Laboratori 0 - Data preprocessing

```
In [1]: options(repr.plot.width=6, repr.plot.height=6)
```

INSTRUCCIONS

No cal entregar res, cal assimilar

S'ha de fer amb calma, sense córrer, mirant d'entendre en tot moment què s'està fent --a nivell conceptual-- i quin efecte té

Podeu deixar el codi R en si (crides, paràmetres, sintaxi) per una segona lectura o com a treball personal. El codi R és un mitjà, no un objectiu.

1.1 SECTION 1: READING THE FILE CREDSCO.TXT (loan data: credit scoring)

Reading properly a data set is non-trivial because you need to know its data format: decimal separator, column separator, is there a header? how are strings quoted? how (if any) are missing values coded? should character vectors be converted to factors? should white spaces be stripped?, ...)

It is a good idea to consult `?read.csv` and play with useful control parameters, like

`header=TRUE  na.strings="?"  dec = "."  sep = ";"  quote = "\"`

.. and some others

after opening the file `credsco.csv` and inspecting it, we decide the following settings:

```
In [2]: Credit <- read.csv("credsco.csv", header = TRUE, quote = "\"", dec = ".", check.names=TR
```

the dimensions of the data set are

```
In [3]: dim(Credit)
```

1. 4455 2. 14

which means 4,455 examples described by 14 variables

Basic questions:

- Which is the target variable? where is it? how many different values? is it a classification problem or a regression problem?
- *answers:* the target variable is located in column 1 and is called 'Assessment'; it has two possible values (therfore it is a classification problem)

What are the other variables?

```
In [4]: names(Credit)
```

1. 'Assessment' 2. 'YearsInJob' 3. 'Housing' 4. 'Deadline' 5. 'Age' 6. 'MaritalStatus' 7. 'Records' 8. 'TypeOfJob' 9. 'Expenses' 10. 'Income' 11. 'Capital' 12. 'ChargesOnCapital' 13. 'AmountRequested' 14. 'MarketPrice'

You can consult the file "Credsco-traduccions.txt" for translation into Catalan

inspect the first 4 examples

```
In [5]: Credit[1:4,]
```

Assessment	YearsInJob	Housing	Deadline	Age	MaritalStatus	Records	TypeOfJob	Expenses
1	9	1	60	30	2	1	3	73
1	17	1	60	58	3	1	1	48
2	10	2	36	46	2	2	3	90
1	0	1	60	24	1	1	1	63

inspect predictive variables 4, 5, 6 and 7 for the first example

```
In [6]: Credit[1,5:8]
```

Age	MaritalStatus	Records	TypeOfJob
30	2	1	3

1.2 SECTION 2: BASIC INSPECTION OF THE DATASET

Perform a basic inspection of the dataset. Have a look at the minimum and maximum values for each variable; find possible errors and abnormal values (outliers); find possible missing values; decide which variables are continuous and which are categorical; if there are mixed types, we have three options: recode continuous to categorical, recode categorical to continuous or leave them as they are. In the latter case, either the method accepts both kinds of information, or it does not, in which case R will convert the categorical ones to continuous using a dummy code.

```
In [7]: summary(Credit)
```

```
   Assessment      YearsInJob        Housing         Deadline
 Min.   :0.000   Min.   : 0.000   Min.   :0.000   Min.   : 6.00
 1st Qu.:1.000   1st Qu.: 2.000   1st Qu.:2.000   1st Qu.:36.00
 Median :1.000   Median : 5.000   Median :2.000   Median :48.00
 Mean   :1.281   Mean   : 7.987   Mean   :2.657   Mean   :46.44
 3rd Qu.:2.000   3rd Qu.:12.000   3rd Qu.:4.000   3rd Qu.:60.00
 Max.   :2.000   Max.   :48.000   Max.   :6.000   Max.   :72.00
      Age         MaritalStatus      Records         TypeOfJob
 Min.   :18.00   Min.   :0.000   Min.   :1.000   Min.   :0.000
 1st Qu.:28.00   1st Qu.:2.000   1st Qu.:1.000   1st Qu.:1.000
 Median :36.00   Median :2.000   Median :1.000   Median :1.000
 Mean   :37.08   Mean   :1.879   Mean   :1.174   Mean   :1.676
 3rd Qu.:45.00   3rd Qu.:2.000   3rd Qu.:1.000   3rd Qu.:3.000
 Max.   :68.00   Max.   :5.000   Max.   :2.000   Max.   :4.000
    Expenses          Income            Capital         ChargesOnCapital
```

```
 Min.   : 35.00   Min.   :       0   Min.   :       0   Min.   :       0
 1st Qu.: 35.00   1st Qu.:      80   1st Qu.:       0   1st Qu.:       0
 Median : 51.00   Median :     120   Median :    3500   Median :       0
 Mean   : 55.57   Mean   :  763317   Mean   : 1060341   Mean   :  404382
 3rd Qu.: 72.00   3rd Qu.:     166   3rd Qu.:    6000   3rd Qu.:       0
 Max.   :180.00   Max.   :99999999   Max.   :99999999   Max.   :99999999
 AmountRequested  MarketPrice
 Min.   : 100    Min.   :  105
 1st Qu.: 700    1st Qu.: 1118
 Median :1000    Median : 1400
 Mean   :1039    Mean   : 1463
 3rd Qu.:1300    3rd Qu.: 1692
 Max.   :5000    Max.   :11140
```

Assessment,Housing,MaritalStatus,Records,TypeOfJob are categorical and need to be treated properly

In particular, Assessment is the target variable; we need to identify correct values

Capital, ChargesOnCapital and Income present abnormally high maximums (99999999)

There are also suspicious zeros, in both types of variables, which we identify with missing values

1.3 SECTION 3: DEALING WITH MISSING VALUES

Sometimes we need to take a decision on a sensible treatment for the missing values and apply it; it is wise to write down the possible consequences of this decision and the alternatives that could be considered in case the final results are not satisfactory

the easiest way is of course to eliminate the involved rows or columns; this can be done partially. For example, we could decide to eliminate the variables with the highest proportion of missing values.

Deleting instances and/or variables containing missing values results in loss of relevant data and is also frustrating because of the effort in collecting the sacrificed information.

CAREFUL! R does not know magically which entries are missing values: they have to be explicitly declared as NA's

therefore this code is not useful:

```
In [8]: ?na.omit

        Credit.complete <- na.omit(Credit)
        dim(Credit.complete)
```

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the previous code does nothing! (but it seems it does)

In the present case we have decided to perform a step-by-step treatment, separate for the categorical and continuous information

We first decide to remove those rows with with missing values in the categorical variables (there are few)

```
In [9]: table(Credit[,1]==0)
        table(Credit[,3]==0)
        table(Credit[,6]==0)
        table(Credit[,8]==0)

        Credit <- Credit[Credit[,1] != 0 & Credit[,3] != 0 & Credit[,6] != 0 & Credit[,8] != 0,]

        dim(Credit)
```

```
FALSE  TRUE
 4454     1
```

```
FALSE  TRUE
 4449     6
```

```
FALSE  TRUE
 4454     1
```

```
FALSE  TRUE
 4453     2
```

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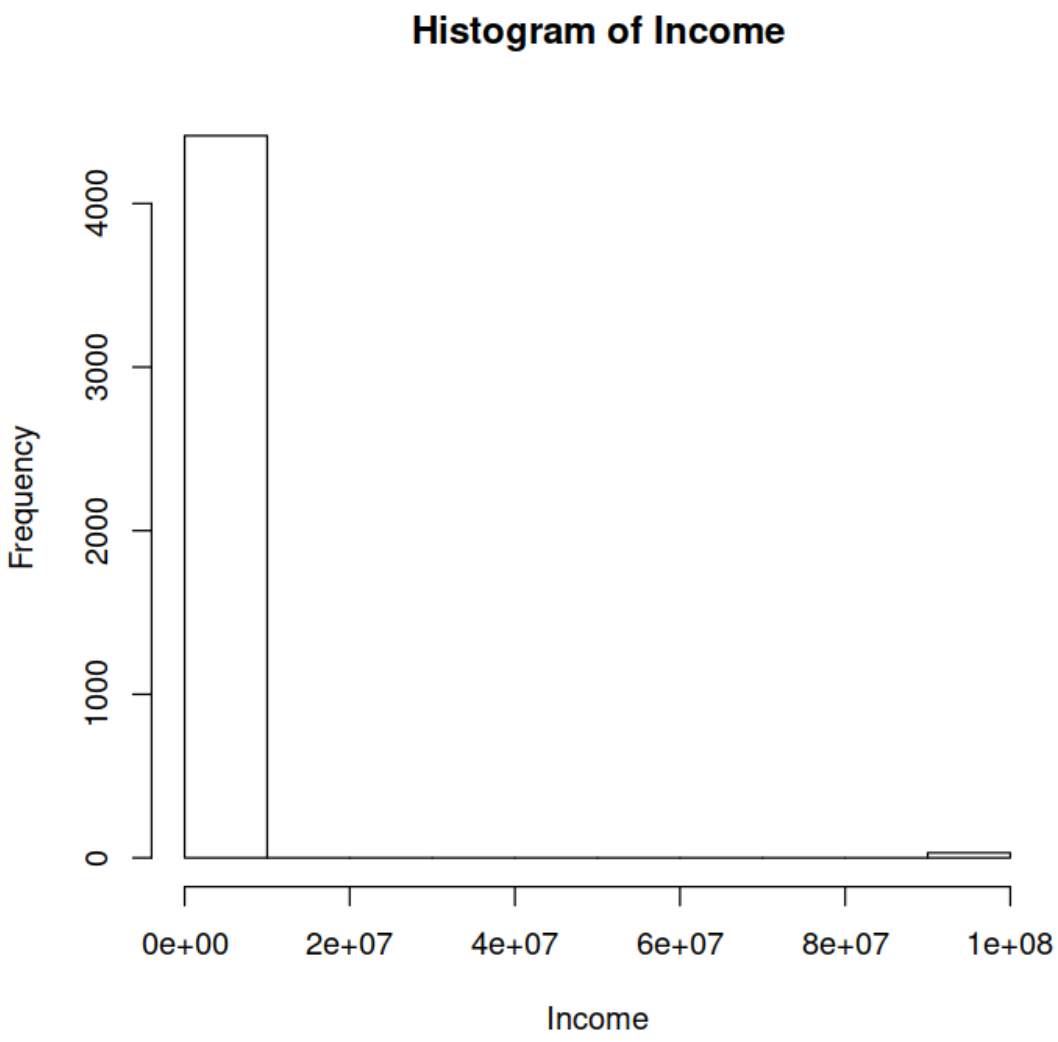
Process rows with missing values in the continuous variables (code 99999999)

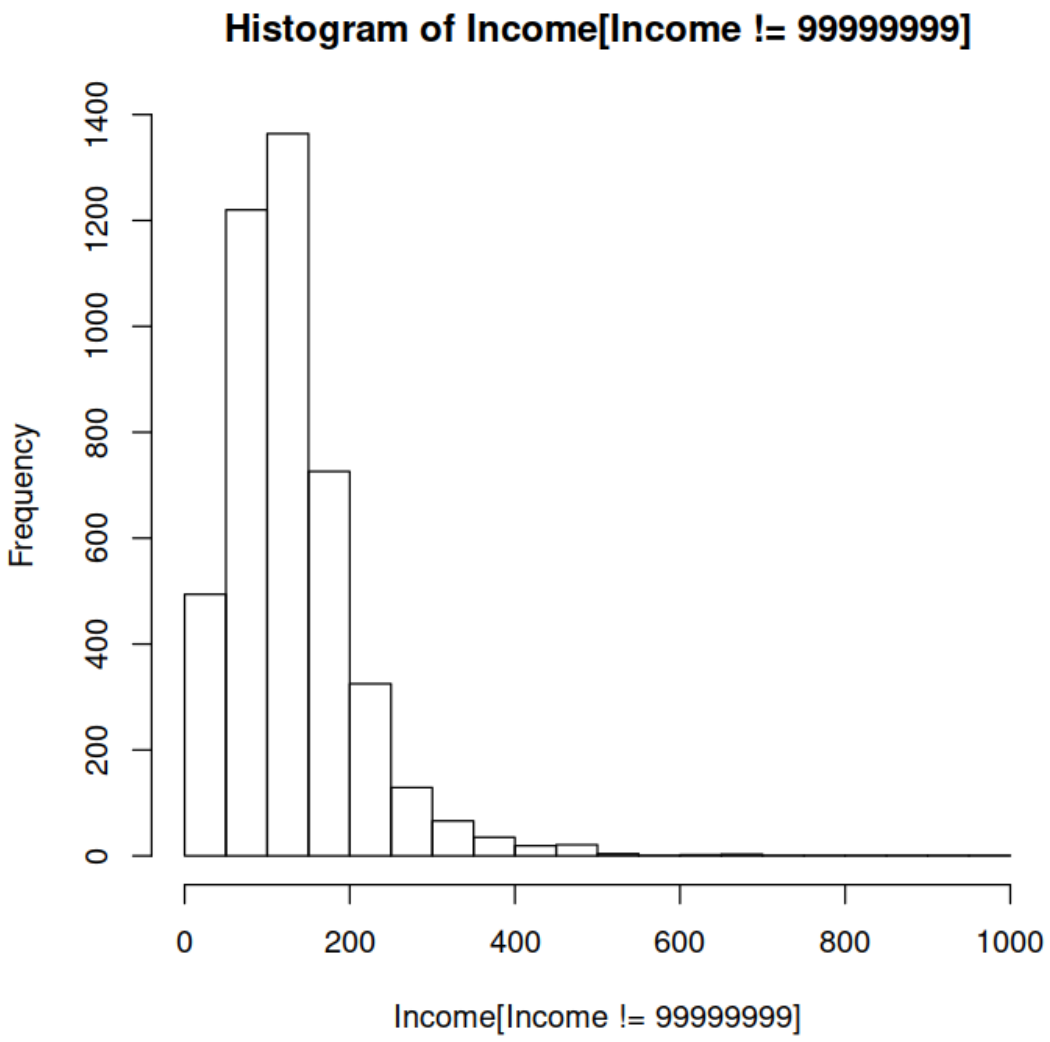
```
In [10]: # this allows the column names of Credit to be visible (use with care)
         attach(Credit)
```

look at that:

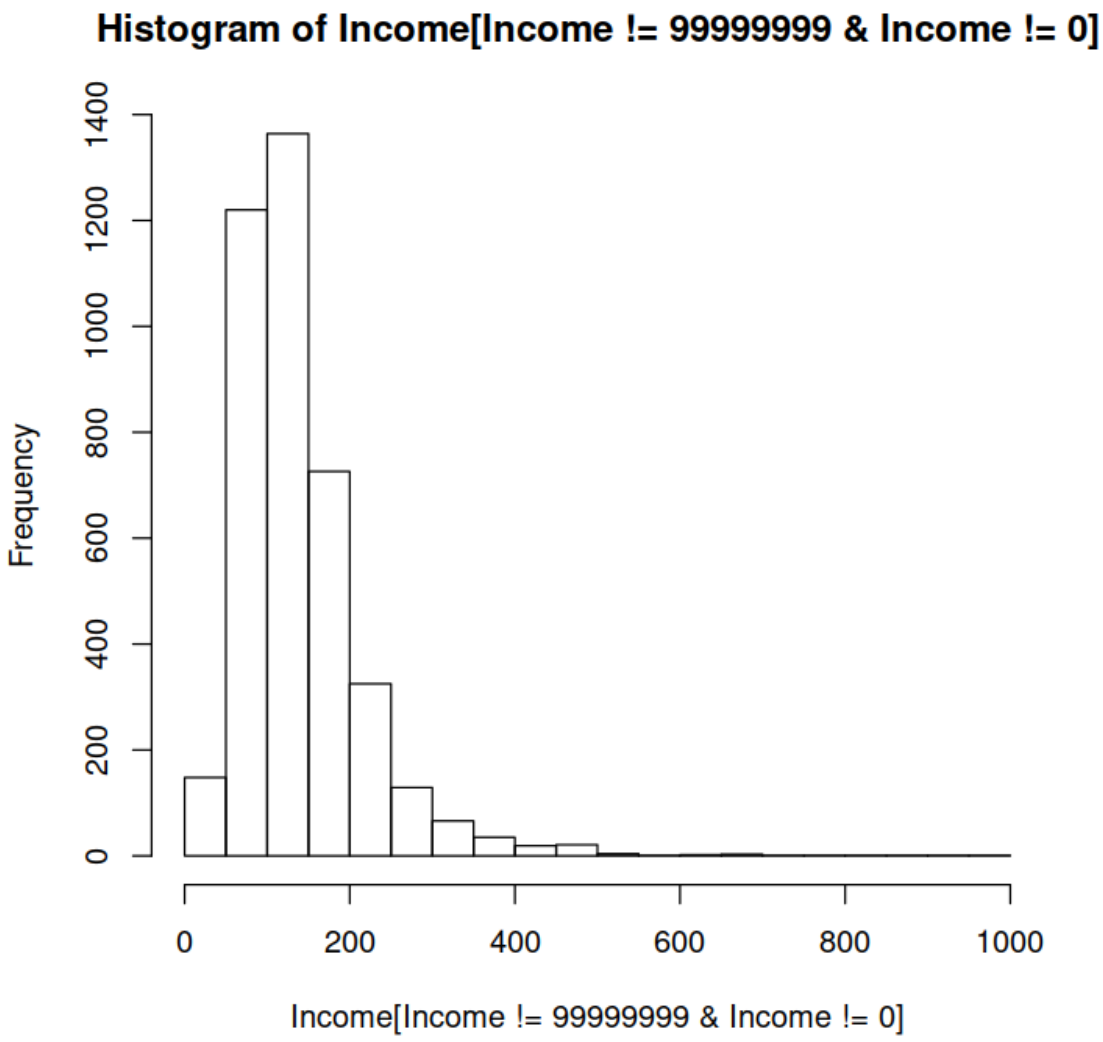
```
In [11]: options(repr.plot.width=6, repr.plot.height=6)
         hist(Income)
```




```
In [12]: hist(Income[Income != 99999999])
```




```
In [13]: hist(Income[Income != 99999999 & Income != 0], breaks=15)
```



these are then clearly incorrect

```
In [14]: table(Income == 99999999)

         table(Income == 0)

         table(Capital == 99999999)

         table(ChargesOnCapital == 99999999)
```

```
FALSE  TRUE
 4415    31
```

```
FALSE  TRUE
 4100   346
```

```
FALSE  TRUE
 4405    41
```

```
FALSE  TRUE
 4434    12
```

what do we do with this one? let's assume it is correct

```
In [15]: table(YearsInJob == 0)
```

```
FALSE  TRUE
 3914   532
```

Continuous variables have too many missing values, we can not eliminate them just like that: we must devise a treatment for these missing values

first we mark them to 'NA', including those from no 'Income'

```
In [16]: Income[Income == 99999999 | Income == 0] <- NA
         Capital[Capital == 99999999] <- NA
         ChargesOnCapital[ChargesOnCapital == 99999999] <- NA
```

see the difference?

```
In [17]: summary(Credit[,10])
         summary(Income)
```

```
   Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
      0       80      120   697386      166 99999999
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
    6.0    90.0   125.0   141.7   170.0   959.0     377
```

The word 'imputation' refers to assigning a value to every missing value. Here we perform imputation by a method known as 1NN: for every individual with a missing 'Income', we look for the most similar individual (according to the remaining variables) and then copy its 'Income' value

```
In [18]: library(class) # knn
```

Imputation of 'Income'

```
In [19]: aux <- Credit[,-10]
         dim(aux)
         aux1 <- aux[!is.na(Income),]
         dim(aux1)
         aux2 <- aux[is.na(Income),]
         dim(aux2)
```

1. 4446 2. 13
1. 4069 2. 13
1. 377 2. 13
Neither of aux1, aux2 can contain NAs

```
In [20]: knn.inc <- knn(aux1,aux2,Income[!is.na(Income)])
         Income[is.na(Income)] <- as.numeric(as.character(knn.inc))
```

Imputation of 'Capital'

```
In [21]: aux <- Credit[,-11]
         aux1 <- aux[!is.na(Capital),]
         aux2 <- aux[is.na(Capital),]
         knn.cap <- knn(aux1,aux2,Capital[!is.na(Capital)])
         Capital[is.na(Capital)] <- as.numeric(as.character(knn.cap))
```

Imputation of 'ChargesOnCapital'

```
In [22]: aux <- Credit[,-12]
         aux1 <- aux[!is.na(ChargesOnCapital),]
         aux2 <- aux[is.na(ChargesOnCapital),]
         knn.cac <- knn(aux1,aux2, ChargesOnCapital[!is.na(ChargesOnCapital)])
         ChargesOnCapital[is.na(ChargesOnCapital)] <- as.numeric(as.character(knn.cac))

         ChargesOnCapital[Capital==0] <- 0
```

assign back to the dataframe

```
In [23]: Credit[,10] <- Income
         Credit[,11] <- Capital
         Credit[,12] <- ChargesOnCapital
```

inspect again the result, especially the new statistics

```
In [24]: dim(Credit)
         summary(Credit)
```

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```
  Assessment      YearsInJob        Housing        Deadline
 Min.   :1.000   Min.   : 0.000   Min.   :1.00   Min.   : 6.00
 1st Qu.:1.000   1st Qu.: 2.000   1st Qu.:2.00   1st Qu.:36.00
 Median :1.000   Median : 5.000   Median :2.00   Median :48.00
 Mean   :1.281   Mean   : 7.991   Mean   :2.66   Mean   :46.45
 3rd Qu.:2.000   3rd Qu.:12.000   3rd Qu.:4.00   3rd Qu.:60.00
 Max.   :2.000   Max.   :48.000   Max.   :6.00   Max.   :72.00
     Age        MaritalStatus     Records        TypeOfJob        Expenses
 Min.   :18.00   Min.   :1.00   Min.   :1.000   Min.   :1.000   Min.   : 35.0
 1st Qu.:28.00   1st Qu.:2.00   1st Qu.:1.000   1st Qu.:1.000   1st Qu.: 35.0
 Median :36.00   Median :2.00   Median :1.000   Median :1.000   Median : 51.0
 Mean   :37.08   Mean   :1.88   Mean   :1.173   Mean   :1.676   Mean   : 55.6
 3rd Qu.:45.00   3rd Qu.:2.00   3rd Qu.:1.000   3rd Qu.:3.000   3rd Qu.: 72.0
 Max.   :68.00   Max.   :5.00   Max.   :2.000   Max.   :4.000   Max.   :180.0
    Income         Capital       ChargesOnCapital  AmountRequested
 Min.   :  6.0   Min.   :     0   Min.   :    0.0   Min.   : 100
 1st Qu.: 90.0   1st Qu.:     0   1st Qu.:    0.0   1st Qu.: 700
 Median :125.0   Median :  3000   Median :    0.0   Median :1000
 Mean   :142.6   Mean   :  5596   Mean   :  342.3   Mean   :1039
 3rd Qu.:173.0   3rd Qu.:  6000   3rd Qu.:    0.0   3rd Qu.:1300
 Max.   :959.0   Max.   :300000   Max.   :30000.0   Max.   :5000
  MarketPrice
 Min.   :  105
 1st Qu.: 1116
 Median : 1400
 Mean   : 1462
 3rd Qu.: 1692
 Max.   :11140
```

1.4 SECTION 4: TREATMENT OF MIXED DATA TYPES

In this case we have decided to keep the original type and leave the decision for later, depending on the specific analysis

we explicitly declare categorical variables as such (called 'factors' in R)

```
In [25]: Assessment    <- as.factor(Assessment)
         Housing     <- as.factor(Housing)
         MaritalStatus <- as.factor(MaritalStatus)
         Records    <- as.factor(Records)
         TypeOfJob <- as.factor(TypeOfJob)

         levels(Assessment)
         levels(Housing)
         levels(MaritalStatus)
         levels(Records)
         levels(TypeOfJob)
```

1. '1' 2. '2'
1. '1' 2. '2' 3. '3' 4. '4' 5. '5' 6. '6'
1. '1' 2. '2' 3. '3' 4. '4' 5. '5'
1. '1' 2. '2'
1. '1' 2. '2' 3. '3' 4. '4'
not very nice, right? let's recode

```
In [26]: levels(Assessment) <- c("positive","negative")
         levels(Housing) <- c("rent","owner","private","ignore","parents","other")
         levels(MaritalStatus) <- c("single","married","widower","split","divorced")
         levels(Records) <- c("no","yes")
         levels(TypeOfJob) <- c("indefinite","temporal","self-employed","other")
```

WARNING! some R programmers do not like 'attach', look what happens

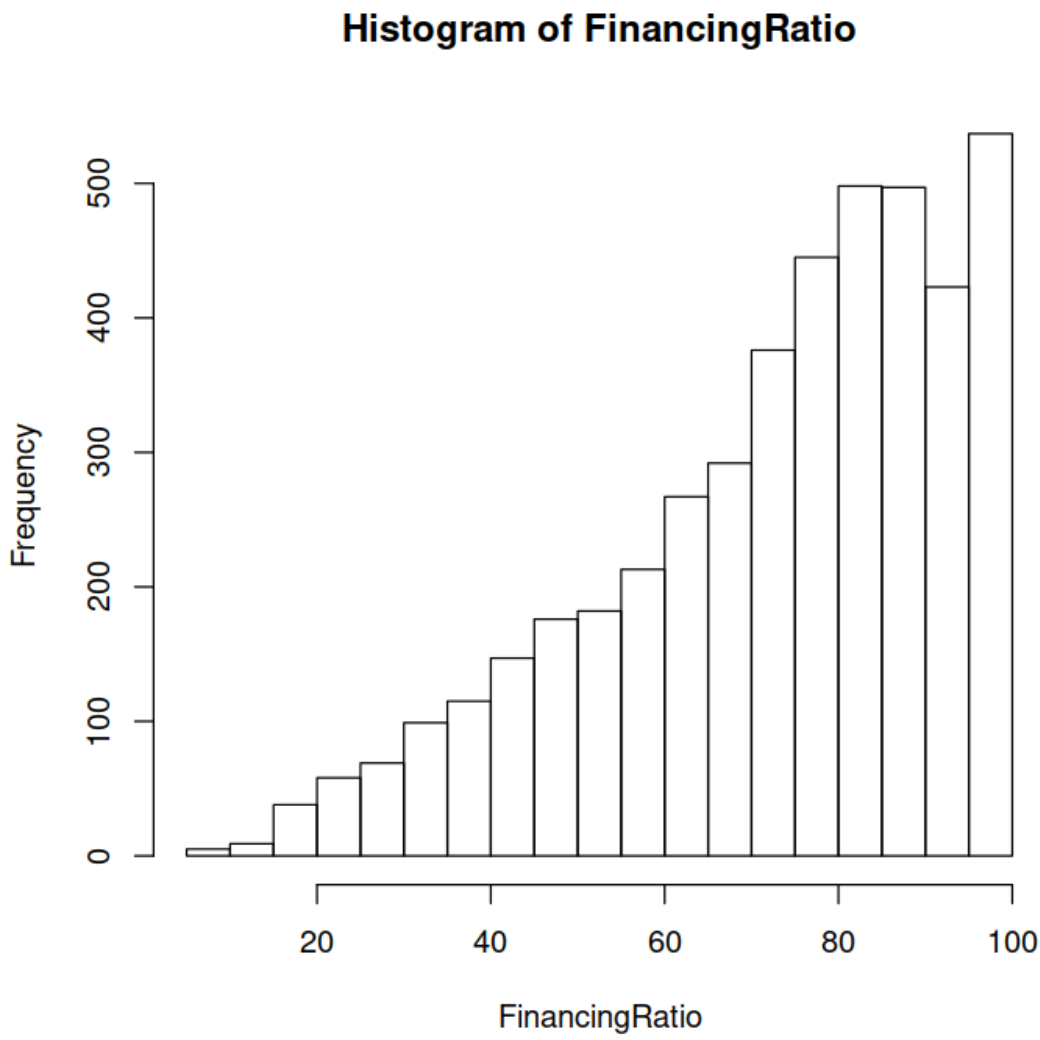
```
In [27]: is.factor(Assessment)
         is.factor(Credit[,1])
```

TRUE
FALSE
(we'll fix this later)

1.5 SECTION 5: DERIVATION OF NEW VARIABLES: FEATURE EXTRACTION

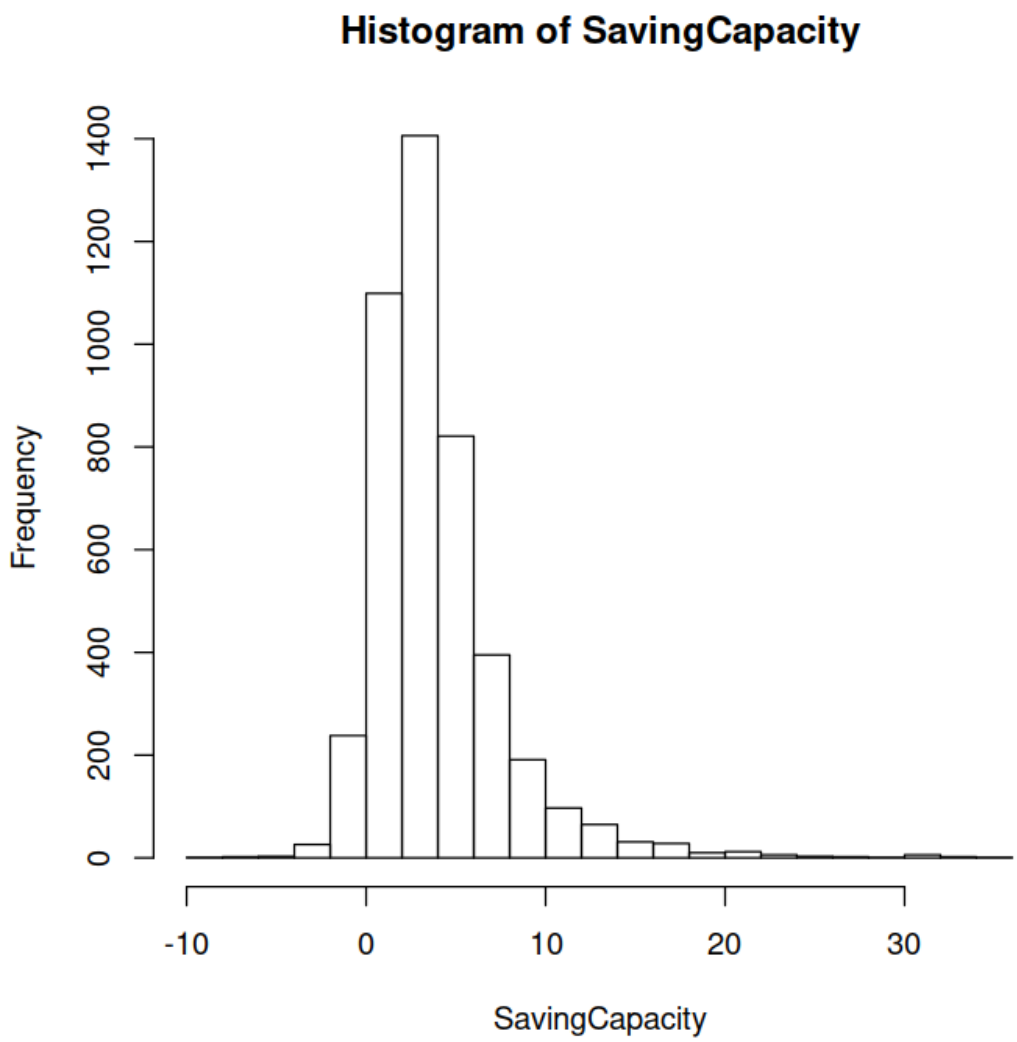
We decide whether it can be sensible to derive new variables; we extract two new continuous and one new categorical variable (for the sake of illustration):
Financing ratio (continuous)

```
In [28]: FinancingRatio <- 100*AmountRequested/MarketPrice

         hist(FinancingRatio)
```



Saving capacity (continuous)

```
In [29]: SavingCapacity <- (Income-Expenses-(ChargesOnCapital/100))/(AmountRequested/Deadline)

         hist(SavingCapacity, breaks=16)
```



Amount Requested greater than the median by people younger than 1.25 times the mean (categorical):

```
In [30]: Dubious <- rep("No", nrow(Credit))
         Dubious[AmountRequested > median(AmountRequested, na.rm = TRUE) & Age < 1.25*mean (Age,
         Dubious <- as.factor(Dubious)

         table(Dubious,Assessment)
```

```
       Assessment
Dubious positive negative
    No      2200      668
    Yes      997      581
```

1.6 SECTION 6: WHAT WE HAVE DONE SO FAR

Create a new dataframe that gathers everything and inspect it again

```
In [31]: Credit.new <- data.frame(Assessment,YearsInJob,Housing,Deadline,Age,
                                  MaritalStatus,Records,TypeOfJob,Expenses,
                                  Income,Capital,ChargesOnCapital,
                                  AmountRequested,MarketPrice,
                                  FinancingRatio,SavingCapacity,Dubious)

         summary(Credit.new)
         dim(Credit.new)
```

```
   Assessment     YearsInJob        Housing        Deadline
 positive:3197   Min.   : 0.000   rent   : 973   Min.   : 6.00
 negative:1249   1st Qu.: 2.000   owner  :2106   1st Qu.:36.00
                 Median : 5.000   private: 246   Median :48.00
                 Mean   : 7.991   ignore :  20   Mean   :46.45
                 3rd Qu.:12.000   parents: 782   3rd Qu.:60.00
                 Max.   :48.000   other  : 319   Max.   :72.00
      Age          MaritalStatus  Records            TypeOfJob
 Min.   :18.00   single  : 973   no :3677   indefinite   :2803
 1st Qu.:28.00   married :3238   yes: 769   temporal     : 451
 Median :36.00   widower :  67              self-employed:1021
 Mean   :37.08   split   : 130              other        : 171
 3rd Qu.:45.00   divorced:  38
 Max.   :68.00
    Expenses         Income         Capital       ChargesOnCapital
 Min.   : 35.0   Min.   :  6.0   Min.   :     0   Min.   :    0.0
 1st Qu.: 35.0   1st Qu.: 90.0   1st Qu.:     0   1st Qu.:    0.0
 Median : 51.0   Median :125.0   Median :  3000   Median :    0.0
 Mean   : 55.6   Mean   :142.6   Mean   :  5596   Mean   :  342.3
 3rd Qu.: 72.0   3rd Qu.:173.0   3rd Qu.:  6000   3rd Qu.:    0.0
 Max.   :180.0   Max.   :959.0   Max.   :300000   Max.   :30000.0
 AmountRequested  MarketPrice    FinancingRatio    SavingCapacity   Dubious
 Min.   : 100    Min.   :  105   Min.   :  6.702   Min.   :-8.160   No :2868
 1st Qu.: 700    1st Qu.: 1116   1st Qu.: 60.030   1st Qu.: 1.672   Yes:1578
 Median :1000    Median : 1400   Median : 77.097   Median : 3.162
 Mean   :1039    Mean   : 1462   Mean   : 72.616   Mean   : 3.944
 3rd Qu.:1300    3rd Qu.: 1692   3rd Qu.: 88.460   3rd Qu.: 5.271
 Max.   :5000    Max.   :11140   Max.   :100.000   Max.   :35.750
```

1. 4446 2. 17

```
In [32]: # this undoes the attach (recommended)
         detach(Credit)
```

```
In [33]: attach(Credit.new)
         is.factor(Credit.new[,1])
```

```
The following objects are masked _by_ .GlobalEnv:

    Assessment, Capital, ChargesOnCapital, Dubious, FinancingRatio,
    Housing, Income, MaritalStatus, Records, SavingCapacity, TypeOfJob
```

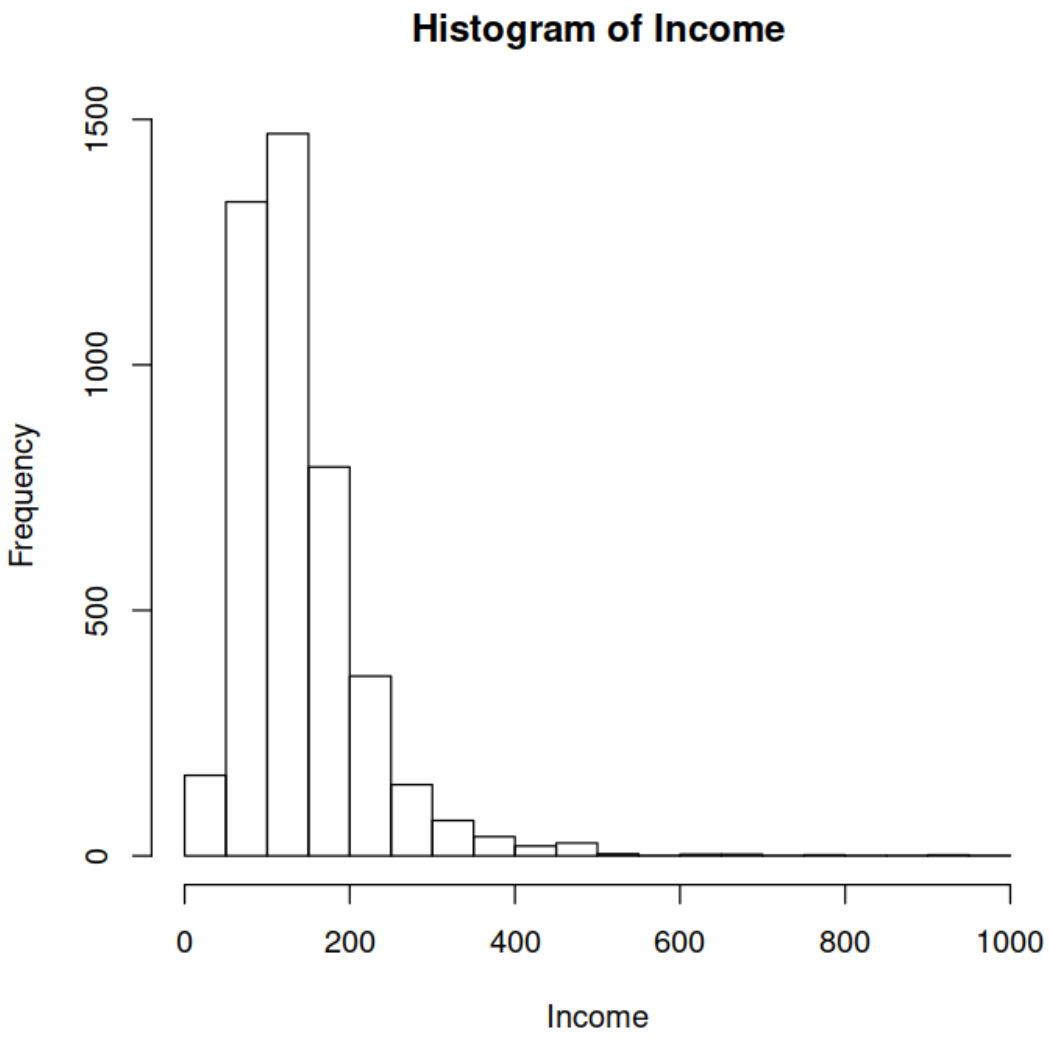
TRUE

1.7 SECTION 7: GAUSSIANITY AND TRANSFORMATIONS

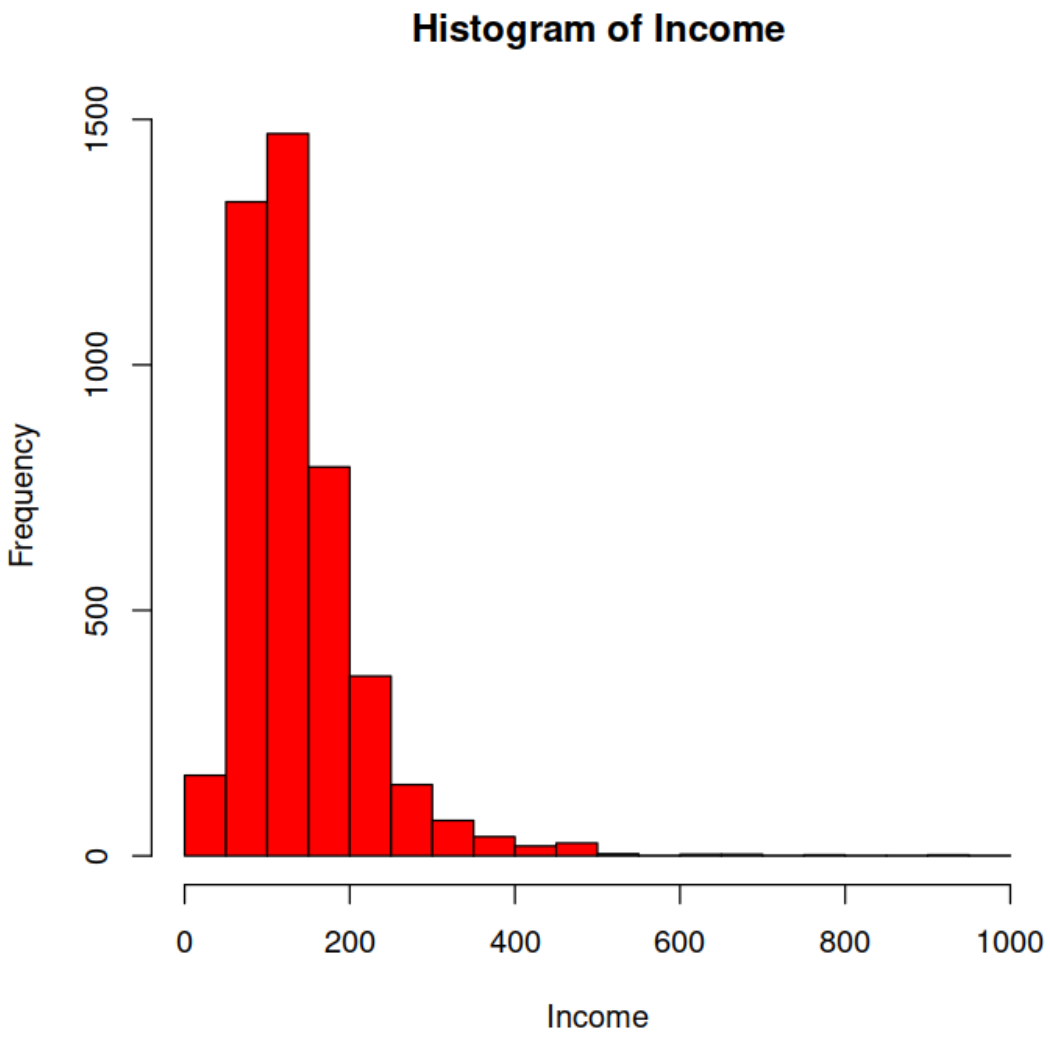
Perform a graphical summary of some of the variables (both categorical and continuous), using the boxplot() and hist() procedures

For continuous data: histograms and boxplots

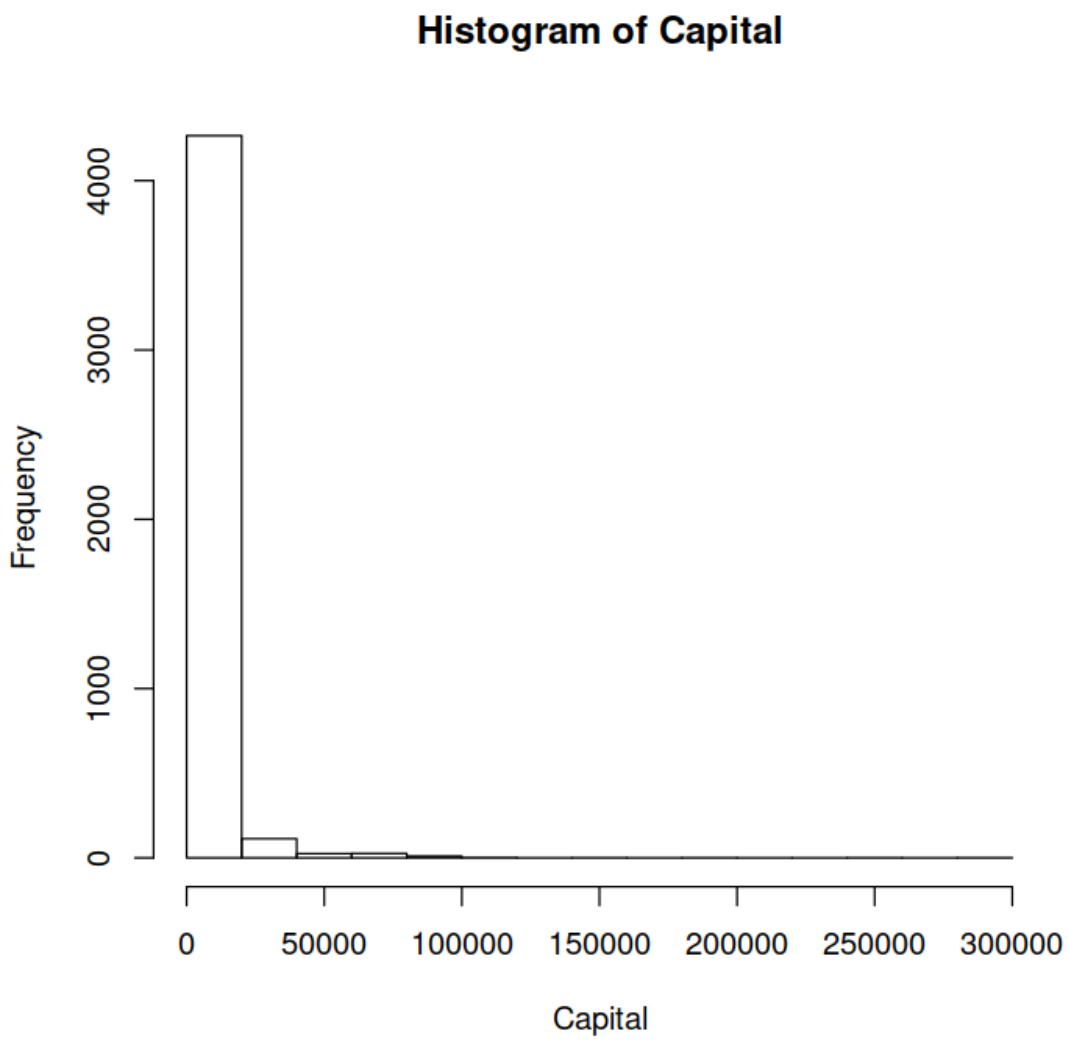
```
In [34]: hist(Income)
```



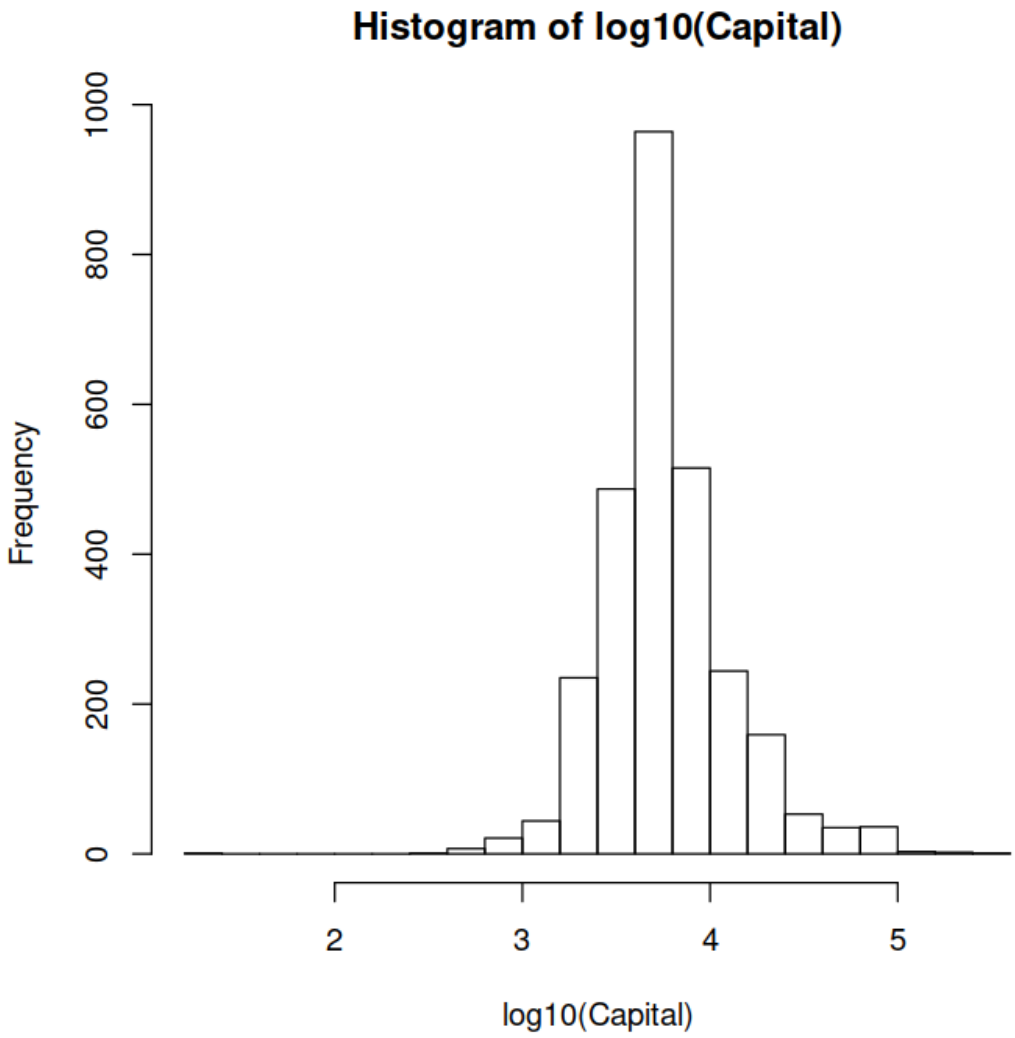

```
In [35]: hist(Income,col=2)
```



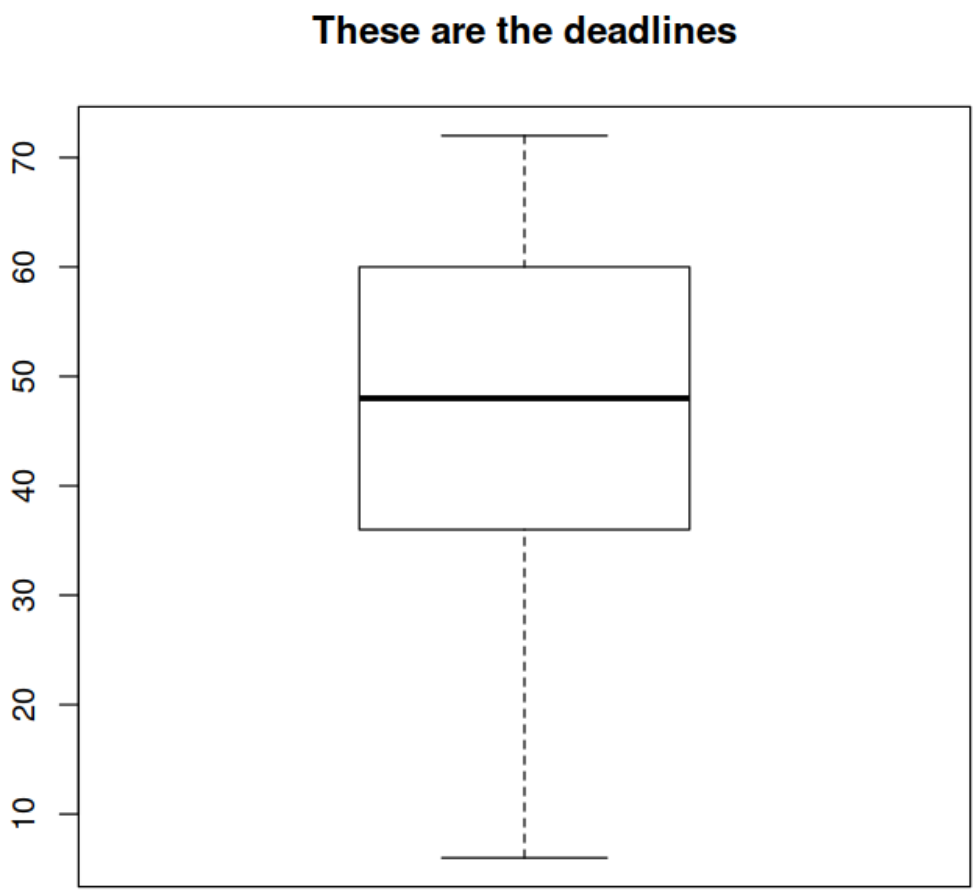

```
In [36]: hist(Capital)
```



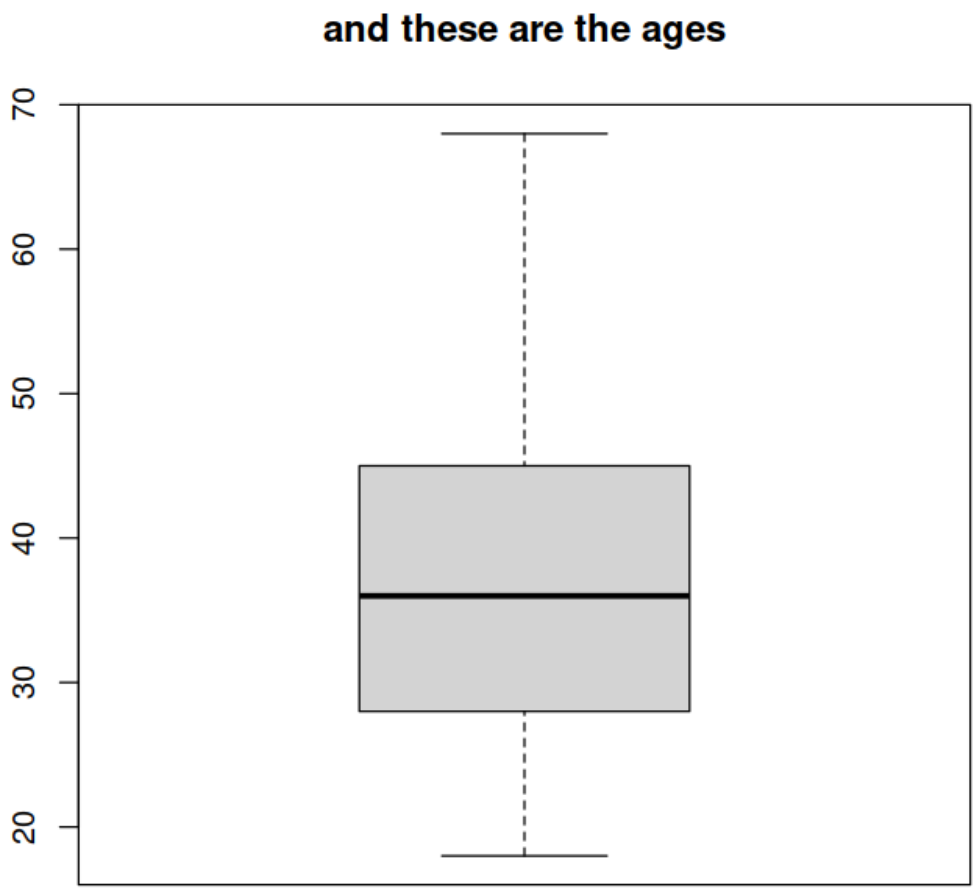

```
In [37]: hist(log10(Capital), breaks=20)
```



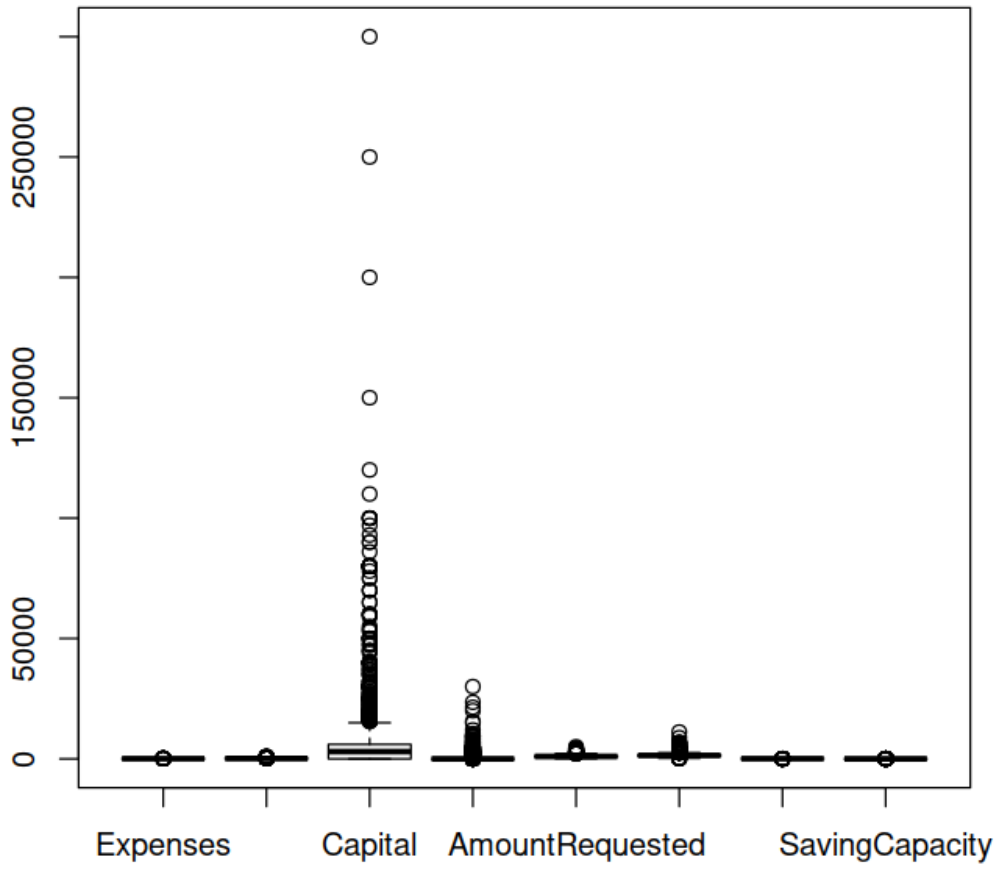

```
In [38]: boxplot (Deadline)
         title ("These are the deadlines")
```



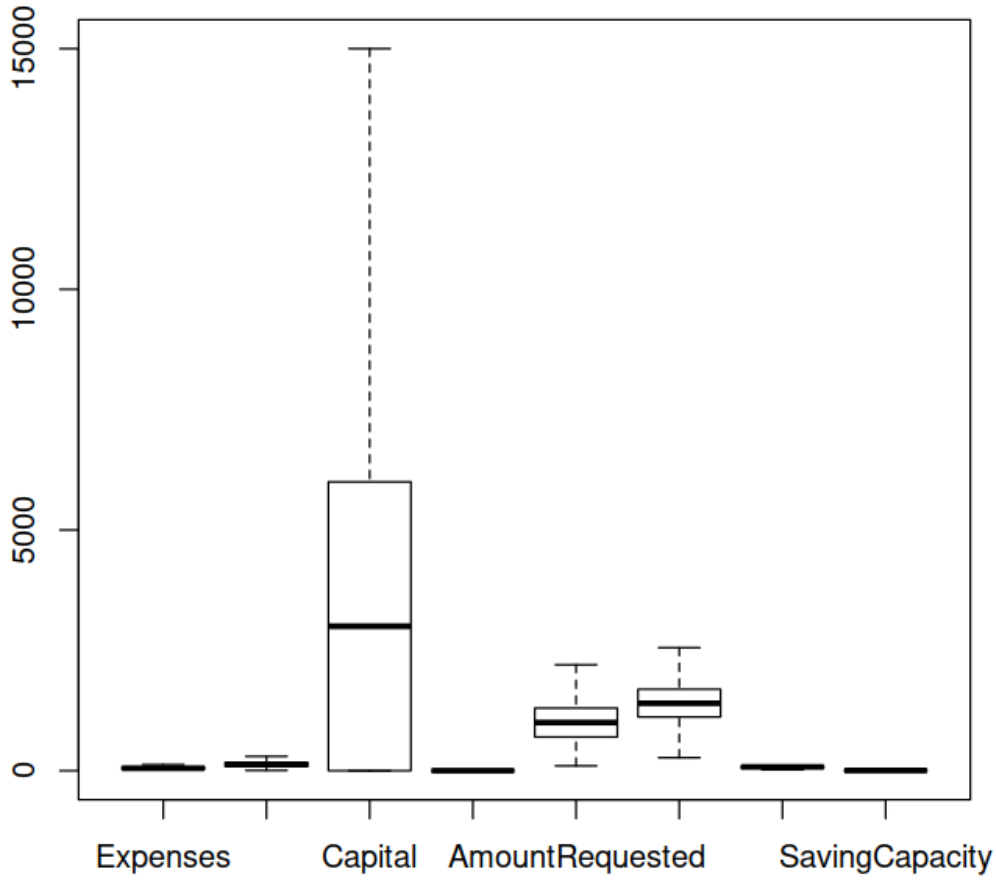

```
In [39]: boxplot (Age, col = "lightgray")
         title ("and these are the ages")
```




```
In [40]: boxplot(Credit.new[,9:16], outline=TRUE)
```




```
In [41]: boxplot(Credit.new[,9:16], outline=FALSE) # much better, but would be nicer one by one
```



the previous plots suggest to take logs on some variables: Capital and ChargesOnCapital (we'll do it later)

For categorical data: Frequency tables, Contingency tables, Bar charts, Pie charts

should we treat Age as categorical? probably not

```
In [42]: table(Age)
```

```
Age
 18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34  35  36  37
  8  28  49  82 112 127 152 141 163 153 178 131 156 153 159 141 155 120 145 142
 38  39  40  41  42  43  44  45  46  47  48  49  50  51  52  53  54  55  56  57
135 126 139 114 112  93  78  88  95  89  60  90  81  83  82  70  58  65  48  31
 58  59  60  61  62  63  64  65  66  68
 40  34  34  27  20  22  14  12   9   2
```

```
In [43]: min(Age)
         max(Age)
```

18
68

```
In [44]: # WARNING! we are generating NAs
         Age.cat <- cut(Age, breaks = seq(30, 90, 10))
         Age.cat[1:20]
```

1. <NA> 2. (50,60] 3. (40,50] 4. <NA> 5. <NA> 6. (30,40] 7. (40,50] 8. <NA> 9. (30,40] 10. (40,50] 11. (30,40] 12. <NA> 13. <NA> 14. (30,40] 15. <NA> 16. (60,70] 17. (50,60] 18. (60,70] 19. (30,40] 20. (30,40]

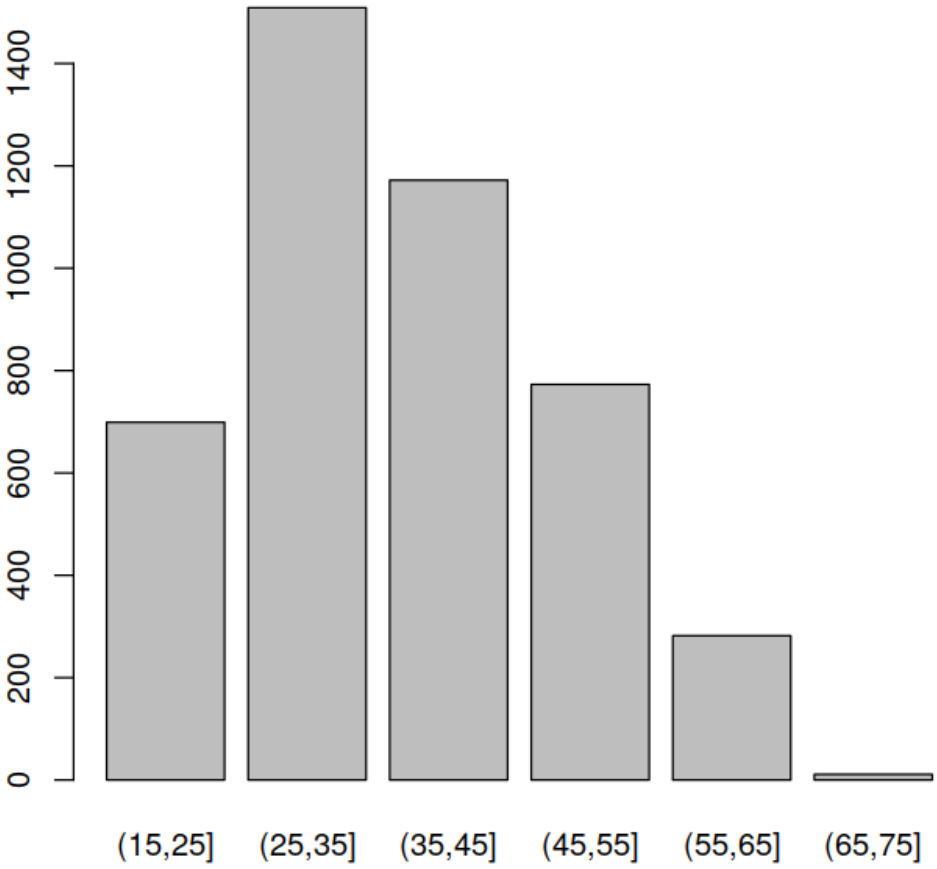
Levels: 1. '(30,40]' 2. '(40,50]' 3. '(50,60]' 4. '(60,70]' 5. '(70,80]' 6. '(80,90]'

```
In [45]: Age.cat <- cut(Age, breaks = seq(15, 75, 10))
```

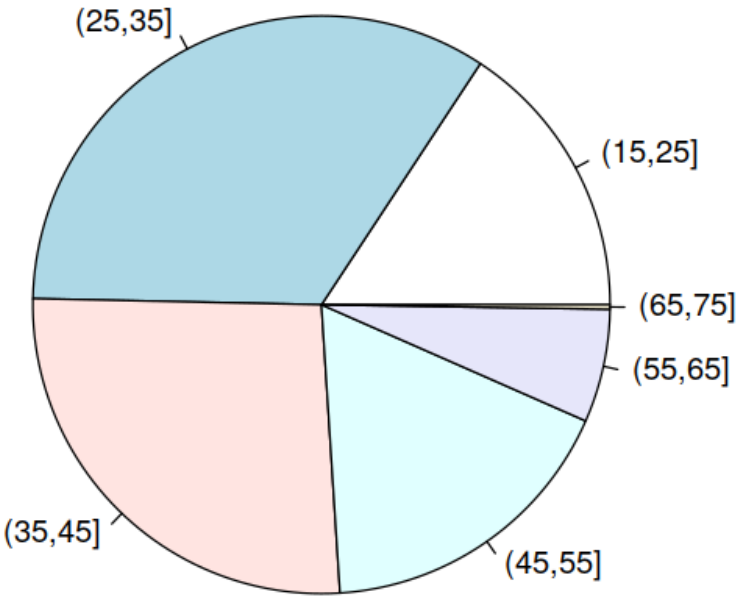
```
In [46]: Age.tab <- table(Age.cat)
         Age.tab
```

```
Age.cat
(15,25] (25,35] (35,45] (45,55] (55,65] (65,75]
    699    1509    1172     773     282      11
```

```
In [47]: barplot(Age.tab) # bar chart
```




```
In [48]: pie(Age.tab) # pie chart
```



incidentally, this is how we could generate another new variable based on Age:

```
In [49]: Age2.cat <- factor(as.integer(Age < 55))
         levels(Age2.cat) <- c("over55","under55")

In [50]: # contingency table
         TypeOfJob.Age <- table(TypeOfJob, Age.cat)
         TypeOfJob.Age

                Age.cat
TypeOfJob        (15,25] (25,35] (35,45] (45,55] (55,65] (65,75]
  indefinite         408    1054     742     463     132       4
  temporal           183     155      81      30       2       0
  self-employed       91     272     319     250      87       2
```

```
  other              17      28      30      30      61       5
```

```
In [51]: margin.table(TypeOfJob.Age, 1) # row sums
         margin.table(TypeOfJob.Age, 2) # column sums
```

```
TypeOfJob
   indefinite      temporal self-employed         other
         2803           451          1021           171


Age.cat
(15,25] (25,35] (35,45] (45,55] (55,65] (65,75]
    699    1509    1172     773     282      11
```

```
In [52]: prop.table(TypeOfJob.Age) # relative frequencies
```

```
               Age.cat
TypeOfJob            (15,25]      (25,35]      (35,45]      (45,55]
  indefinite    0.0917678812 0.2370670265 0.1668915879 0.1041385515
  temporal      0.0411605938 0.0348627980 0.0182186235 0.0067476383
  self-employed 0.0204678363 0.0611785875 0.0717498875 0.0562303194
  other         0.0038236617 0.0062977958 0.0067476383 0.0067476383
               Age.cat
TypeOfJob            (55,65]      (65,75]
  indefinite    0.0296896086 0.0008996851
  temporal      0.0004498426 0.0000000000
  self-employed 0.0195681511 0.0004498426
  other         0.0137201979 0.0011246064
```

```
In [53]: round(prop.table(TypeOfJob.Age), digits=3) # idem, rounded to 3 digits
```

```
               Age.cat
TypeOfJob       (15,25] (25,35] (35,45] (45,55] (55,65] (65,75]
  indefinite      0.092   0.237   0.167   0.104   0.030   0.001
  temporal        0.041   0.035   0.018   0.007   0.000   0.000
  self-employed   0.020   0.061   0.072   0.056   0.020   0.000
  other           0.004   0.006   0.007   0.007   0.014   0.001
```

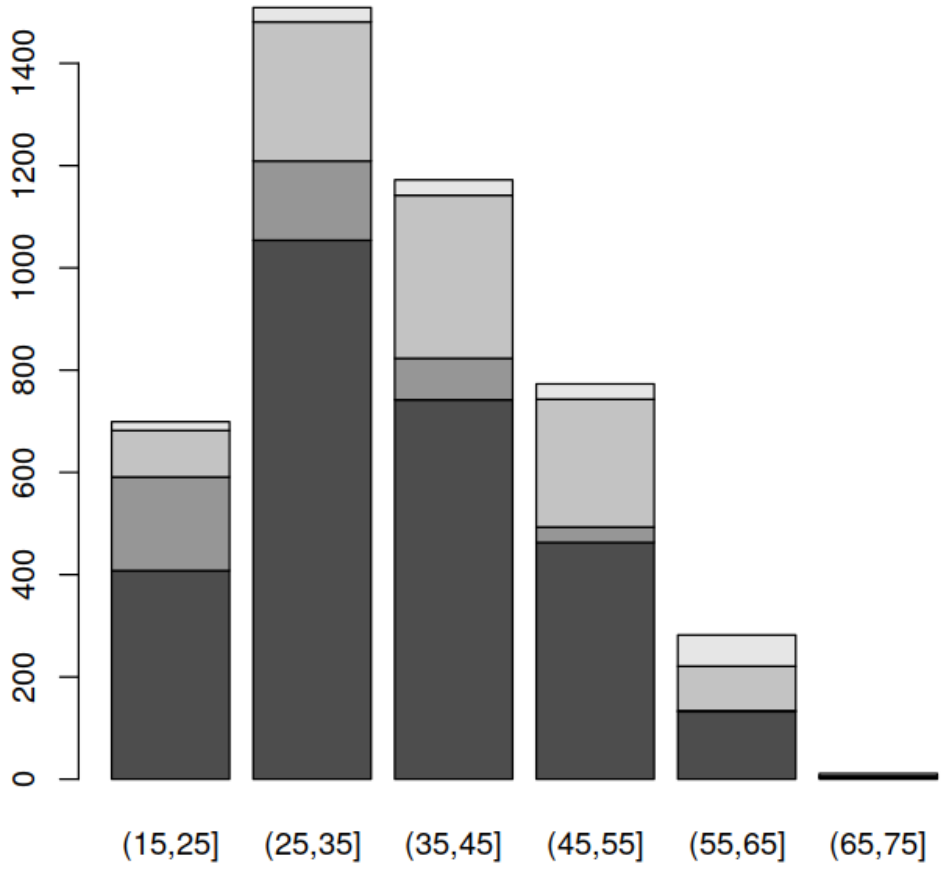
```
In [54]: round(prop.table(TypeOfJob.Age) * 100, digits=3) # total percentages
```

```
               Age.cat
TypeOfJob       (15,25] (25,35] (35,45] (45,55] (55,65] (65,75]
  indefinite      9.177  23.707  16.689  10.414   2.969   0.090
  temporal        4.116   3.486   1.822   0.675   0.045   0.000
  self-employed   2.047   6.118   7.175   5.623   1.957   0.045
  other           0.382   0.630   0.675   0.675   1.372   0.112
```

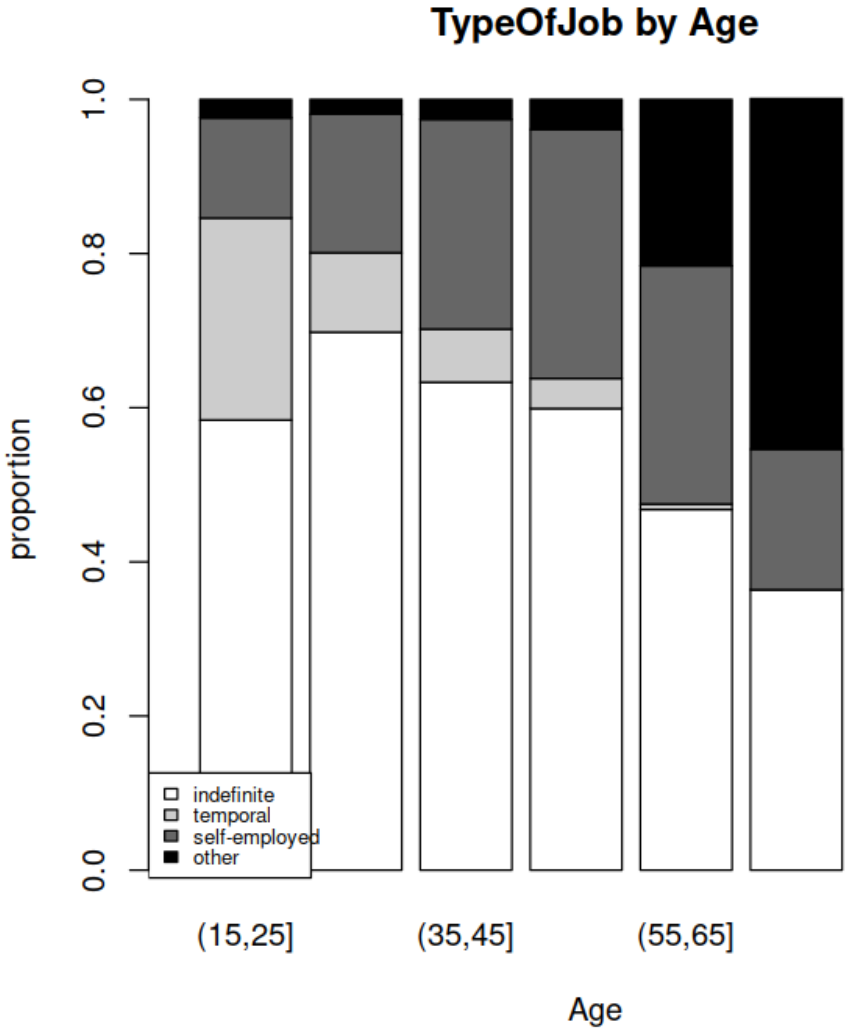
```
In [55]: # table of relative frequencies (row-wise)
         round(prop.table(TypeOfJob.Age, 1), digits=3)
         # table of relative frequencies (column-wise)
         TypeOfJob.Age.rel <- round(prop.table(TypeOfJob.Age, 2), digits=3)
```

```
               Age.cat
TypeOfJob       (15,25] (25,35] (35,45] (45,55] (55,65] (65,75]
  indefinite      0.146   0.376   0.265   0.165   0.047   0.001
  temporal        0.406   0.344   0.180   0.067   0.004   0.000
  self-employed   0.089   0.266   0.312   0.245   0.085   0.002
  other           0.099   0.164   0.175   0.175   0.357   0.029
```

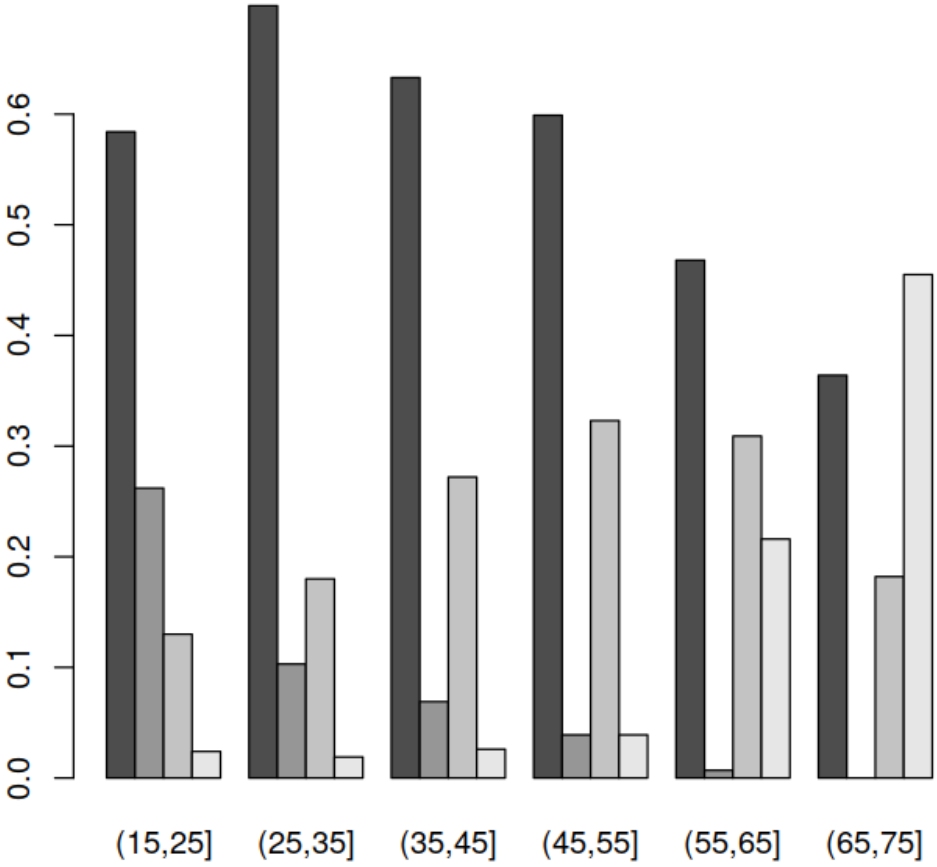
```
In [56]: barplot(TypeOfJob.Age) # basic stacked bar chart
```



```
In [57]: barplot(TypeOfJob.Age.rel, yaxt="n", xlab="Age", ylab="proportion",
                 col = c("white", "grey80", "grey40", "black"),
                 main = "TypeOfJob by Age", xlim=c(0,9)) # stacked bar chart

         legend("bottomleft", legend=rownames(TypeOfJob.Age.rel), col="black",
               fill = c("white", "grey80", "grey40", "black"), cex=0.65)

         axis(2, at=seq(0, 1, 0.2))
```

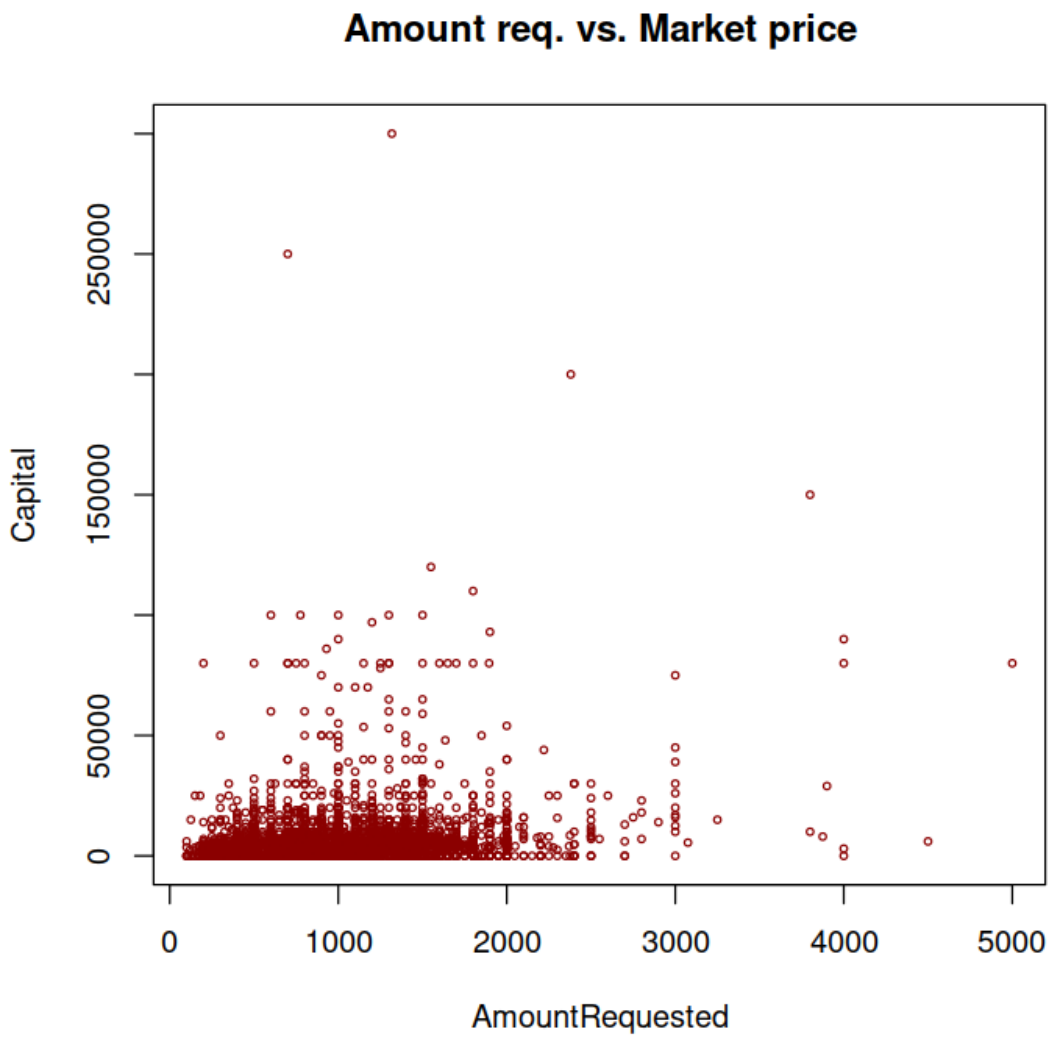



```
In [58]: barplot(TypeOfJob.Age.rel, beside = TRUE) # grouped bar chart
```

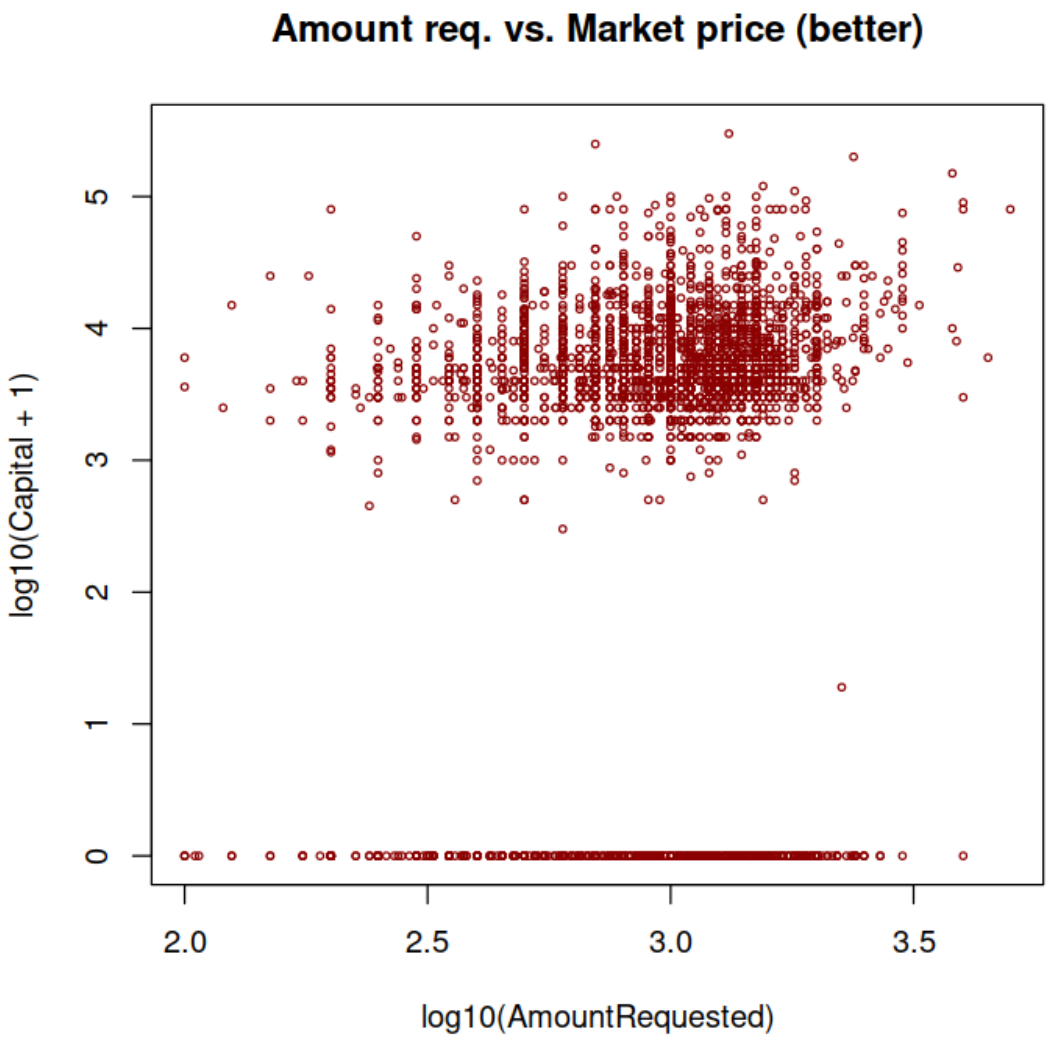


we can perform graphical comparisons between some pairs of variables (both categorical and continuous), using the plot(), pairs() and identify() procedures

```
In [59]: plot (AmountRequested, Capital, main = "Amount req. vs. Market price",
                cex = .5, col = "dark red")
```

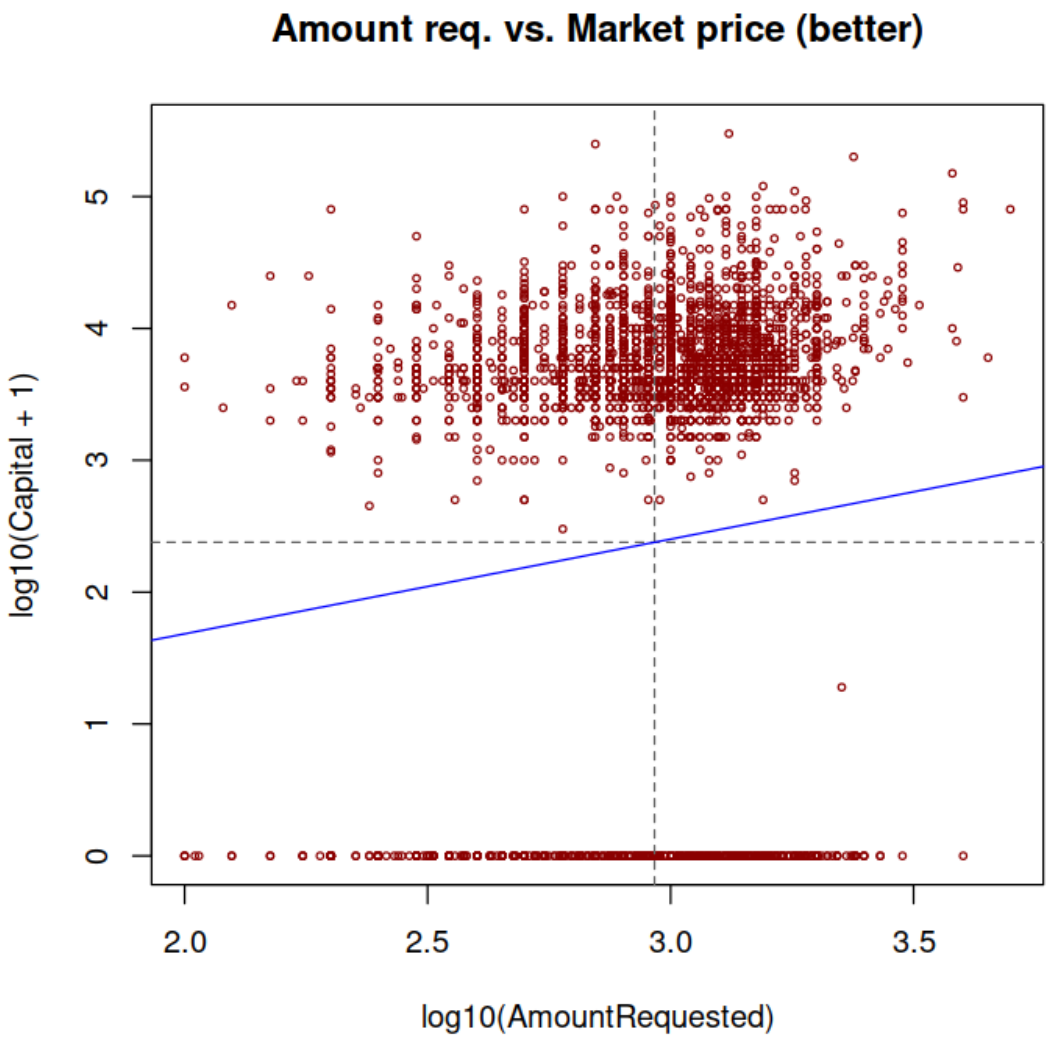



```
In [60]: plot (log10(AmountRequested), log10(Capital+1),
                main = "Amount req. vs. Market price (better)", cex = .5, col = "dark red")
```



adding a center (dashed) and a regression line (blue)

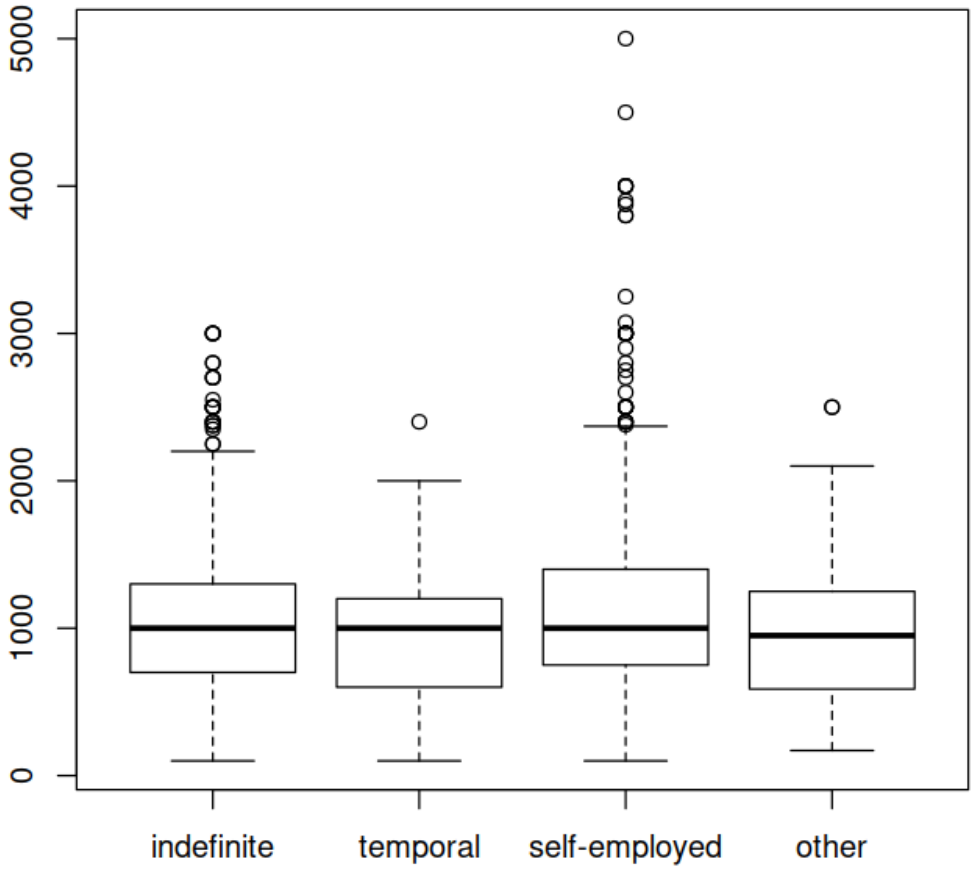
```
In [61]: plot (log10(AmountRequested), log10(Capital+1),
               main = "Amount req. vs. Market price (better)", cex = .5, col = "dark red")
         abline(v = mean(log10(AmountRequested)), lty = 2, col = "grey40")
         abline(h = mean(log10(Capital+1)), lty = 2, col = "grey40")
         abline(lm(log10(Capital+1) ~ log10(AmountRequested)), col = "blue")
```



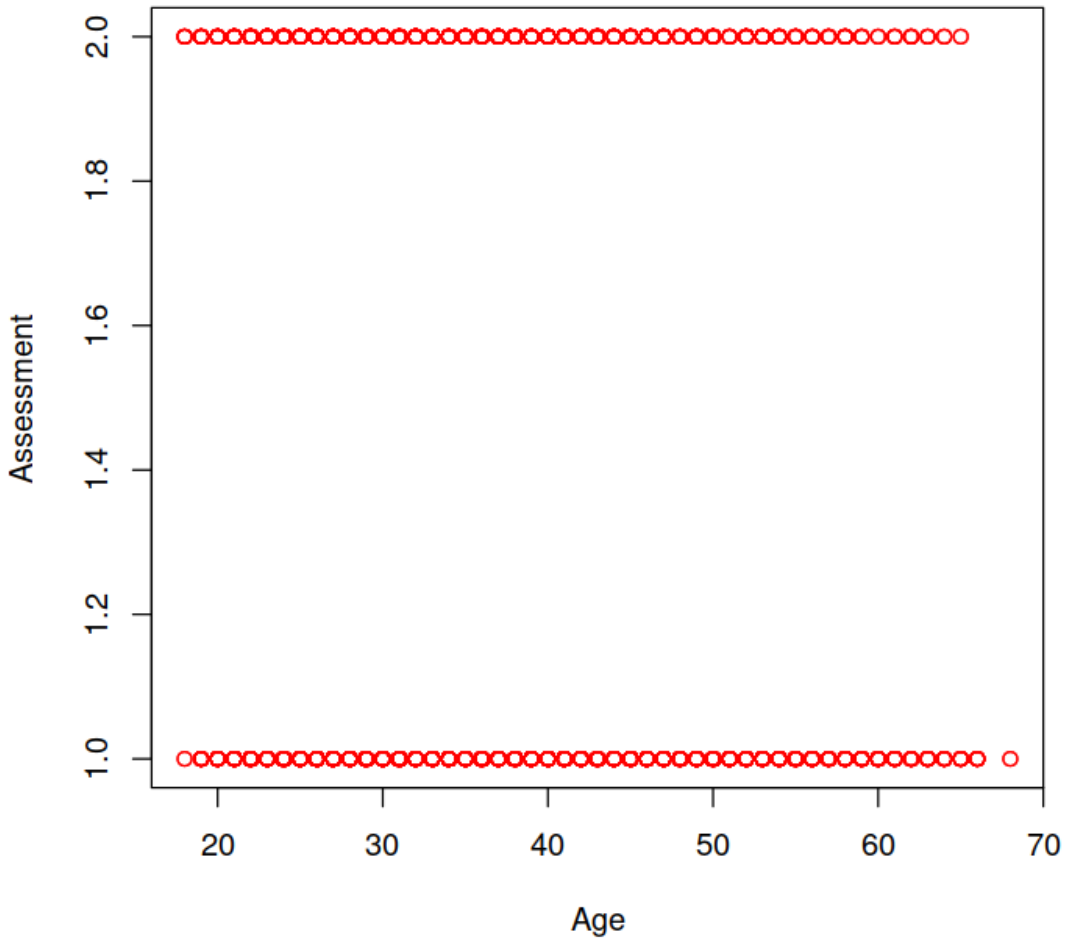
(note that log10(x+1)=0 for x=0, so our transformation keeps the zeros)

On the other hand, these same zeros spoil the regression: perhaps it would be more sensible to do the regression without them

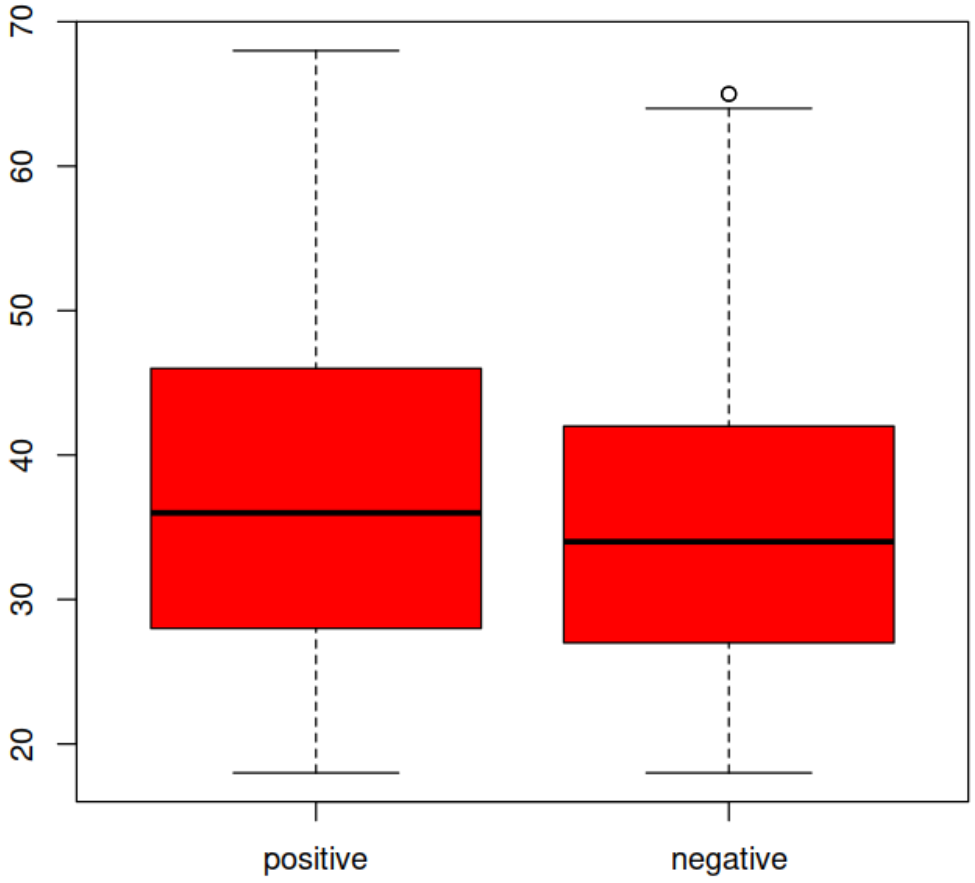
```
In [62]: par(mfrow=c(1,1))

         plot (TypeOfJob, AmountRequested)
```



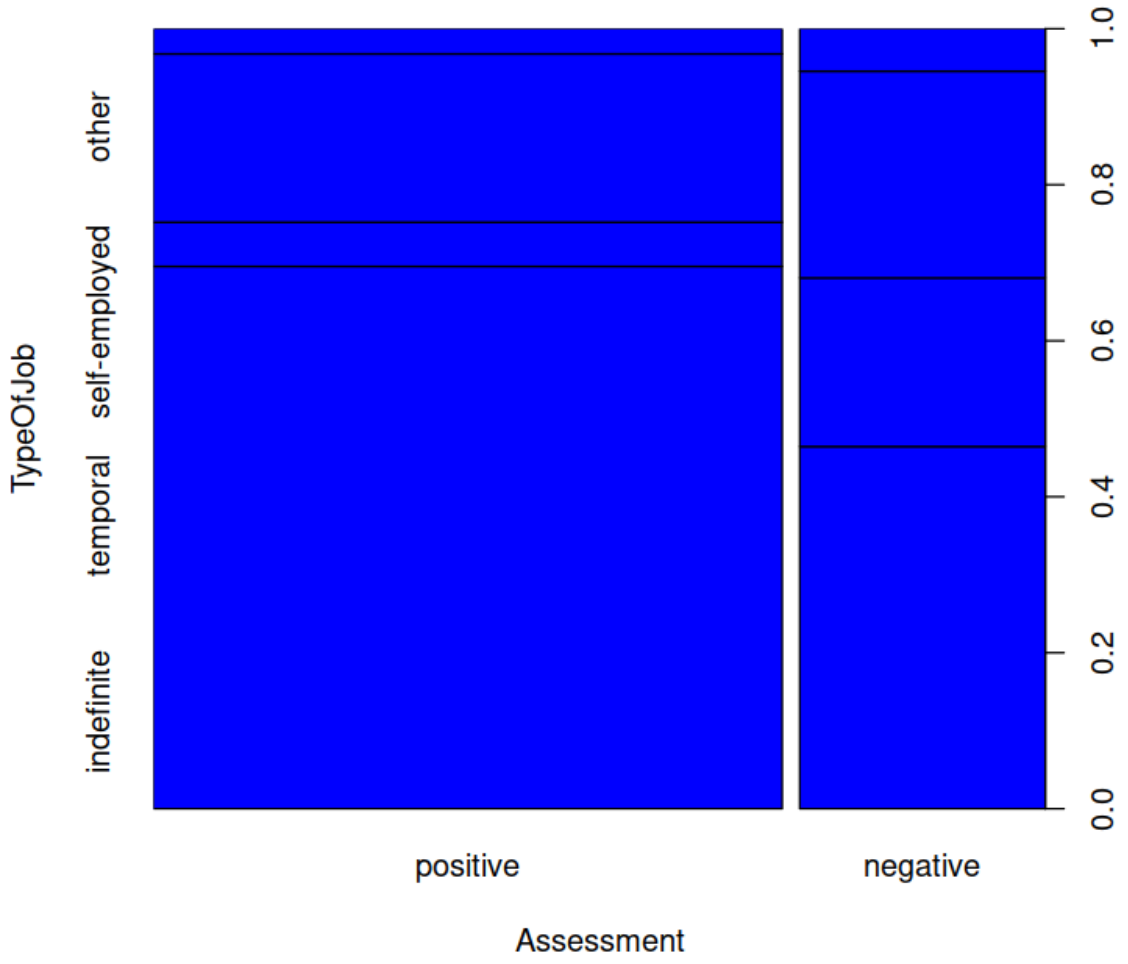

```
In [63]: plot (Age,Assessment, col="red") # WARNING!
```



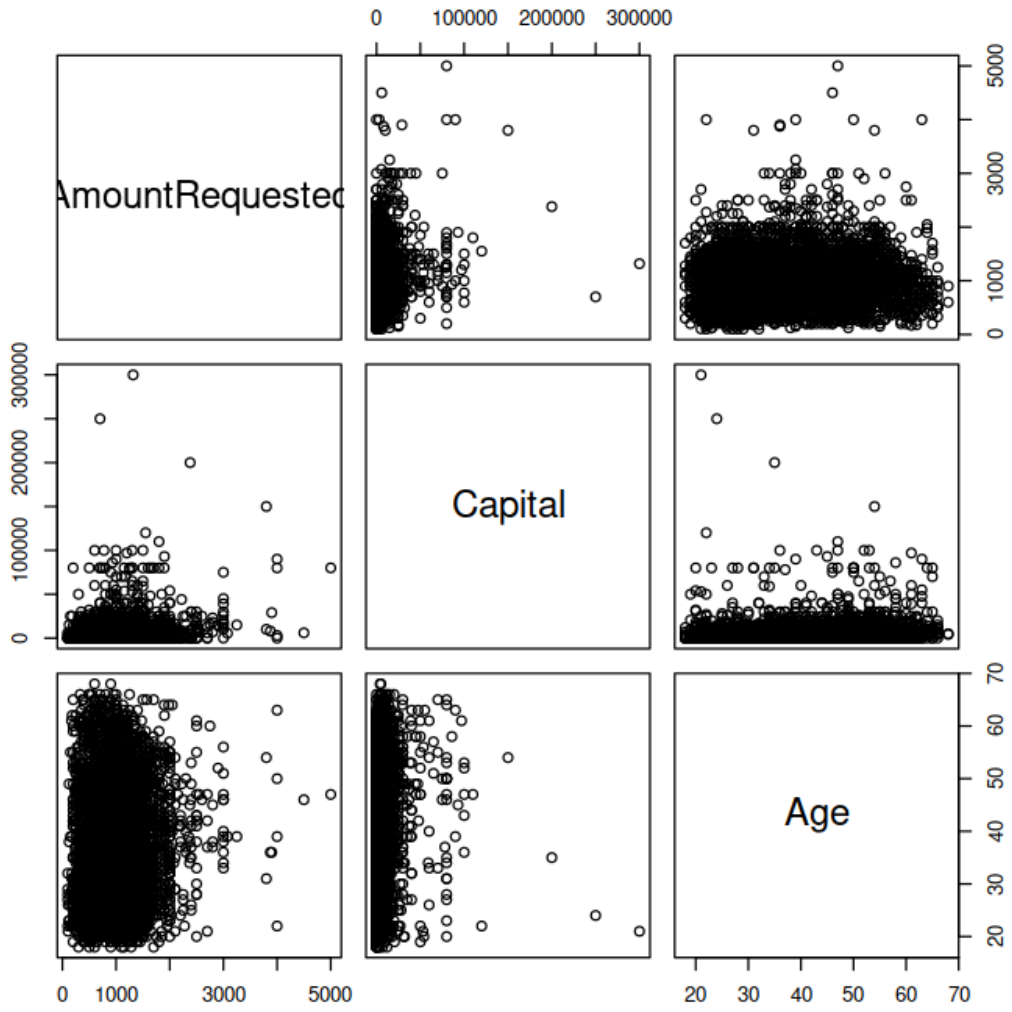

```
In [64]: plot (Assessment, Age, col="red") # better
```




```
In [65]: plot (Assessment, TypeOfJob,col="blue", xlab="Assessment",ylab="TypeOfJob")
```

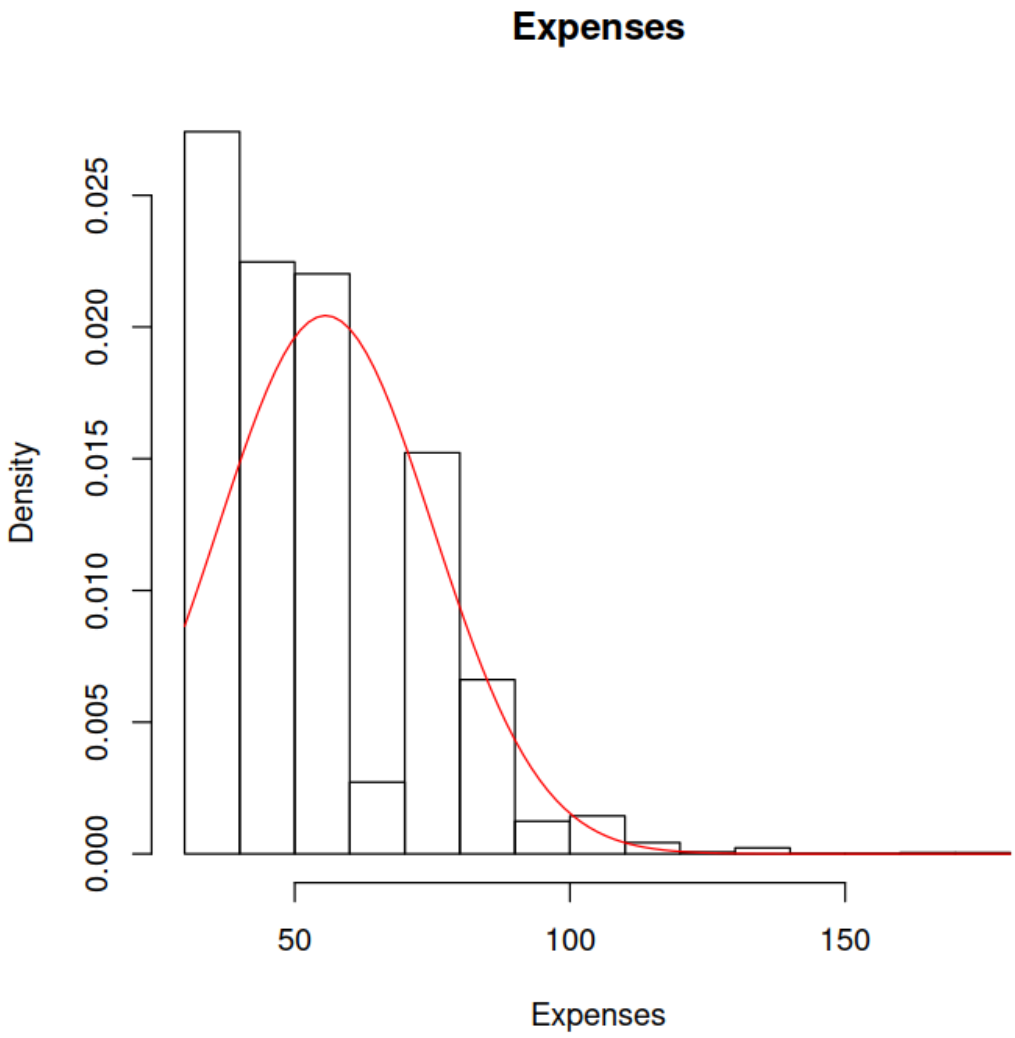



```
In [66]: pairs(~ AmountRequested + Capital + Age)
```

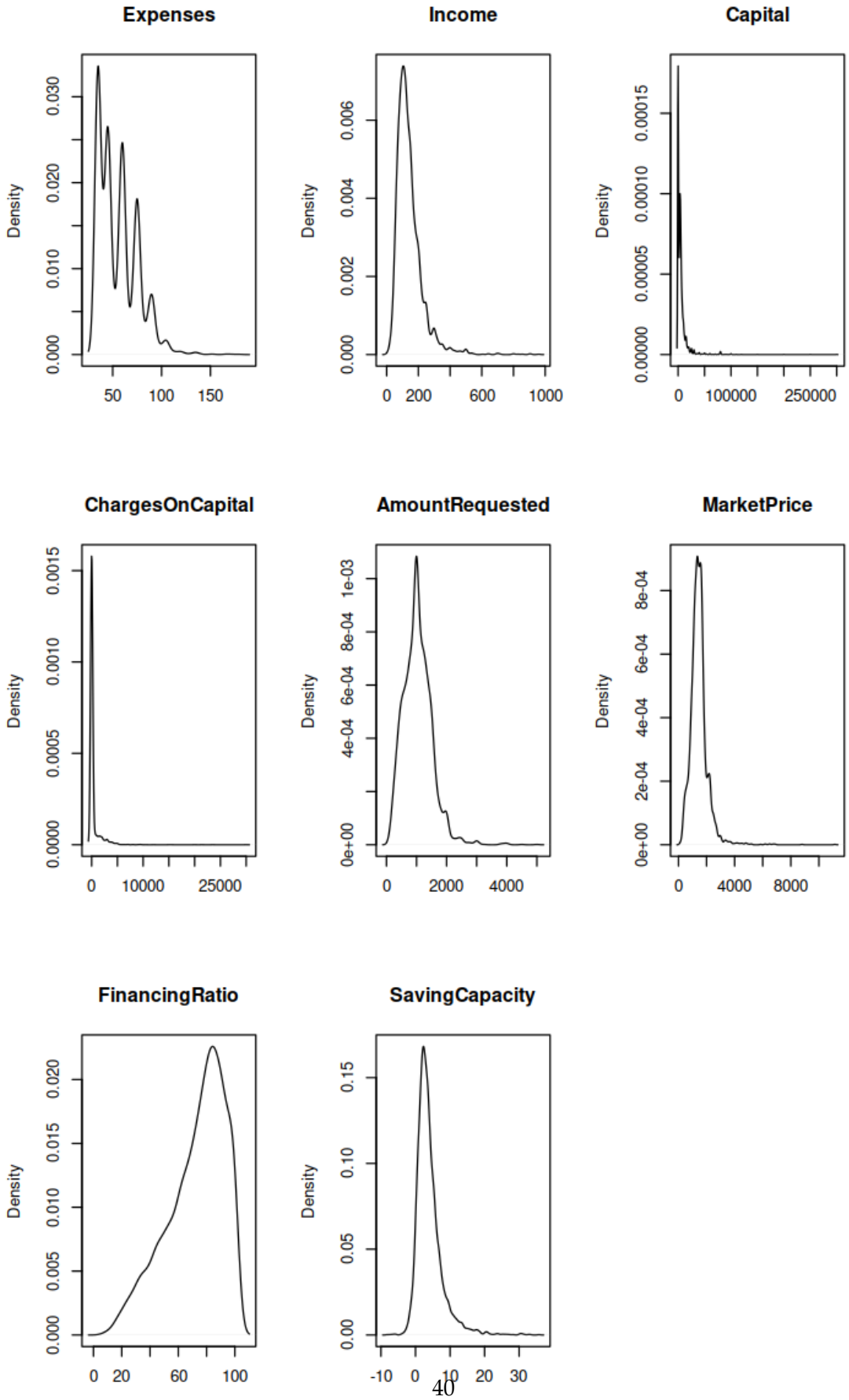


Plotting a variable against the normal pdf in red

```
In [67]: hist.with.normal <- function (x, main, xlabel=deparse(substitute(x)), ...)
         {
           h <- hist(x,plot=F, ...)
           s <- sd(x)
           m <- mean(x)
           ylim <- range(0,h$density,dnorm(0,sd=s))
           hist(x,freq=FALSE,ylim=ylim,xlab=xlabel, main=main, ...)
           curve(dnorm(x,m,s),add=T,col="red")
         }

         hist.with.normal (Expenses, "Expenses")
```



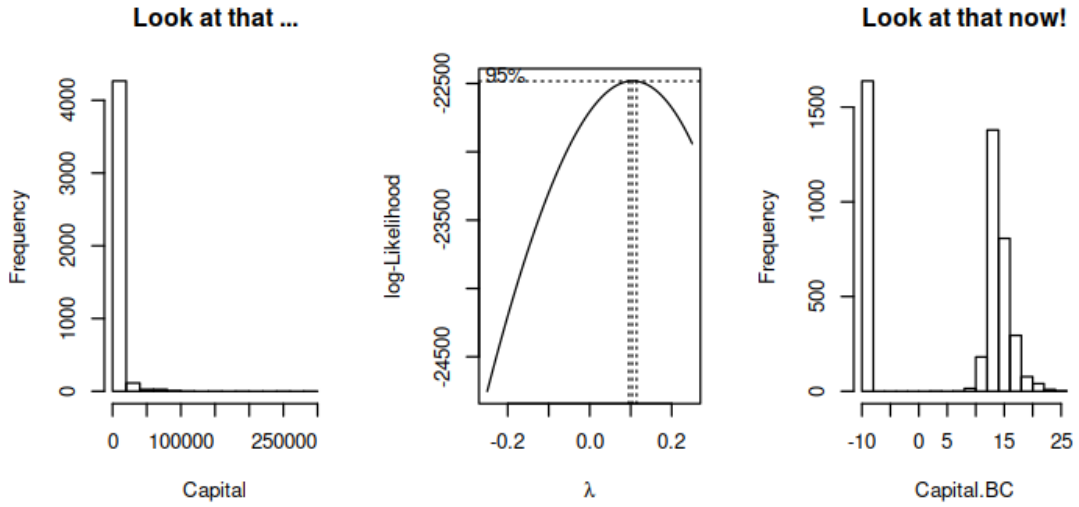

```
In [68]: options(repr.plot.width=6, repr.plot.height=10)
         par(mfrow=c(3,3))
         for (i in 0:7)
           { plot(density(Credit.new[,i+9]), xlab="",
                  main=names(Credit.new)[i+9])
           }
```


Expenses
Density
0.000
0.010
0.020
0.030
50
100
150
Income
Density
0.000
0.002
0.004
0.006
0
200
600
1000
Capital
Density
0.00000
0.00005
0.00010
0.00015
0
100000
250000
ChargesOnCapital
Density
0.0000
0.0005
0.0010
0.0015
0
10000
25000
AmountRequested
Density
0e+00
4e-04
6e-04
8e-04
1e-03
0
2000
4000
MarketPrice
Density
0e+00
2e-04
4e-04
6e-04
8e-04
0
4000
8000
FinancingRatio
Density
0.000
0.005
0.010
0.015
0.020
0
20
60
100
SavingCapacity
Density
0.00
0.05
0.10
0.15
-10
0
10
20
30

do any of the continuous variables "look" Gaussian? features to look for in comparing to a Gaussian: outliers, asymmetries, long tails

A useful tool for "Gaussianization" is the Box-Cox power transformation

```
In [69]: options(repr.plot.width=6, repr.plot.height=3)
         library(MASS)

         par(mfrow=c(1,3))

         hist(Capital, main="Look at that ...")

         bx <- boxcox(I(Capital+1) ~ . - Assessment, data = Credit.new,
                      lambda = seq(-0.25, 0.25, length = 10))

         lambda <- bx$x[which.max(bx$y)]

         Capital.BC <- (Capital^lambda - 1)/lambda

         hist(Capital.BC, main="Look at that now!")

         par (mfrow=c(1,1))
```



1.8 SECTION 8: ENDING THE PREPROCESSING

Shuffle the data (to avoid possible ordering biases)

```
In [70]: set.seed (104)
         Credit.new <- Credit.new[sample.int(nrow(Credit.new)),]
```

Save the preprocessed data into a file for future use

WARNING! This creates a .Rdata file (binary and gzip compressed) This is very convenient, but the file cannot be opened with a text editor If you want a text file, set 'ascii'=TRUE

```
In [71]: save(Credit.new, file = "Credsco-processed.Rdata")
```

remove (almost) everything in the working environment

```
In [72]: rm(list = ls())

         load("Credsco-processed.Rdata")
         objects()
```

'Credit.new'