APA-L0-python

September 7, 2018

1 APA Laboratori 0 - Data preprocessing

```
In [1]: # Uncomment to upgrade packages
        # !pip install pandas --upgrade
        # !pip install numpy --upgrade
        # !pip install scipy --upgrade
        # !pip install statsmodels --upgrade
        %load_ext autoreload
```

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

```
In [2]: #%matplotlib notebook
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sn
        import pandas as pd
        from IPython.core.interactiveshell import InteractiveShell
        InteractiveShell.ast_node_interactivity = "all"
        pd.set_option('precision', 3)
```

```
In [3]: # extra imports
        from pandas import read_csv
        from sklearn.neighbors import KNeighborsClassifier
        from statsmodels.genmod.generalized_linear_model import GLM
        from pandas.plotting import scatter_matrix
        from scipy.stats import boxcox
```

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 pandas.read_csv and play with useful control parameters.
after opening the file `credsco.csv` and inspecting it, we decide the following settings:

```
In [4]: Credit = read_csv("credsco.csv", header=0, delimiter=',')
        Credit.shape
```

```
Out[4]: (4455, 14)
```

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 [5]: Credit.columns
```

```
Out[5]: Index(['Assessment', 'YearsInJob', 'Housing', 'Deadline', 'Age',
               'MaritalStatus', 'Records', 'TypeOfJob', 'Expenses', 'Income',
               'Capital', 'ChargesOnCapital', 'AmountRequested', 'MarketPrice'],
              dtype='object')
```

You can consult the file "Credsco-traduccions.txt" for translation into Catalan
inspect the first 4 examples

```
In [6]: Credit[:4]
```

```
Out[6]:    Assessment  YearsInJob  Housing  Deadline  Age  MaritalStatus  Records  \
        0           1           9        1        60   30              2        1
        1           1          17        1        60   58              3        1
        2           2          10        2        36   46              2        2
        3           1           0        1        60   24              1        1

           TypeOfJob  Expenses  Income  Capital  ChargesOnCapital  AmountRequested  \
        0          3        73     129        0                 0              800
        1          1        48     131        0                 0             1000
        2          3        90     200     3000                 0             2000
        3          1        63     182     2500                 0              900

           MarketPrice
        0          846
        1         1658
        2         2985
        3         1325
```

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

```
In [7]: Credit.iloc[0,4:8]
```

```
Out[7]: Age              30
        MaritalStatus     2
        Records           1
        TypeOfJob         3
        Name: 0, dtype: int64
```

Alternatively you can use the variable names

```
In [8]: Credit.loc[0,'Age':'TypeOfJob']
```

```
Out[8]: Age              30
        MaritalStatus     2
        Records           1
        TypeOfJob         3
        Name: 0, dtype: int64
```

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 python will convert the categorical ones to continuous using a dummy code.

```
In [9]: Credit.describe()
```

```
Out[9]:        Assessment  YearsInJob   Housing  Deadline       Age  MaritalStatus  \
        count    4455.000    4455.000  4455.000  4455.000  4455.000       4455.000
        mean        1.281       7.987     2.657    46.442    37.078          1.879
        std         0.450       8.173     1.610    14.655    10.985          0.644
        min         0.000       0.000     0.000     6.000    18.000          0.000
        25%         1.000       2.000     2.000    36.000    28.000          2.000
        50%         1.000       5.000     2.000    48.000    36.000          2.000
        75%         2.000      12.000     4.000    60.000    45.000          2.000
        max         2.000      48.000     6.000    72.000    68.000          5.000

                Records  TypeOfJob  Expenses     Income    Capital  ChargesOnCapital  \
        count  4455.000   4455.000  4455.000  4.455e+03  4.455e+03         4.455e+03
        mean      1.174      1.676    55.569  7.633e+05  1.060e+06         4.044e+05
        std       0.379      0.954    19.516  8.704e+06  1.022e+07         6.344e+06
        min       1.000      0.000    35.000  0.000e+00  0.000e+00         0.000e+00
        25%       1.000      1.000    35.000  8.000e+01  0.000e+00         0.000e+00
        50%       1.000      1.000    51.000  1.200e+02  3.500e+03         0.000e+00
        75%       1.000      3.000    72.000  1.660e+02  6.000e+03         0.000e+00
```

```
max         2.000      4.000   180.000  1.000e+08  1.000e+08           1.000e+08

       AmountRequested  MarketPrice
count         4455.000     4455.000
mean          1039.022     1462.876
std            474.543      628.090
min            100.000      105.000
25%            700.000     1117.500
50%           1000.000     1400.000
75%           1300.000     1692.000
max           5000.000    11140.000
```

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! python 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 [10]: Credit_complete = Credit.dropna()
         Credit_complete.shape
```

```
Out[10]: (4455, 14)
```

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 [11]: (Credit.Assessment==0).value_counts()
         (Credit.Housing==0).value_counts()
         (Credit.MaritalStatus==0).value_counts()
         (Credit.TypeOfJob==0).value_counts()
```

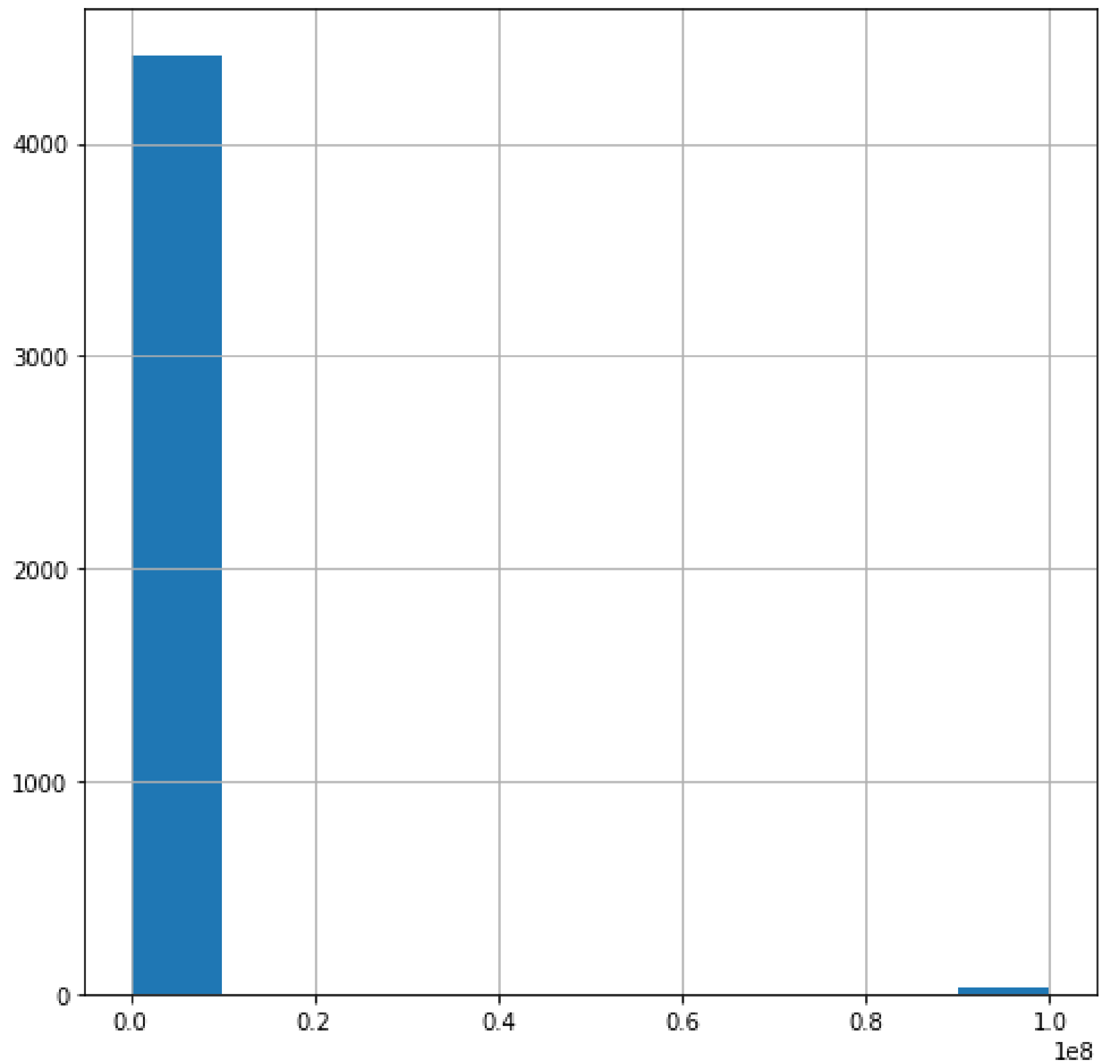
```
Out[11]: False    4454
         True        1
         Name: Assessment, dtype: int64

Out[11]: False    4449
         True        6
         Name: Housing, dtype: int64

Out[11]: False    4454
         True        1
         Name: MaritalStatus, dtype: int64

Out[11]: False    4453
         True        2
         Name: TypeOfJob, dtype: int64
```

```
In [12]: Credit=  Credit[(Credit.Assessment!=0) & (Credit.Housing!=0)
                        &(Credit.MaritalStatus!=0)&(Credit.TypeOfJob!=0)]
         Credit.shape
```

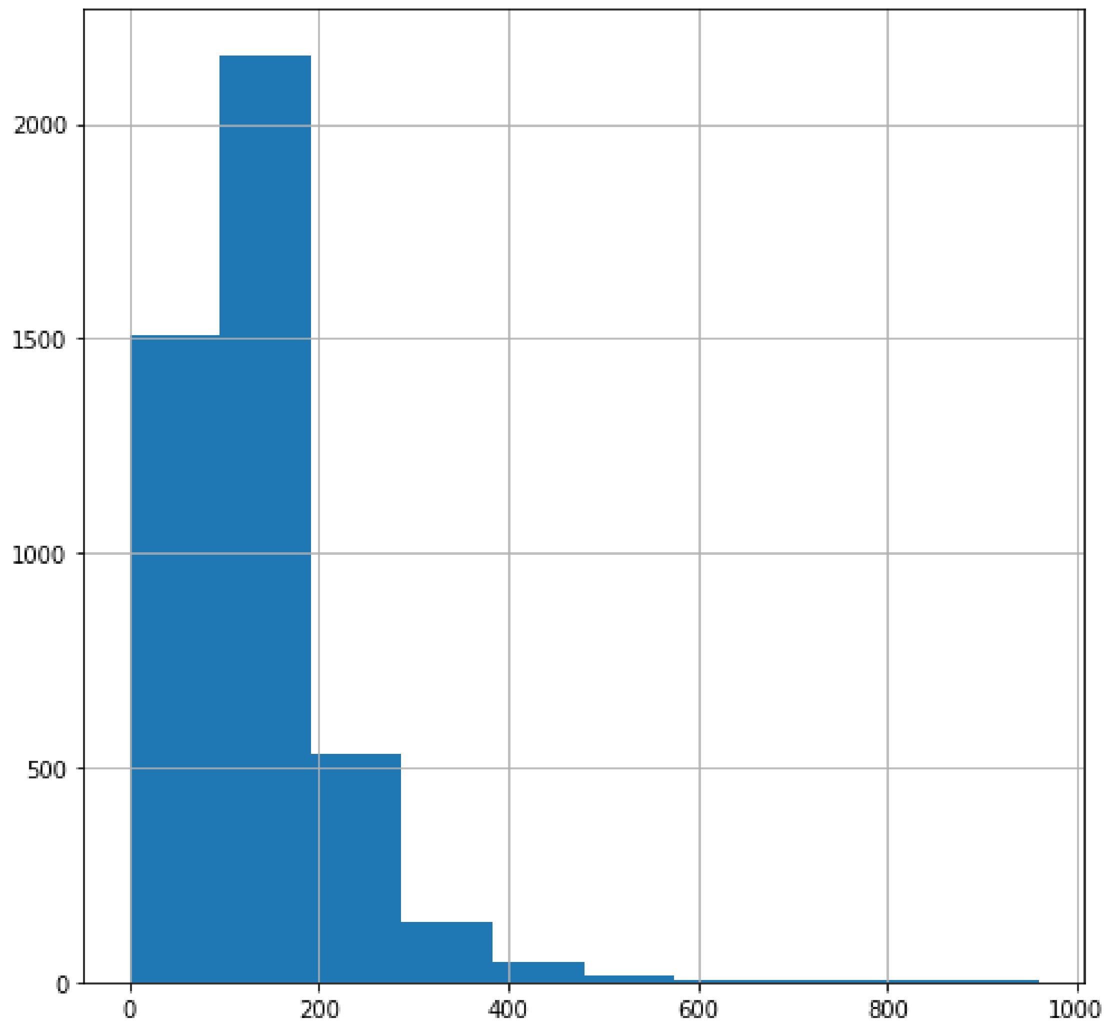
```
Out[12]: (4446, 14)
```

Process rows with missing values in the continuous variables (code 99999999) look at that:

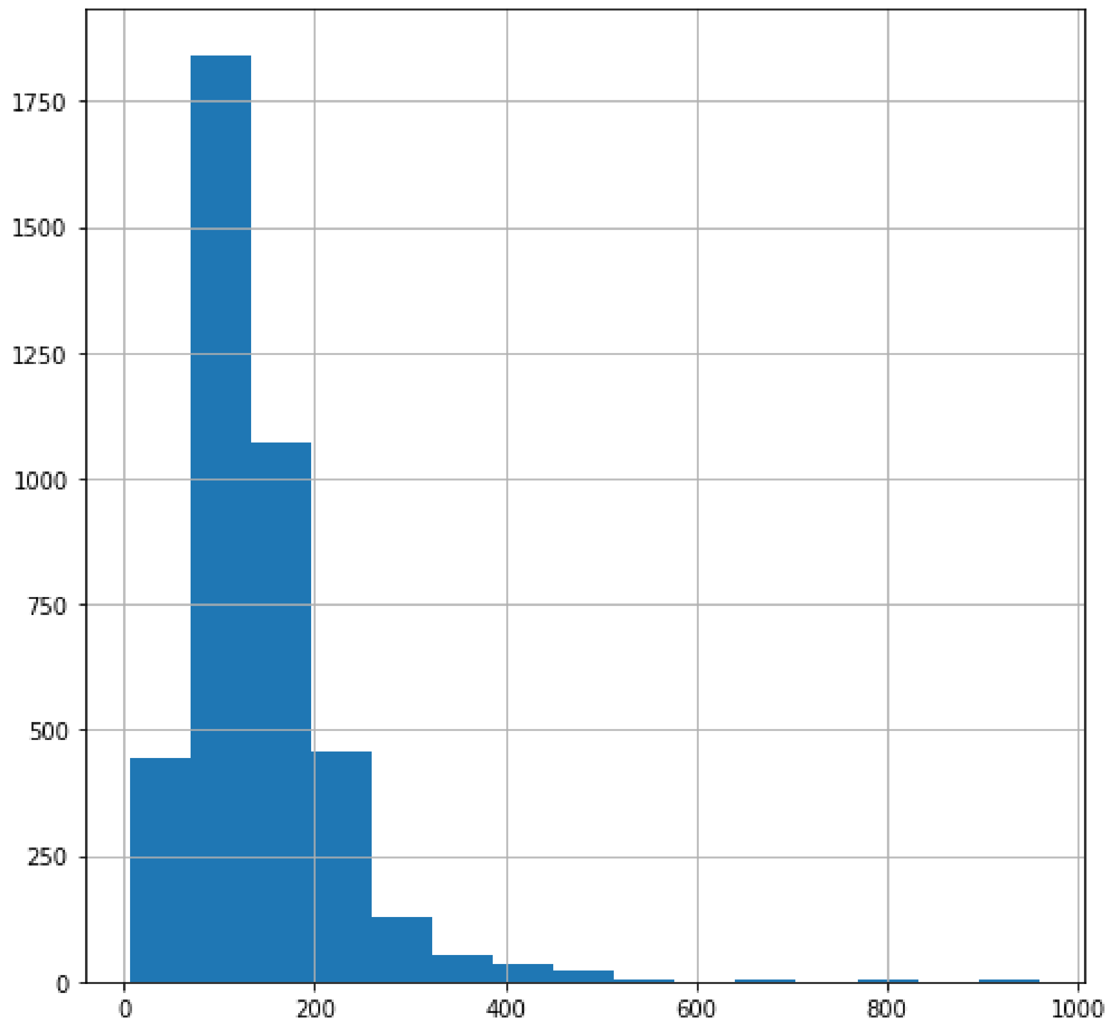
```
In [13]: Credit.Income.hist(figsize=(8,8));
```




```
In [14]: Credit.Income[Credit.Income!=99999999].hist(figsize=(8,8));
```




```
In [15]: Credit.Income[(Credit.Income!=99999999)&
                       (Credit.Income!=0)].hist(bins=15,figsize=(8,8));
```



these are then clearly incorrect

```
In [16]: (Credit.Income==99999999).value_counts()
         (Credit.Income==0).value_counts()
         (Credit.Capital==99999999).value_counts()
         (Credit.ChargesOnCapital==99999999).value_counts()
```

```
Out[16]: False    4415
         True       31
         Name: Income, dtype: int64
```

```
Out[16]: False    4100
         True      346
         Name: Income, dtype: int64
```

```
Out[16]: False    4405
         True       41
         Name: Capital, dtype: int64
```

```
Out[16]: False    4434
         True       12
         Name: ChargesOnCapital, dtype: int64
```

```
In [17]: (Credit.Income==99999999).value_counts()
```

```
Out[17]: False    4415
         True       31
         Name: Income, dtype: int64
```

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

```
In [18]: (Credit.YearsInJob==0).value_counts()
```

```
Out[18]: False    3914
         True      532
         Name: YearsInJob, dtype: int64
```

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 [19]: Credit.Income[(Credit.Income == 99999999) | (Credit.Income == 0)] = np.nan
         Credit.Capital[Credit.Capital == 99999999]  = np.nan
         Credit.ChargesOnCapital[Credit.ChargesOnCapital == 99999999]  = np.nan
```

see the difference?

```
In [20]: Credit.Income.describe()
```

```
Out[20]: count    4069.000
         mean      141.704
         std        80.694
         min         6.000
         25%        90.000
         50%       125.000
         75%       170.000
         max       959.000
         Name: Income, dtype: float64
```

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.

As we can not have missing values in any column for computing the 1KNN we will make a classifier dropping the columns with missing values and training a classifier for each column

```
In [21]: aux = Credit.drop(columns='Income')\
             .drop(columns='Capital')\
             .drop(columns='ChargesOnCapital')
```

```
aux.shape
aux1 = aux[Credit.Income.notna() &
           Credit.Capital.notna() &
           Credit.ChargesOnCapital.notna()]
aux1.shape
aux2 = aux[Credit.Income.isna()]
aux2.shape
```

```
Out[21]: (4446, 11)

Out[21]: (4039, 11)

Out[21]: (377, 11)
```

Neither of aux1, aux2 can contain NAs

```
In [22]: knn = KNeighborsClassifier(n_neighbors=1)
         knn.fit(aux1, Credit.Income[Credit.Income.notna() &
                                      Credit.Capital.notna() &
                                      Credit.ChargesOnCapital.notna()])
         knn_inc = knn.predict(aux2);
```

Imputation of 'Capital'

```
In [23]: aux2 = aux[Credit.Capital.isna()]

In [24]: knn = KNeighborsClassifier(n_neighbors=1)
         knn.fit(aux1, Credit.Capital[Credit.Income.notna()&
                                       Credit.Capital.notna() &
                                       Credit.ChargesOnCapital.notna()])
         knn_cap = knn.predict(aux2);
```

Imputation of 'ChargesOnCapital'

```
In [25]: aux2 = aux[Credit.ChargesOnCapital.isna()]

In [26]: knn = KNeighborsClassifier(n_neighbors=1)
         knn.fit(aux1, Credit.ChargesOnCapital[Credit.Income.notna()&
                                                Credit.Capital.notna() &
                                                Credit.ChargesOnCapital.notna()])
         knn_cop = knn.predict(aux2);

In [27]: Credit.Income[Credit.Income.isna()] =knn_inc
         Credit.Capital[Credit.Capital.isna()] =knn_cap
         Credit.ChargesOnCapital[Credit.ChargesOnCapital.isna()] =knn_cop
         Credit.ChargesOnCapital[Credit.Capital==0] = 0
```

```
/usr/local/lib/python3.6/site-packages/ipykernel_launcher.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  after removing the cwd from sys.path.
```

There are other less computational expensive methods for missing value imputations such as replacing with mean, median or mode. All these can be computed using pandas `replace` and `fillna` functions, you can find more info here

The Scikit-learn library has also a method for the most simple missing value imputation Imputer

inspect again the result, especially the new statistics

```
In [28]: Credit.shape
         Credit.describe()
```

```
Out[28]: (4446, 14)
```

Out[28]:

	Assessment	YearsInJob	Housing	Deadline	Age	MaritalStatus
count	4446.000	4446.000	4446.000	4446.000	4446.000	4446.000
mean	1.281	7.991	2.660	46.453	37.084	1.880
std	0.450	8.176	1.609	14.648	10.986	0.643
min	1.000	0.000	1.000	6.000	18.000	1.000
25%	1.000	2.000	2.000	36.000	28.000	2.000
50%	1.000	5.000	2.000	48.000	36.000	2.000
75%	2.000	12.000	4.000	60.000	45.000	2.000
max	2.000	48.000	6.000	72.000	68.000	5.000

	Records	TypeOfJob	Expenses	Income	Capital	ChargesOnCapital
count	4446.000	4446.000	4446.000	4446.000	4446.000	4446.000
mean	1.173	1.676	55.601	141.689	5383.702	343.312
std	0.378	0.954	19.521	80.082	11527.920	1245.731
min	1.000	1.000	35.000	6.000	0.000	0.000
25%	1.000	1.000	35.000	90.000	0.000	0.000
50%	1.000	1.000	51.000	125.000	3000.000	0.000
75%	1.000	3.000	72.000	171.000	6000.000	0.000
max	2.000	4.000	180.000	959.000	300000.000	30000.000

	AmountRequested	MarketPrice
count	4446.000	4446.000
mean	1038.763	1462.480
std	474.748	628.555
min	100.000	105.000
25%	700.000	1116.250
50%	1000.000	1400.000
75%	1300.000	1691.500
max	5000.000	11140.000

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

```
In [29]: Credit.dtypes

Out[29]: Assessment            int64
         YearsInJob            int64
         Housing               int64
         Deadline              int64
         Age                   int64
         MaritalStatus         int64
         Records               int64
         TypeOfJob             int64
         Expenses              int64
         Income              float64
         Capital             float64
         ChargesOnCapital    float64
         AmountRequested       int64
         MarketPrice           int64
         dtype: object
```

```
In [30]: # There is a categorical datatype in pandas, but for most things this will do
         Credit.Assessment = Credit.Assessment.astype('object')
         Credit.Housing = Credit.Housing.astype('object')
         Credit.MaritalStatus = Credit.MaritalStatus.astype('object')
         Credit.Records = Credit.Records.astype('object')
         Credit.TypeOfJob = Credit.TypeOfJob.astype('object')

         Credit.Assessment.unique()
         Credit.Housing .unique()
         Credit.MaritalStatus.unique()
         Credit.Records.unique()
         Credit.TypeOfJob.unique()

Out[30]: array([1, 2], dtype=object)

Out[30]: array([1, 2, 5, 3, 6, 4], dtype=object)

Out[30]: array([2, 3, 1, 4, 5], dtype=object)

Out[30]: array([1, 2], dtype=object)

Out[30]: array([3, 1, 2, 4], dtype=object)
```

not very nice, right? let's recode

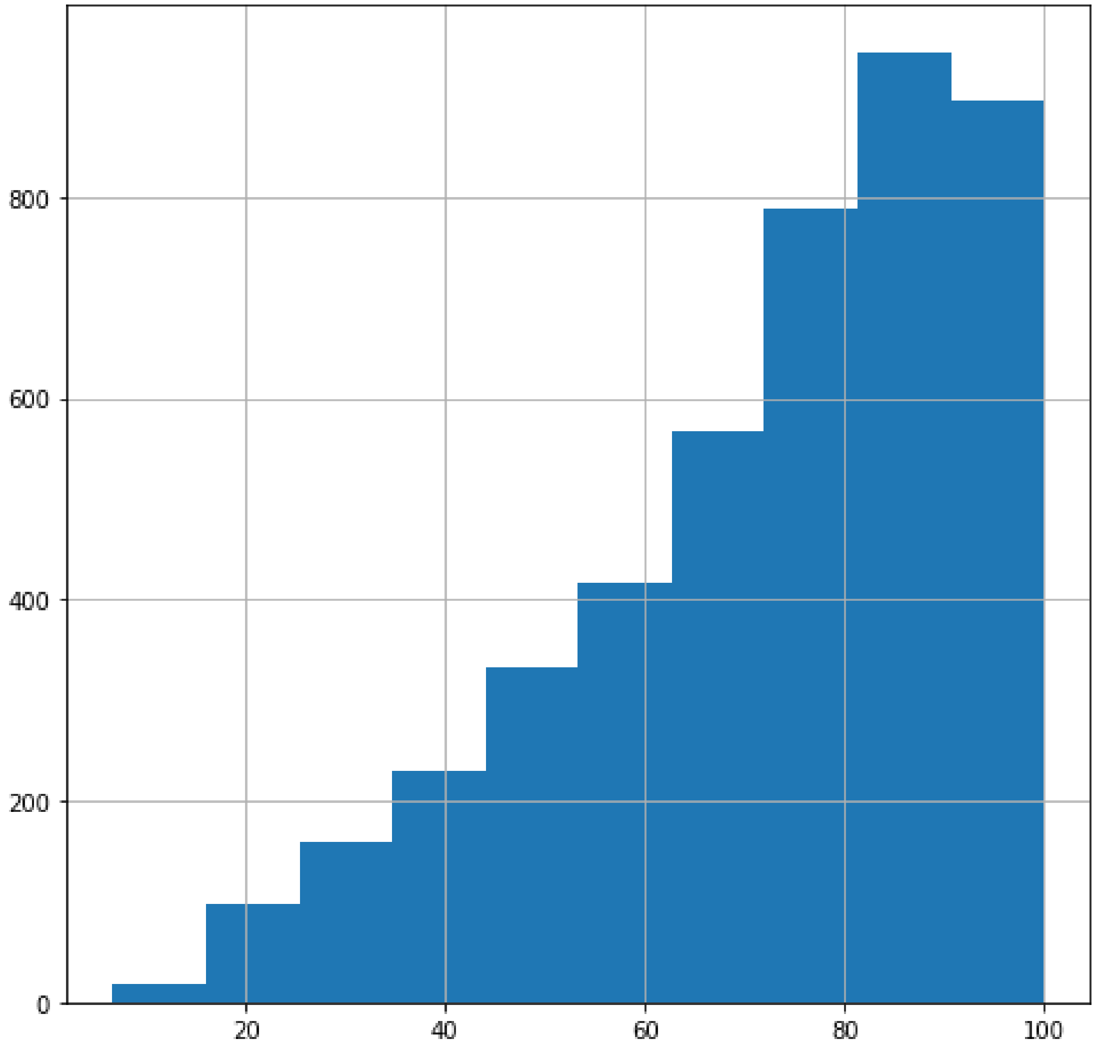
```
In [31]: Credit.Assessment.replace([1, 2],
                                   ["positive","negative"],
                                   inplace=True)
         Credit.Housing.replace([1,2,3,4,5,6],
                                ["rent","owner","private","ignore","parents","other"],
                                inplace=True)
```

```
Credit.MaritalStatus.replace([1,2,3,4,5],
                              ["single","married","widower","split","divorced"],
                              inplace=True)
Credit.Records.replace([1, 2],
                        ["no","yes"], inplace=True)
Credit.TypeOfJob.replace([1,2,3,4],
                          ["indefinite","temporal","self-employed","other"],
                          inplace=True)
```

1.5 SECTION 5: DERIVATION OF NEW VARIABLES: FEATURE EXTRACTION

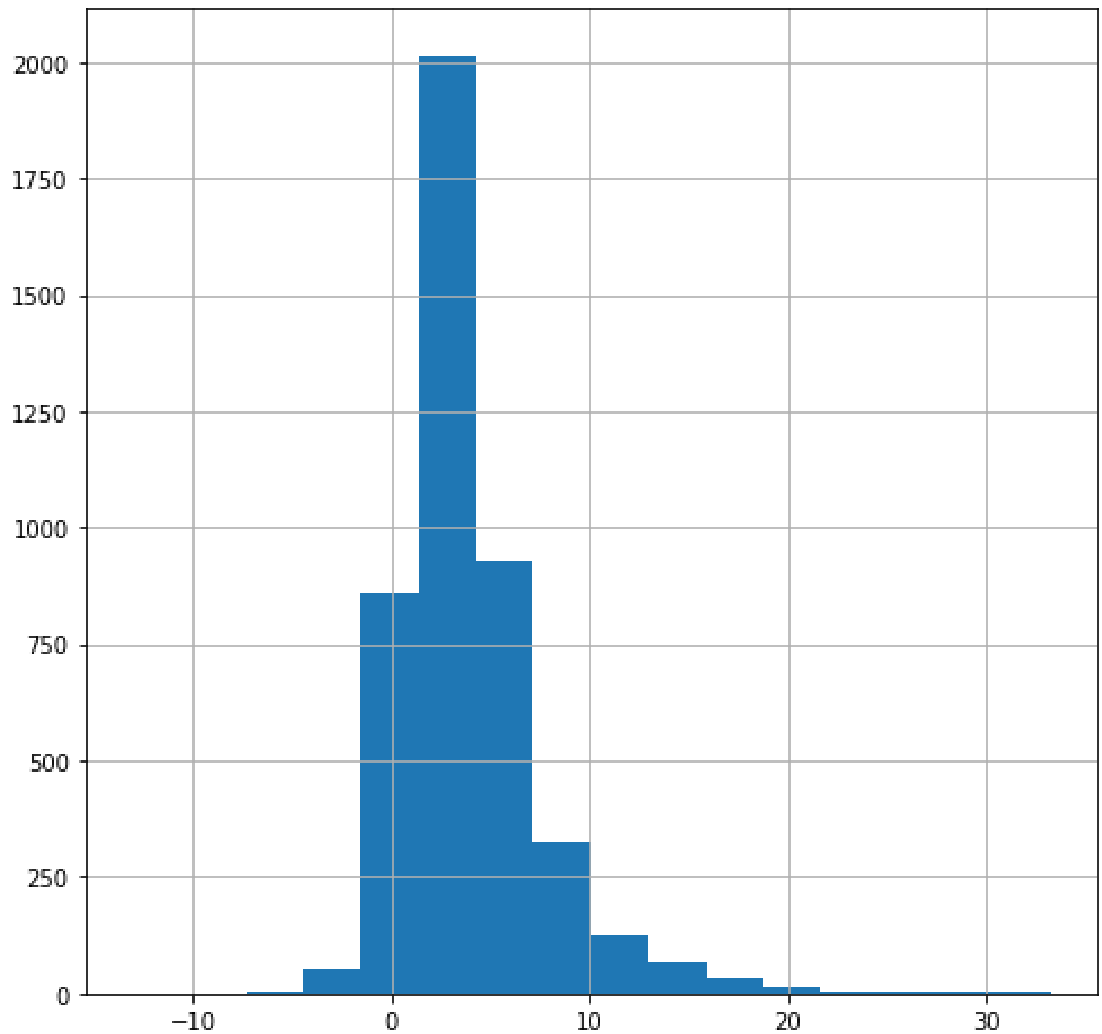
We decide whether it can be sensible to derive new variables; we extract two new continuous and one new categorical variable (for the sake of illustration):
Financing ratio (continuous)

```
In [32]: Credit['FinancingRatio'] = 100*Credit.AmountRequested/Credit.MarketPrice
         Credit.FinancingRatio.hist(figsize=(8,8));
```



Saving capacity (continuous)

```
In [33]: Credit['SavingCapacity'] = (Credit.Income- Credit.Expenses-(Credit.ChargesOnCapital/100
                                    /(Credit.AmountRequested/Credit.Deadline)
         Credit.SavingCapacity.hist(bins=16,figsize=(8,8));
```



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

```
In [34]: Credit['Dubious'] = ['No']*Credit.shape[0]
         Credit.Dubious[(Credit.AmountRequested > Credit.AmountRequested.median(skipna=True)) &
                        (Credit.Age < 1.25*Credit.Age.mean(skipna=True))] = "Yes"
         pd.crosstab(Credit.Dubious, Credit.Assessment)
```

```
/usr/local/lib/python3.6/site-packages/ipykernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  This is separate from the ipykernel package so we can avoid doing imports until
```

```
Out[34]: Assessment  negative  positive
         Dubious
```

```
No                 668      2200
Yes                581       997
```

1.6 SECTION 6: WHAT WE HAVE DONE SO FAR

Create a new dataframe that gathers everything and inspect it again

In [35]:
```python
Credit_new =Credit.copy()

Credit_new.describe(include='all')
Credit_new.shape
```

Out[35]:
```
       Assessment  YearsInJob Housing  Deadline       Age MaritalStatus  \
count        4446    4446.000    4446  4446.000  4446.000          4446
unique          2         NaN       6       NaN       NaN             5
top      positive         NaN   owner       NaN       NaN       married
freq         3197         NaN    2106       NaN       NaN          3238
mean          NaN       7.991     NaN    46.453    37.084           NaN
std           NaN       8.176     NaN    14.648    10.986           NaN
min           NaN       0.000     NaN     6.000    18.000           NaN
25%           NaN       2.000     NaN    36.000    28.000           NaN
50%           NaN       5.000     NaN    48.000    36.000           NaN
75%           NaN      12.000     NaN    60.000    45.000           NaN
max           NaN      48.000     NaN    72.000    68.000           NaN

       Records   TypeOfJob  Expenses    Income     Capital  ChargesOnCapital  \
count     4446        4446  4446.000  4446.000    4446.000          4446.000
unique       2           4       NaN       NaN         NaN               NaN
top         no  indefinite       NaN       NaN         NaN               NaN
freq      3677        2803       NaN       NaN         NaN               NaN
mean       NaN         NaN    55.601   141.689    5383.702           343.312
std        NaN         NaN    19.521    80.082   11527.920          1245.731
min        NaN         NaN    35.000     6.000       0.000             0.000
25%        NaN         NaN    35.000    90.000       0.000             0.000
50%        NaN         NaN    51.000   125.000    3000.000             0.000
75%        NaN         NaN    72.000   171.000    6000.000             0.000
max        NaN         NaN   180.000   959.000  300000.000         30000.000

        AmountRequested  MarketPrice  FinancingRatio  SavingCapacity Dubious
count          4446.000     4446.000        4446.000        4446.000    4446
unique              NaN          NaN             NaN             NaN       2
top                 NaN          NaN             NaN             NaN      No
freq                NaN          NaN             NaN             NaN    2868
mean           1038.763     1462.480          72.616           3.911     NaN
std             474.748      628.555          20.391           3.738     NaN
min             100.000      105.000           6.702         -13.104     NaN
25%             700.000     1116.250          60.030           1.680     NaN
```

50%	1000.000	1400.000	77.097	3.142	NaN
75%	1300.000	1691.500	88.460	5.232	NaN
max	5000.000	11140.000	100.000	33.250	NaN

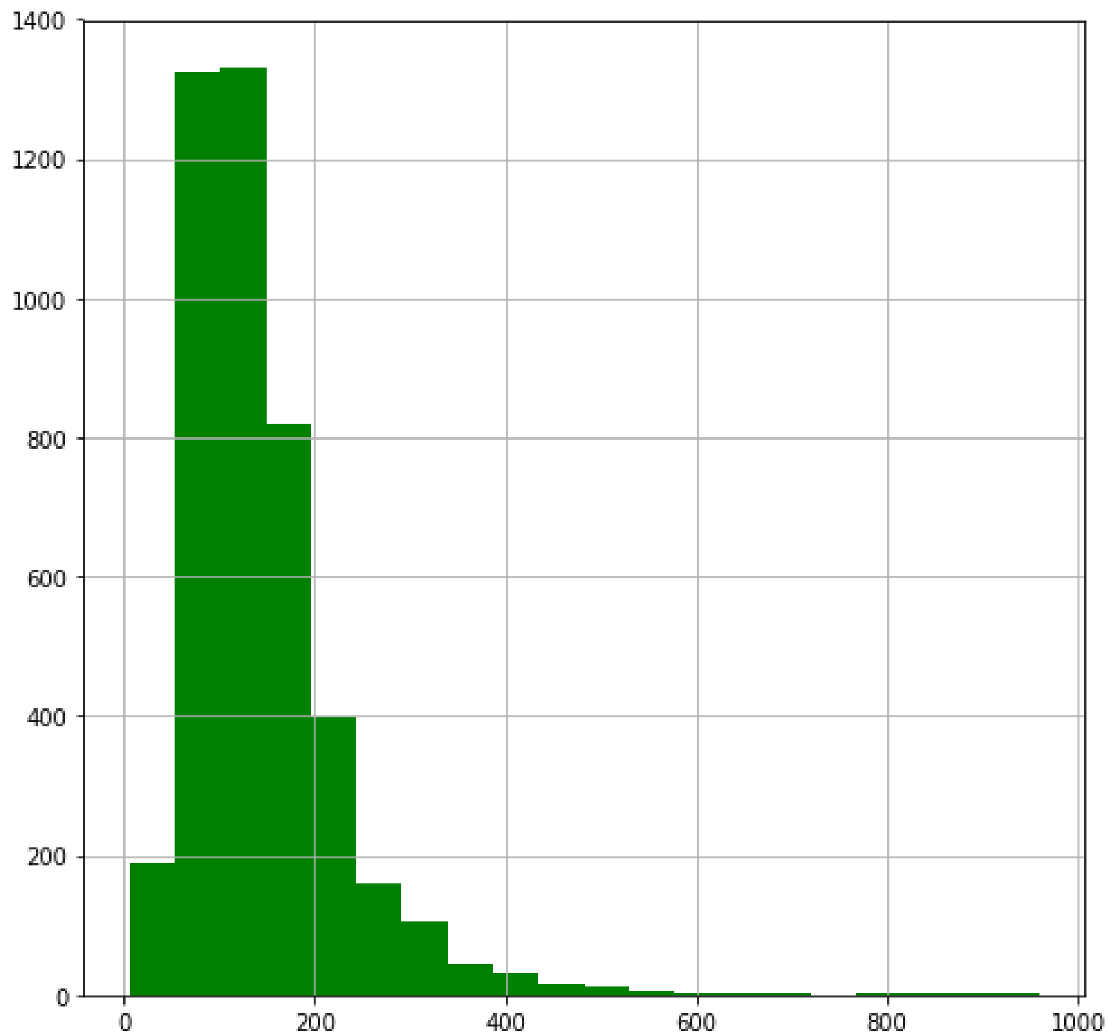
Out[35]: (4446, 17)

1.7 SECTION 7: GAUSSIANITY AND TRANSFORMATIONS

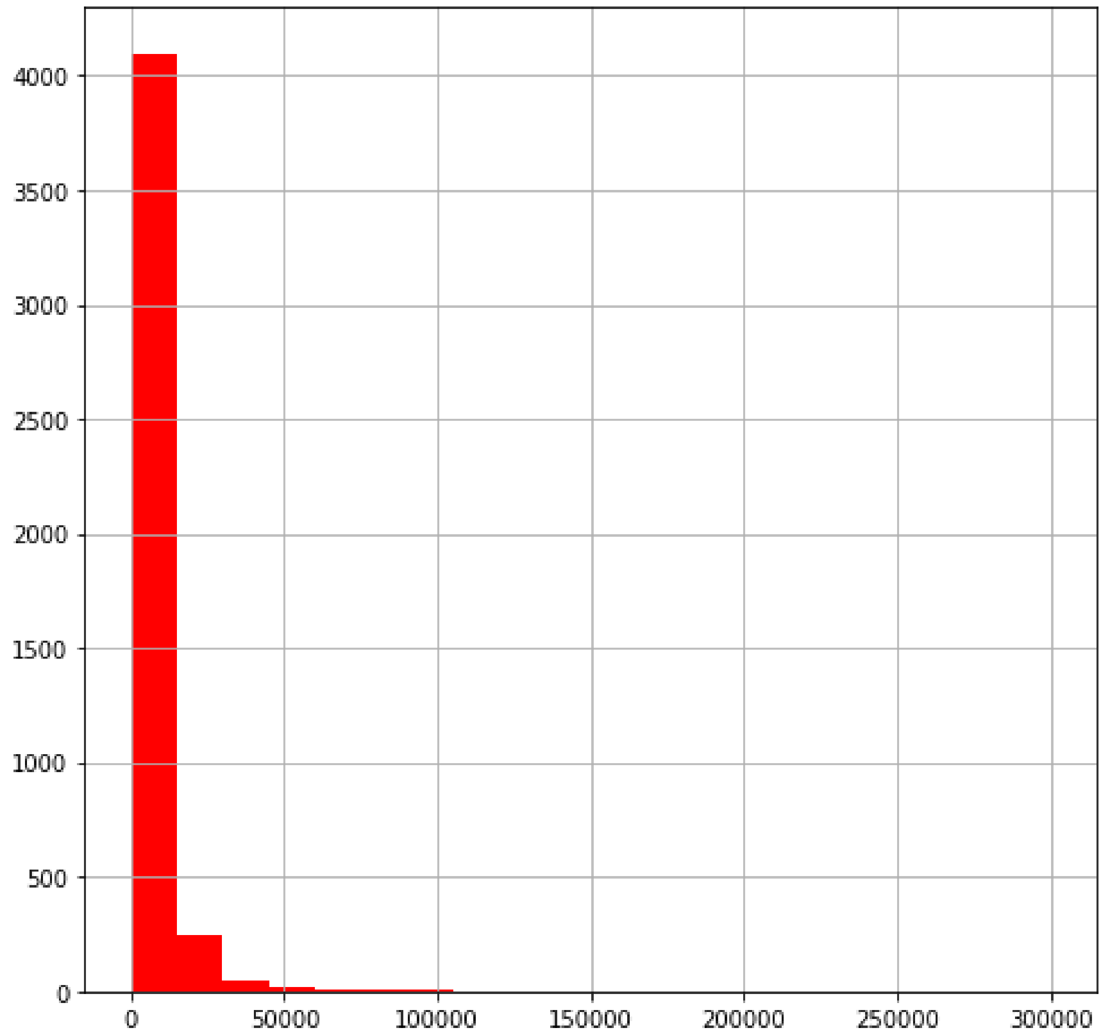
Perform a graphical summary of some of the variables (both categorical and continuous), using the boxplot() and hist() procedures

For continuous data: histograms and boxplots

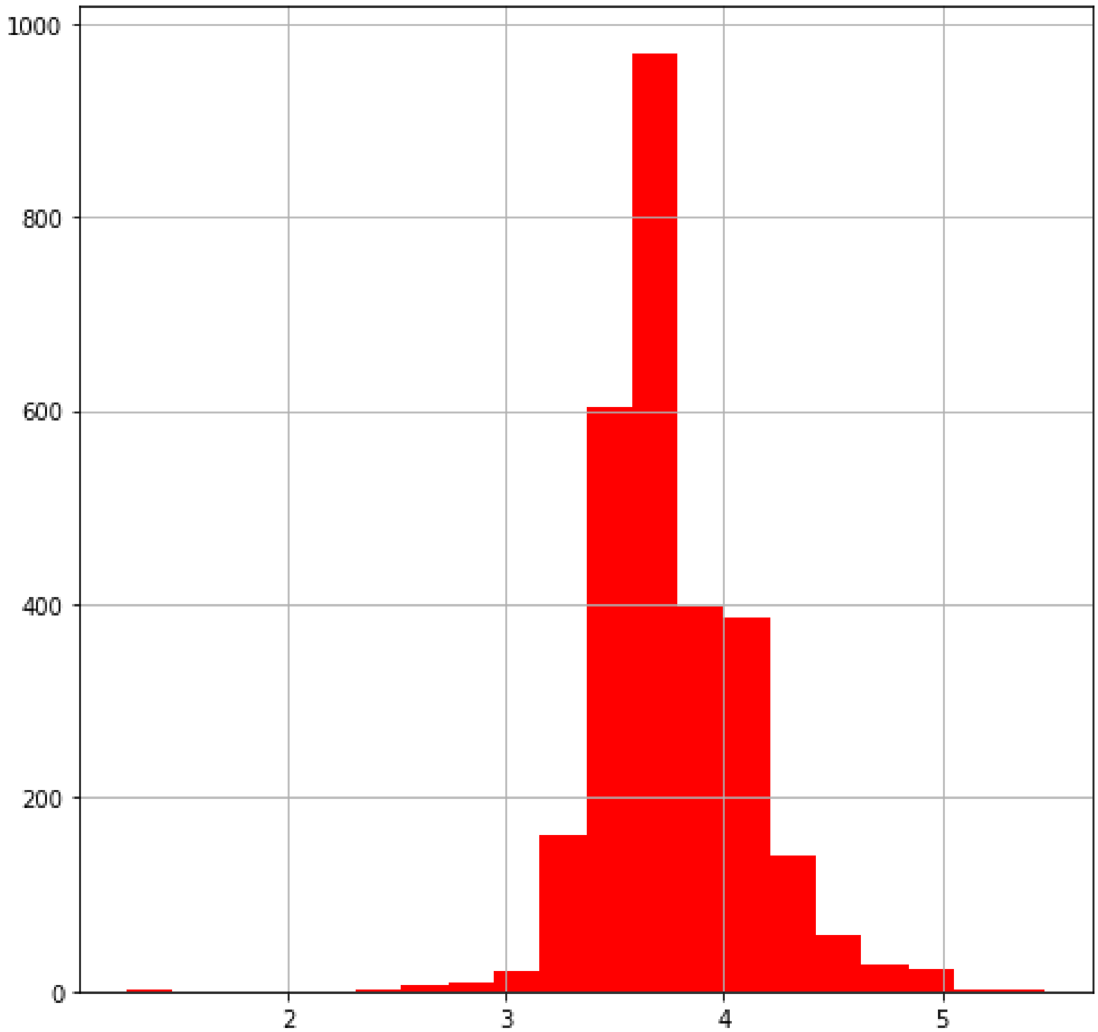
```
In [36]: Credit_new.Income.hist(bins=20,figsize=(8,8), color='green');
```



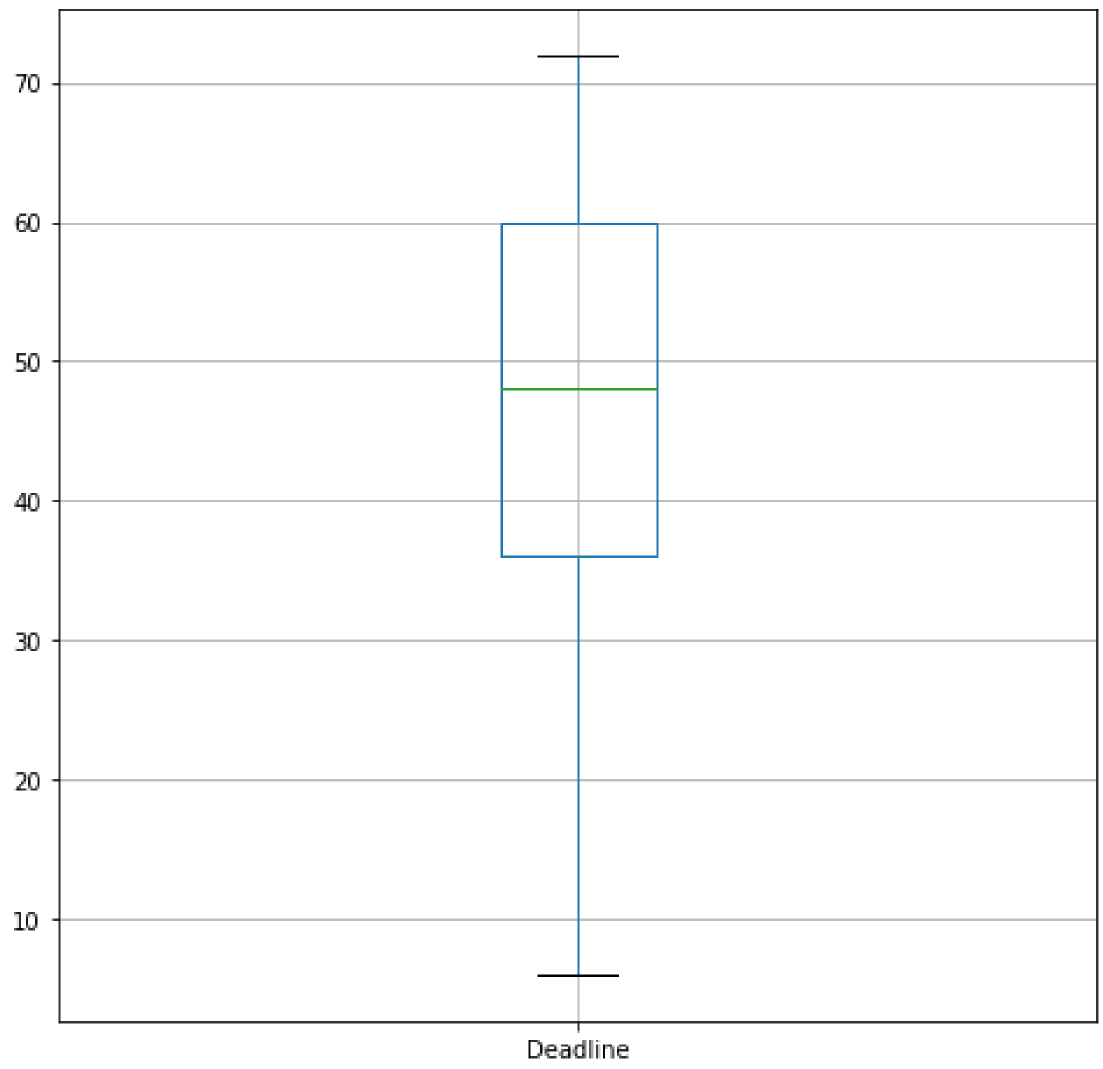
```
In [37]: Credit_new.Capital.hist(bins=20,figsize=(8,8), color='red');
```



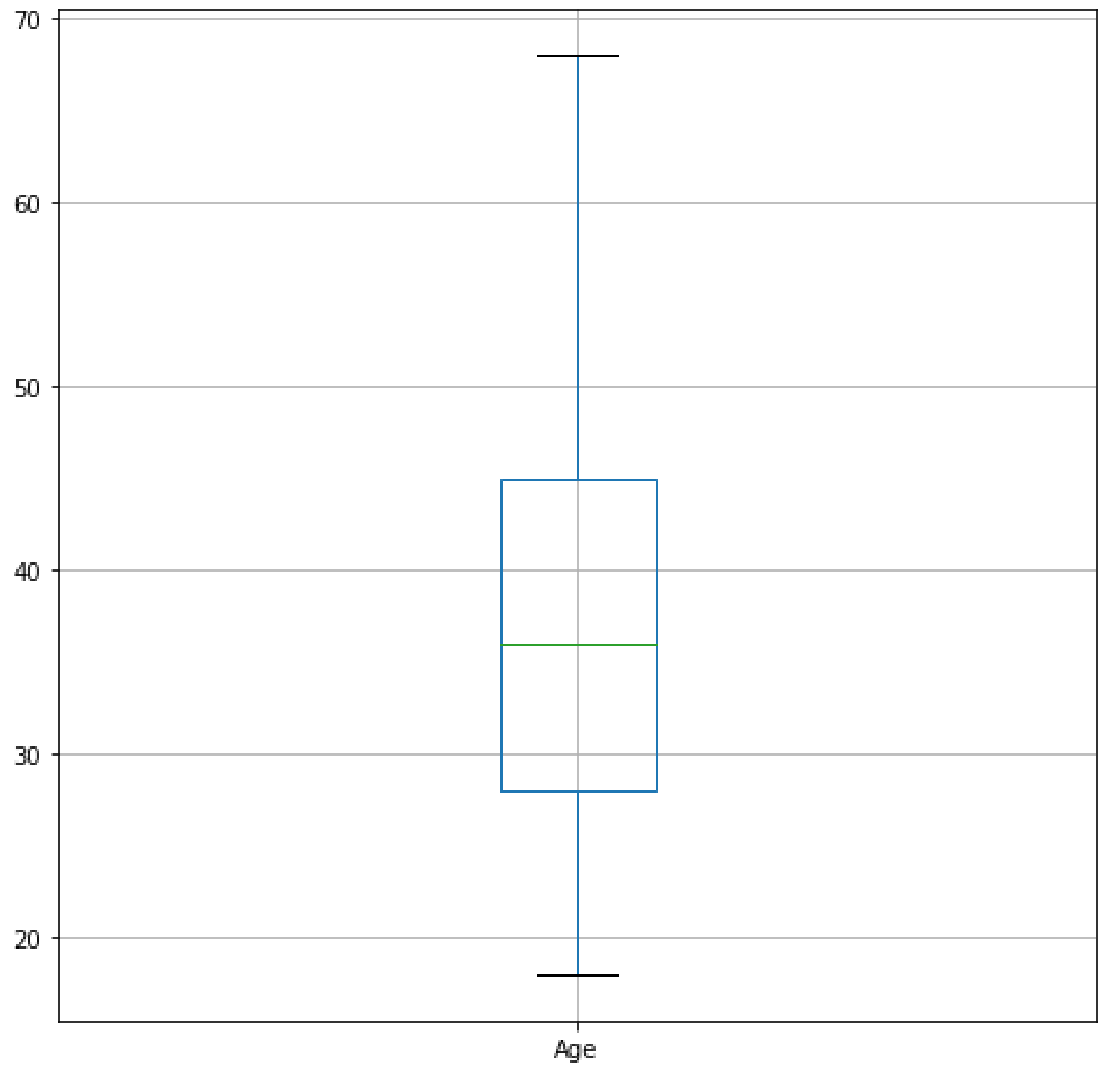

```
In [38]: pd.options.mode.use_inf_as_na = True
         Credit_new.Capital.apply(np.log10).hist(bins=20,figsize=(8,8), color='red');
```



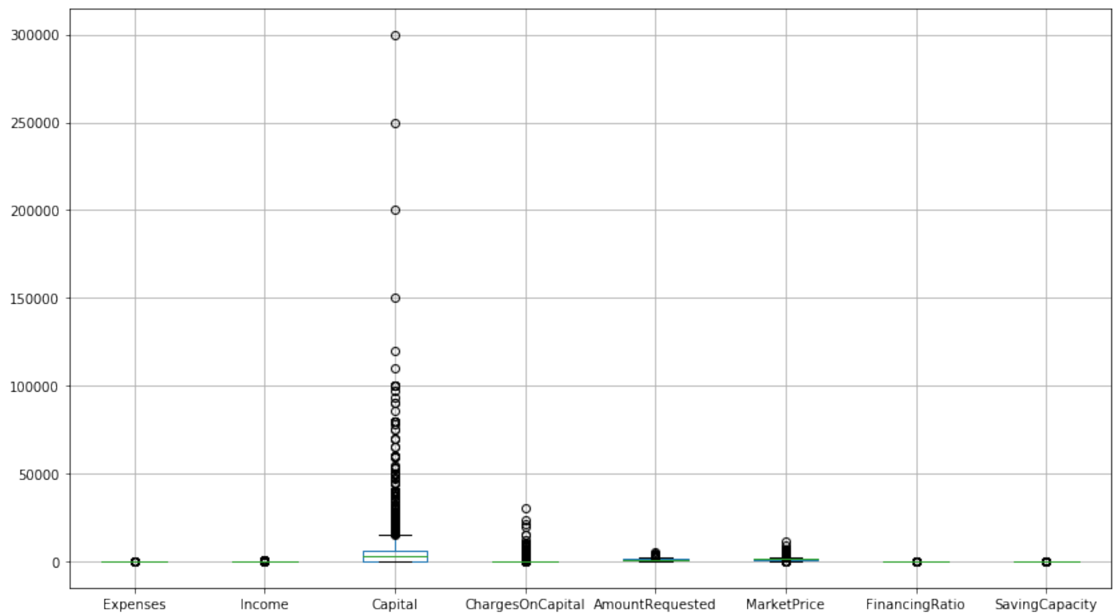

```
In [39]: Credit_new.boxplot(column='Deadline',figsize=(8,8));
```



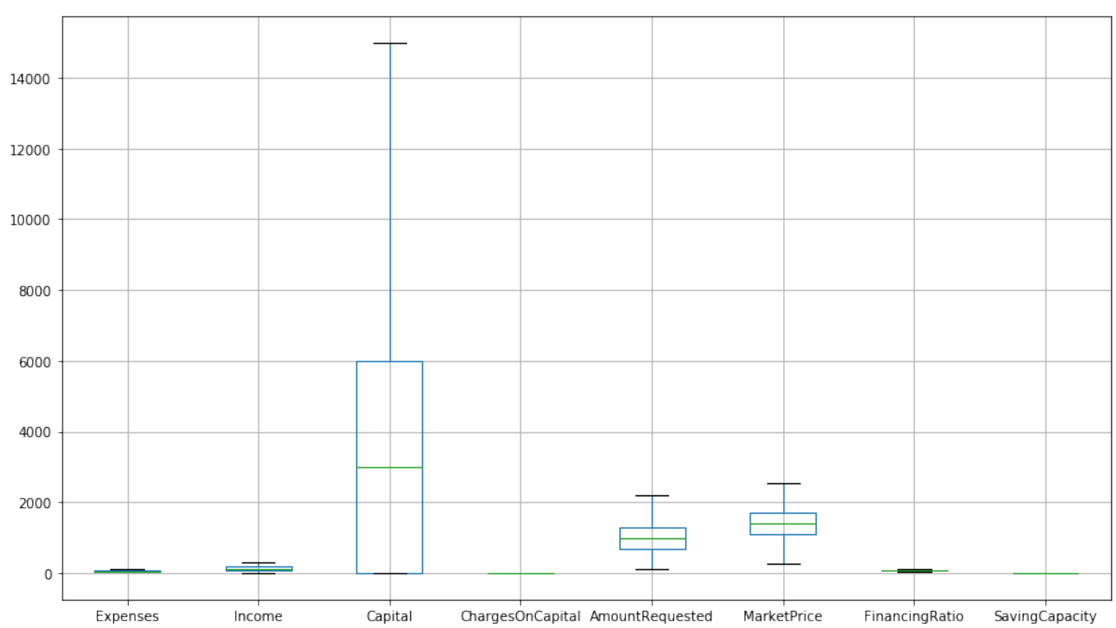

```
In [40]: Credit_new.boxplot(column='Age',figsize=(8,8));
```




```
In [41]: Credit_new.loc[:,"Expenses":"SavingCapacity"].boxplot(figsize=(14,8));
```




```
In [42]: Credit_new.loc[:,"Expenses":"SavingCapacity"].boxplot(figsize=(14,8),showfliers=False);
```



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 [43]: Credit_new.Age.unique()

Out[43]: array([30, 58, 46, 24, 26, 36, 44, 27, 32, 41, 34, 29, 37, 21, 68, 52, 31,
                25, 22, 45, 51, 54, 43, 23, 39, 35, 62, 56, 64, 42, 61, 49, 47, 28,
                63, 55, 40, 53, 38, 57, 33, 66, 50, 48, 59, 60, 19, 65, 20, 18])

In [44]: Credit_new.Age.min()
         Credit_new.Age.max()

Out[44]: 18

Out[44]: 68

In [45]: bins = pd.IntervalIndex.from_tuples([(0, 1), (2, 3), (4, 5)])
         bins

Out[45]: IntervalIndex([(0, 1], (2, 3], (4, 5]]
                       closed='right',
                       dtype='interval[int64]')

In [46]: pd.interval_range(start=30, end=90,freq=10)

Out[46]: IntervalIndex([(30, 40], (40, 50], (50, 60], (60, 70], (70, 80], (80, 90]]
                       closed='right',
                       dtype='interval[int64]')

In [47]: pd.cut(Credit_new.Age,
                bins=pd.interval_range(start=30, end=90,freq=10))
         # WARNING! we are generating NAs

Out[47]: 0           NaN
         1      (50, 60]
         2      (40, 50]
         3           NaN
         4           NaN
         5      (30, 40]
         6      (40, 50]
         7           NaN
         8      (30, 40]
         9      (40, 50]
         10     (30, 40]
         11          NaN
         12          NaN
         13     (30, 40]
         14          NaN
         15     (60, 70]
         16     (50, 60]
         17     (60, 70]
         18     (30, 40]
```

```
19      (30, 40]
20           NaN
21           NaN
22      (40, 50]
23      (40, 50]
24      (50, 60]
25      (50, 60]
26      (40, 50]
27      (40, 50]
28           NaN
30           NaN
          ...
4425    (40, 50]
4426         NaN
4427    (40, 50]
4428    (40, 50]
4429         NaN
4430    (30, 40]
4431    (60, 70]
4432    (30, 40]
4433    (30, 40]
4434    (50, 60]
4435    (30, 40]
4436         NaN
4437         NaN
4438    (30, 40]
4439    (30, 40]
4440    (30, 40]
4441    (40, 50]
4442    (30, 40]
4443    (30, 40]
4444    (30, 40]
4445         NaN
4446    (40, 50]
4447    (50, 60]
4448    (40, 50]
4449         NaN
4450    (30, 40]
4451    (40, 50]
4452    (30, 40]
4453         NaN
4454    (30, 40]
Name: Age, Length: 4446, dtype: category
Categories (6, interval[int64]): [(30, 40] < (40, 50] < (50, 60] < (60, 70] < (70, 80]
```

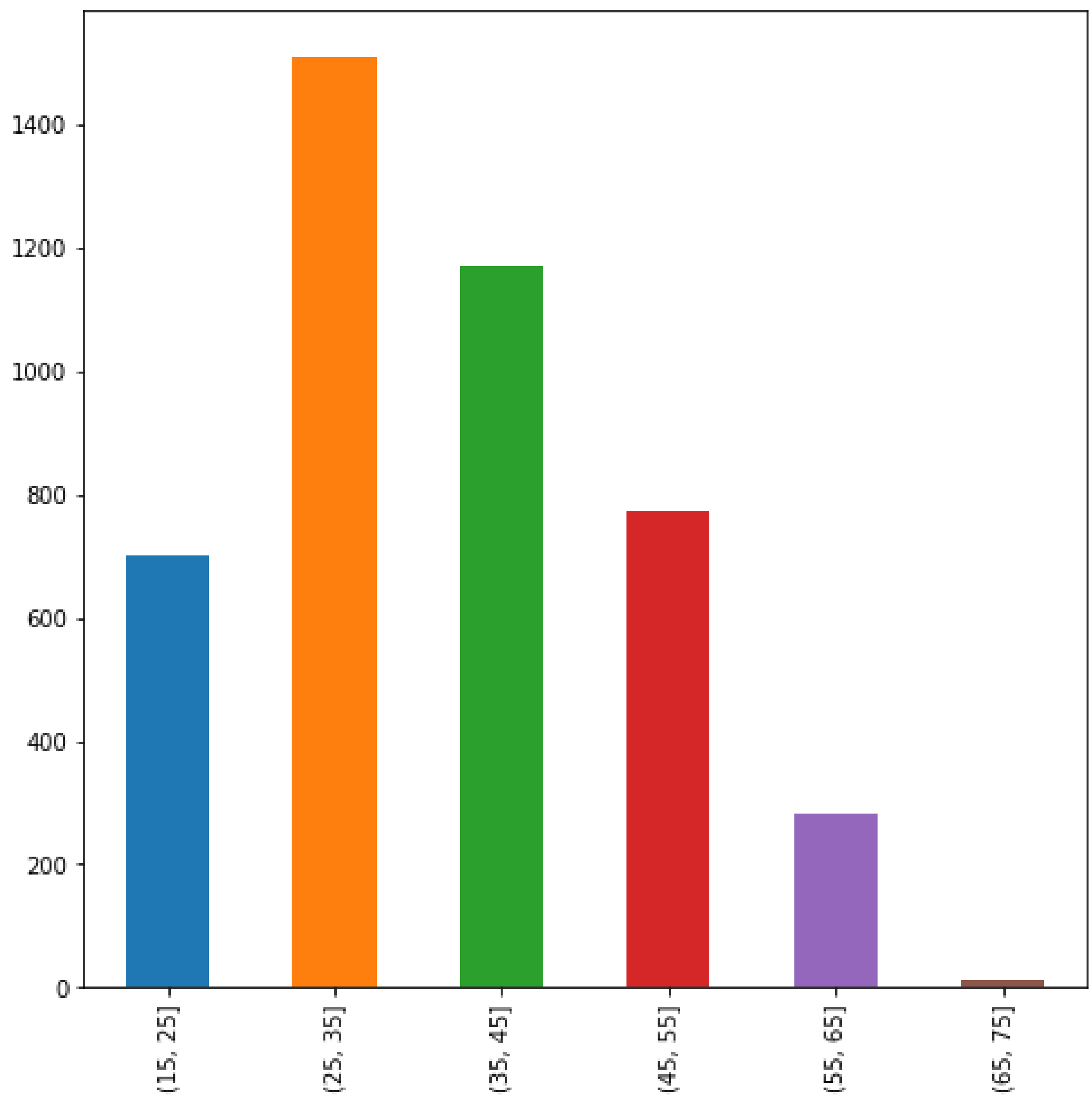
In [48]:
```
Age_cut = pd.cut(Credit_new.Age,
                 bins=pd.interval_range(start=15, end=75,freq=10)) ;
```

In [49]:
```
Credit_new['Age_cat'] = Age_cut.astype('str')
```

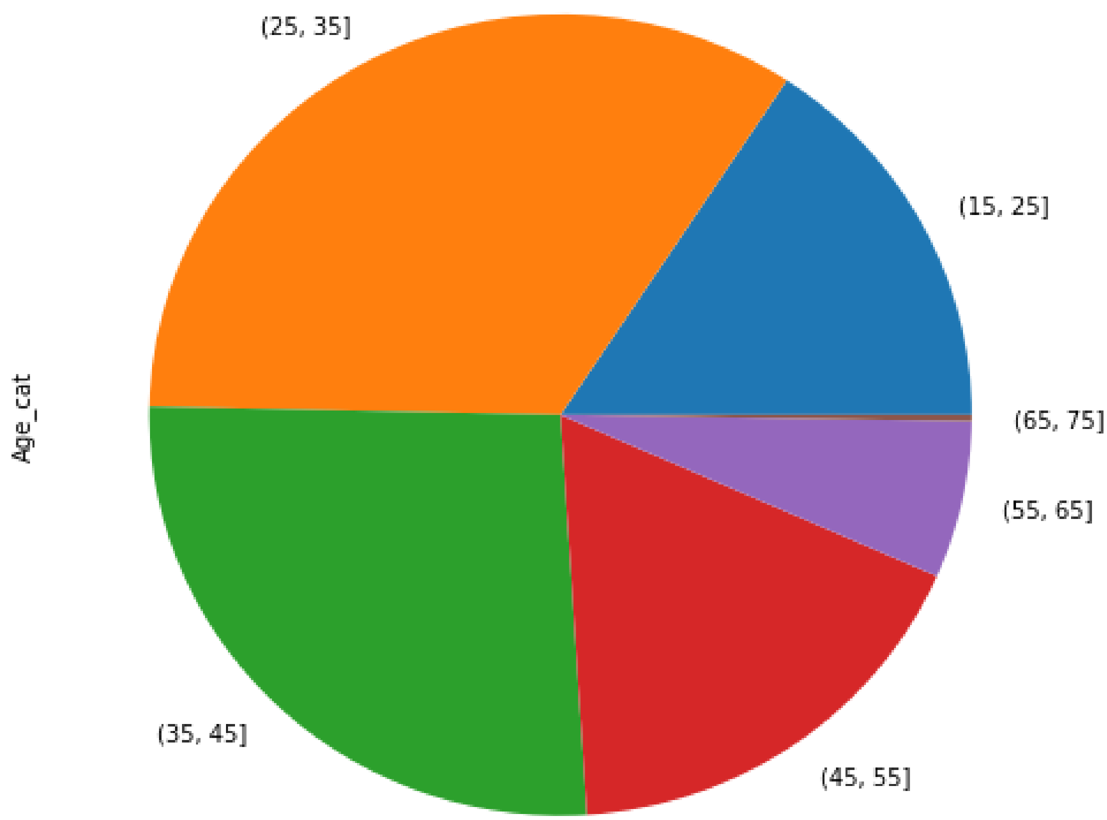
```
In [50]: Credit_new.Age_cat.value_counts().sort_index()
```

```
Out[50]: (15, 25]     699
         (25, 35]    1509
         (35, 45]    1172
         (45, 55]     773
         (55, 65]     282
         (65, 75]      11
         Name: Age_cat, dtype: int64
```

```
In [51]: Credit_new.Age_cat.value_counts().sort_index().plot.bar(figsize=(8,8));
```




```
In [52]: Credit_new.Age_cat.value_counts().sort_index().plot.pie(figsize=(8,8));
```



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

```
In [53]: Credit_new['Age2_cat'] = Credit_new.Age.apply(lambda x :
                                          'under55' if x < 55 else 'over55')

In [54]: TypeOfJob_Age= pd.crosstab(Credit_new.TypeOfJob, Credit_new.Age_cat)
         TypeOfJob_Age

Out[54]: Age_cat        (15, 25]  (25, 35]  (35, 45]  (45, 55]  (55, 65]  (65, 75]
         TypeOfJob
         indefinite          408      1054       742       463       132         4
         other                17        28        30        30        61         5
         self-employed        91       272       319       250        87         2
         temporal            183       155        81        30         2         0

In [55]: TypeOfJob_Age.sum(axis=0) # row sums
         TypeOfJob_Age.sum(axis=1) # column sums
```

Out[55]:
```
Age_cat
(15, 25]     699
(25, 35]    1509
(35, 45]    1172
(45, 55]     773
(55, 65]     282
(65, 75]      11
dtype: int64
```

Out[55]:
```
TypeOfJob
indefinite       2803
other             171
self-employed    1021
temporal          451
dtype: int64
```

In [56]:
```
pd.crosstab(Credit_new.TypeOfJob,
            Credit_new.Age_cat,
            normalize=True,
            margins=True) # relative frequencies
```

Out[56]:
```
Age_cat        (15, 25]  (25, 35]  (35, 45]  (45, 55]   (55, 65]   (65, 75]  \
TypeOfJob
indefinite        0.092     0.237     0.167     0.104  2.969e-02  8.997e-04
other             0.004     0.006     0.007     0.007  1.372e-02  1.125e-03
self-employed     0.020     0.061     0.072     0.056  1.957e-02  4.498e-04
temporal          0.041     0.035     0.018     0.007  4.498e-04  0.000e+00
All               0.157     0.339     0.264     0.174  6.343e-02  2.474e-03

Age_cat          All
TypeOfJob
indefinite     0.630
other          0.038
self-employed  0.230
temporal       0.101
All            1.000
```

In [57]:
```
pd.crosstab(Credit_new.TypeOfJob,
            Credit_new.Age_cat,
            normalize=True,margins=True).round(decimals=3)
            # idem, rounded to 3 digits
```

Out[57]:
```
Age_cat        (15, 25]  (25, 35]  (35, 45]  (45, 55]  (55, 65]  (65, 75]  \
TypeOfJob
indefinite        0.092     0.237     0.167     0.104     0.030     0.001
other             0.004     0.006     0.007     0.007     0.014     0.001
self-employed     0.020     0.061     0.072     0.056     0.020     0.000
temporal          0.041     0.035     0.018     0.007     0.000     0.000
All               0.157     0.339     0.264     0.174     0.063     0.002
```

```
Age_cat           All
TypeOfJob
indefinite      0.630
other           0.038
self-employed   0.230
temporal        0.101
All             1.000
```

In [58]:
```
(pd.crosstab(Credit_new.TypeOfJob,
             Credit_new.Age_cat,
             normalize=True,
             margins=True)*100).round(decimals=3)
             # total percentages
```

Out[58]:
```
Age_cat        (15, 25]  (25, 35]  (35, 45]  (45, 55]  (55, 65]  (65, 75]  \
TypeOfJob
indefinite        9.177    23.707    16.689    10.414     2.969     0.090
other             0.382     0.630     0.675     0.675     1.372     0.112
self-employed     2.047     6.118     7.175     5.623     1.957     0.045
temporal          4.116     3.486     1.822     0.675     0.045     0.000
All              15.722    33.941    26.361    17.386     6.343     0.247

Age_cat            All
TypeOfJob
indefinite      63.045
other            3.846
self-employed   22.964
temporal        10.144
All            100.000
```

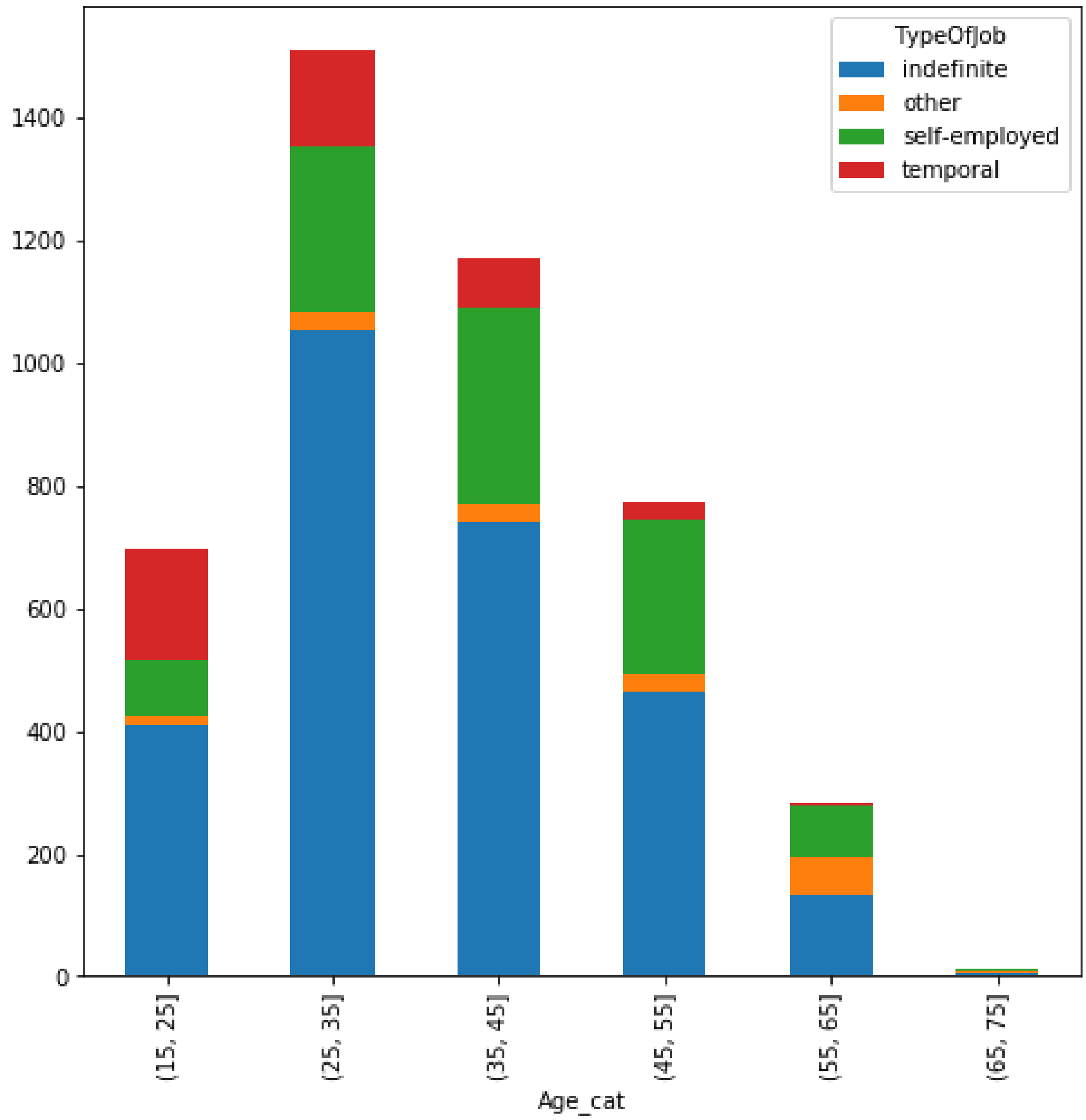
In [59]:
```
pd.crosstab(Credit_new.TypeOfJob,
            Credit_new.Age_cat,
            normalize="index").round(decimals=3)
            # table of relative frequencies (column-wise)
pd.crosstab(Credit_new.TypeOfJob,
            Credit_new.Age_cat,
            normalize="columns").round(decimals=3)
            # table of relative frequencies (row-wise)
```

Out[59]:
```
Age_cat        (15, 25]  (25, 35]  (35, 45]  (45, 55]  (55, 65]  (65, 75]
TypeOfJob
indefinite        0.146     0.376     0.265     0.165     0.047     0.001
other             0.099     0.164     0.175     0.175     0.357     0.029
self-employed     0.089     0.266     0.312     0.245     0.085     0.002
temporal          0.406     0.344     0.180     0.067     0.004     0.000
```

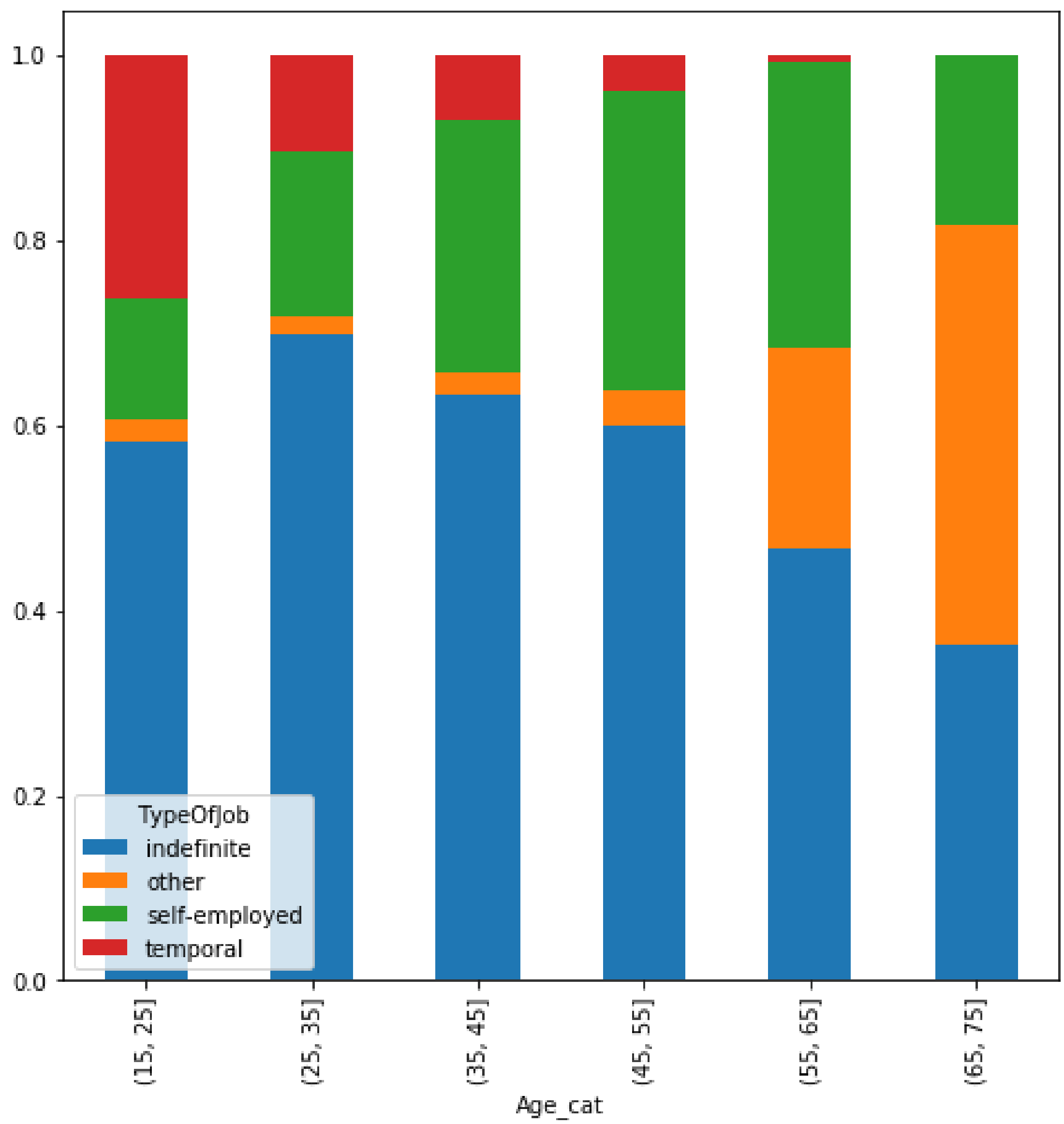
Out[59]:
```
Age_cat        (15, 25]  (25, 35]  (35, 45]  (45, 55]  (55, 65]  (65, 75]
TypeOfJob
```

indefinite	0.584	0.698	0.633	0.599	0.468	0.364
other	0.024	0.019	0.026	0.039	0.216	0.455
self-employed	0.130	0.180	0.272	0.323	0.309	0.182
temporal	0.262	0.103	0.069	0.039	0.007	0.000

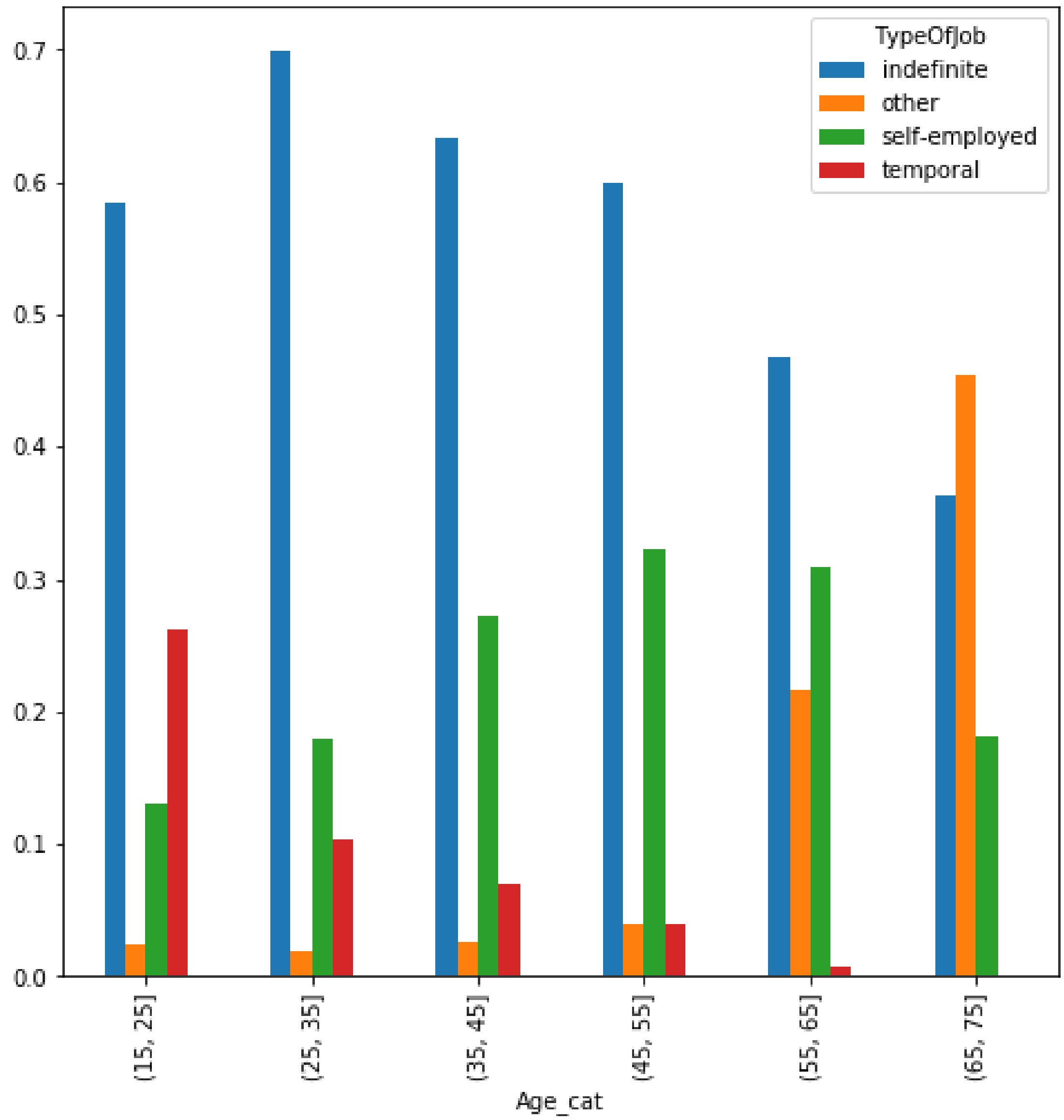
In [60]:
```
# basic stacked bar chart
TypeOfJob_Age.T.plot.bar(stacked=True, figsize=(8,8));
```



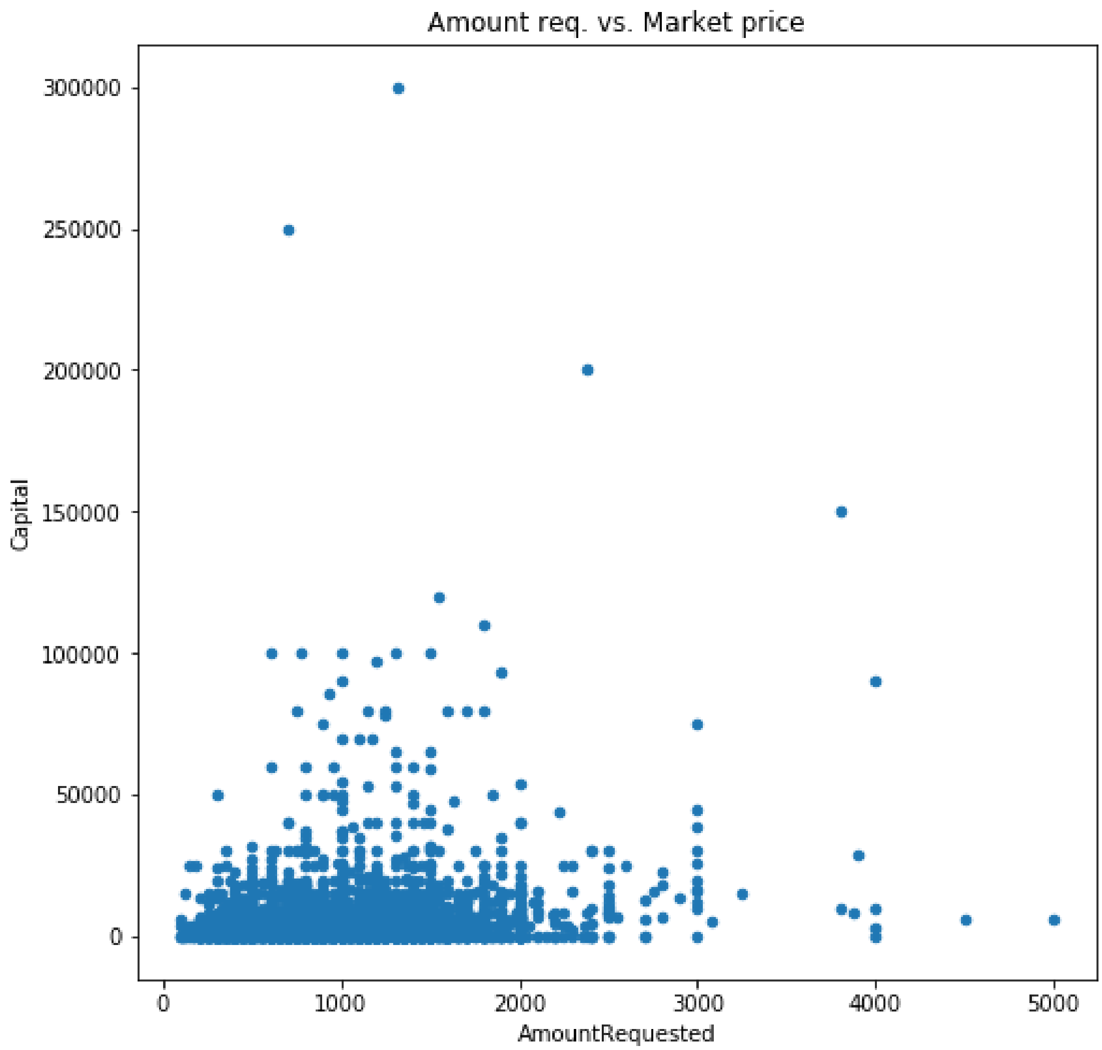
In [61]:
```
pd.crosstab(Credit_new.TypeOfJob,
            Credit_new.Age_cat,
            normalize="columns").T.plot.bar(stacked=True, figsize=(8,8));
```



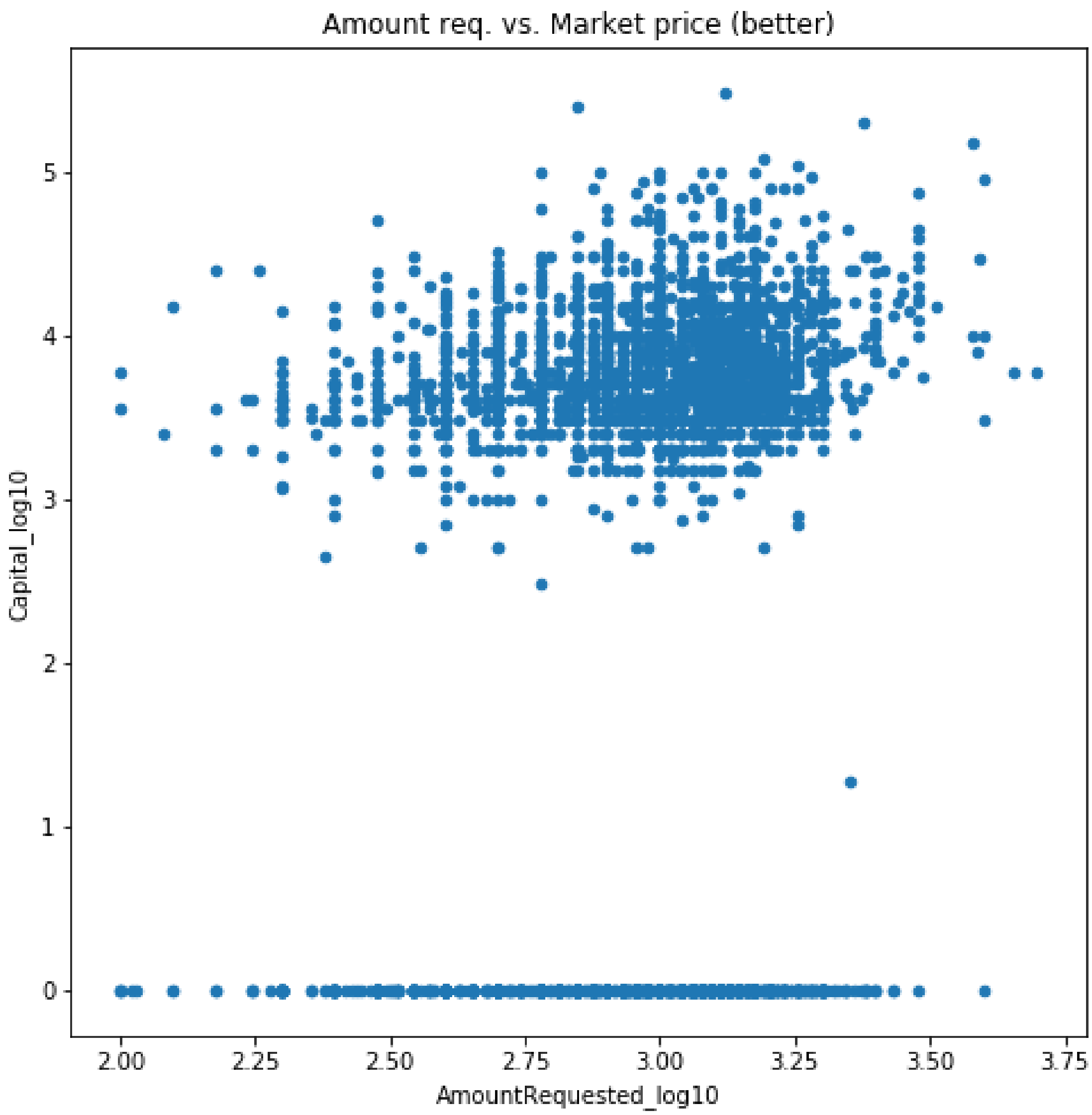
In [62]:
```
# grouped bar chart
pd.crosstab(Credit_new.TypeOfJob,
            Credit_new.Age_cat,
            normalize="columns").T.plot.bar(figsize=(8,8));
```




```
In [63]: Credit_new.plot.scatter(y='Capital',
                                 x='AmountRequested',
                                 figsize=(8,8),
                                 title='Amount req. vs. Market price');
```



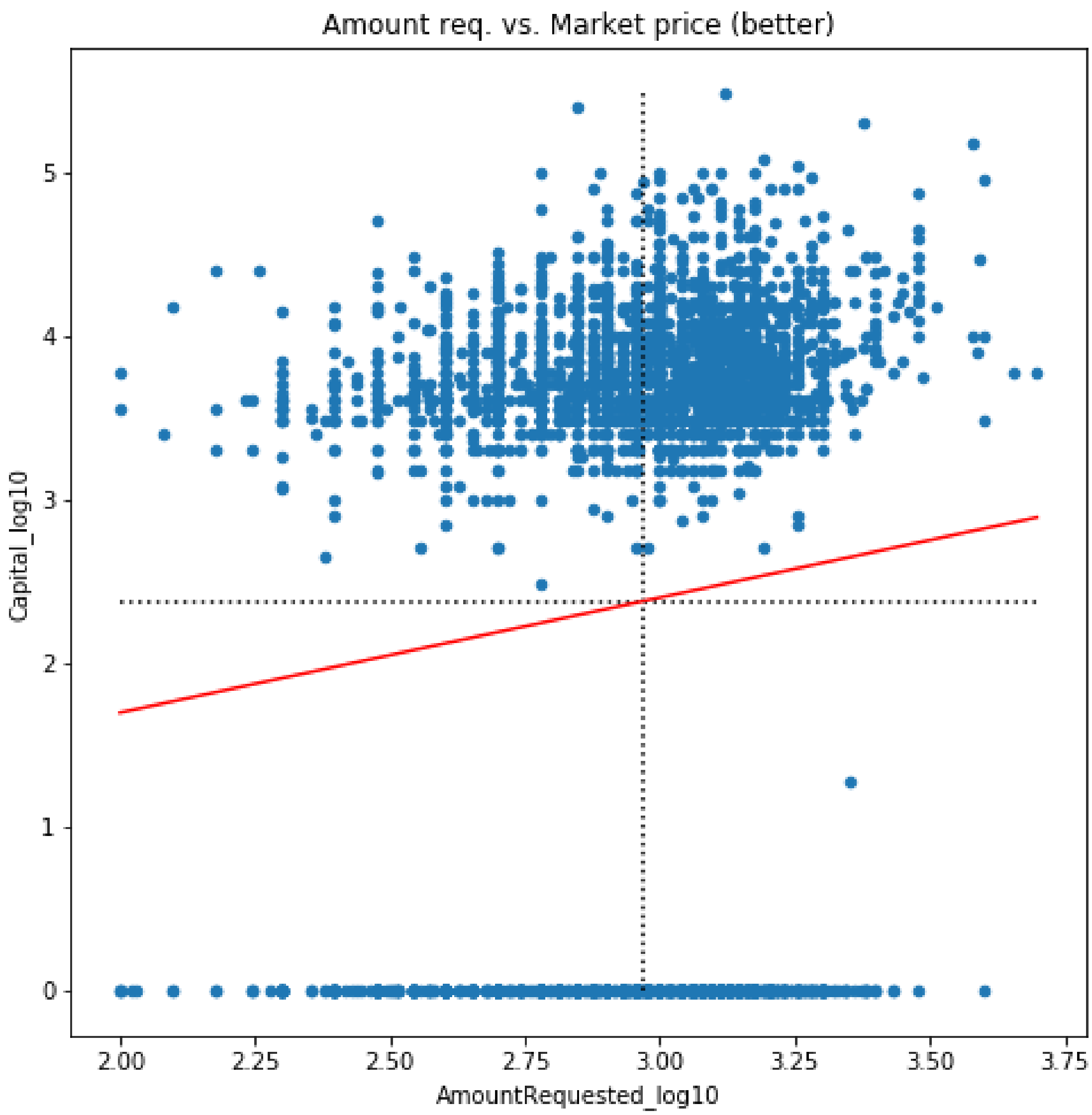
In [64]:
```
Credit_new['Capital_log10'] = (Credit_new.Capital+1).apply(np.log10)
Credit_new['AmountRequested_log10'] = (Credit_new.AmountRequested).apply(np.log10)
Credit_new.plot.scatter(y='Capital_log10',
                        x='AmountRequested_log10',
                        figsize=(8,8),
                        title='Amount req. vs. Market price (better)');
```



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

```
In [65]: model = GLM.from_formula('Capital_log10 ~ AmountRequested_log10', Credit_new)
         result = model.fit()

         Credit_new.plot.scatter(y='Capital_log10',
                                 x='AmountRequested_log10',
                                 figsize=(8,8))
         plt.title('Amount req. vs. Market price (better)');
         plt.plot([Credit_new.AmountRequested_log10.mean()]*2,
                  [Credit_new.Capital_log10.min(),
                   Credit_new.Capital_log10.max()],
                  'k:');
         plt.plot([Credit_new.AmountRequested_log10.min(),
```

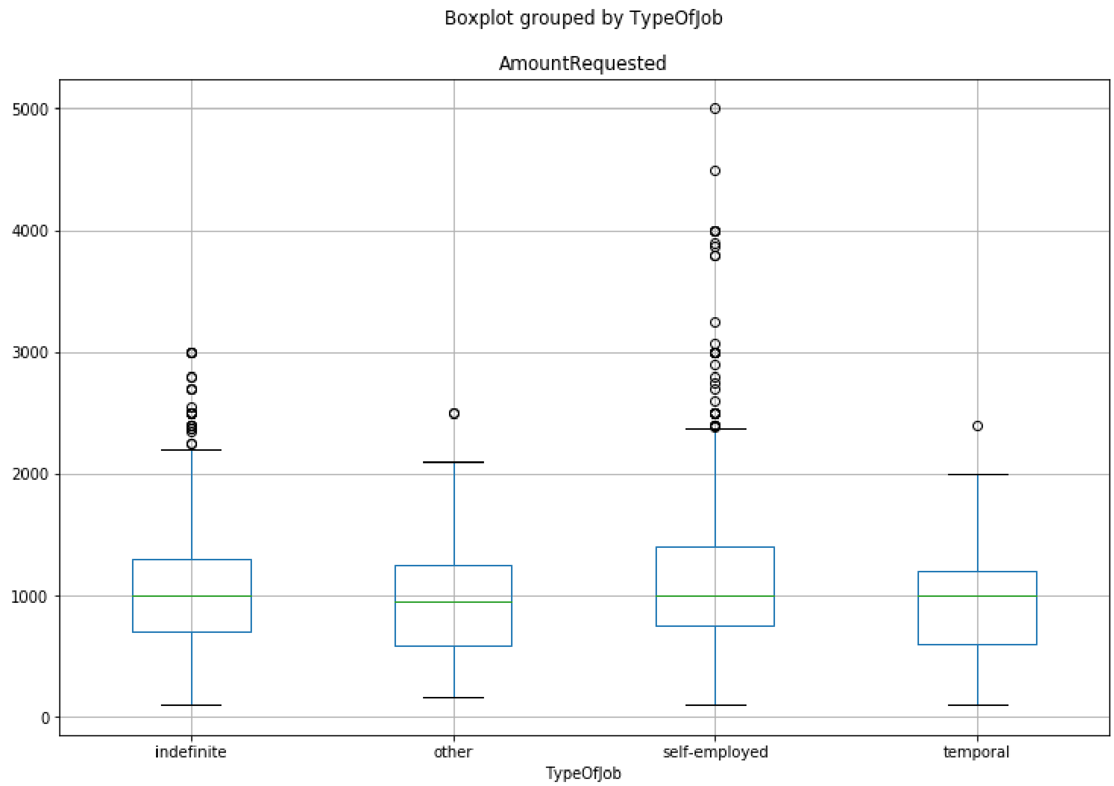
```
               Credit_new.AmountRequested_log10.max()],
              [Credit_new.Capital_log10.mean()]*2,
              'k:');
plt.plot(np.linspace(Credit_new.AmountRequested_log10.min(),
                     Credit_new.AmountRequested_log10.max(),
                     num=30),
         result.params.Intercept+
         result.params.AmountRequested_log10*
         np.linspace(Credit_new.AmountRequested_log10.min(),
                     Credit_new.AmountRequested_log10.max(),num=30),'r');
```



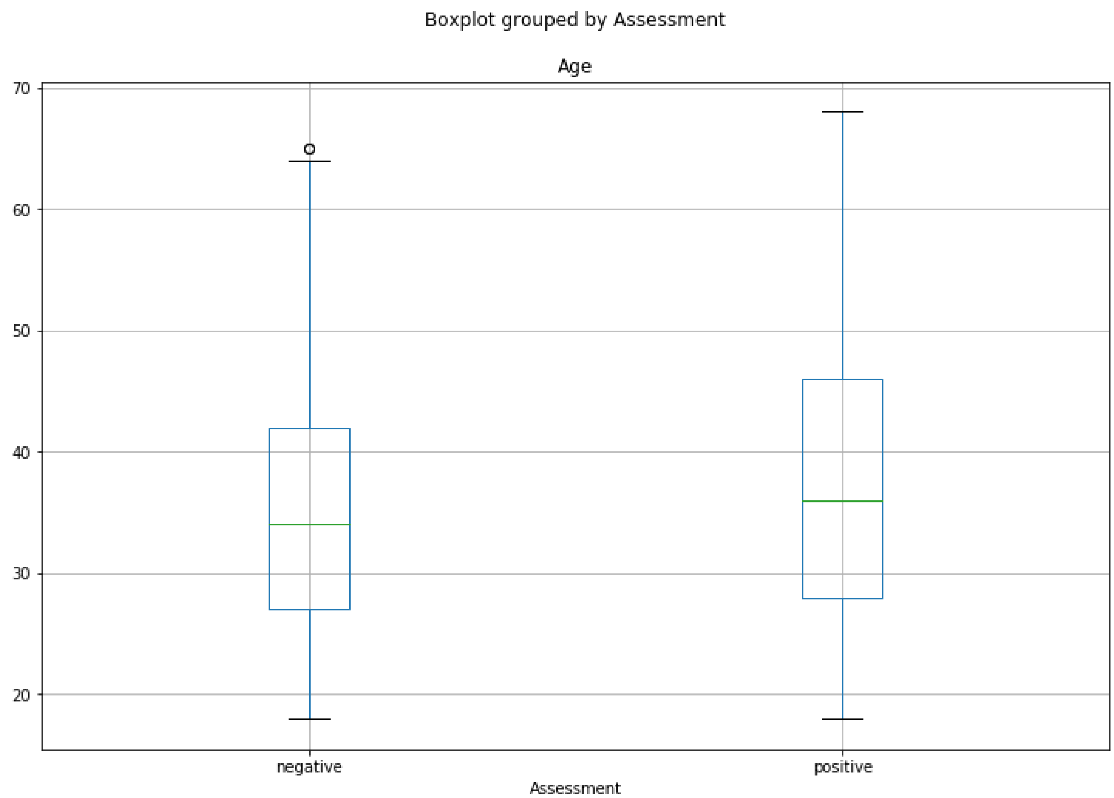
(note that log10(x+1)=0 for x=0, so our transformation keeps the zeros)

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

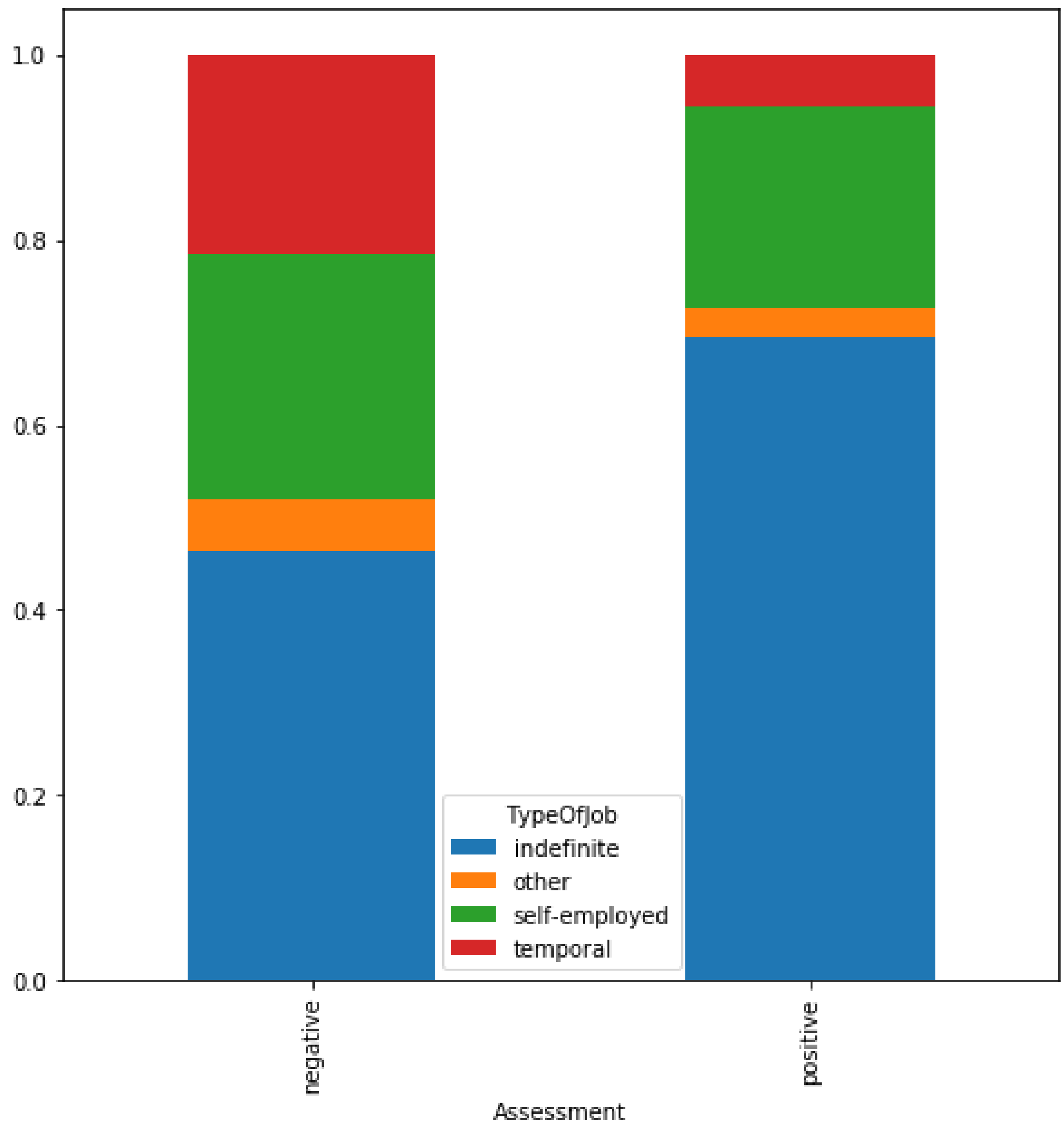
```
In [66]: Credit_new.boxplot(column='AmountRequested',
                            by='TypeOfJob',
                            figsize=(12,8));
```



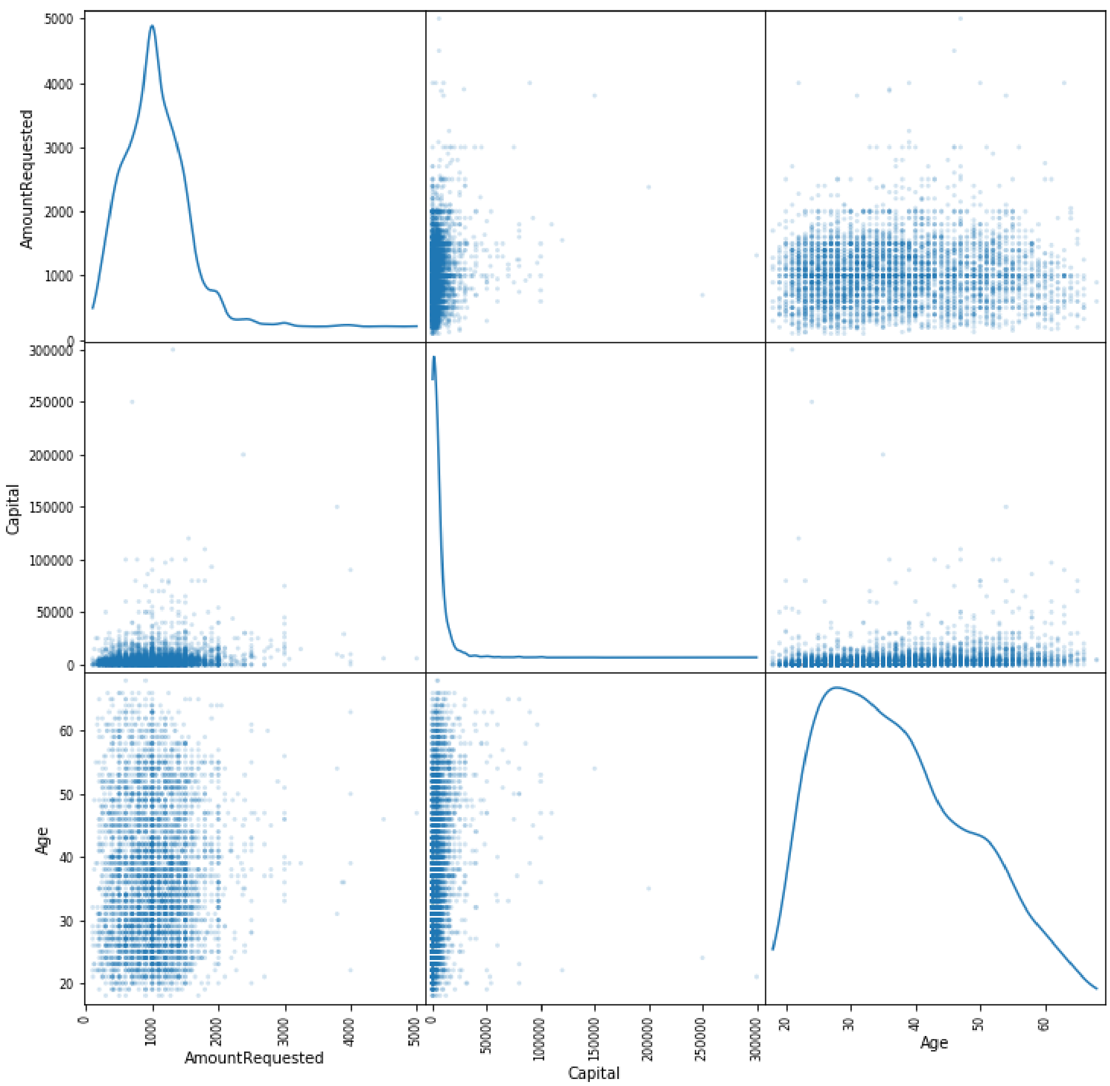

```
In [67]: Credit_new.boxplot(column='Age',
                            by='Assessment',
                            figsize=(12,8));
```



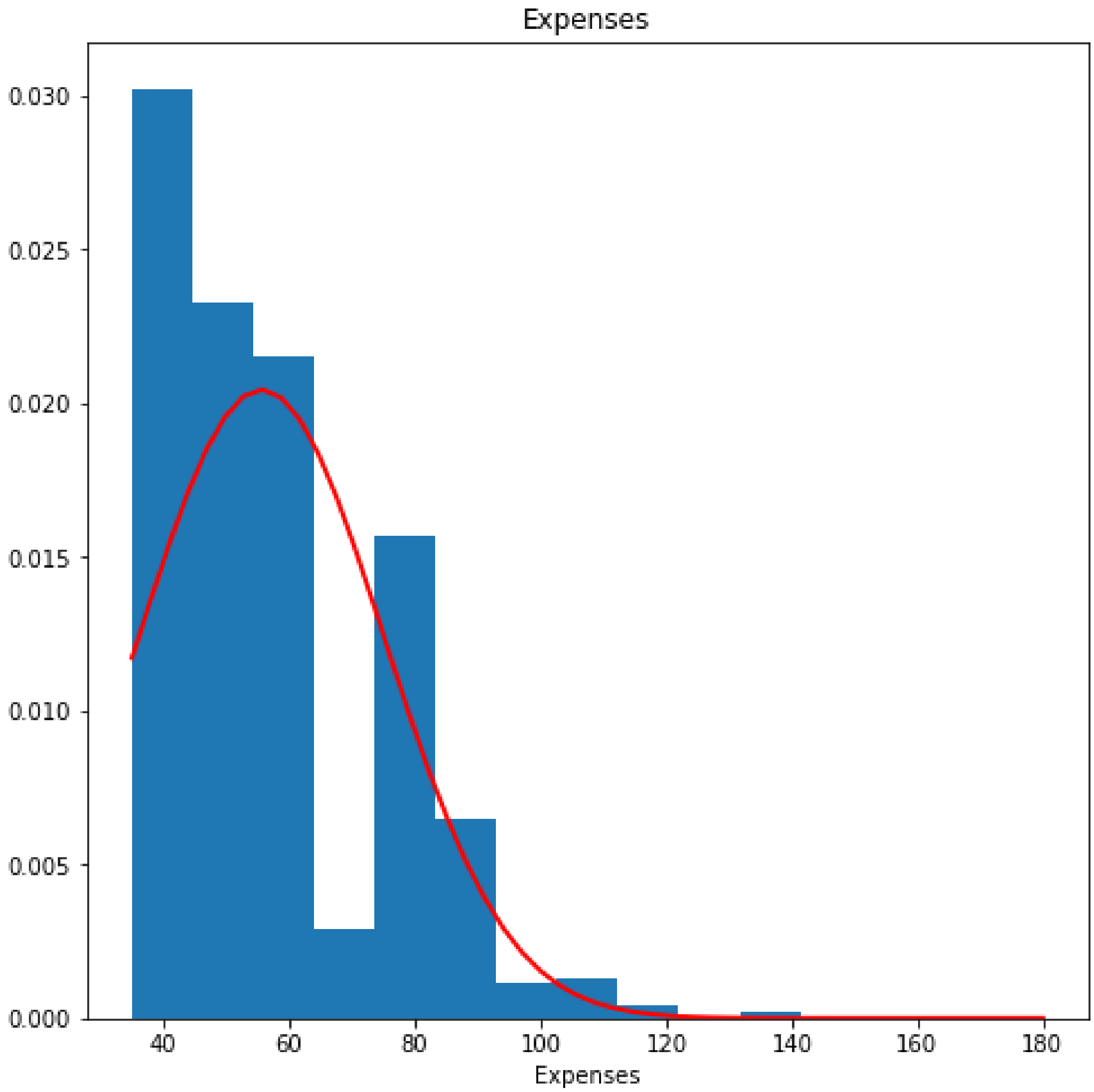

```
In [68]: pd.crosstab(Credit_new.TypeOfJob,
                     Credit_new.Assessment,
                     normalize="columns").T.plot.bar(stacked=True,
                                                      figsize=(8,8));
```



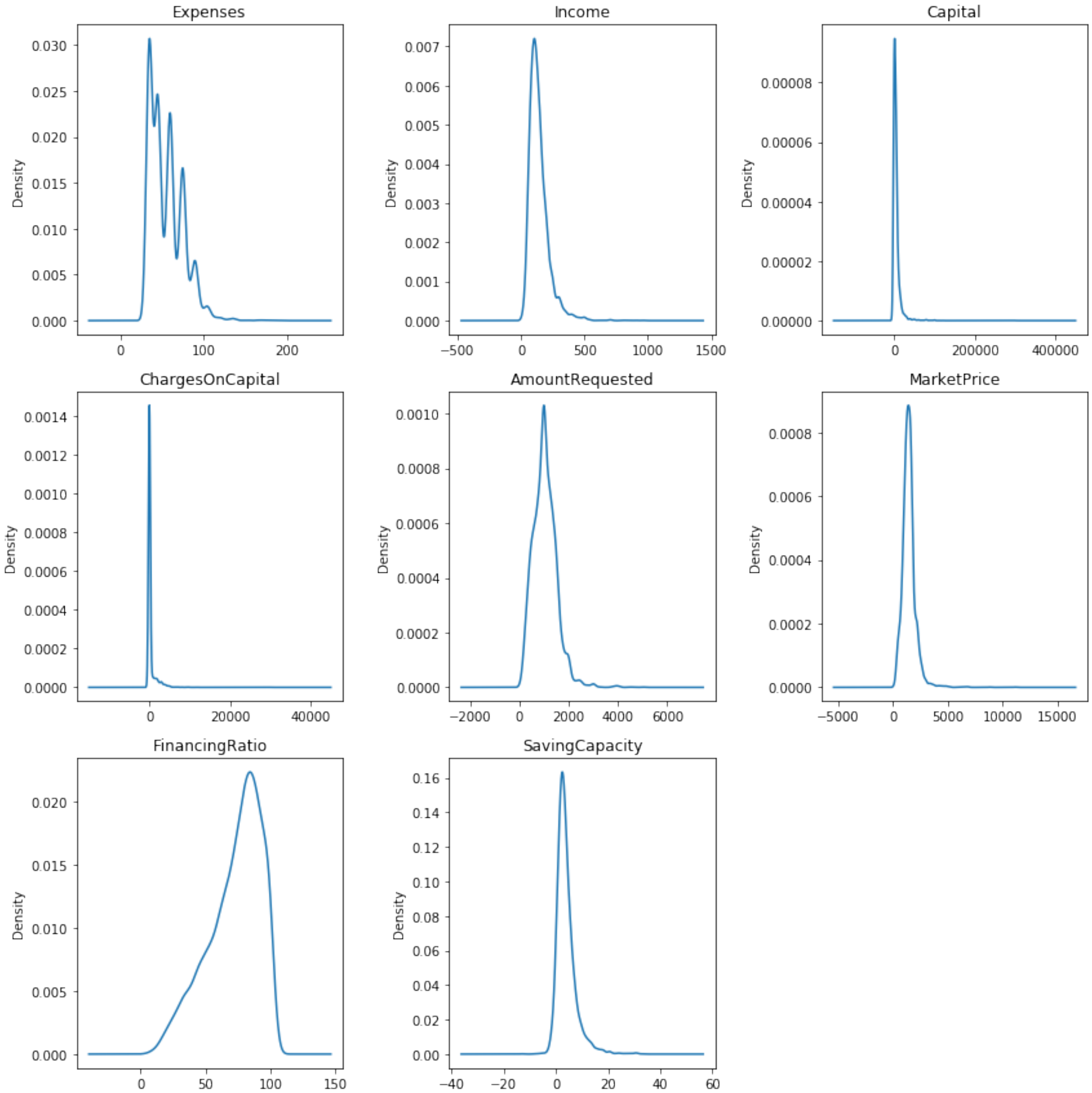

```
In [69]: scatter_matrix(Credit_new.loc[:,['AmountRequested','Capital','Age']],
                        alpha=0.2, figsize=(12, 12),
                        diagonal='kde', marker='.');
```



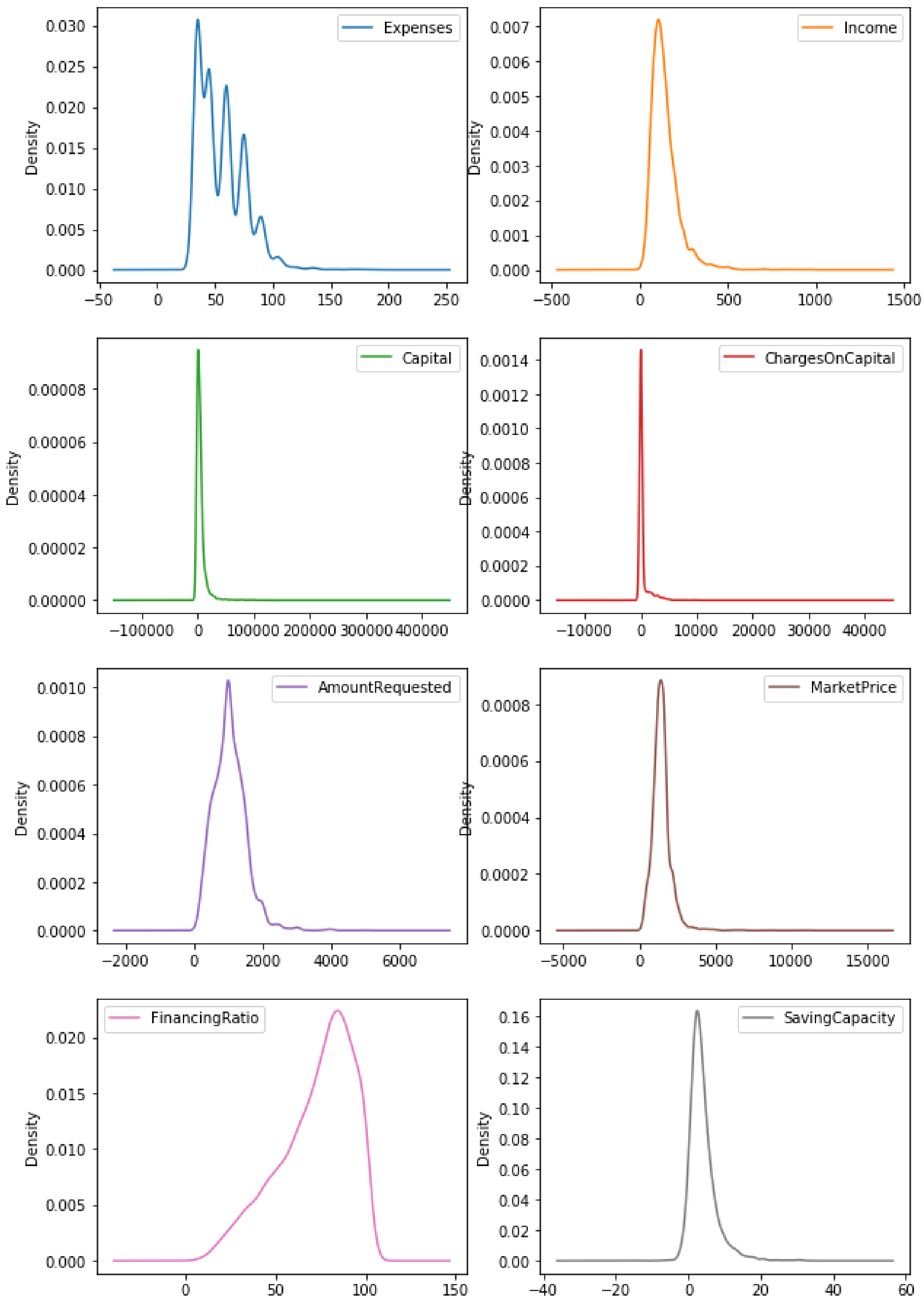

```
In [70]: sigma=  Credit_new.Expenses.std()
         mu=  Credit_new.Expenses.mean()
         fig, ax = plt.subplots(figsize=(8,8))
         count, bins, ignored = plt.hist(Credit_new.Expenses, 15, density=True)
         dbins = np.linspace(bins[0], bins[-1])
         plt.title("Expenses")
         ax.set_xlabel("Expenses")
         plt.plot(dbins, 1/(sigma * np.sqrt(2 * np.pi)) *
                         np.exp( - (dbins - mu)**2 / (2 * sigma**2) ),
                  linewidth=2, color='r');
```




```
In [71]: fig = plt.figure(figsize=(12,12))
         for i in range(8):
             ax = fig.add_subplot(3, 3, i+1)
             Credit_new[Credit.columns[i+8]].plot.kde()
             plt.title(Credit.columns[i+8])
         fig.tight_layout();
```




```
In [72]: Credit_new.loc[:,'Expenses':'SavingCapacity'].plot.kde(subplots=True,
                                                          layout=(4,2),
                                                          sharex=False,
                                                          figsize=(10,16));
```

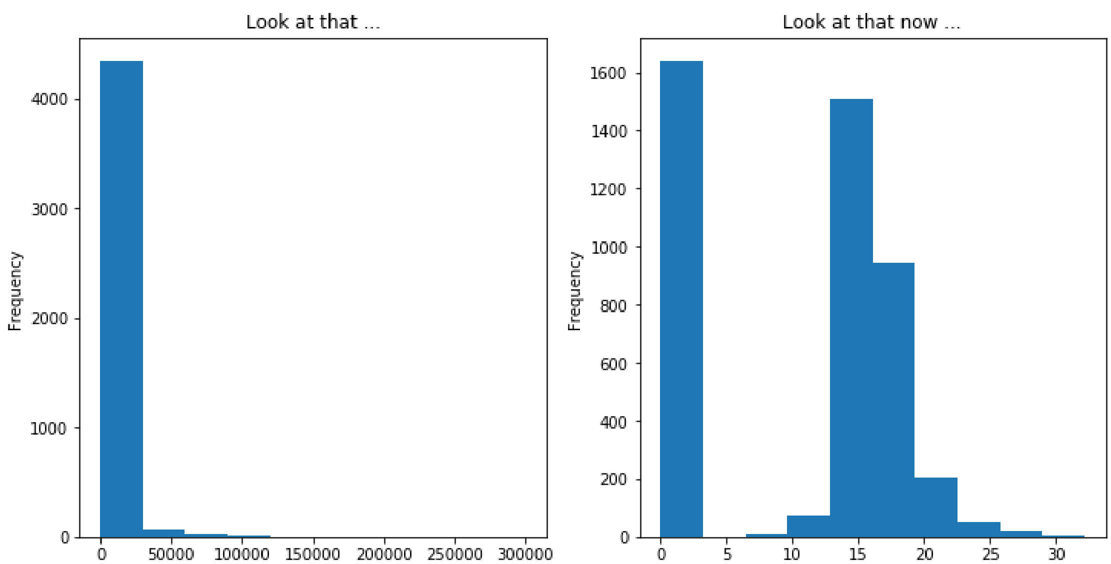


do any of the continuous variables "look" Gaussian? features to look for in comparing to a

Gaussian: outliers, asymmetries, long tails

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

```
In [73]: fig = plt.figure(figsize=(12,6))
         ax = fig.add_subplot(1, 2, 1)
         Credit_new.Capital.plot.hist(title='Look at that ...')

         # the boxcox function transforms the data using
         # the power transformation (x**lambda -1)/ lambda
         # the function takes care of finding the optimal lambda
         x, _= boxcox(Credit_new.Capital+1)

         Credit_new['Capital_BC'] = x
         ax = fig.add_subplot(1, 2, 2)
         Credit_new.Capital_BC.plot.hist(title='Look at that now ...');
```



1.8 SECTION 8: ENDING THE PREPROCESSING

Shuffle the data (to avoid possible ordering biases)

```
In [74]: np.random.seed(144)
         Credit_new = Credit_new.sample(frac=1).reset_index(drop=True)
```

Save the preprocessed data into a file for future use

Pandas allows to save the data in a lot of different formats as you can see here among others CSV, pickle, HDF5, JSON, Excel as well as other data storages like SQL databases, Google Big Query, parquet or feather.

The simplest way is to save the data as a csv with `to_csv` or as a pickle file (native python store format) with `to_pickle`, this last one allows also to compress the data.

```
In [75]: Credit_new.to_pickle('Credsco-processed.pkl.bz2',compression='bz2')

In [76]: Credit_load =pd.read_pickle('Credsco-processed.pkl.bz2',compression='bz2')
         Credit_load.head()

Out[76]:   Assessment  YearsInJob  Housing  Deadline  Age MaritalStatus Records  \
         0   negative           5    other        60   33        single      no
         1   positive           5    owner        48   43       married      no
         2   negative           2  parents        36   21        single      no
         3   positive           7    owner        36   33       married      no
         4   negative           8     rent        60   25       married     yes

               TypeOfJob  Expenses  Income     ...      AmountRequested  MarketPrice  \
         0    indefinite        35    57.0     ...                 1000         1415
         1  self-employed       45   145.0     ...                  680         1350
         2  self-employed       35   221.0     ...                  500          650
         3    indefinite        45   208.0     ...                  500         1288
         4    indefinite        73   280.0     ...                  600         1364

            FinancingRatio  SavingCapacity  Dubious   Age_cat Age2_cat Capital_log10  \
         0          70.671           1.320       No  (25, 35]  under55         0.000
         1          50.370           7.059       No  (35, 45]  under55         3.699
         2          76.923          13.392       No  (15, 25]  under55         0.000
         3          38.820          11.736       No  (25, 35]  under55         3.602
         4          43.988          20.700       No  (15, 25]  under55         0.000

           AmountRequested_log10  Capital_BC
         0                 3.000       0.000
         1                 2.833      15.660
         2                 2.699       0.000
         3                 2.699      14.989
         4                 2.778       0.000

         [5 rows x 22 columns]
```