APA-L0-python

September 6, 2018

1 APA Laboratori 0 - Data preprocessing

```
In [78]: # Uncomment to upgrade packages
         # !pip install pandas --upgrade
         # !pip install numpy --upgrade
         # !pip install scipy --upgrade
         # !pip install statsmodels --upgrade
         %load_ext autoreload
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_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 [79]: #%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 [80]: # 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 [81]: Credit = read_csv("credsco.csv", header=0, delimiter=',')
         Credit.shape
```

```
Out[81]: (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 [82]: Credit.columns
```

```
Out[82]: 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 [83]: Credit[:4].style.hide_index()
```

```
Out[83]: <pandas.io.formats.style.Styler at 0x7f30b0917748>
```

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

```
In [84]: Credit.iloc[0,4:8]
```

```
Out[84]: Age              30
         MaritalStatus     2
         Records           1
         TypeOfJob         3
         Name: 0, dtype: int64
```

Alternatively you can use the variable names

```
In [85]: Credit.loc[0,'Age':'TypeOfJob']
```

```
Out[85]: 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 [86]: Credit.describe()
```

```
Out[86]:        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 [87]: Credit_complete = Credit.dropna()
         Credit_complete.shape
```

```
Out[87]: (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 [88]: (Credit.Assessment==0).value_counts()
         (Credit.Housing==0).value_counts()
         (Credit.MaritalStatus==0).value_counts()
         (Credit.TypeOfJob==0).value_counts()
```

```
Out[88]: False    4454
         True        1
         Name: Assessment, dtype: int64
```

```
Out[88]: False    4449
         True        6
         Name: Housing, dtype: int64
```

```
Out[88]: False    4454
         True        1
         Name: MaritalStatus, dtype: int64
```

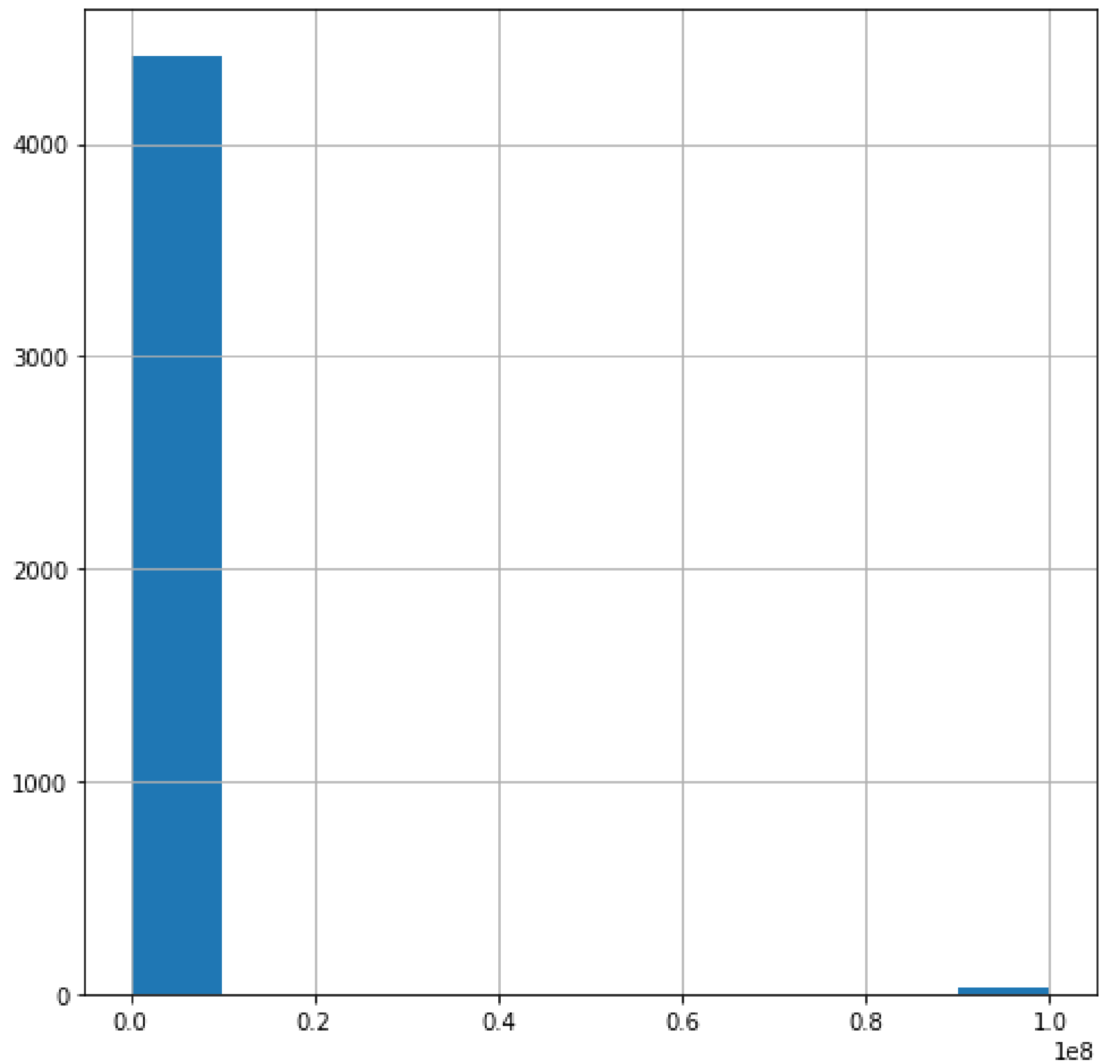
Out[88]: False   4453
True   2
Name: TypeOfJob, dtype: int64

```
In [89]: Credit=  Credit[(Credit.Assessment!=0) & (Credit.Housing!=0)
                        &(Credit.MaritalStatus!=0)&(Credit.TypeOfJob!=0)]
         Credit.shape
```

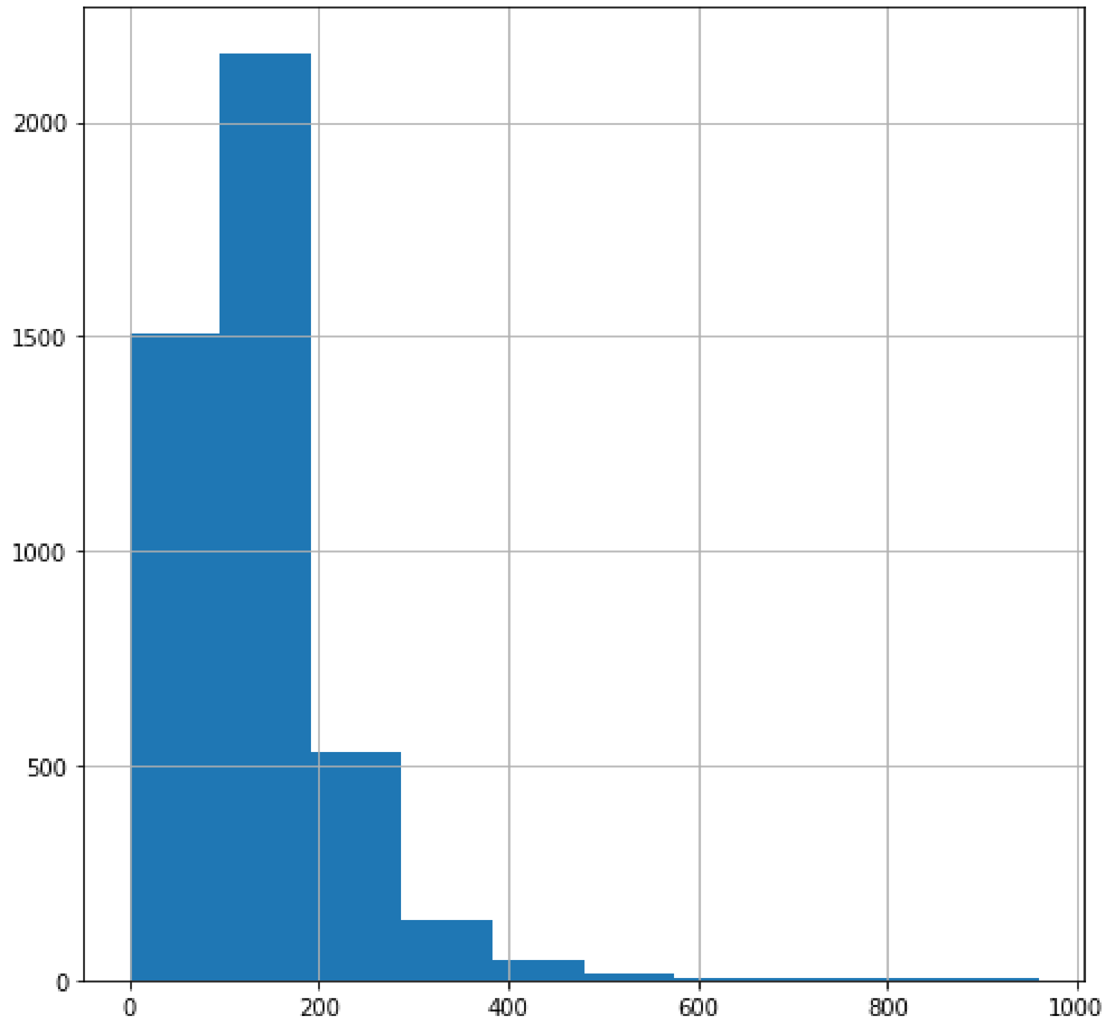
Out[89]: (4446, 14)

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

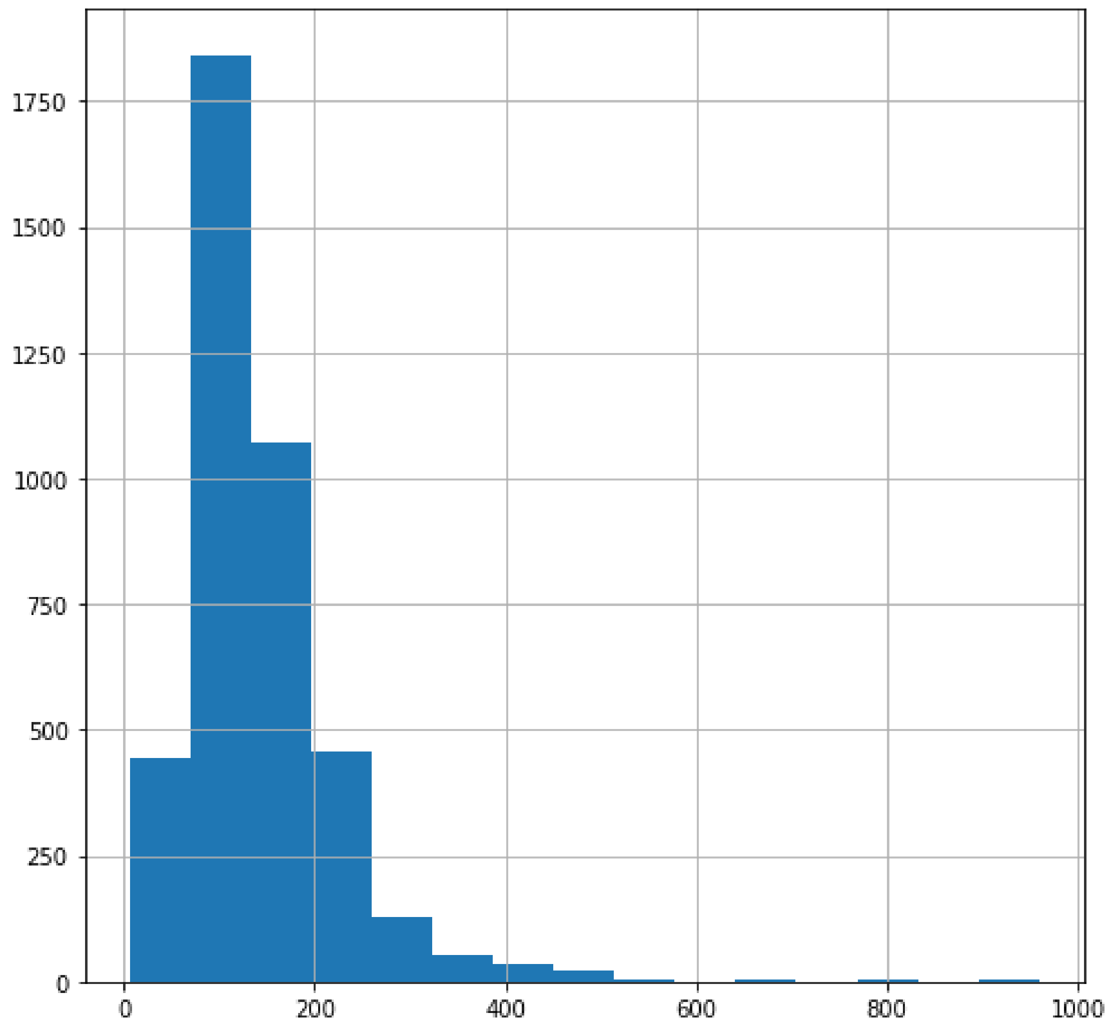
```
In [90]: Credit.Income.hist(figsize=(8,8));
```



```
In [91]: Credit.Income[Credit.Income!=99999999].hist(figsize=(8,8));
```




```
In [92]: Credit.Income[(Credit.Income!=99999999)&
                        (Credit.Income!=0)].hist(bins=15,figsize=(8,8));
```



these are then clearly incorrect

```
In [93]: (Credit.Income==99999999).value_counts()
         (Credit.Income==0).value_counts()
         (Credit.Capital==99999999).value_counts()
         (Credit.ChargesOnCapital==99999999).value_counts()

Out[93]: False    4415
         True       31
         Name: Income, dtype: int64

Out[93]: False    4100
         True      346
         Name: Income, dtype: int64

Out[93]: False    4405
         True       41
         Name: Capital, dtype: int64
```

```
Out[93]: False    4434
         True       12
         Name: ChargesOnCapital, dtype: int64
```

```
In [94]: (Credit.Income==99999999).value_counts()
```

```
Out[94]: False    4415
         True       31
         Name: Income, dtype: int64
```

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

```
In [95]: (Credit.YearsInJob==0).value_counts()
```

```
Out[95]: 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 [96]: 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 [97]: Credit.Income.describe()
```

```
Out[97]: 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 [98]: 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[98]: (4446, 11)

Out[98]: (4039, 11)

Out[98]: (377, 11)
```

Neither of aux1, aux2 can contain NAs

```
In [99]: 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 [100]: aux2 = aux[Credit.Capital.isna()]

In [101]: 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 [102]: aux2 = aux[Credit.ChargesOnCapital.isna()]

In [103]: 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 [104]: 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 [105]:
```
Credit.shape
Credit.describe()
```

Out[105]:
```
(4446, 14)
```

Out[105]:

	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 [106]: Credit.dtypes
```

```
Out[106]: 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 [107]: # 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[107]: array([1, 2], dtype=object)

Out[107]: array([1, 2, 5, 3, 6, 4], dtype=object)

Out[107]: array([2, 3, 1, 4, 5], dtype=object)

Out[107]: array([1, 2], dtype=object)

Out[107]: array([3, 1, 2, 4], dtype=object)
```

not very nice, right? let's recode

```
In [108]: 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)
```

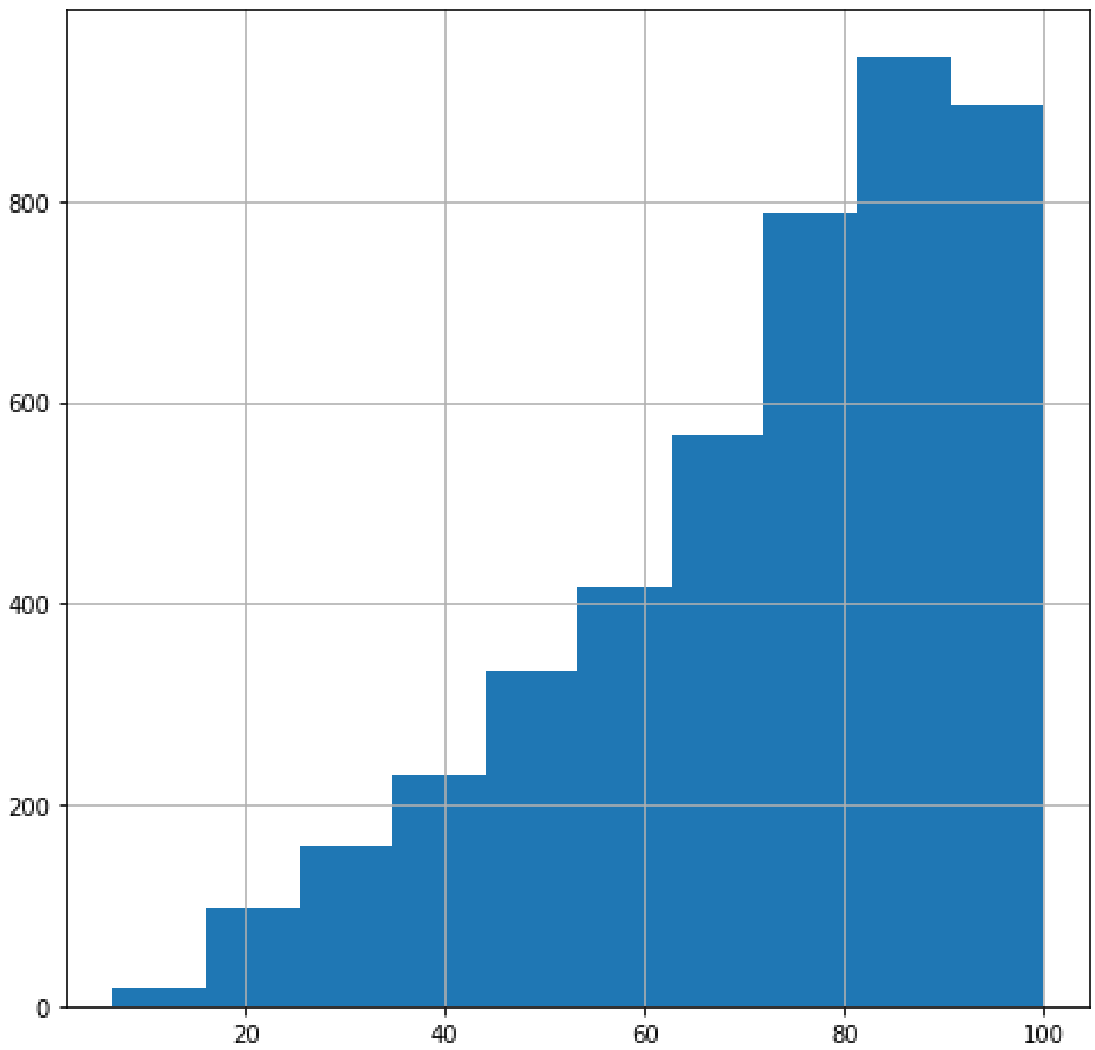
```
Credit.MaritalStatus.replace([1,2,3,4,5],
                             ["single","married","widower","split","divorced"],
                             inplace=True)
Credit.Records.replace([1, 2],
                       ["no","yes"], inplace=True)
Credit.TypeOfJob.replace([1,2,3,4],
             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

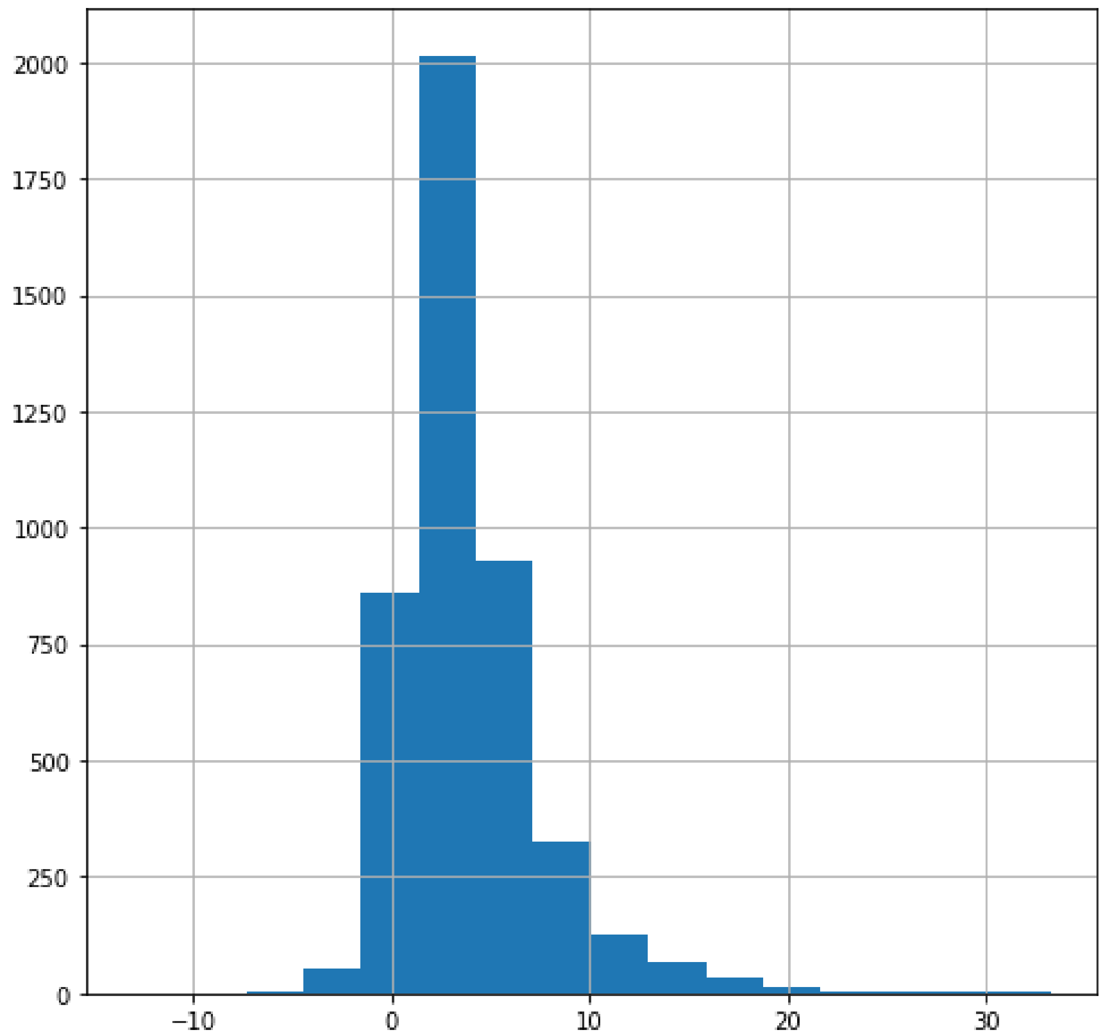
Financing ratio (continuous)

```
In [109]: Credit['FinancingRatio'] = 100*Credit.AmountRequested/Credit.MarketPrice
          Credit.FinancingRatio.hist(figsize=(8,8));
```



Saving capacity (continuous)

```
In [110]: Credit['SavingCapacity'] = (Credit.Income- Credit.Expenses-(Credit.ChargesOnCapital/10
                                     /(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 [111]: 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[111]: 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 [112]:
```
Credit_new =Credit.copy()

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

Out[112]:

	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
```

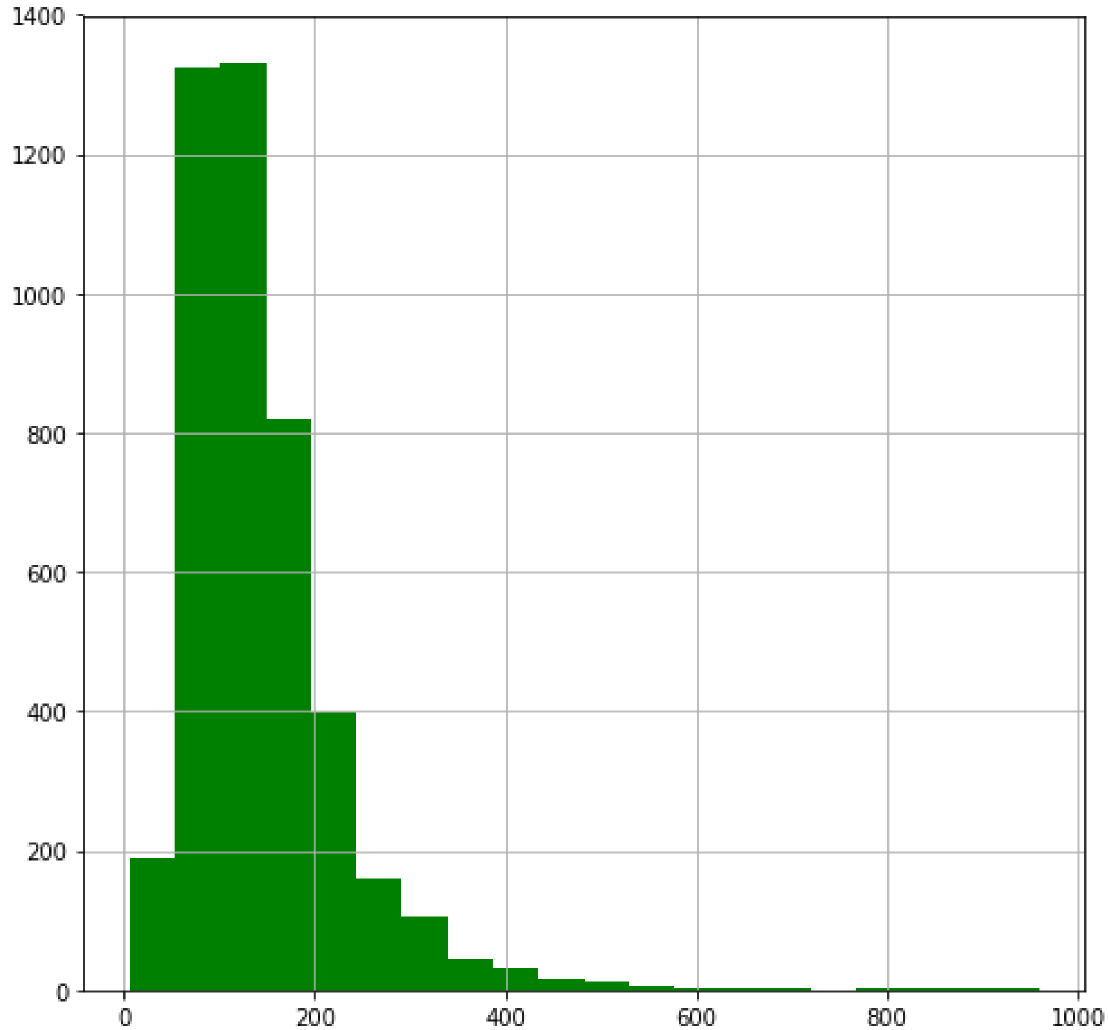
Out[112]: (4446, 17)

1.7 SECTION 7: GAUSSIANITY AND TRANSFORMATIONS

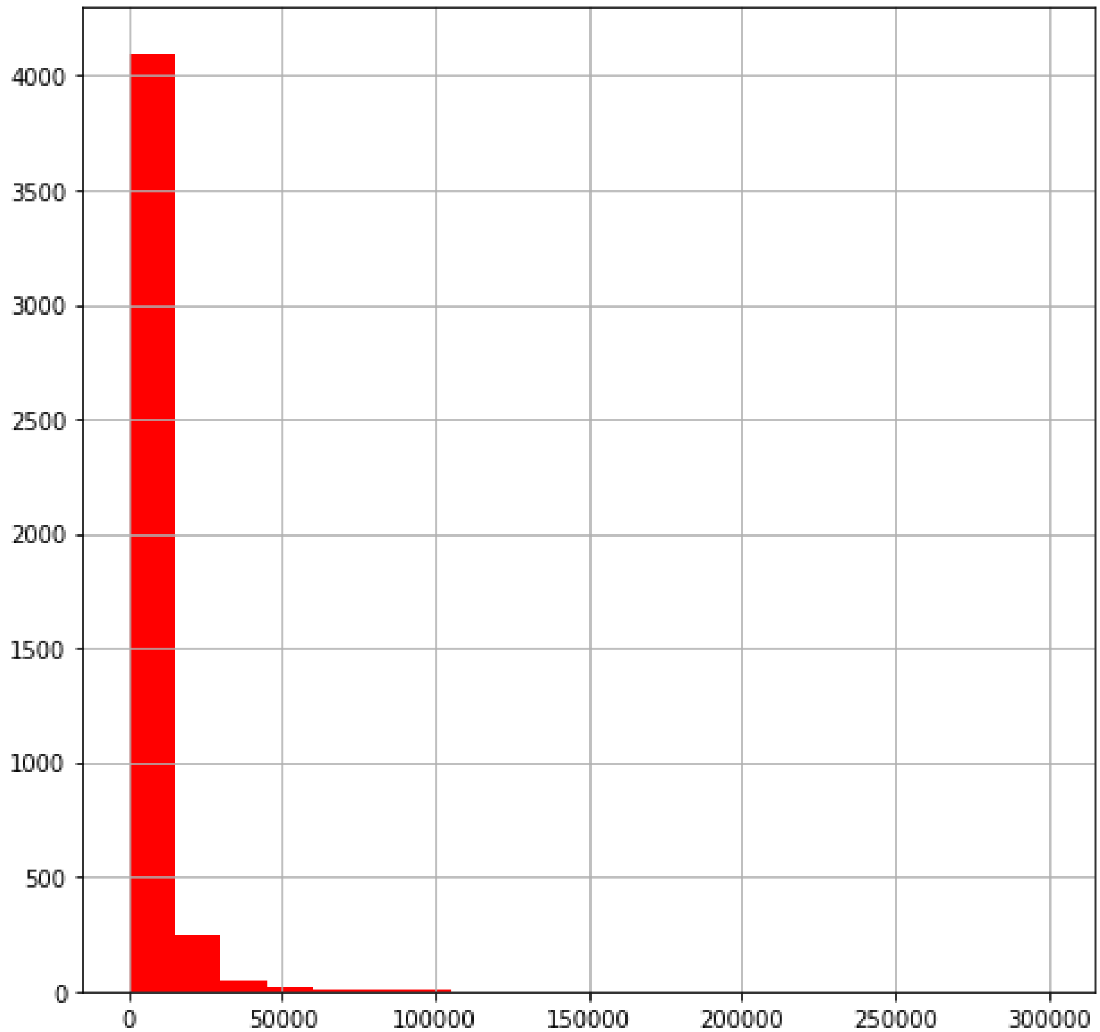
Perform a graphical summary of some of the variables (both categorical and continuous), using the boxplot() and hist() procedures

For continuous data: histograms and boxplots

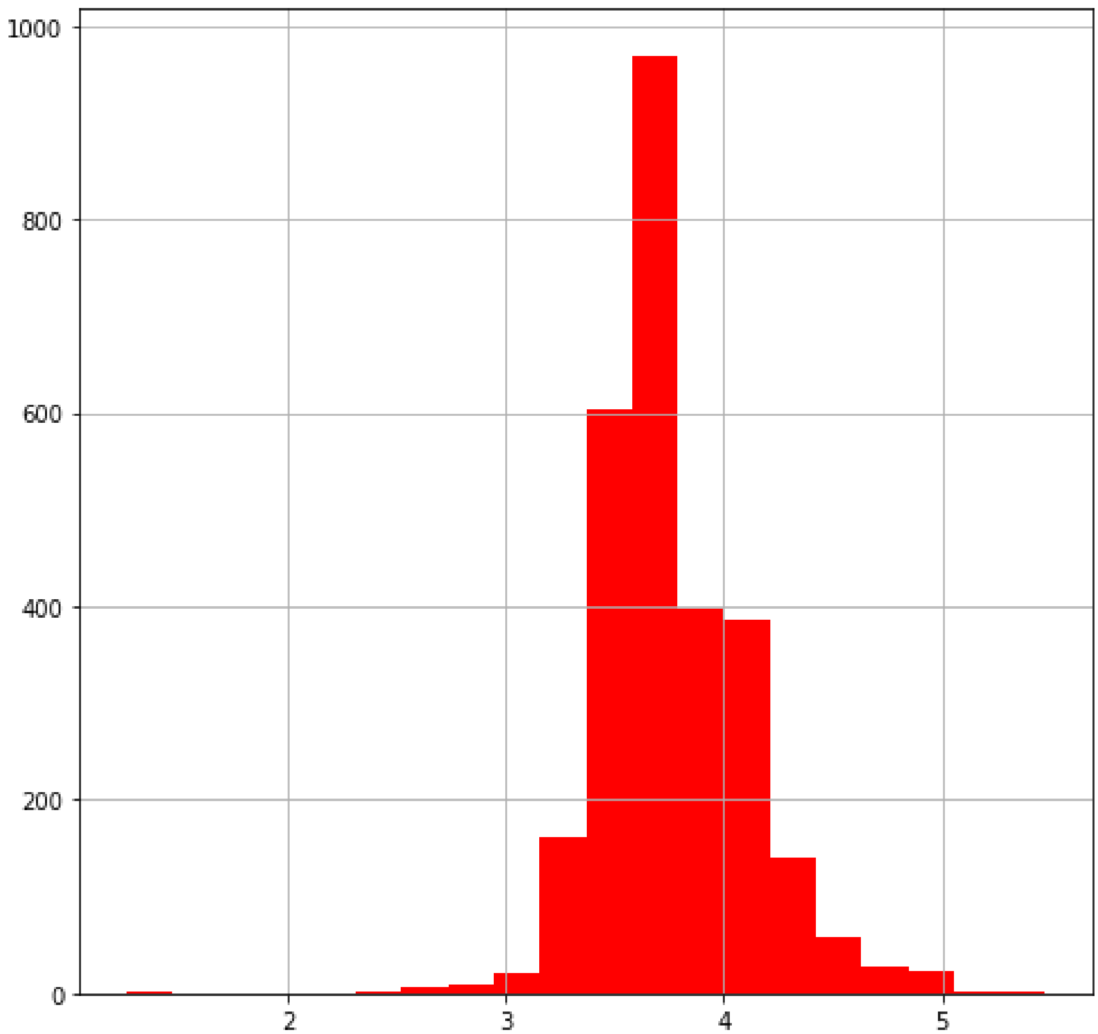
In [113]:
```
Credit_new.Income.hist(bins=20,figsize=(8,8), color='green');
```



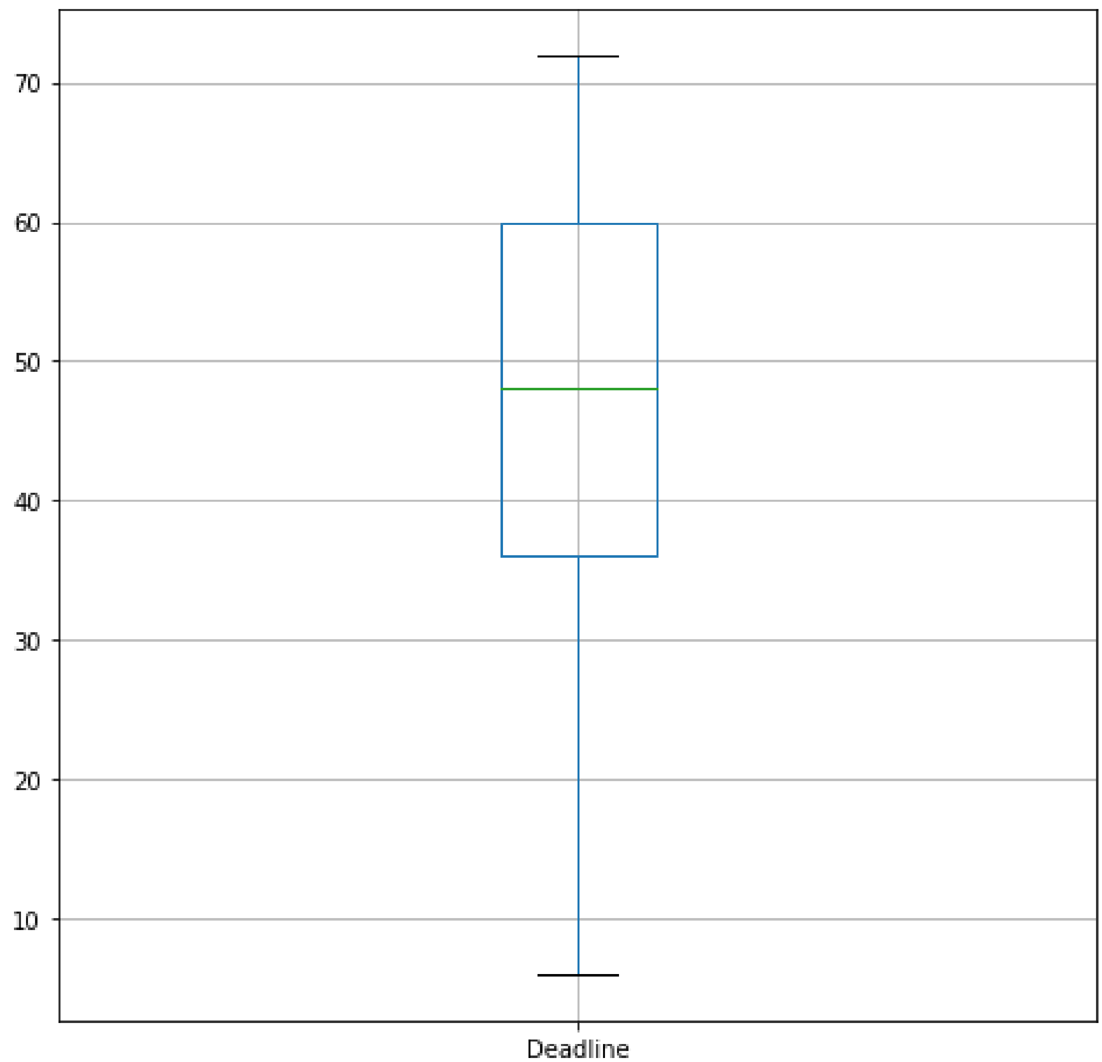
```
In [114]: Credit_new.Capital.hist(bins=20,figsize=(8,8), color='red');
```



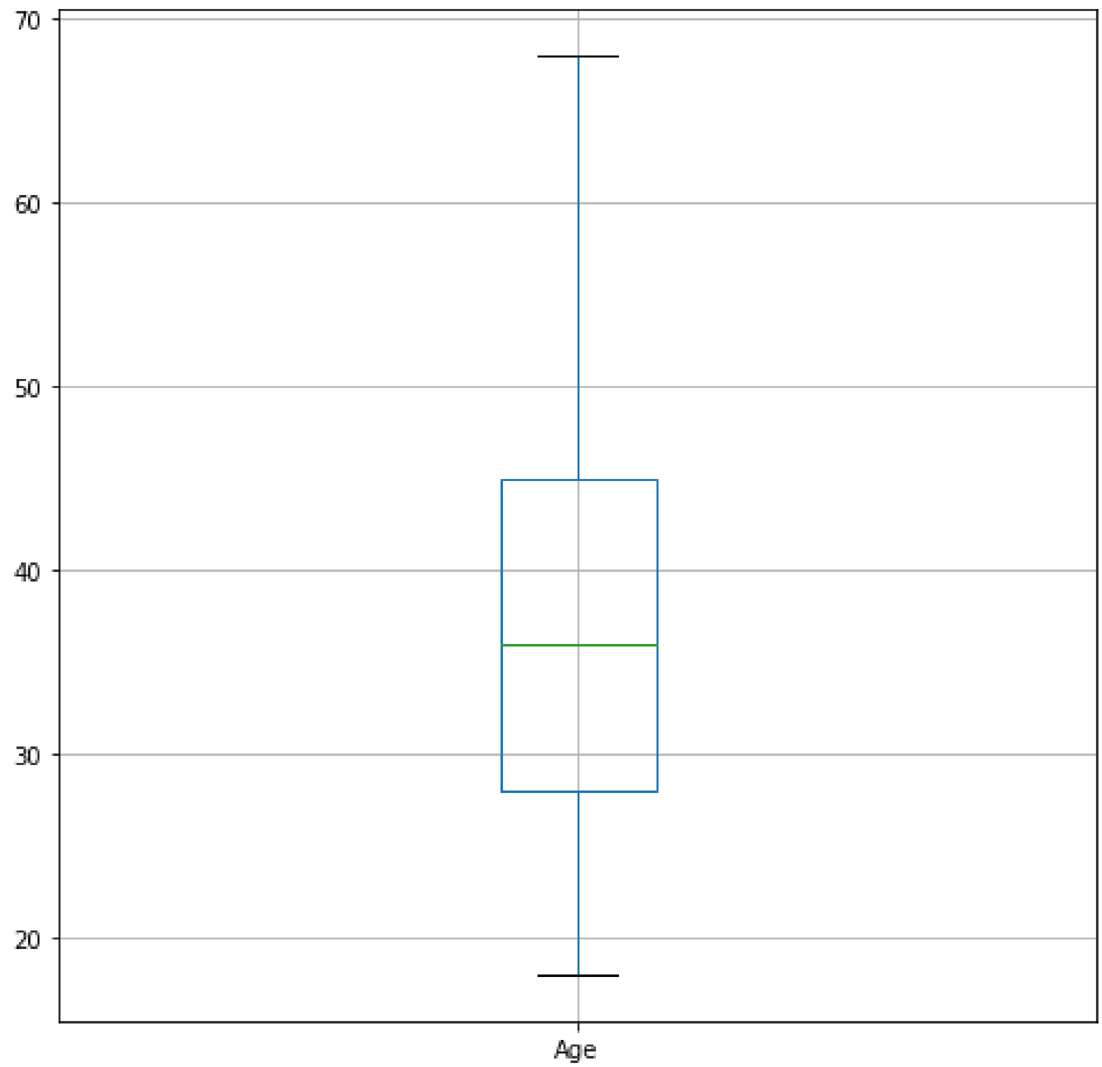

```
In [115]: pd.options.mode.use_inf_as_na = True
          Credit_new.Capital.apply(np.log10).hist(bins=20,figsize=(8,8), color='red');
```



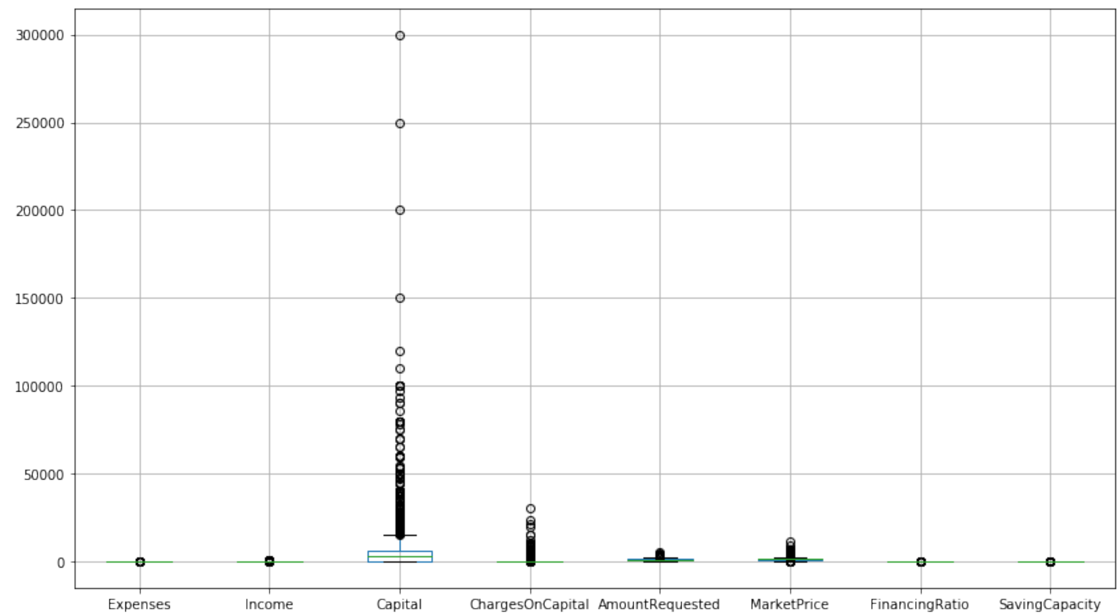

```
In [116]: Credit_new.boxplot(column='Deadline',figsize=(8,8));
```



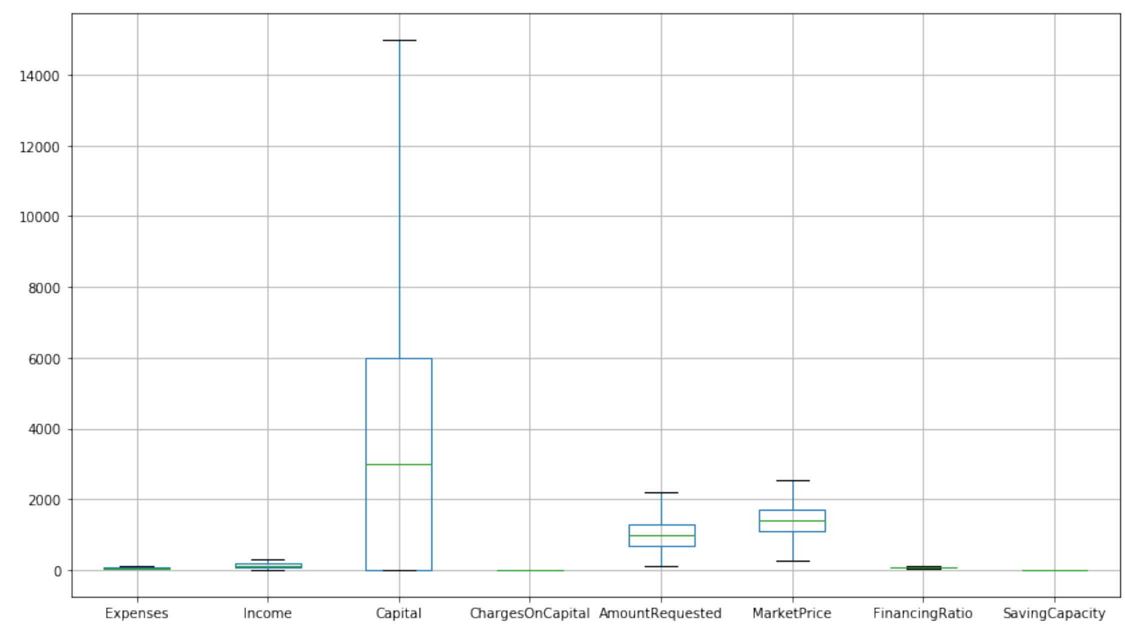

```
In [117]: Credit_new.boxplot(column='Age',figsize=(8,8));
```




```
In [118]: Credit_new.loc[:,"Expenses":"SavingCapacity"].boxplot(figsize=(14,8));
```




```
In [119]: 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 [120]:
```
Credit_new.Age.unique()
```

Out[120]:
```
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 [121]:
```
Credit_new.Age.min()
Credit_new.Age.max()
```

Out[121]:
```
18
```

Out[121]:
```
68
```

In [122]:
```
bins = pd.IntervalIndex.from_tuples([(0, 1), (2, 3), (4, 5)])
bins
```

Out[122]:
```
IntervalIndex([(0, 1], (2, 3], (4, 5]]
              closed='right',
              dtype='interval[int64]')
```

In [123]:
```
pd.interval_range(start=30, end=90,freq=10)
```

Out[123]:
```
IntervalIndex([(30, 40], (40, 50], (50, 60], (60, 70], (70, 80], (80, 90]]
              closed='right',
              dtype='interval[int64]')
```

In [124]:
```
pd.cut(Credit_new.Age,
       bins=pd.interval_range(start=30, end=90,freq=10))
# WARNING! we are generating NAs
```

Out[124]:
```
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]
```

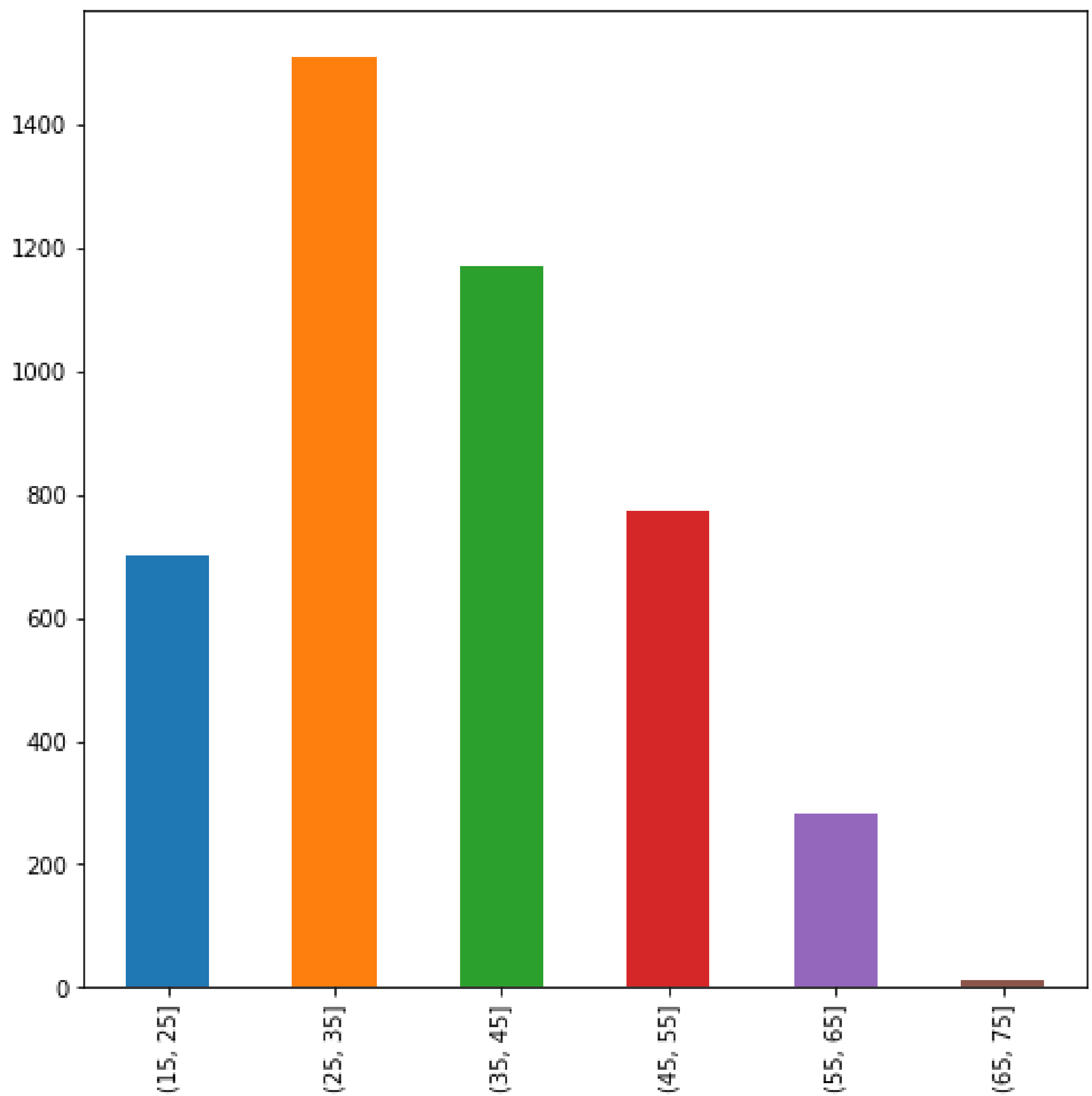
```
In [125]: Age_cut = pd.cut(Credit_new.Age,
                           bins=pd.interval_range(start=15, end=75,freq=10)) ;
```

```
In [126]: Credit_new['Age_cat'] = Age_cut.astype('str')
```

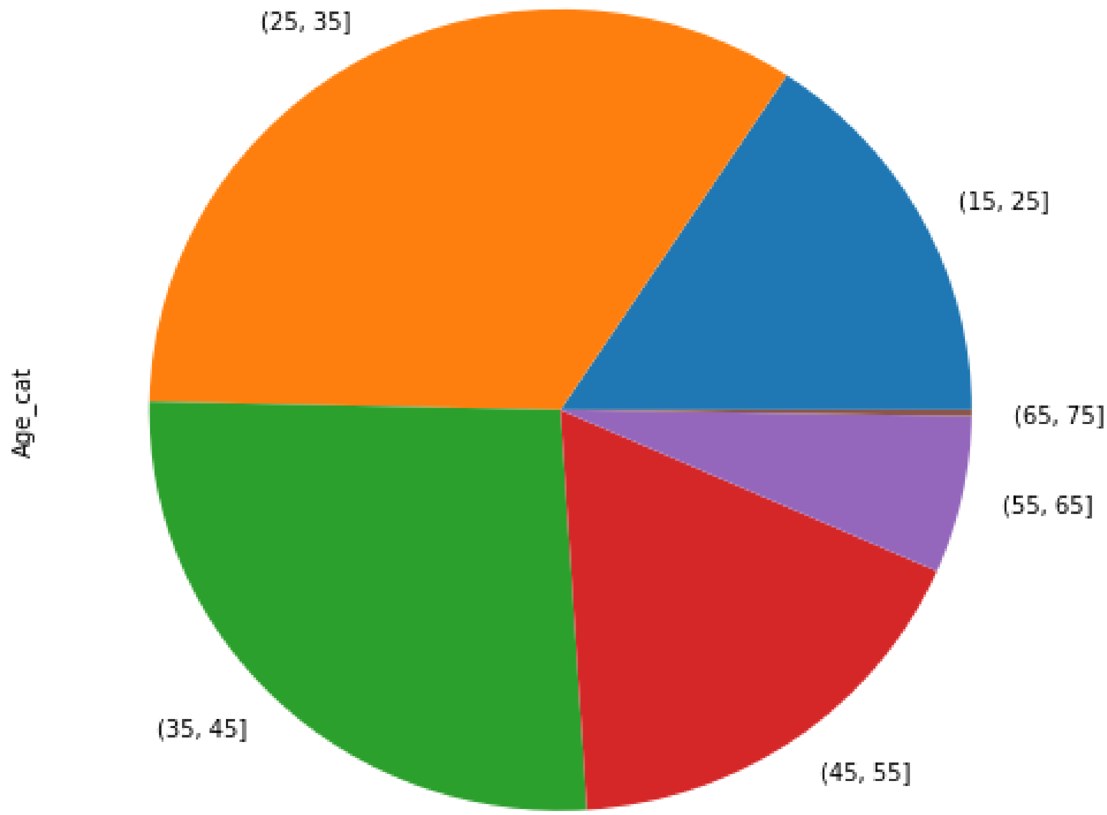
In [127]: Credit_new.Age_cat.value_counts().sort_index()

Out[127]:
```
(15, 25]      699
(25, 35]     1509
(35, 45]     1172
(45, 55]      773
(55, 65]      282
(65, 75]       11
Name: Age_cat, dtype: int64
```

In [128]:
```
Credit_new.Age_cat.value_counts().sort_index().plot.bar(figsize=(8,8));
```



In [129]:
```
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 [130]: Credit_new['Age2_cat'] = Credit_new.Age.apply(lambda x :
                                        'under55' if x < 55 else 'over55')
```

```
In [131]: TypeOfJob_Age= pd.crosstab(Credit_new.TypeOfJob, Credit_new.Age_cat)
          TypeOfJob_Age
```

Out[131]:

Age_cat TypeOfJob	(15, 25]	(25, 35]	(35, 45]	(45, 55]	(55, 65]	(65, 75]
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 [132]: TypeOfJob_Age.sum(axis=0) # row sums
          TypeOfJob_Age.sum(axis=1) # column sums
```

```
Out[132]: Age_cat
          (15, 25]     699
          (25, 35]    1509
          (35, 45]    1172
          (45, 55]     773
          (55, 65]     282
          (65, 75]      11
          dtype: int64
```

```
Out[132]: TypeOfJob
          indefinite       2803
          other             171
          self-employed    1021
          temporal          451
          dtype: int64
```

```
In [133]: pd.crosstab(Credit_new.TypeOfJob,
                      Credit_new.Age_cat,
                      normalize=True,
                      margins=True) # relative frequencies
```

```
Out[133]: 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 [134]: pd.crosstab(Credit_new.TypeOfJob,
                      Credit_new.Age_cat,
                      normalize=True,margins=True).round(decimals=3)
                      # idem, rounded to 3 digits
```

```
Out[134]: 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 [135]: (pd.crosstab(Credit_new.TypeOfJob,
                        Credit_new.Age_cat,
                        normalize=True,
                        margins=True)*100).round(decimals=3)
                        # total percentages
```

```
Out[135]: 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
```

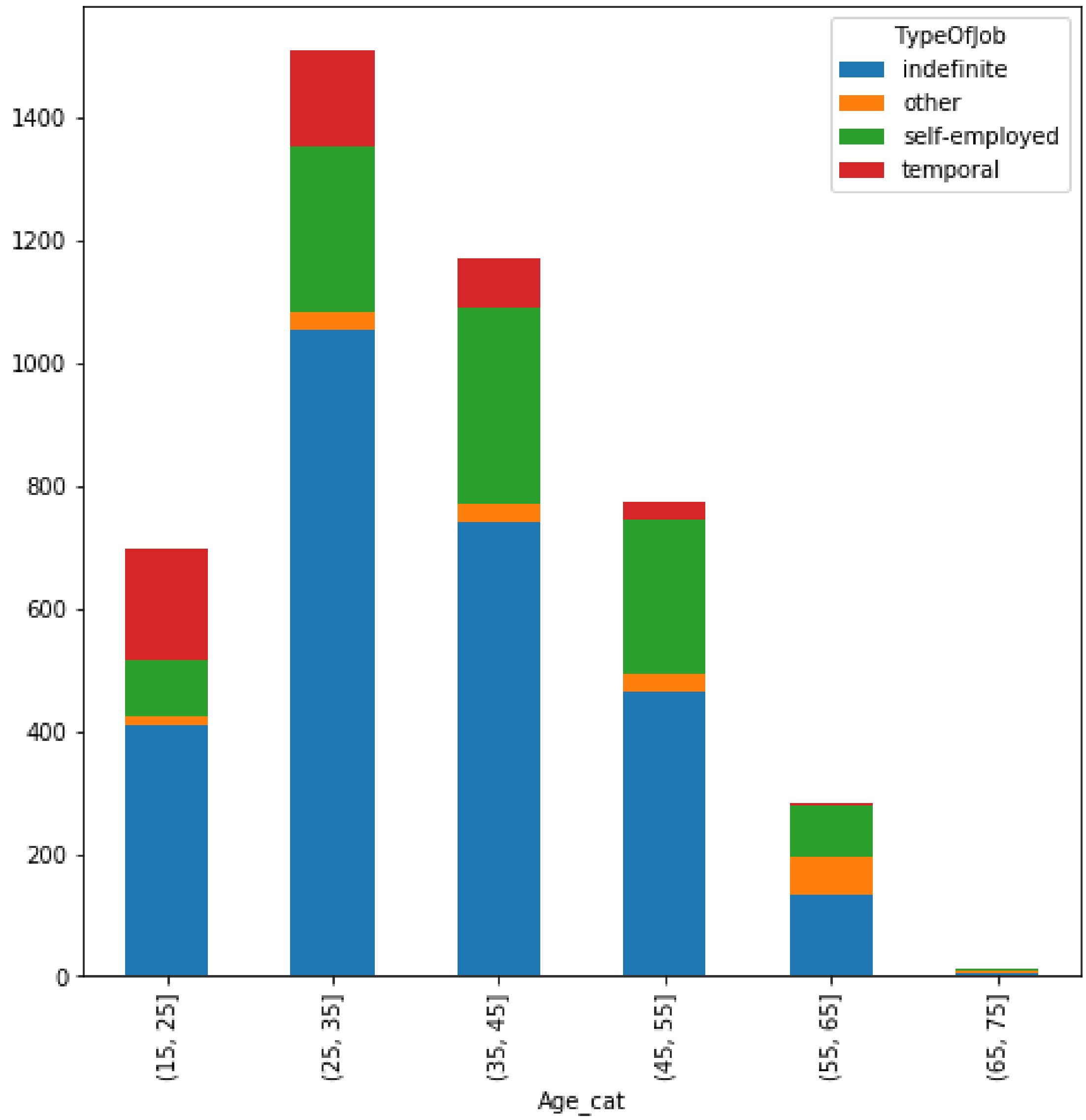
```
In [136]: pd.crosstab(Credit_new.TypeOfJob,
                      Credit_new.Age_cat,
                      normalize="index").round(decimals=3)
                      # table of relative frequencies (column-wise)
          pd.crosstab(Credit_new.TypeOfJob,
                      Credit_new.Age_cat,
                      normalize="columns").round(decimals=3)
                      # table of relative frequencies (row-wise)
```

```
Out[136]: 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
```

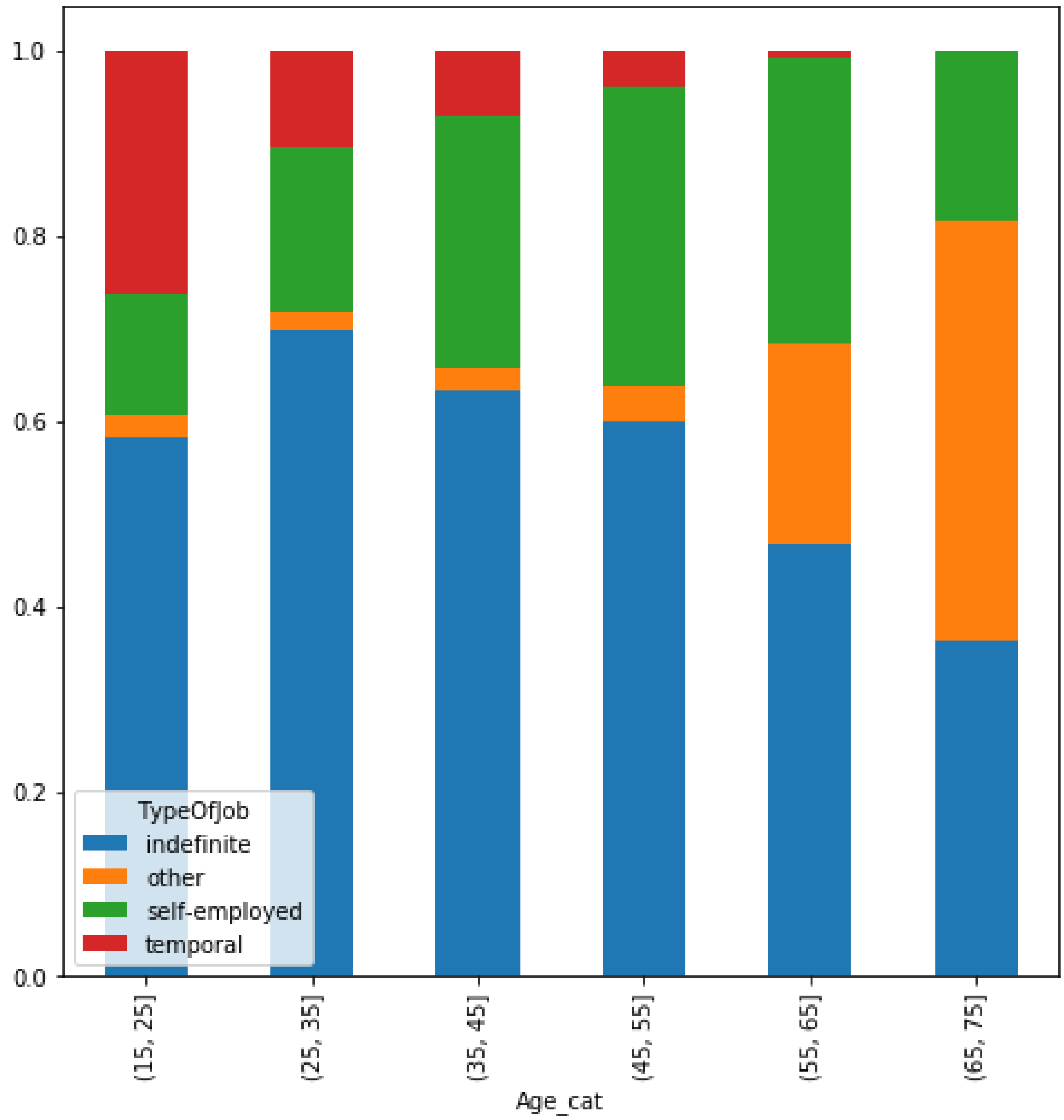
```
Out[136]: Age_cat         (15, 25]  (25, 35]  (35, 45]  (45, 55]  (55, 65]  (65, 75]
          TypeOfJob
```

```
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
```

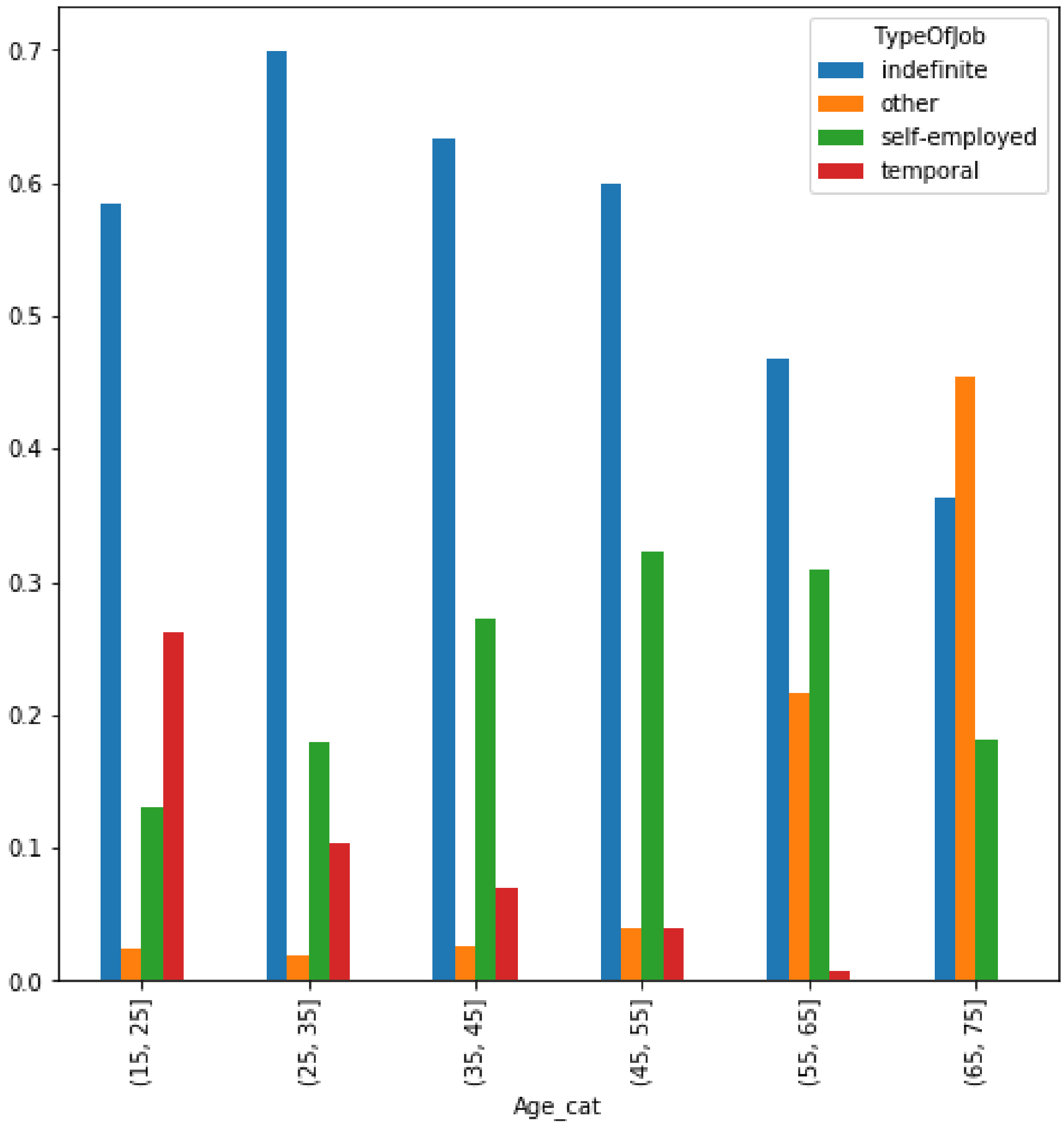
In [137]:
```
# basic stacked bar chart
TypeOfJob_Age.T.plot.bar(stacked=True, figsize=(8,8));
```



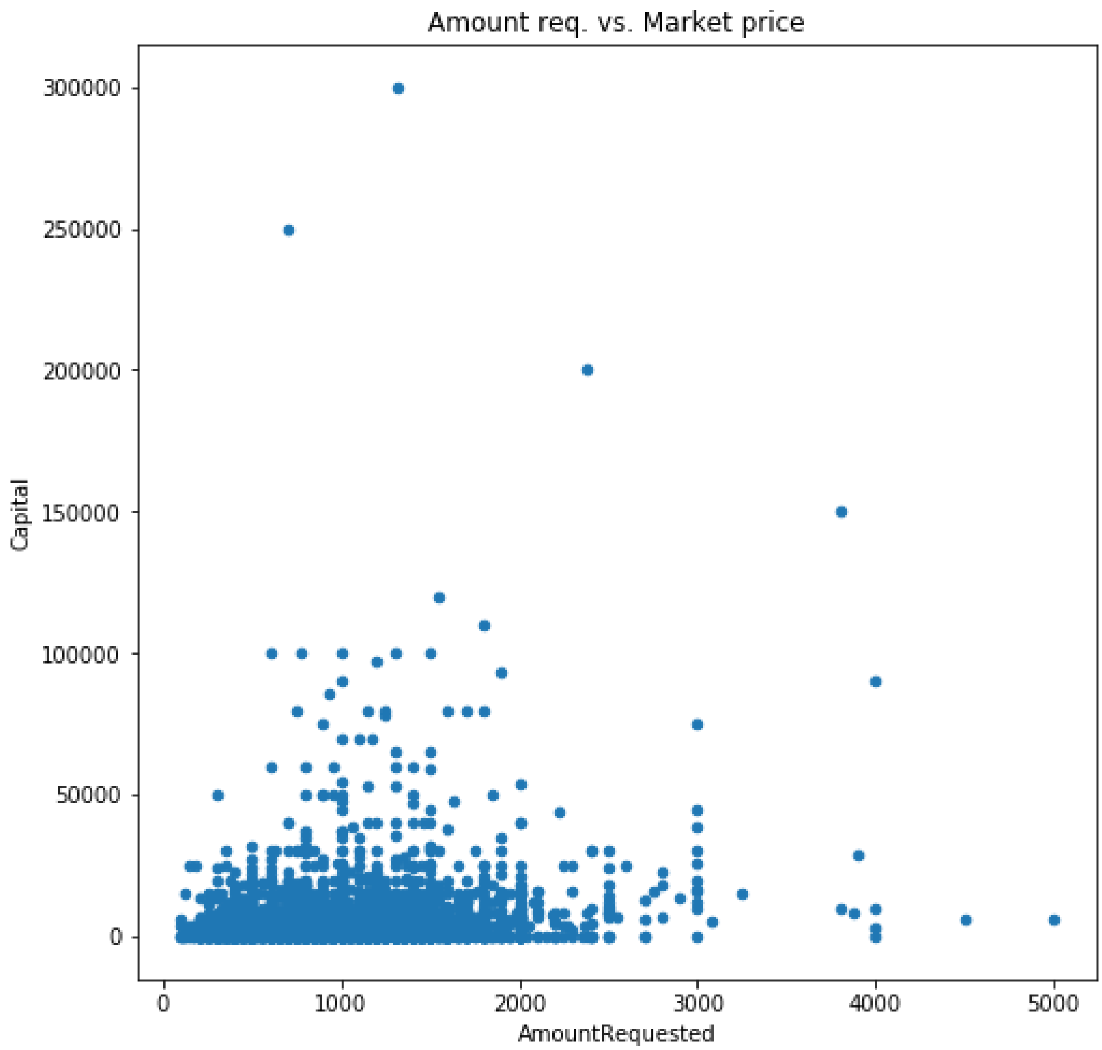
In [138]:
```
pd.crosstab(Credit_new.TypeOfJob,
            Credit_new.Age_cat,
            normalize="columns").T.plot.bar(stacked=True, figsize=(8,8));
```



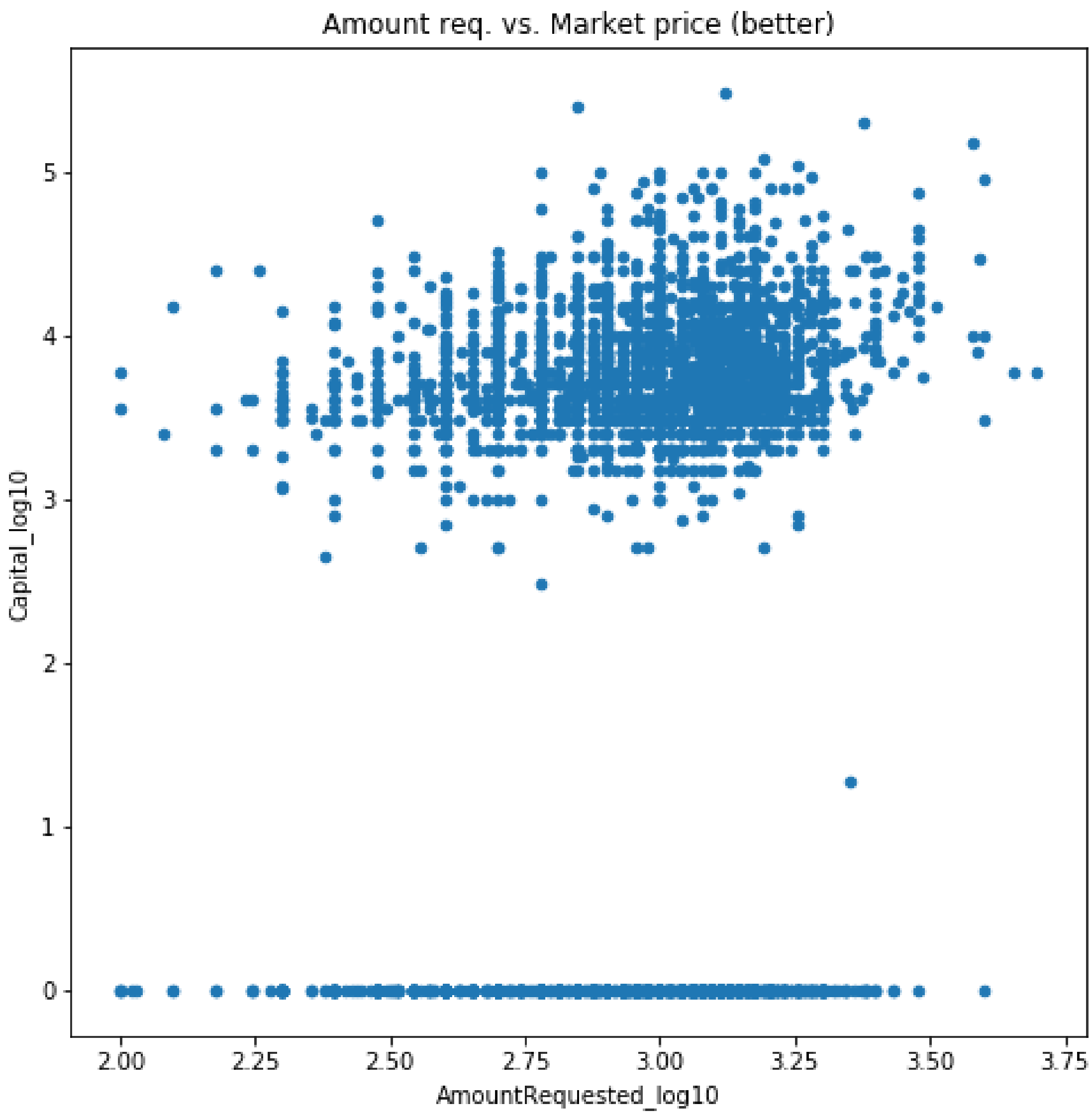
In [139]:
```
# grouped bar chart
pd.crosstab(Credit_new.TypeOfJob,
            Credit_new.Age_cat,
            normalize="columns").T.plot.bar(figsize=(8,8));
```




```
In [140]: Credit_new.plot.scatter(y='Capital',
                                  x='AmountRequested',
                                  figsize=(8,8),
                                  title='Amount req. vs. Market price');
```




```
In [141]: 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)');
```

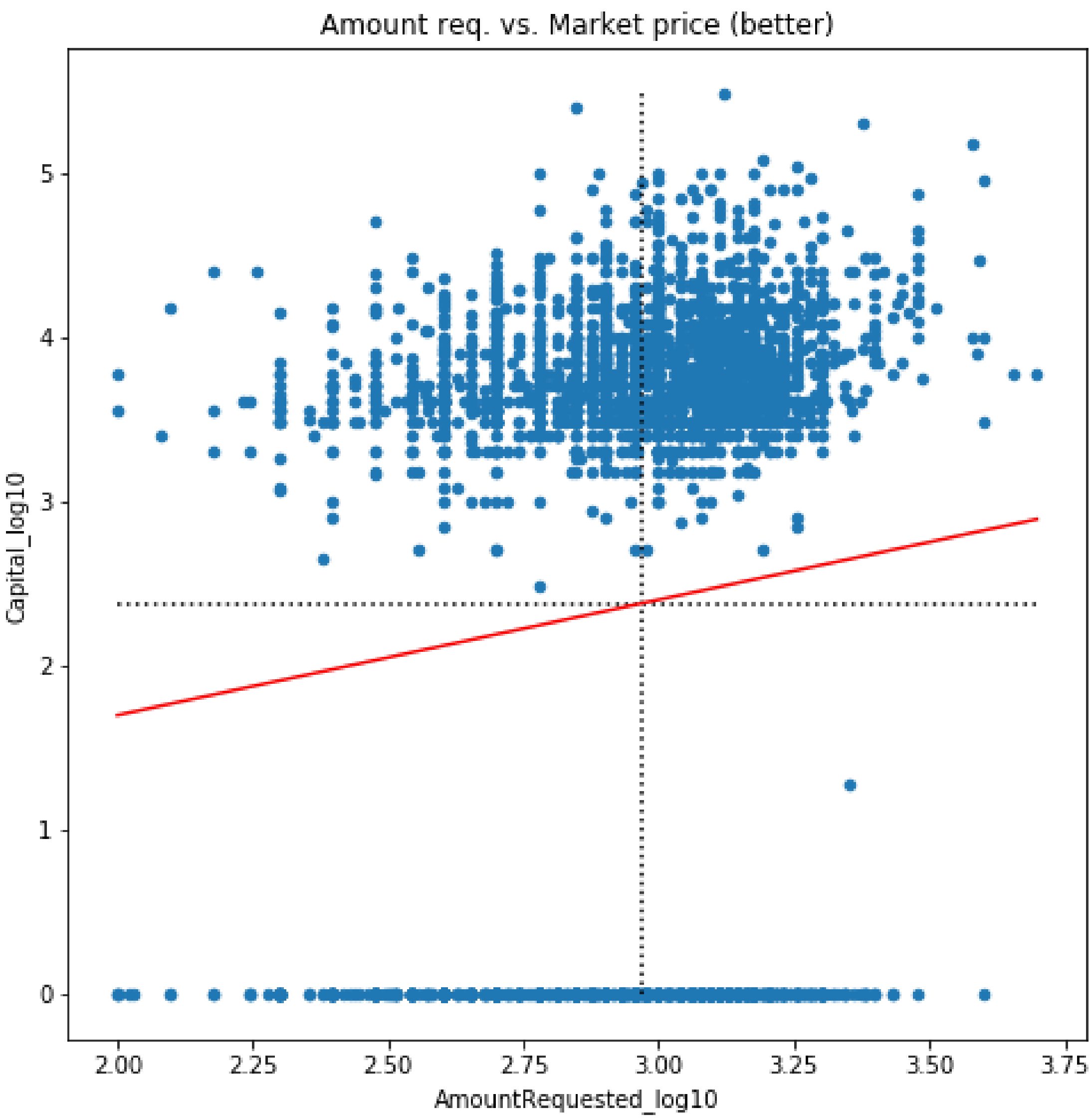


adding a center (dashed) and a regression line (blue)

```
In [142]: 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(),
```

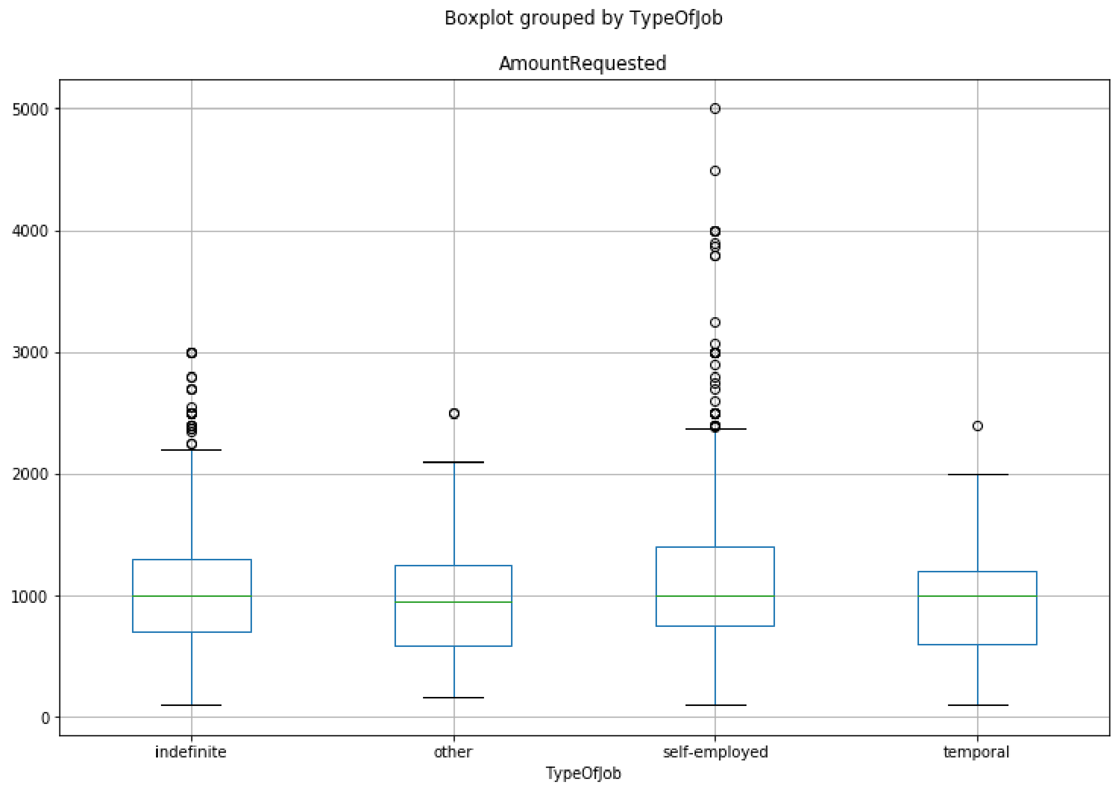
```
              Credit_new.AmountRequested_log10.max()],
             [Credit_new.Capital_log10.mean()]*2,
             'k:');
plt.plot(np.linspace(Credit_new.AmountRequested_log10.min(),
                     Credit_new.AmountRequested_log10.max(),
                     num=30),
         result.params.Intercept+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



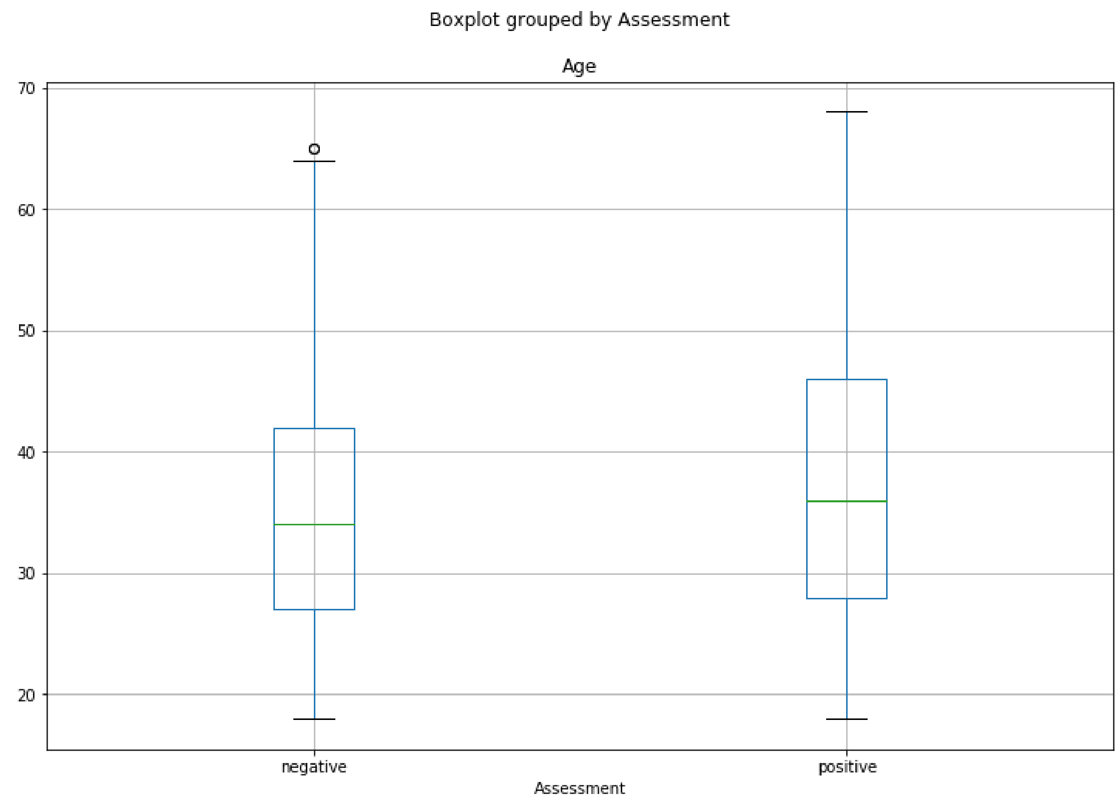
(note that log10(x+1)=0 for x=0, so our transformation keeps the zeros)

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

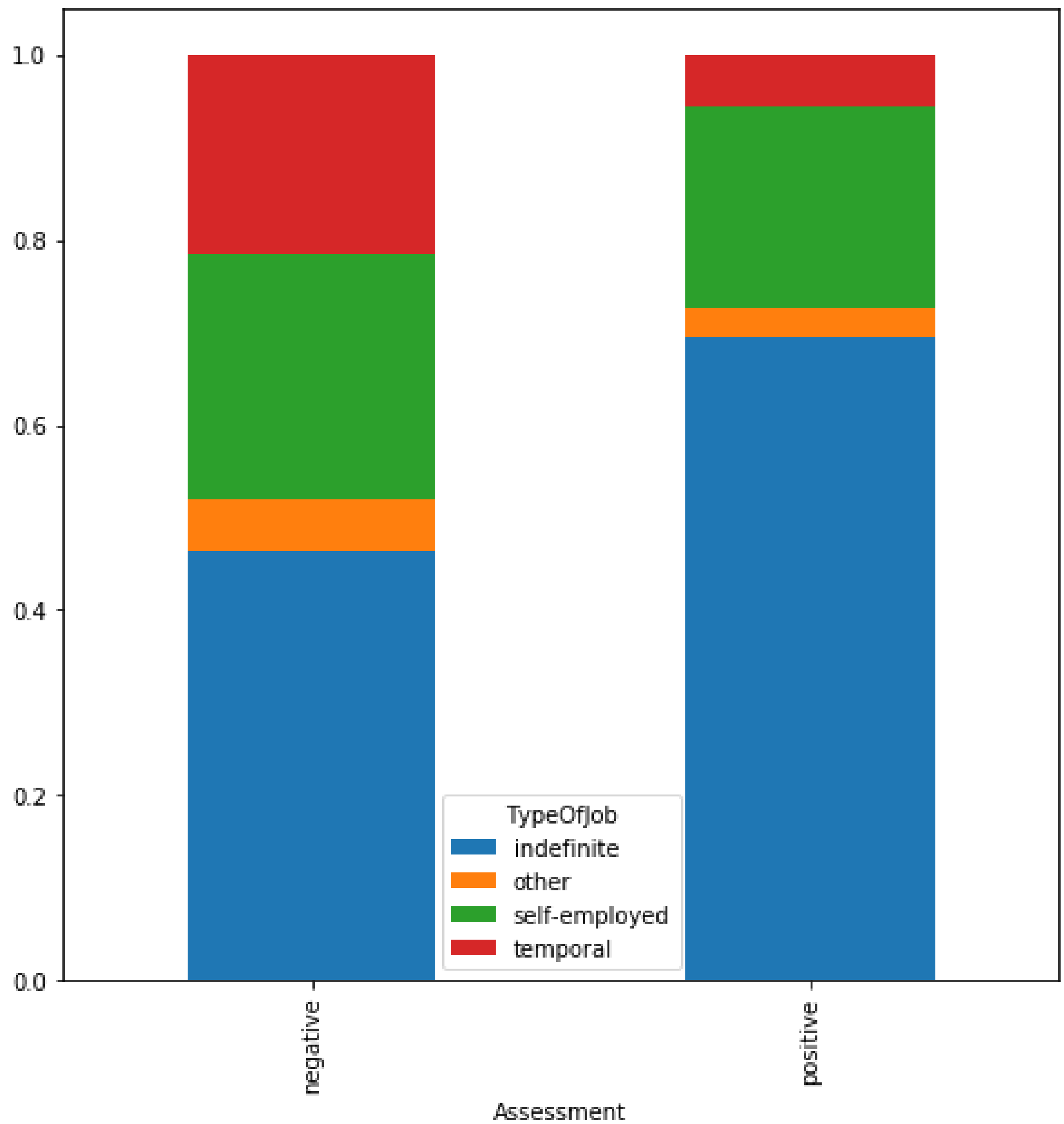
```
In [143]: Credit_new.boxplot(column='AmountRequested',
                             by='TypeOfJob',
                             figsize=(12,8));
```



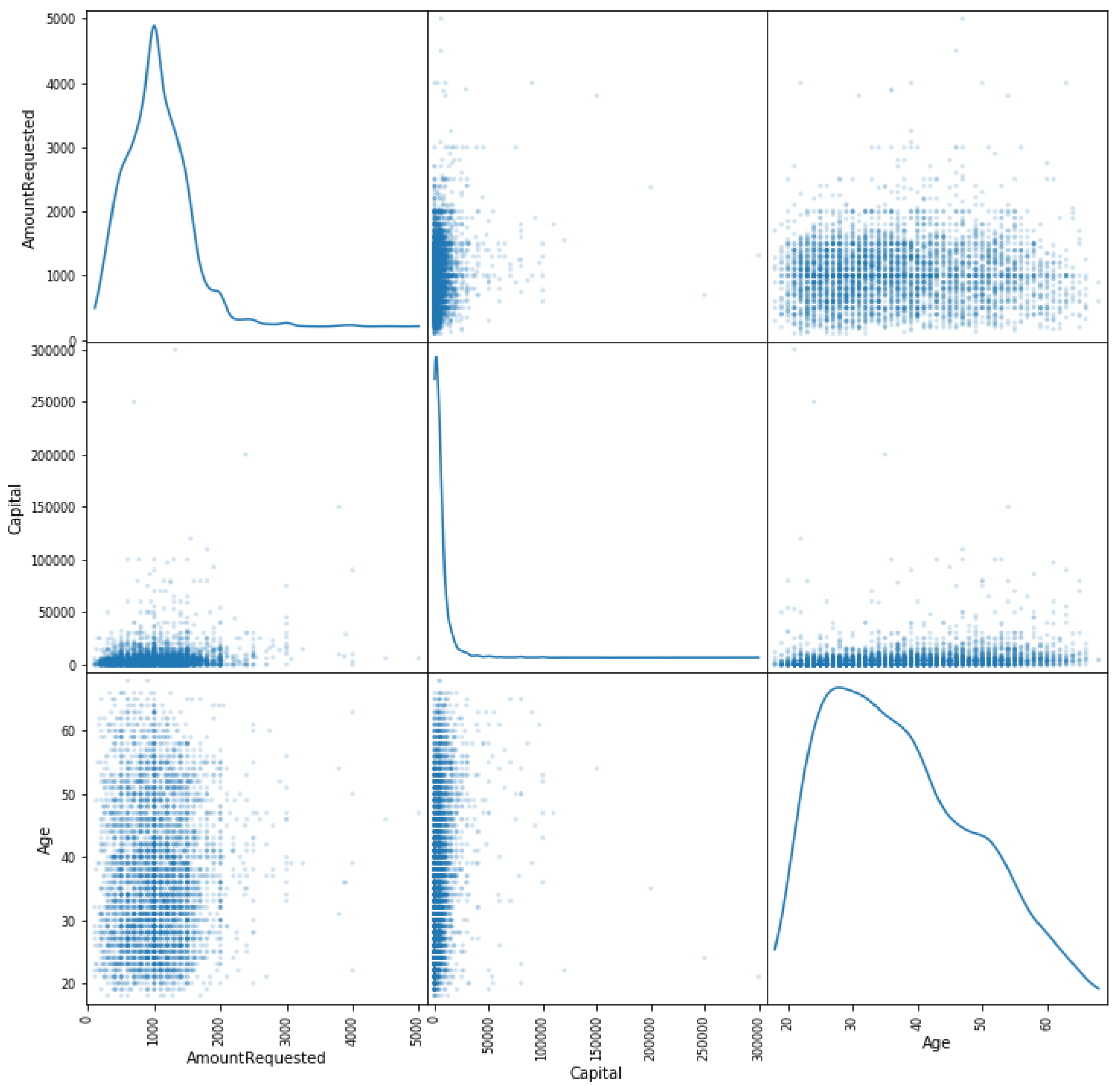

```
In [144]: Credit_new.boxplot(column='Age',
                             by='Assessment',
                             figsize=(12,8));
```



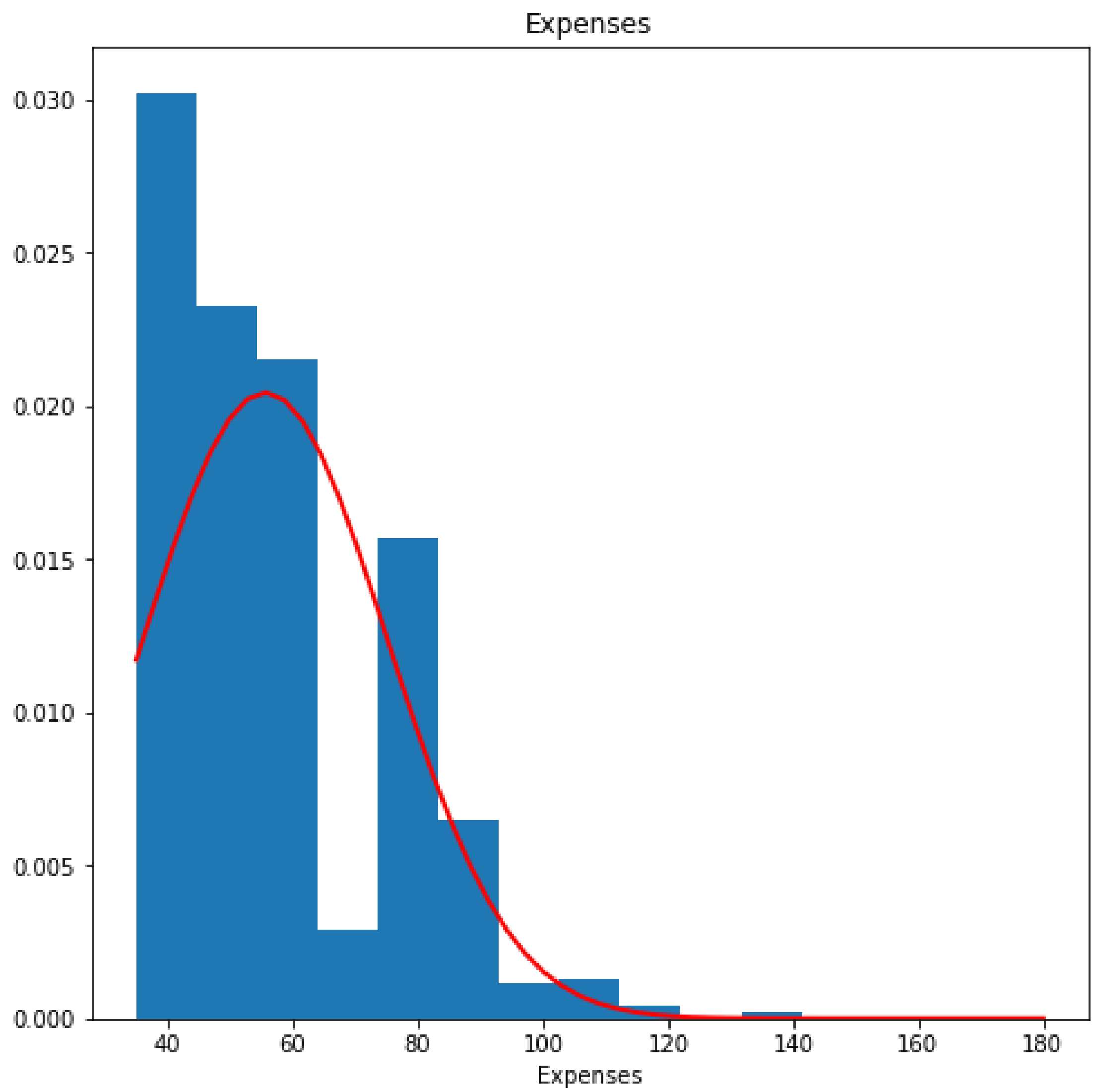

```
In [145]: pd.crosstab(Credit_new.TypeOfJob,
                      Credit_new.Assessment,
                      normalize="columns").T.plot.bar(stacked=True,
                                                      figsize=(8,8));
```



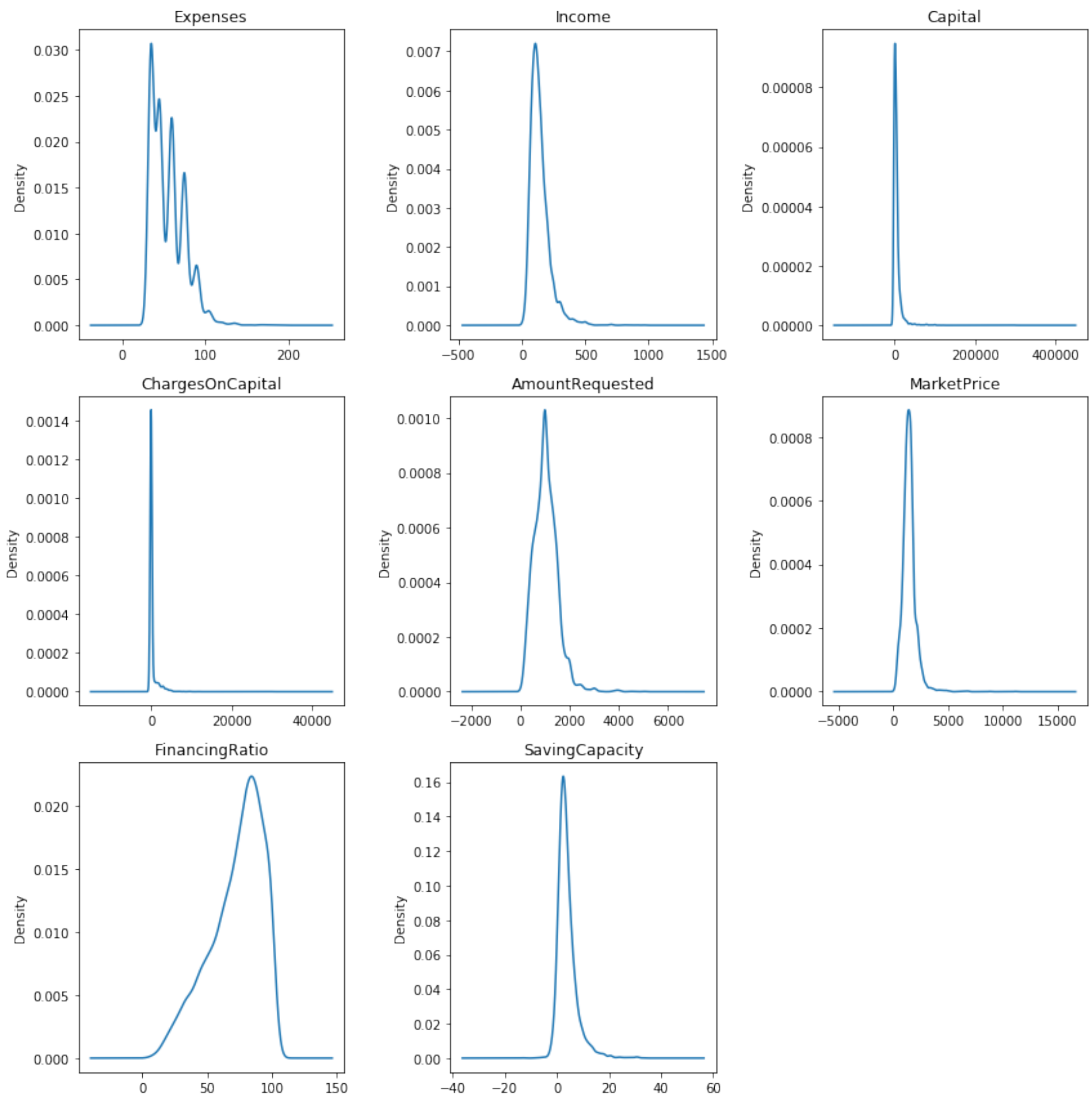

```
In [146]: scatter_matrix(Credit_new.loc[:,['AmountRequested','Capital','Age']],
                         alpha=0.2, figsize=(12, 12),
                         diagonal='kde', marker='.');
```



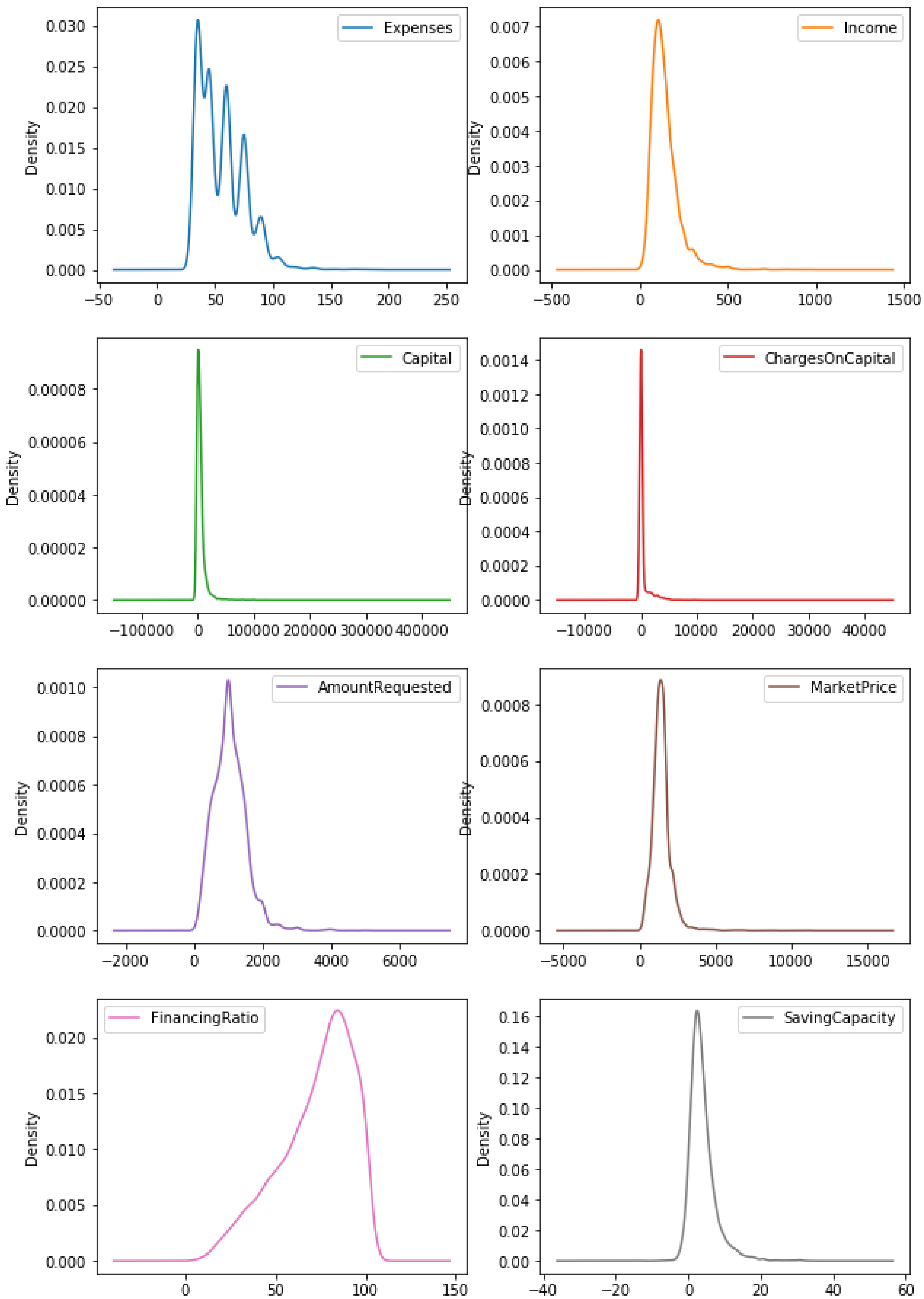

```
In [147]: sigma=  Credit_new.Expenses.std()
          mu=  Credit_new.Expenses.mean()
          fig, ax = plt.subplots(figsize=(8,8))
          count, bins, ignored = plt.hist(Credit_new.Expenses, 15, density=True)
          dbins = np.linspace(bins[0], bins[-1])
          plt.title("Expenses")
          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 [148]: 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 [149]: 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

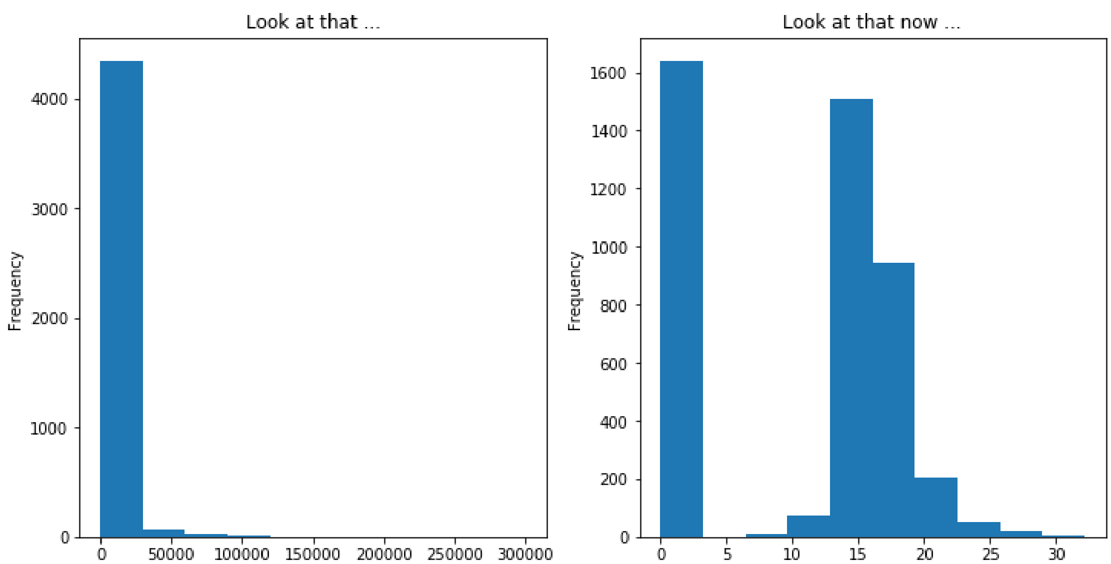
Gaussian: outliers, asymmetries, long tails

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

```
In [150]: 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 [151]: 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 [152]: Credit_new.to_pickle('Credsco-processed.pkl.bz2',compression='bz2')
```

```
In [153]: Credit_load =pd.read_pickle('Credsco-processed.pkl.bz2',compression='bz2')
          Credit_load.head()
```

```
Out[153]:   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]
```