kagglePython19July

July 19, 2020

1 Give me some Credit

https://www.kaggle.com/regivm/data-cleaning-and-eda-tutorial/notebook

Let's work with a fairly complicated data to understand the nuances of Data preparation. This data is quite challenging to clean and you may not agree with my approach. Note following points:- - I have not used the best of Python coding as I am new to Python. My approach was quite functional; check if the output is providing the answer or not. - There are many approaches to data cleaning (treatment of missing values and outliers). Consider this approach as one of the many possible. - The approach adopted is more connected to Analytics rather than Machine Learning. Hence, treatment is 'manual'!! You may notice that each of the variables are not treated in so much detail by ML professionals.

Introduction:- Banks play a crucial role in market economies. They decide who can get finance and on what terms and can make or break investment decisions. For markets and society to function, individuals and companies need access to credit.

Credit scoring algorithms, which make a guess at the probability of default, are the method banks use to determine whether or not a loan should be granted. The objective is to improve on the state of the art in credit scoring, by predicting the probability that somebody will experience financial distress in the next two years.

[17]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(color_codes=True)

%matplotlib inline
```

[24]:
```
#df = pd.read_csv("../input/cs-training.csv")
df = pd.read_csv("CredData/cs-training.csv")
```

[25]:
```
df.head(2)
```

[25]:

	Unnamed: 0	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	\
0	1	1	0.766127	45	
1	2	0	0.957151	40	

```
   NumberOfTime30-59DaysPastDueNotWorse  DebtRatio  MonthlyIncome  \
0                                     2   0.802982         9120.0
1                                     0   0.121876         2600.0

   NumberOfOpenCreditLinesAndLoans  NumberOfTimes90DaysLate  \
0                               13                        0
1                                4                        0

   NumberRealEstateLoansOrLines  NumberOfTime60-89DaysPastDueNotWorse  \
0                             6                                     0
1                             0                                     0

   NumberOfDependents
0                 2.0
1                 1.0
```

Note that some of the variables got missing values indicated by 'NaN'. But this is not reliable and we need a summary statistics. Let's take a look at list of variables.

[26]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150000 entries, 0 to 149999
Data columns (total 12 columns):
 #   Column                                Non-Null Count   Dtype
---  ------                                --------------   -----
 0   Unnamed: 0                            150000 non-null  int64
 1   SeriousDlqin2yrs                      150000 non-null  int64
 2   RevolvingUtilizationOfUnsecuredLines  150000 non-null  float64
 3   age                                   150000 non-null  int64
 4   NumberOfTime30-59DaysPastDueNotWorse  150000 non-null  int64
 5   DebtRatio                             150000 non-null  float64
 6   MonthlyIncome                         120269 non-null  float64
 7   NumberOfOpenCreditLinesAndLoans       150000 non-null  int64
 8   NumberOfTimes90DaysLate               150000 non-null  int64
 9   NumberRealEstateLoansOrLines          150000 non-null  int64
 10  NumberOfTime60-89DaysPastDueNotWorse  150000 non-null  int64
 11  NumberOfDependents                    146076 non-null  float64
dtypes: float64(4), int64(8)
memory usage: 13.7 MB
```

The list of variables indicates that all variables are numeric and few of these got missing values. We will look at the summary of these variables.

[27]:
```
df.rename(columns = {df.columns[0]:'ID'}, inplace = True)

df.describe()
```

[27]:

	ID	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines
count	150000.000000	150000.000000	150000.000000
mean	75000.500000	0.066840	6.048438
std	43301.414527	0.249746	249.755371
min	1.000000	0.000000	0.000000
25%	37500.750000	0.000000	0.029867
50%	75000.500000	0.000000	0.154181
75%	112500.250000	0.000000	0.559046
max	150000.000000	1.000000	50708.000000

	age	NumberOfTime30-59DaysPastDueNotWorse	DebtRatio
count	150000.000000	150000.000000	150000.000000
mean	52.295207	0.421033	353.005076
std	14.771866	4.192781	2037.818523
min	0.000000	0.000000	0.000000
25%	41.000000	0.000000	0.175074
50%	52.000000	0.000000	0.366508
75%	63.000000	0.000000	0.868254
max	109.000000	98.000000	329664.000000

	MonthlyIncome	NumberOfOpenCreditLinesAndLoans
count	1.202690e+05	150000.000000
mean	6.670221e+03	8.452760
std	1.438467e+04	5.145951
min	0.000000e+00	0.000000
25%	3.400000e+03	5.000000
50%	5.400000e+03	8.000000
75%	8.249000e+03	11.000000
max	3.008750e+06	58.000000

	NumberOfTimes90DaysLate	NumberRealEstateLoansOrLines
count	150000.000000	150000.000000
mean	0.265973	1.018240
std	4.169304	1.129771
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	1.000000
75%	0.000000	2.000000
max	98.000000	54.000000

	NumberOfTime60-89DaysPastDueNotWorse	NumberOfDependents
count	150000.000000	146076.000000
mean	0.240387	0.757222
std	4.155179	1.115086
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000

```
75%                                0.000000              1.000000
max                               98.000000             20.000000
```

The depdendent variable is 'SeriousDlqin2yrs'. There are also variables like 'NumberOfTime30_59DaysPastDueNotW', 'NumberOfTime60_89DaysPastDueNotW', 'NumberOfTimes90DaysLate'. These variables give info on how much customers were delayed in payment and frequency. In Financial Industry, these types of variables are the inputs for creating the dependent variable. Hence, these variables cannot be used as independent variables.

Moreover, the use of this model is to score a new customer and obviously these variables will not be available for a new customer. Hence, let's remove these variables straight away.

[28]:
```
df.drop(df.columns[[4, 8, 10]], axis=1, inplace=True)
df.head(2)
```

[28]:
```
   ID  SeriousDlqin2yrs  RevolvingUtilizationOfUnsecuredLines  age  DebtRatio  \
0   1                 1                              0.766127   45   0.802982
1   2                 0                              0.957151   40   0.121876

   MonthlyIncome  NumberOfOpenCreditLinesAndLoans  \
0         9120.0                               13
1         2600.0                                4

   NumberRealEstateLoansOrLines  NumberOfDependents
0                             6                2.0
1                             0                1.0
```

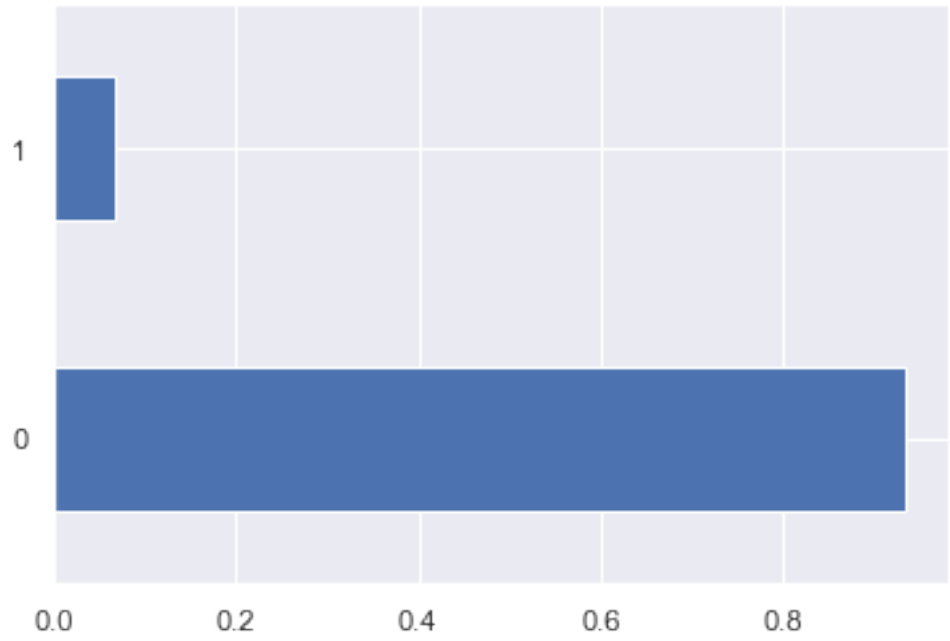
[29]:
```
P = df.groupby('SeriousDlqin2yrs')['ID'].count().reset_index()

P['Percentage'] = 100 * P['ID']  / P['ID'].sum()

print(P)
```

```
   SeriousDlqin2yrs      ID  Percentage
0                 0  139974      93.316
1                 1   10026       6.684
```

Freq table shows that there are no missing values and as expected it contains 0 and 1. Delinquents are 6.68%

[30]:
```
df['SeriousDlqin2yrs'].value_counts(normalize=True).plot(kind='barh')
```

[30]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae1293f88>
```



1.1 RevolvingUtilizationOfUnsecuredLines

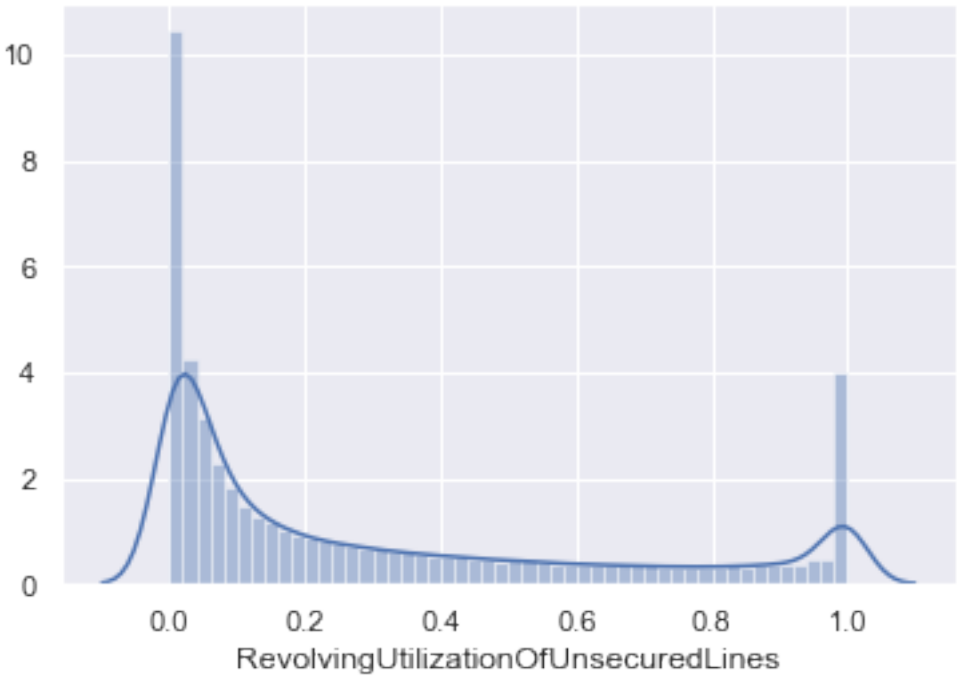
[31]:
```
df['RevolvingUtilizationOfUnsecuredLines'].describe()
```

[31]:
```
count    150000.000000
mean          6.048438
std         249.755371
min           0.000000
25%           0.029867
50%           0.154181
75%           0.559046
max       50708.000000
Name: RevolvingUtilizationOfUnsecuredLines, dtype: float64
```

there are no missing values. the lower value of 0 is fine but max value is ridiculous as it is rarley more than 1

[32]:
```
df3=df.loc[df['RevolvingUtilizationOfUnsecuredLines'] <=1]
sns.distplot(df3['RevolvingUtilizationOfUnsecuredLines'])
```

[32]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae12f9fc8>
```



[33]:
```
len(df[(df['RevolvingUtilizationOfUnsecuredLines']>1)])
```

[33]:
```
3321
```

this shows that about 3300 observations got values more than 1 and hence it is not appropriate to consider all these as outliers and cap to 1. A better approach is to make these missing and impute the values

[34]:
```
df['RevolvingUtilizationOfUnsecuredLines'] =␣
↪df['RevolvingUtilizationOfUnsecuredLines'].map(lambda x: np.NaN if x >1 else␣
↪x)
```

[35]:
```
df['RevolvingUtilizationOfUnsecuredLines'].describe()
```

[35]:
```
count    146679.000000
mean          0.303782
std           0.337892
min           0.000000
25%           0.028608
50%           0.144476
75%           0.519980
max           1.000000
Name: RevolvingUtilizationOfUnsecuredLines, dtype: float64
```

For imputation, we will use ffill method which will retain the distribution and mean of the variable.

[36]:
```
df['RevolvingUtilizationOfUnsecuredLines'].fillna(method='ffill', inplace=True)
```

[37]:
```
df['RevolvingUtilizationOfUnsecuredLines'].describe()
```

[37]:
```
count    150000.000000
mean          0.303669
std           0.337852
min           0.000000
25%           0.028578
50%           0.144257
75%           0.520104
max           1.000000
Name: RevolvingUtilizationOfUnsecuredLines, dtype: float64
```

1.2 age

Let's take a look at univariate analysis and distribution.

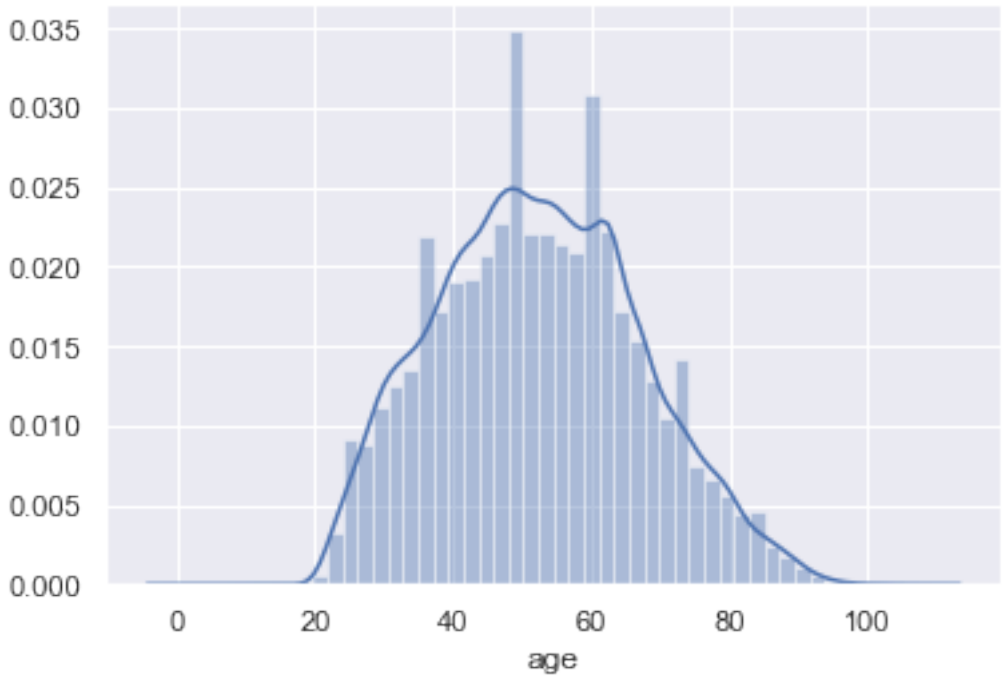
[38]:
```
df['age'].describe()
```

[38]:
```
count    150000.000000
mean         52.295207
std          14.771866
min           0.000000
25%          41.000000
50%          52.000000
75%          63.000000
max         109.000000
Name: age, dtype: float64
```

there are no missing values. the lower value of 0 and max value of 109 are outliers. Typical age range is 18-80.

[39]:
```
sns.distplot(df['age'])
```

[39]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae177fbc8>
```

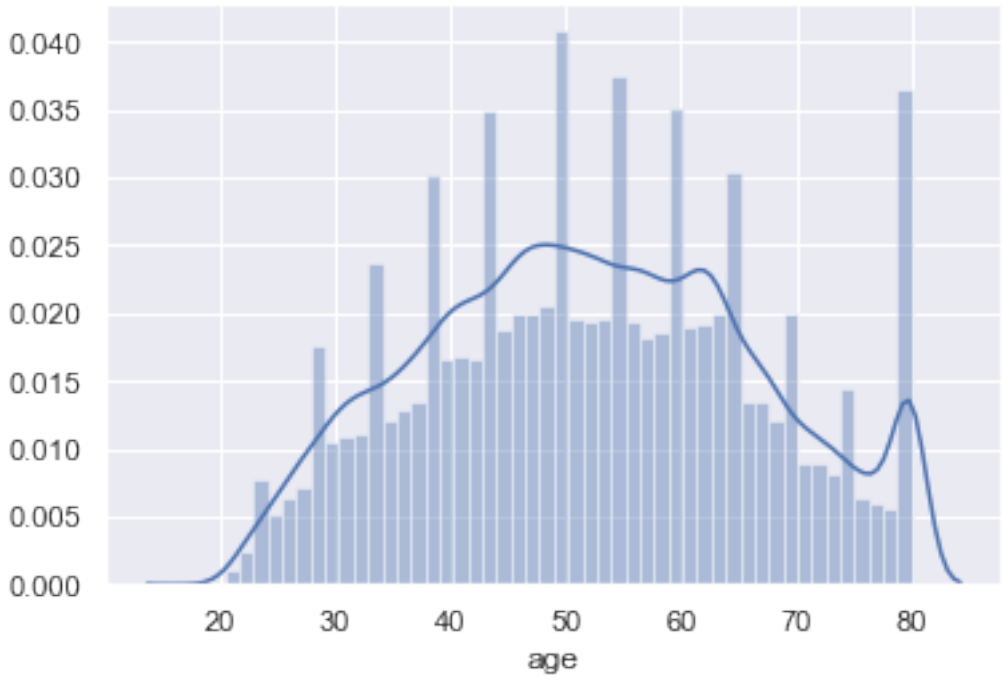


this shows that about there are only very few observations outside 18-80 range. Hence, it is ok to cap the values

[40]:
```
df.loc[df['age']>80, 'age']=80
df.loc[df['age']<18, 'age']=18
```

[41]:
```
sns.distplot(df['age'])
```

[41]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae13e3a48>
```



[42]:
```
df['age'].describe()
```

[42]:
```
count    150000.000000
mean         52.120087
std          14.389418
min          18.000000
25%          41.000000
50%          52.000000
75%          63.000000
max          80.000000
Name: age, dtype: float64
```

1.3 DebtRatio

[43]:
```
df['DebtRatio'].describe()
```

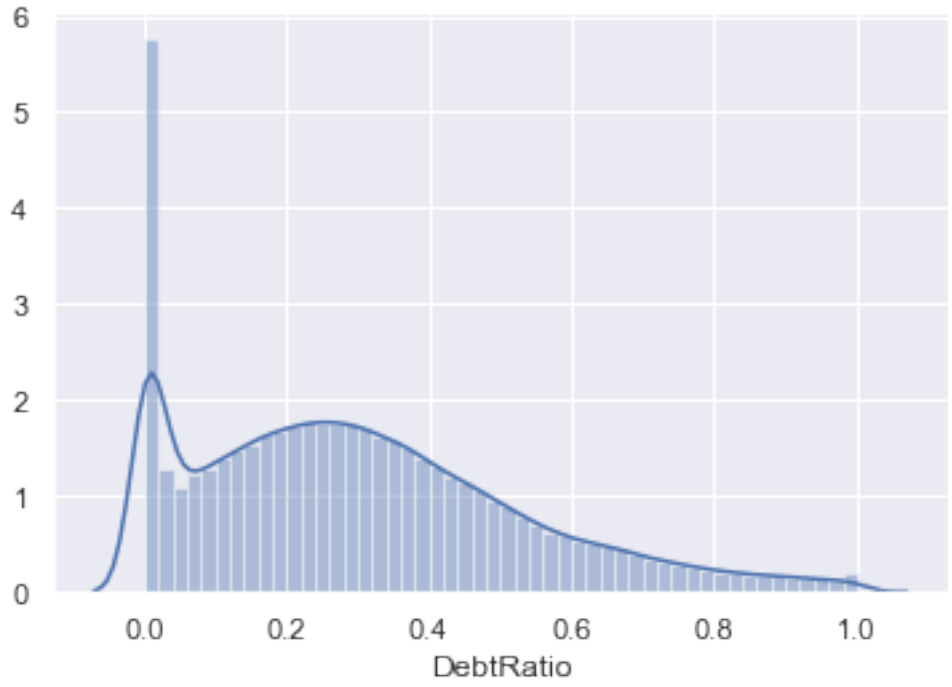
[43]:
```
count    150000.000000
mean        353.005076
std        2037.818523
min           0.000000
25%           0.175074
50%           0.366508
75%           0.868254
max      329664.000000
```

```
Name: DebtRatio, dtype: float64
```

This variable refers to debt to income ratio.there are no missing values. the lower value of 0 is fine but max value is ridiculous as it is rarley more than

[44]:
```
df2=df[df['DebtRatio']<=1]
sns.distplot(df2['DebtRatio'])
```

[44]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae2858f88>
```



[45]:
```
df2=df[df['DebtRatio']>1]
df2['DebtRatio'].describe()
```

[45]:
```
count     35137.000000
mean       1505.989566
std        3999.026847
min           1.000500
25%          42.000000
50%         907.000000
75%        2210.000000
max      329664.000000
Name: DebtRatio, dtype: float64
```

Typical value of Debt Income ratio is 0.4. But almost 35000 observations got values higher than 1 and hence cannot be treated as outliers. Best approach is to consider it as missing and impute

values

[46]:
```
df.loc[df['DebtRatio']>1, 'DebtRatio']=np.NaN
```

[47]:
```
df['DebtRatio'].describe()
```

[47]:
```
count    114863.000000
mean          0.303022
std           0.226287
min           0.000000
25%           0.125981
50%           0.274505
75%           0.438098
max           1.000000
Name: DebtRatio, dtype: float64
```

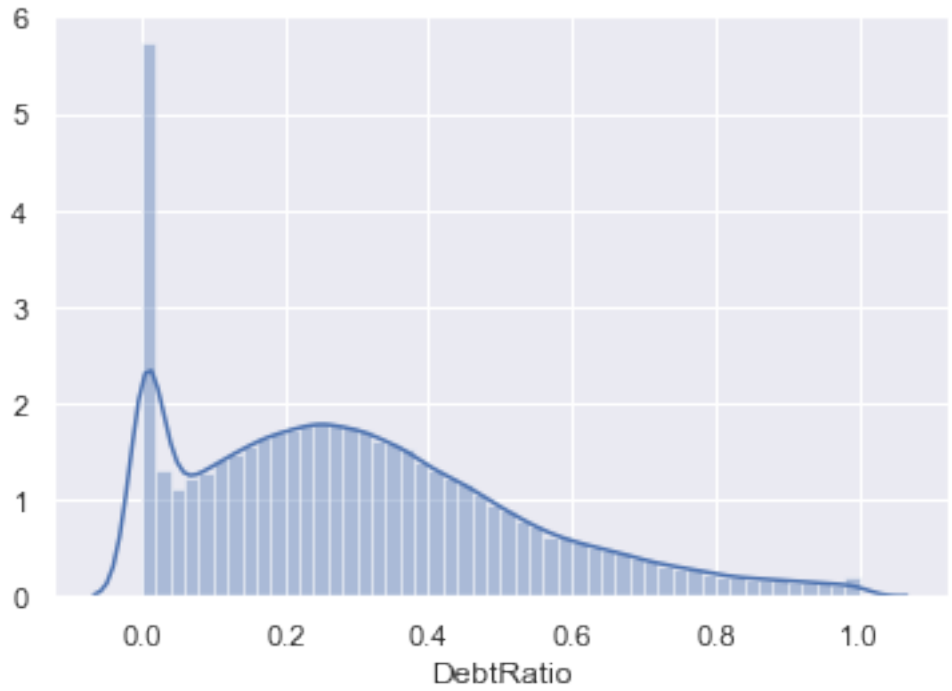
[48]:
```
df['DebtRatio'].fillna(method='ffill', inplace=True)
```

[49]:
```
df['DebtRatio'].describe()
```

[49]:
```
count    150000.000000
mean          0.303109
std           0.226290
min           0.000000
25%           0.126122
50%           0.274252
75%           0.438325
max           1.000000
Name: DebtRatio, dtype: float64
```

[50]:
```
sns.distplot(df['DebtRatio'])
```

[50]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae293b508>
```



1.4 NumberOfOpenCreditLinesAndLoans

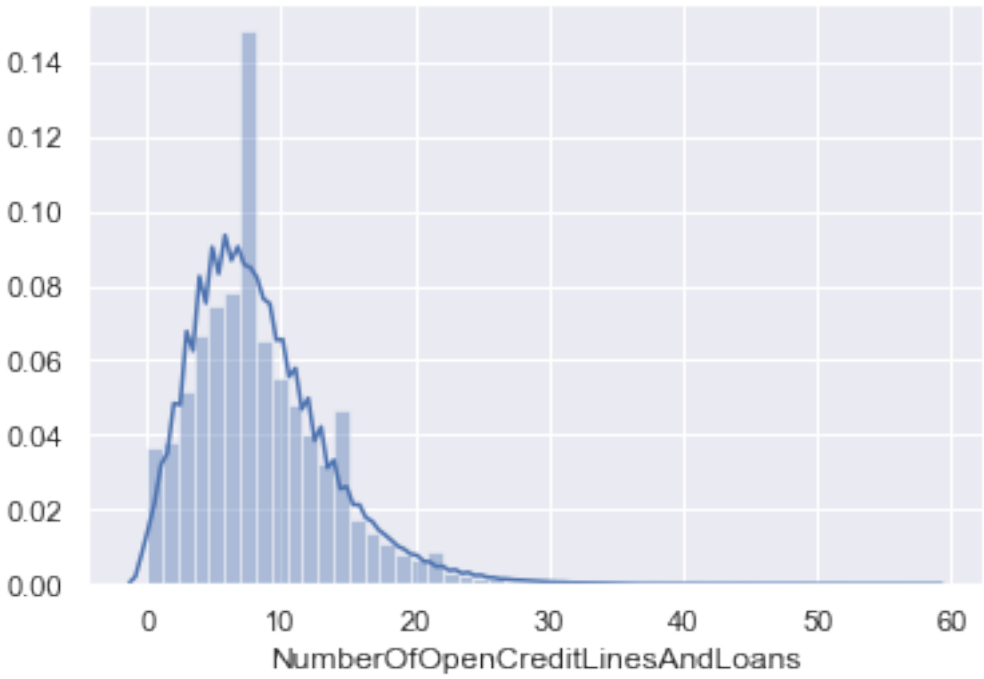
[51]:
```
df['NumberOfOpenCreditLinesAndLoans'].describe()
```

[51]:
```
count    150000.000000
mean          8.452760
std           5.145951
min           0.000000
25%           5.000000
50%           8.000000
75%          11.000000
max          58.000000
Name: NumberOfOpenCreditLinesAndLoans, dtype: float64
```

there are no missing values. the lower value of 0 is fine. Max value of 58 seems to be an outlier as it is much higher than mean (max is 10*std away from mean)

[52]:
```
sns.distplot(df['NumberOfOpenCreditLinesAndLoans'])
```

[52]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae2b7a488>
```



the distribution indicate that it is continuous upto 30. Hence, let's cap at 30

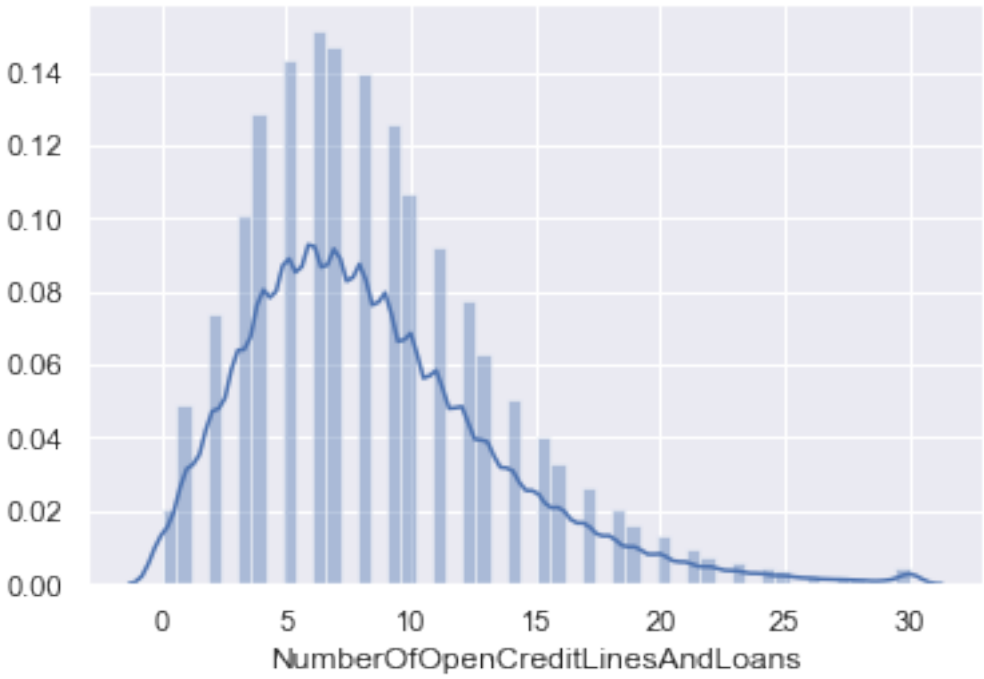
[53]:
```
df.loc[df['NumberOfOpenCreditLinesAndLoans']>30,␣
↪'NumberOfOpenCreditLinesAndLoans']=30
```

[54]:
```
df['NumberOfOpenCreditLinesAndLoans'].describe()
```

[54]:
```
count    150000.000000
mean          8.438793
std           5.070728
min           0.000000
25%           5.000000
50%           8.000000
75%          11.000000
max          30.000000
Name: NumberOfOpenCreditLinesAndLoans, dtype: float64
```

[55]:
```
sns.distplot(df['NumberOfOpenCreditLinesAndLoans'])
```

[55]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae3e7cd48>
```



1.5 MonthlyIncome

[56]:
```
df['MonthlyIncome'].describe()
```

[56]:
```
count    1.202690e+05
mean     6.670221e+03
std      1.438467e+04
min      0.000000e+00
25%      3.400000e+03
50%      5.400000e+03
75%      8.249000e+03
max      3.008750e+06
Name: MonthlyIncome, dtype: float64
```

There are missing values and Max value is too large. Min value of 0 is not ok as finance industry expect a minimum income of 1000.

[57]:
```
df['MonthlyIncome'].isnull().sum()
```

[57]:
```
29731
```

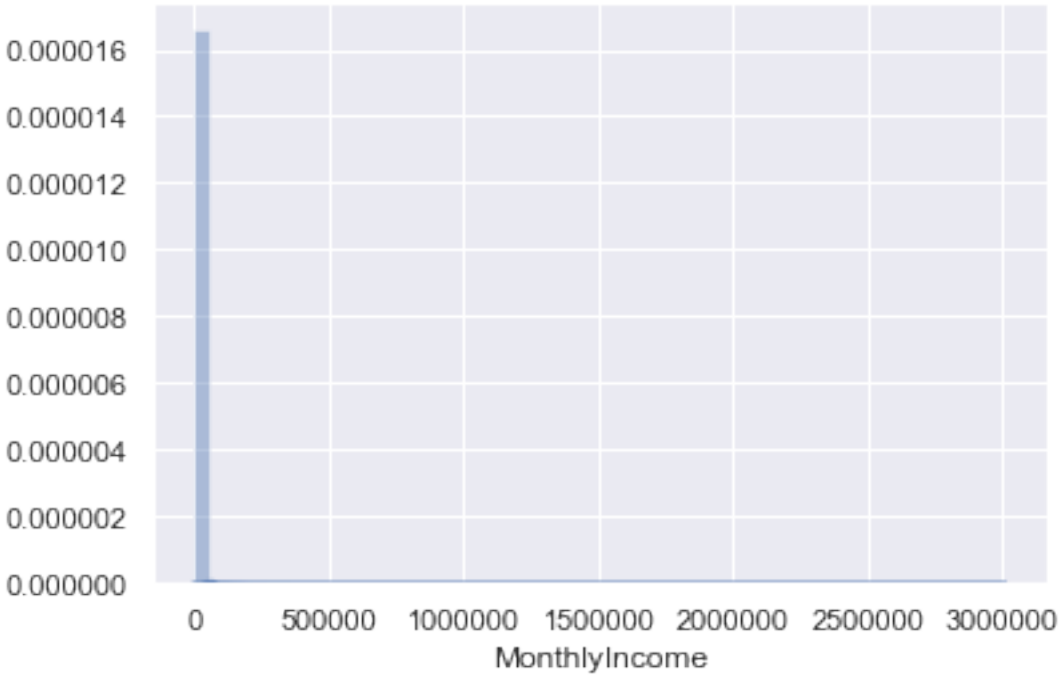
[58]:
```
len(df[df['MonthlyIncome']<1000])
```

[58]:
```
4428
```

Number of obs below 1000 is too large. hence, it is not ok to treat it as outliers and cap to 1000. Lets treat it as missing and then impute the values.

[59]:
```
sns.distplot(df['MonthlyIncome'].dropna())
```

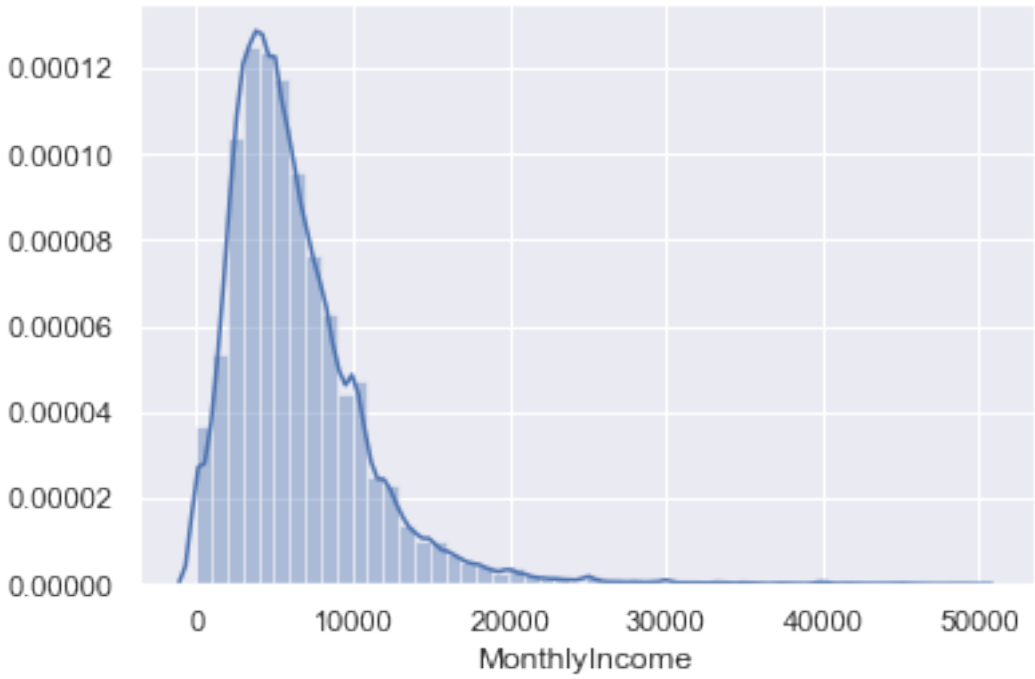
[59]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae3de9708>
```



The max value is too large and hence the plot is not making sense

[60]:
```
df2=df[df['MonthlyIncome']<50000]
sns.distplot(df2['MonthlyIncome'].dropna())
```

[60]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae11d3fc8>
```



Distribution shows that income smoothly decreases upto 25000 and then few outliers of huge values.

[61]:
```
df.loc[df['MonthlyIncome']>25000, 'MonthlyIncome']=25000
df['MonthlyIncome'].describe()
```

[61]:
```
count    120269.000000
mean       6349.112332
std        4358.376183
min           0.000000
25%        3400.000000
50%        5400.000000
75%        8249.000000
max       25000.000000
Name: MonthlyIncome, dtype: float64
```

[62]:
```
df.loc[df['MonthlyIncome']<1000, 'MonthlyIncome']=np.NaN
df['MonthlyIncome'].describe()
```

[62]:
```
count    115841.000000
mean       6579.317737
std        4275.154379
min        1000.000000
25%        3600.000000
50%        5513.000000
75%        8334.000000
```

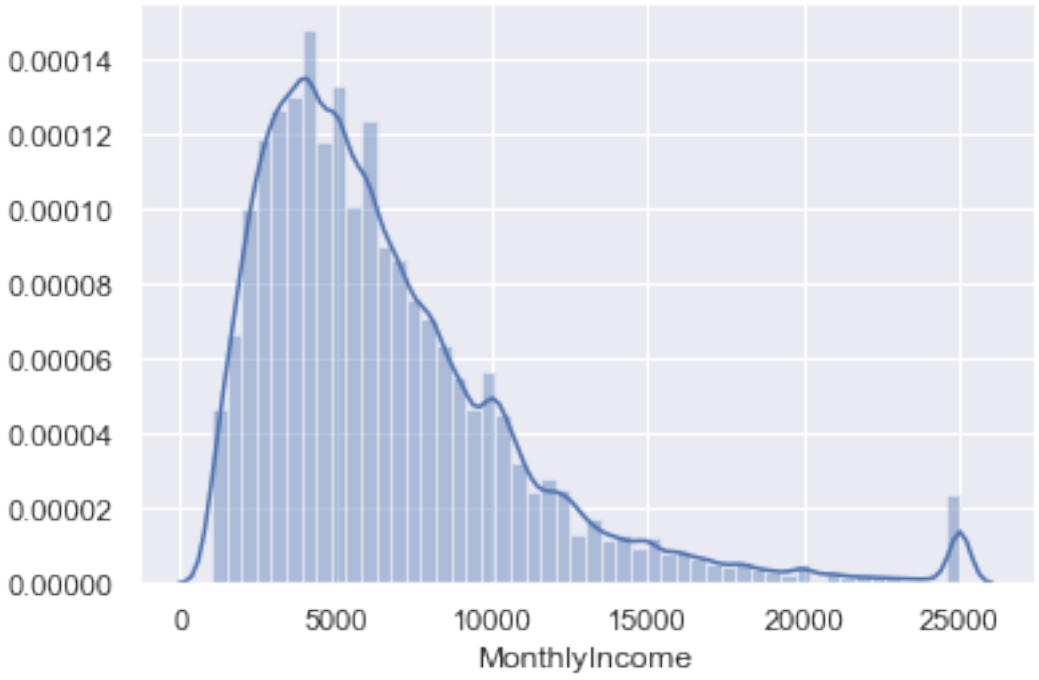
```
max       25000.000000
Name: MonthlyIncome, dtype: float64
```

[63]:
```
df['MonthlyIncome'].fillna(method='ffill', inplace=True)
df['MonthlyIncome'].describe()
```

[63]:
```
count    150000.000000
mean       6578.107227
std        4286.321398
min        1000.000000
25%        3600.000000
50%        5500.000000
75%        8333.000000
max       25000.000000
Name: MonthlyIncome, dtype: float64
```

[64]:
```
sns.distplot(df['MonthlyIncome'])
```

[64]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae2a14a88>
```



1.6 NumberRealEstateLoansOrLines

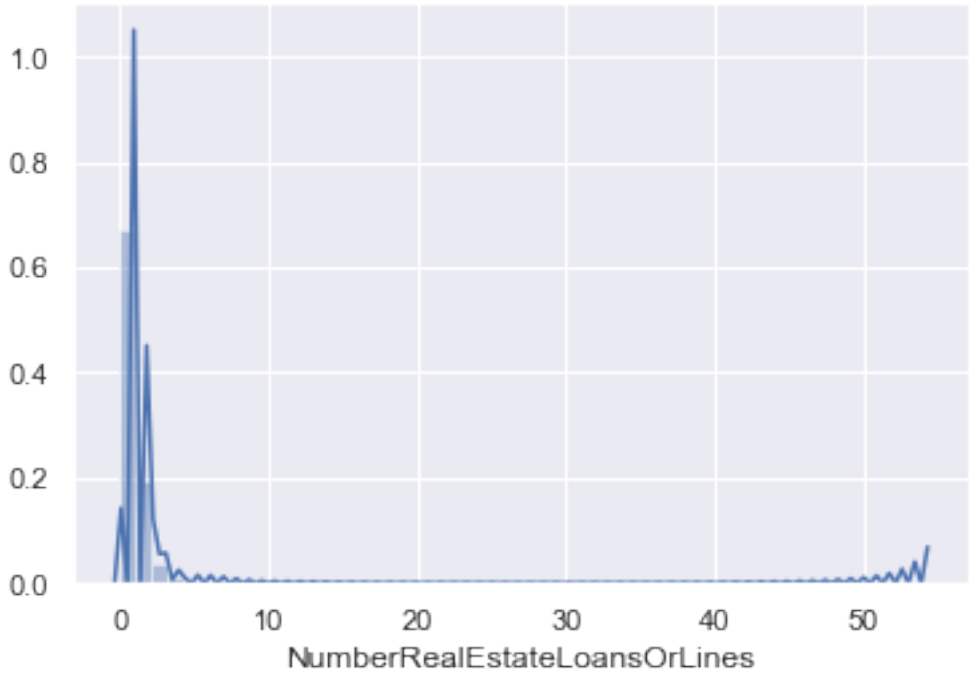
[65]:
```
df['NumberRealEstateLoansOrLines'].describe()
```

[65]:
```
count    150000.000000
mean          1.018240
std           1.129771
min           0.000000
25%           0.000000
50%           1.000000
75%           2.000000
max          54.000000
Name: NumberRealEstateLoansOrLines, dtype: float64
```

There are no missing values but max value is too large. Min value of 0 is ok.

[66]:
```
sns.distplot(df['NumberRealEstateLoansOrLines'])
```

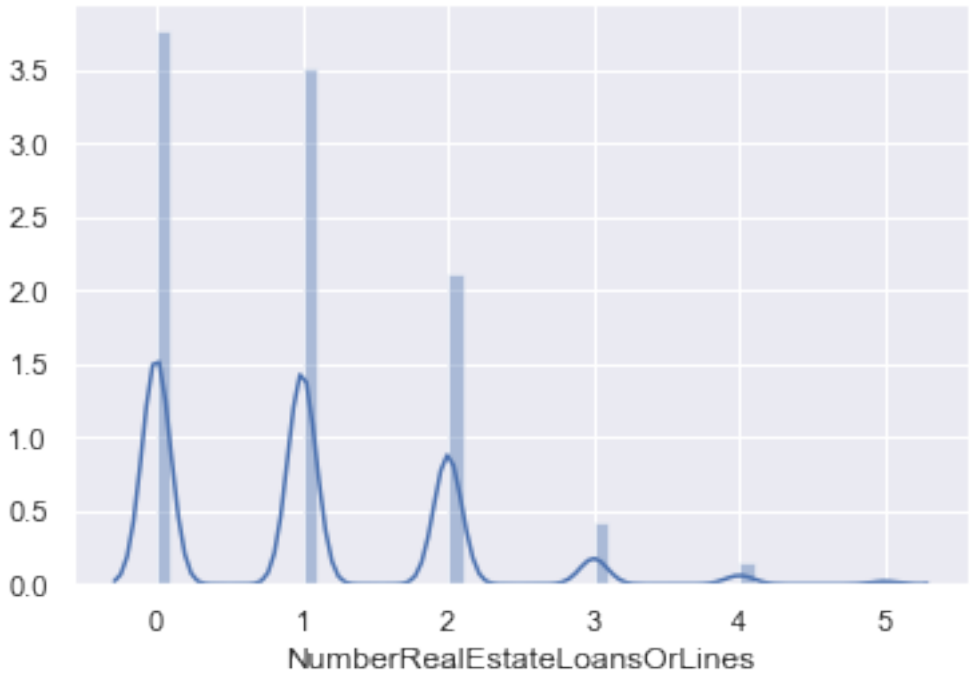
[66]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae3c29ac8>
```



Distribution shows that the variable smoothly decreases upto 10 and then few outliers of large values.

[67]:
```
df2=df[df['NumberRealEstateLoansOrLines']<6]
sns.distplot(df2['NumberRealEstateLoansOrLines'].dropna())
```

[67]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae6318f48>
```

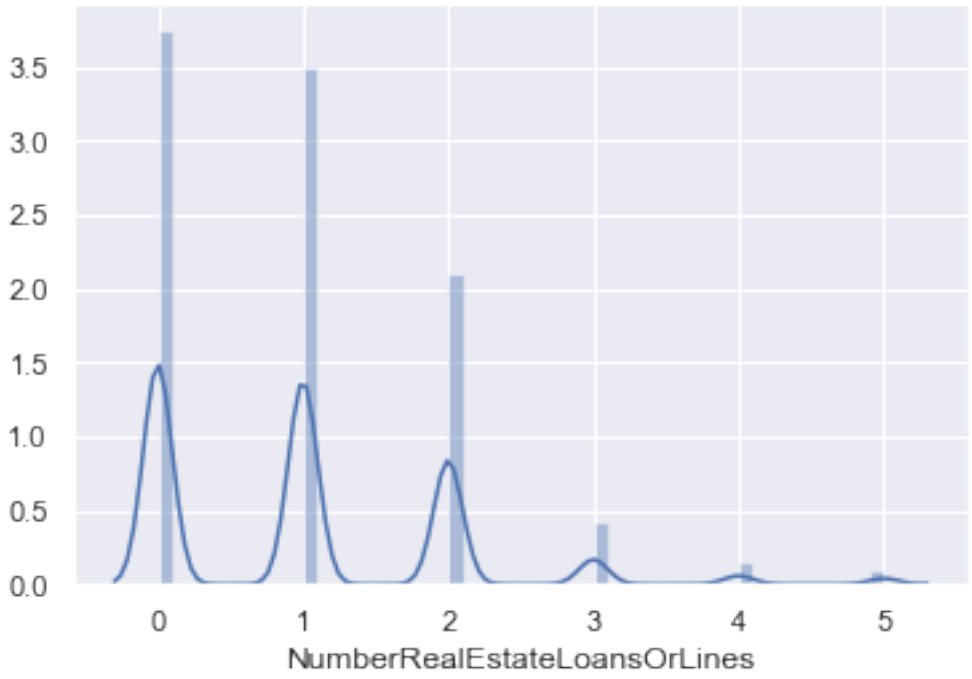


[68]:
```
df.loc[df['NumberRealEstateLoansOrLines']>5, 'NumberRealEstateLoansOrLines']=5
df['NumberRealEstateLoansOrLines'].describe()
```

[68]:
```
count    150000.000000
mean          1.002480
std           1.020301
min           0.000000
25%           0.000000
50%           1.000000
75%           2.000000
max           5.000000
Name: NumberRealEstateLoansOrLines, dtype: float64
```

[69]:
```
sns.distplot(df['NumberRealEstateLoansOrLines'])
```

[69]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae639c208>
```



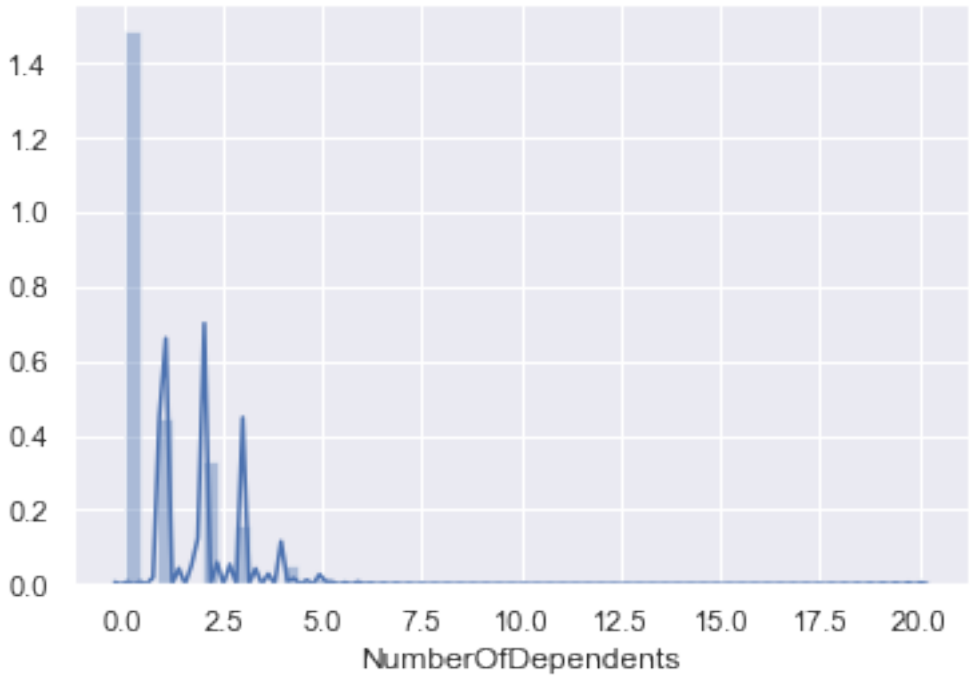
1.6.1 NumOfDependents

[70]:
```
df['NumberOfDependents'].describe()
```

[70]:
```
count    146076.000000
mean          0.757222
std           1.115086
min           0.000000
25%           0.000000
50%           0.000000
75%           1.000000
max          20.000000
Name: NumberOfDependents, dtype: float64
```

[71]:
```
sns.distplot(df['NumberOfDependents'].dropna())
```

[71]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae7472e48>
```



there are missing values. The distribution is continuous upto 5 and then few outliers

[72]:
```
df.loc[df['NumberOfDependents']>5, 'NumberOfDependents']=5
df['NumberOfDependents'].describe()
```

[72]:
```
count    146076.000000
mean          0.754484
std           1.101288
min           0.000000
25%           0.000000
50%           0.000000
75%           1.000000
max           5.000000
Name: NumberOfDependents, dtype: float64
```

Since proportion of missing is large, imputation using mean is not appropriate as this will change the distribution too much. we will impute the missing values using ffill as this will preserve the mean and standard deviation.

[73]:
```
#df['NumberOfDependents'].fillna(df['NumberOfDependents'].mean(), inplace=True)
df['NumberOfDependents'].fillna(method='ffill', inplace=True)
df['NumberOfDependents'].describe()
```

[73]:
```
count    150000.000000
mean          0.754487
```

```
std           1.101377
min           0.000000
25%           0.000000
50%           0.000000
75%           1.000000
max           5.000000
Name: NumberOfDependents, dtype: float64
```

[74]:
```
df.describe()
```

[74]:
```
                 ID  SeriousDlqin2yrs  RevolvingUtilizationOfUnsecuredLines  \
count  150000.000000     150000.000000                         150000.000000
mean    75000.500000          0.066840                              0.303669
std     43301.414527          0.249746                              0.337852
min         1.000000          0.000000                              0.000000
25%     37500.750000          0.000000                              0.028578
50%     75000.500000          0.000000                              0.144257
75%    112500.250000          0.000000                              0.520104
max    150000.000000          1.000000                              1.000000

                 age      DebtRatio  MonthlyIncome  \
count  150000.000000  150000.000000  150000.000000
mean       52.120087       0.303109    6578.107227
std        14.389418       0.226290    4286.321398
min        18.000000       0.000000    1000.000000
25%        41.000000       0.126122    3600.000000
50%        52.000000       0.274252    5500.000000
75%        63.000000       0.438325    8333.000000
max        80.000000       1.000000   25000.000000

       NumberOfOpenCreditLinesAndLoans  NumberRealEstateLoansOrLines  \
count                    150000.000000                 150000.000000
mean                          8.438793                      1.002480
std                           5.070728                      1.020301
min                           0.000000                      0.000000
25%                           5.000000                      0.000000
50%                           8.000000                      1.000000
75%                          11.000000                      2.000000
max                          30.000000                      5.000000

       NumberOfDependents
count       150000.000000
mean             0.754487
std              1.101377
min              0.000000
25%              0.000000
50%              0.000000
```

```
75%                1.000000
max                5.000000
```

Looks like the data is now clean. Lets save it as .pkl file

[75]:
```
df.to_pickle("gmsc_clean.pkl")
```

1.7 Exploratory Data Analysis

[76]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm
from scipy.stats import chisquare
from scipy.stats import chi2_contingency
sns.set(color_codes=True)

%matplotlib inline
```

[77]:
```
df = pd.read_pickle('gmsc_clean.pkl')
df.head()
```

[77]:

	ID	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	DebtRatio	\
0	1	1	0.766127	45	0.802982	
1	2	0	0.957151	40	0.121876	
2	3	0	0.658180	38	0.085113	
3	4	0	0.233810	30	0.036050	
4	5	0	0.907239	49	0.024926	

	MonthlyIncome	NumberOfOpenCreditLinesAndLoans	\
0	9120.0	13	
1	2600.0	4	
2	3042.0	2	
3	3300.0	5	
4	25000.0	7	

	NumberRealEstateLoansOrLines	NumberOfDependents
0	5	2.0
1	0	1.0
2	0	0.0
3	0	0.0
4	1	0.0

[78]:
```
df.describe()
```

[78]:
```
                 ID  SeriousDlqin2yrs  RevolvingUtilizationOfUnsecuredLines  \
count  150000.000000     150000.000000                        150000.000000
mean    75000.500000          0.066840                             0.303669
std     43301.414527          0.249746                             0.337852
min         1.000000          0.000000                             0.000000
25%     37500.750000          0.000000                             0.028578
50%     75000.500000          0.000000                             0.144257
75%    112500.250000          0.000000                             0.520104
max    150000.000000          1.000000                             1.000000

                age      DebtRatio  MonthlyIncome  \
count  150000.000000  150000.000000  150000.000000
mean       52.120087       0.303109    6578.107227
std        14.389418       0.226290    4286.321398
min        18.000000       0.000000    1000.000000
25%        41.000000       0.126122    3600.000000
50%        52.000000       0.274252    5500.000000
75%        63.000000       0.438325    8333.000000
max        80.000000       1.000000   25000.000000

       NumberOfOpenCreditLinesAndLoans  NumberRealEstateLoansOrLines  \
count                    150000.000000                 150000.000000
mean                          8.438793                      1.002480
std                           5.070728                      1.020301
min                           0.000000                      0.000000
25%                           5.000000                      0.000000
50%                           8.000000                      1.000000
75%                          11.000000                      2.000000
max                          30.000000                      5.000000

       NumberOfDependents
count       150000.000000
mean             0.754487
std              1.101377
min              0.000000
25%              0.000000
50%              0.000000
75%              1.000000
max              5.000000
```

[79]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150000 entries, 0 to 149999
Data columns (total 9 columns):
 #   Column                                Non-Null Count   Dtype
---  ------                                --------------   -----
```

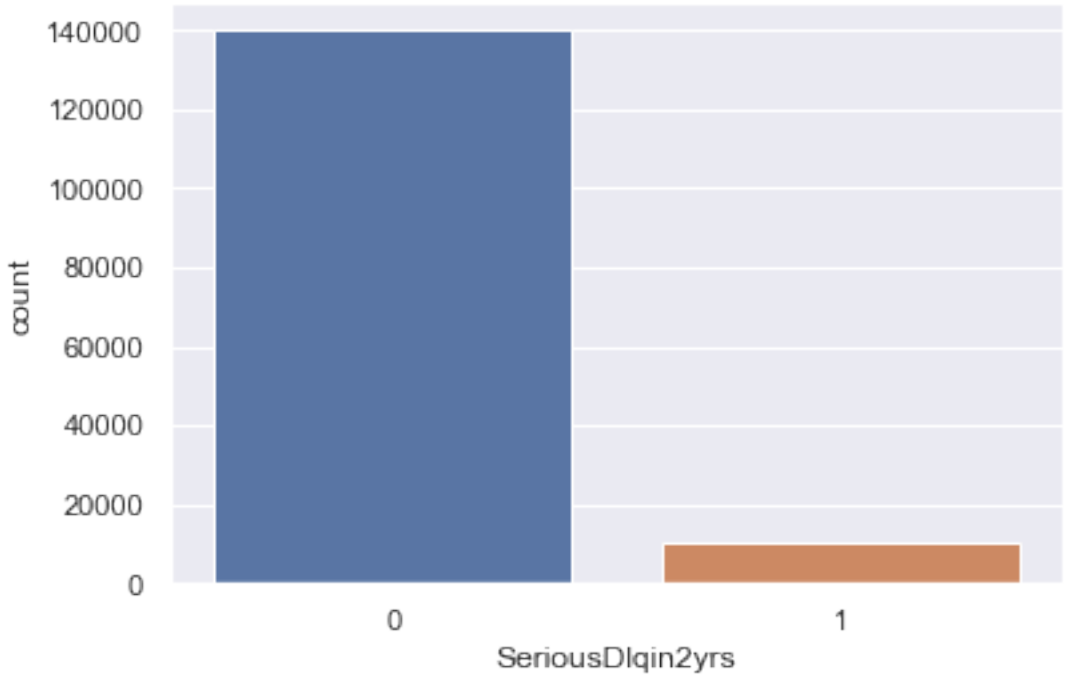
```
 0   ID                                    150000 non-null  int64
 1   SeriousDlqin2yrs                      150000 non-null  int64
 2   RevolvingUtilizationOfUnsecuredLines  150000 non-null  float64
 3   age                                   150000 non-null  int64
 4   DebtRatio                             150000 non-null  float64
 5   MonthlyIncome                         150000 non-null  float64
 6   NumberOfOpenCreditLinesAndLoans       150000 non-null  int64
 7   NumberRealEstateLoansOrLines          150000 non-null  int64
 8   NumberOfDependents                    150000 non-null  float64
dtypes: float64(4), int64(5)
memory usage: 10.3 MB
```

Univariate Analysis

The objective of univariate analysis is to examine each of the variables one by one. The focus will be on the distribution of the variable. Let's start with dependent variable.

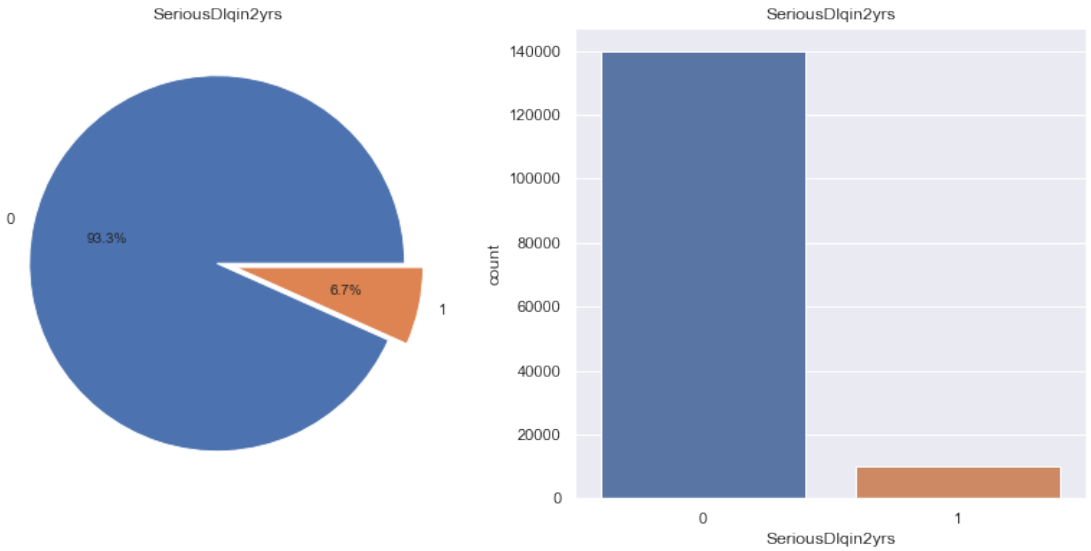
[80]:
```
sns.countplot(x='SeriousDlqin2yrs', data=df)
```

[80]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae879af88>
```



[81]:
```
f,ax=plt.subplots(1,2,figsize=(14,6))
df['SeriousDlqin2yrs'].value_counts().plot.pie(explode=[0,0.1],autopct='%1.
↪1f%%',ax=ax[0],shadow=False)
ax[0].set_title('SeriousDlqin2yrs')
ax[0].set_ylabel('')
```

```
sns.countplot('SeriousDlqin2yrs',data=df,ax=ax[1])
ax[1].set_title('SeriousDlqin2yrs')
plt.show()
```

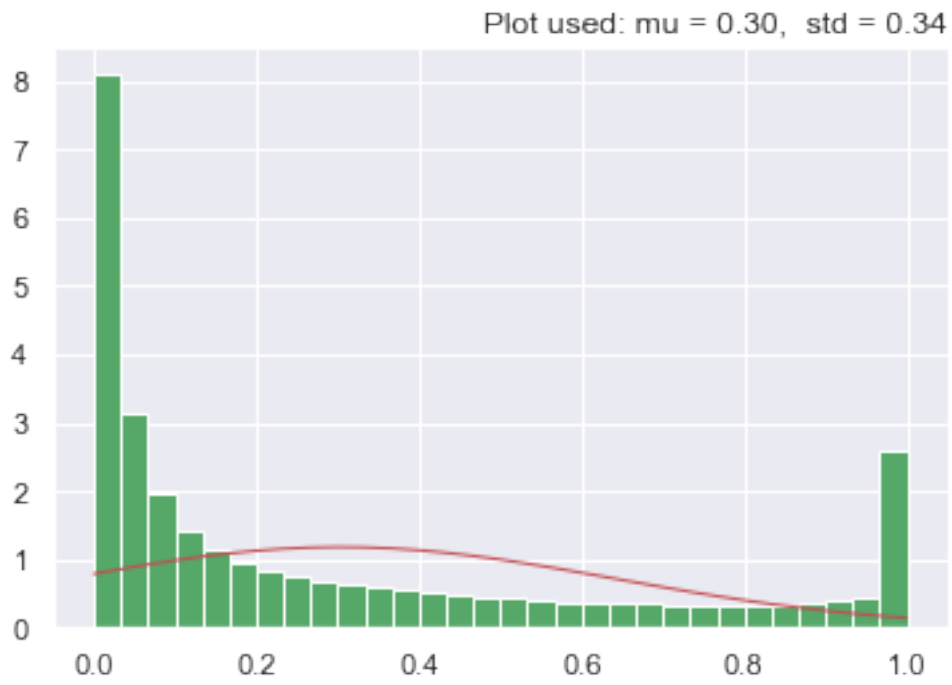


About 6.7% customers were delinquents.

Let's create distribution charts for all independent variables together.

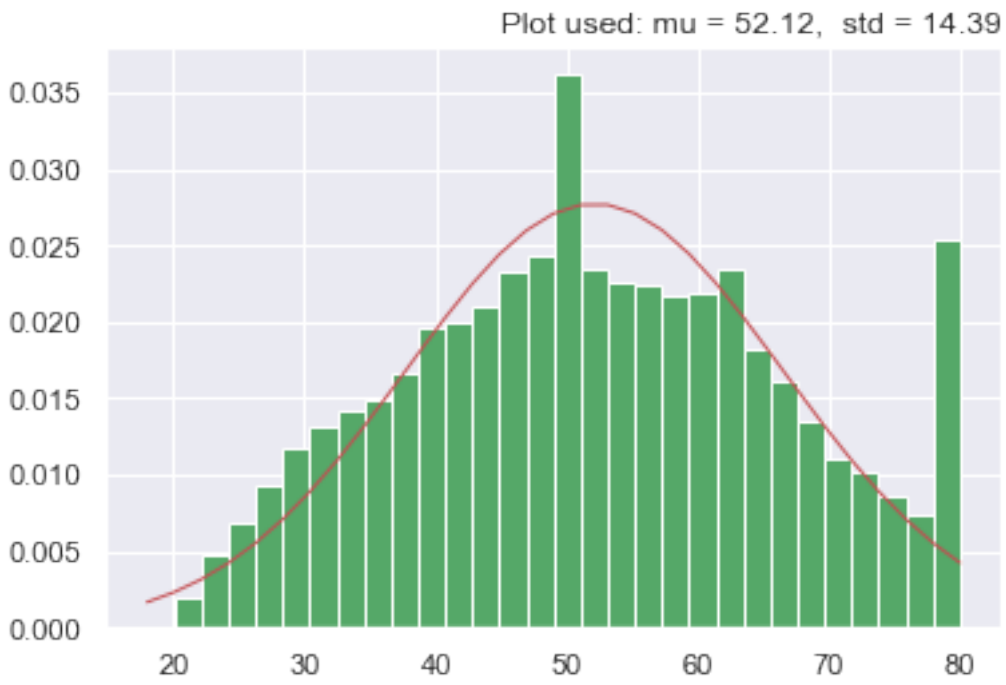
[82]:
```
for column in df.columns[2:]:
    print(column)
    #s=df['column']
    s=df[column]
    mu, sigma =norm.fit(s)
    count, bins, ignored = plt.hist(s, 30, normed=True, color='g')
    plt.plot(bins, 1/(sigma * np.sqrt(2 * np.pi)) *np.exp( - (bins - mu)**2 /␣
↪(2 * sigma**2) ), linewidth=1, color='r')

    title = "Plot used: mu = %.2f,  std = %.2f" % (mu, sigma)
    plt.title(title, loc='right')

    plt.show()
```

```
RevolvingUtilizationOfUnsecuredLines

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:6:
MatplotlibDeprecationWarning:
The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1.
Use 'density' instead.
```

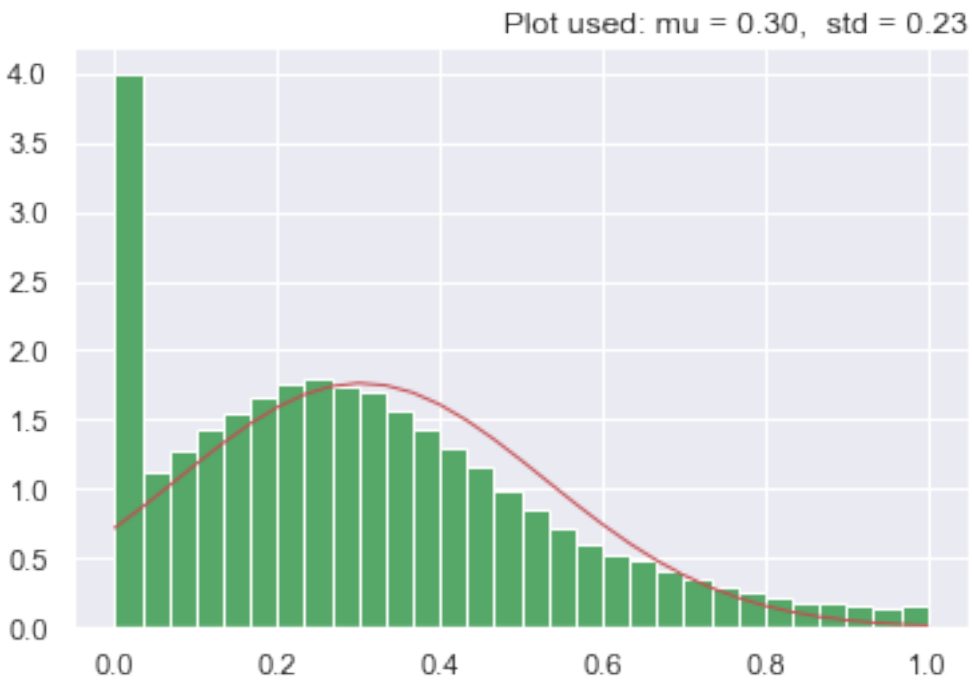



```
age
```

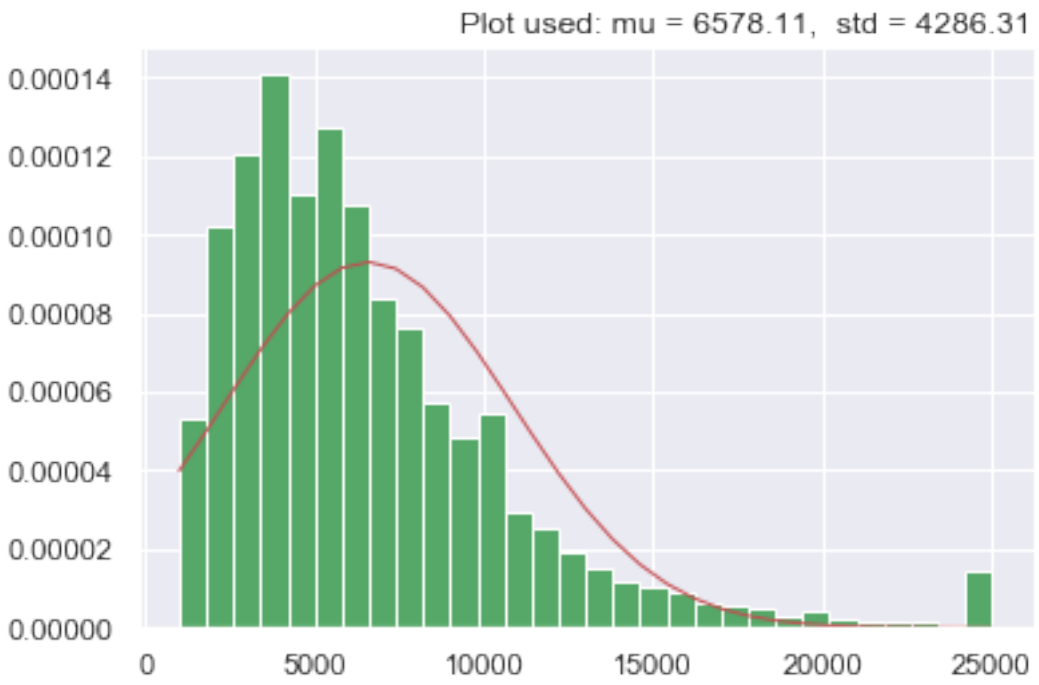
```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:6:
MatplotlibDeprecationWarning:
The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1.
Use 'density' instead.
```



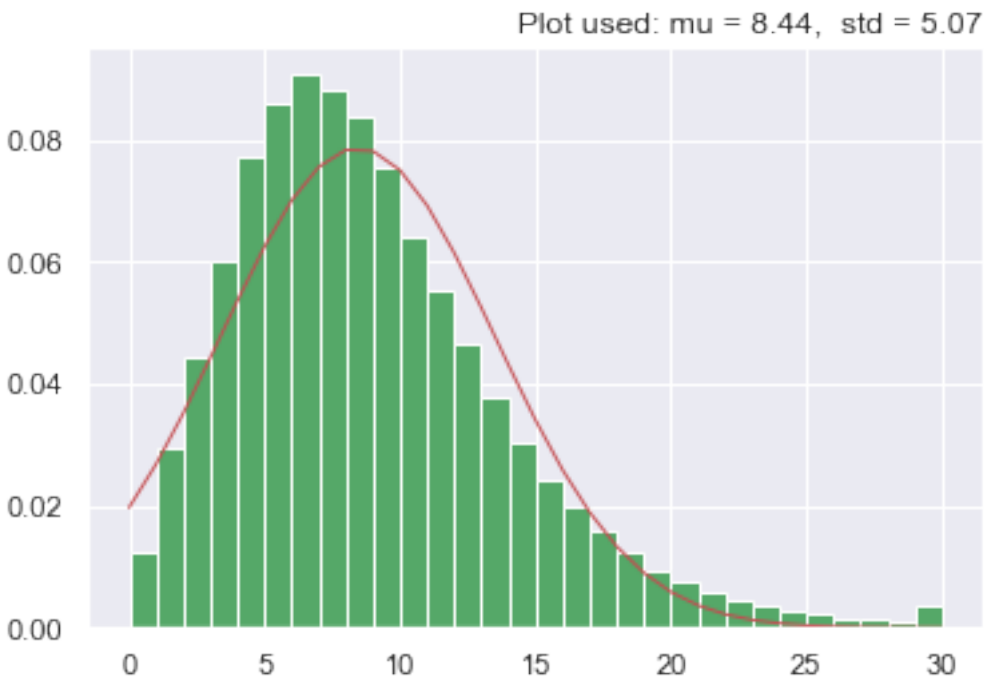

```
DebtRatio

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:6:
MatplotlibDeprecationWarning:
The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1.
Use 'density' instead.
```



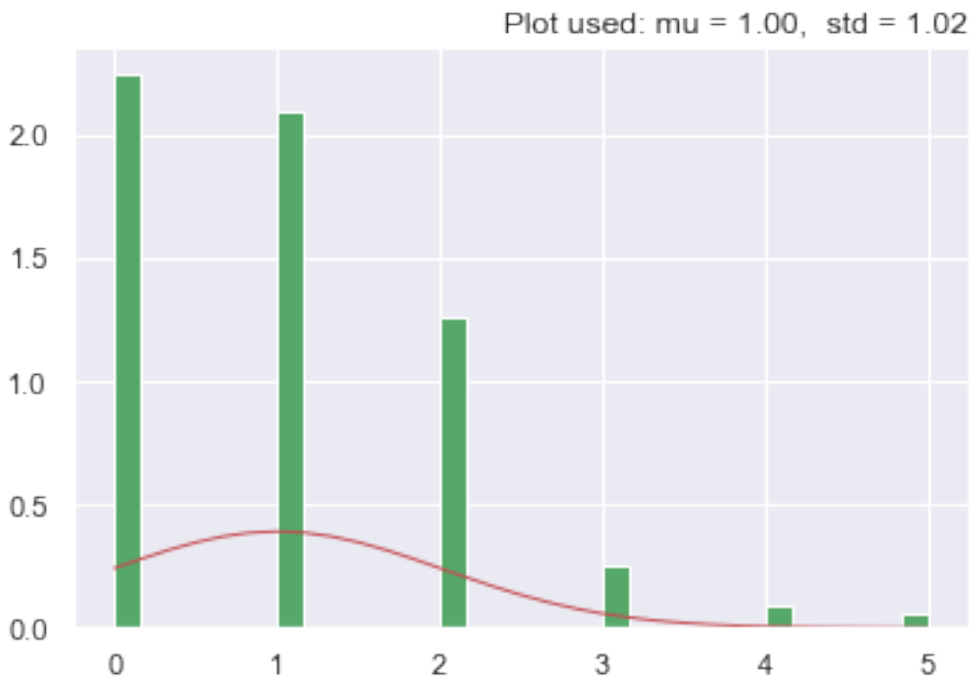

```
MonthlyIncome

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:6:
MatplotlibDeprecationWarning:
The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1.
Use 'density' instead.
```



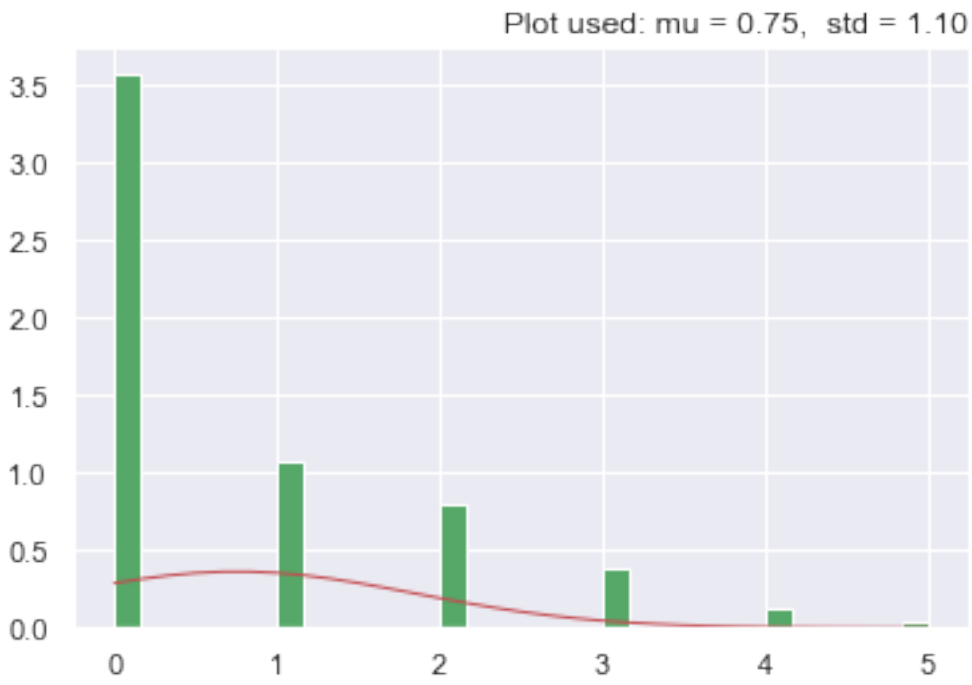

```
NumberOfOpenCreditLinesAndLoans

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:6:
MatplotlibDeprecationWarning:
The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1.
Use 'density' instead.
```




```
NumberRealEstateLoansOrLines

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:6:
MatplotlibDeprecationWarning:
The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1.
Use 'density' instead.
```




```
NumberOfDependents

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:6:
MatplotlibDeprecationWarning:
The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1.
Use 'density' instead.
```



All these variables look fine. Although distribution of some of these variables are not close to a normal distribution, it is not very critical. The techniques we apply are not very sensitive to normality. We also have the option of converting some of these variables to categories for modeling (eg. RevolvingUtilizationOfUnsecuredLines).

Bivariate Analysis

Under bivariate analysis we will examine the realtionship between Dependent variable and each of the independent variables. We will also check selected pairs of independent variables.

1.8 SeriousDlqin2yrs vs RevolvingUtilizationOfUnsecuredLines

Easiest approach is to compare the means of RevolvingUtilizationOfUnsecuredL by two categories of SeriousDlqin2yrs

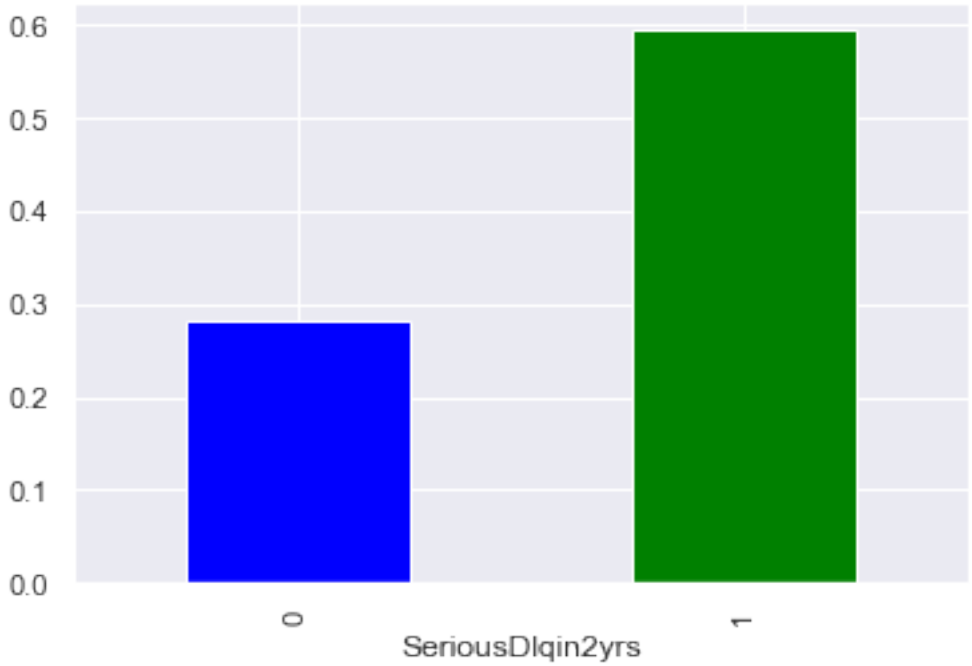
[83]:
```
df.groupby('SeriousDlqin2yrs')['RevolvingUtilizationOfUnsecuredLines'].
↪agg(['count','mean'])
```

[83]:

SeriousDlqin2yrs	count	mean
0	139974	0.282806
1	10026	0.594927

[84]:
```
df['RevolvingUtilizationOfUnsecuredLines'].groupby(df.SeriousDlqin2yrs).mean().
↪plot(kind='bar', color=['blue', 'green'])
```

[84]: <matplotlib.axes._subplots.AxesSubplot at 0x22ae9dcbf48>



As expected, delinquent customers got almost twice the utilization of unsecured lines

Let's now explore the relationship in detail by categorising the varaible. To categorise the variable, we will choose 25, 50 and 75 percentile as cutoffs.

[85]:
```
df['RevolvingUtilizationOfUnsecuredLines'].describe()
```

[85]:
```
count    150000.000000
mean          0.303669
std           0.337852
min           0.000000
25%           0.028578
50%           0.144257
75%           0.520104
max           1.000000
Name: RevolvingUtilizationOfUnsecuredLines, dtype: float64
```

[86]:
```
def cat_ruul(ruul):
    if ruul <0.03:
        return 1
    elif 0.03<= ruul <0.14:
        return 2
    elif 0.14<= ruul <0.52:
        return 3
```

```
    else:
        return 4
```

[87]:
```
df['ruul_cat'] = df['RevolvingUtilizationOfUnsecuredLines'].apply(cat_ruul)
df.head(3)
```

[87]:
```
   ID  SeriousDlqin2yrs  RevolvingUtilizationOfUnsecuredLines  age  DebtRatio  \
0   1                 1                              0.766127   45   0.802982
1   2                 0                              0.957151   40   0.121876
2   3                 0                              0.658180   38   0.085113

   MonthlyIncome  NumberOfOpenCreditLinesAndLoans  \
0         9120.0                               13
1         2600.0                                4
2         3042.0                                2

   NumberRealEstateLoansOrLines  NumberOfDependents  ruul_cat
0                             5                 2.0         4
1                             0                 1.0         4
2                             0                 0.0         4
```

[88]:
```
# lets check if the categorization was done correctly
df.groupby('ruul_cat')['RevolvingUtilizationOfUnsecuredLines'].
 ↪agg(['min','max'])
```

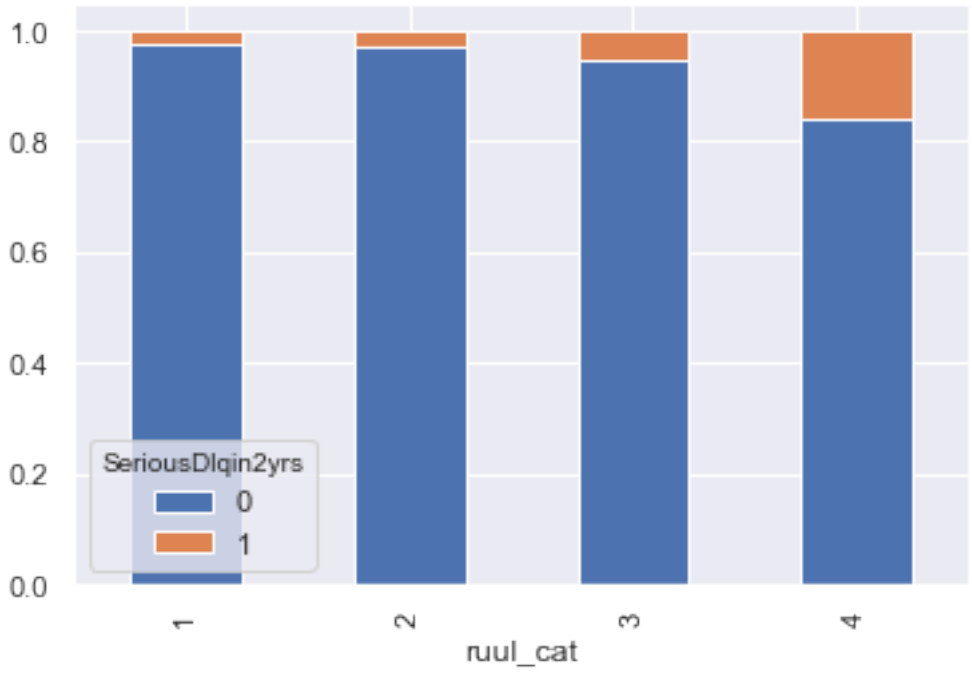
[88]:
```
                min       max
ruul_cat
1          0.000000  0.030000
2          0.030006  0.139999
3          0.140022  0.519983
4          0.520023  1.000000
```

[89]:
```
pd.crosstab(df.SeriousDlqin2yrs, df.ruul_cat, normalize='columns')
```

[89]:
```
ruul_cat                1         2         3        4
SeriousDlqin2yrs
0                0.973692  0.972357  0.946664  0.84043
1                0.026308  0.027643  0.053336  0.15957
```

[90]:
```
sb=pd.crosstab(df.ruul_cat, df.SeriousDlqin2yrs, normalize=0)
sb.plot.bar(stacked=True)
```

[90]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae1510288>
```



As expected, plot shows that there are more delinquents in the category of highest utilization. However there is not much difference between the fiirst two categories.

[91]:
```
df2=pd.crosstab(df.SeriousDlqin2yrs, df.ruul_cat)
chi2_contingency(df2)
```

[91]:
```
(7177.181787116916,
 0.0,
 3,
 array([[35895.86572, 33386.59848, 35691.50368, 35000.03212],
        [ 2571.13428,  2391.40152,  2556.49632,  2506.96788]]))
```

Chi-square test establish that there is significant dependency between utilization and delinquency;

1.9 SeriousDlqin2yrs vs Age

Easiest approach is to compare the means of Age by two categories of SeriousDlqin2yrs.

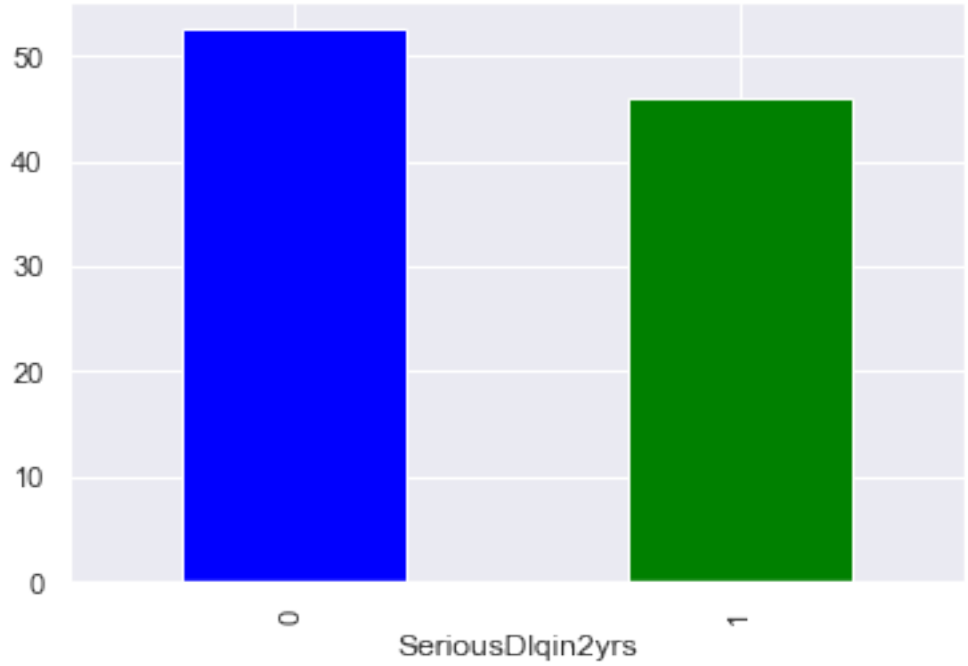
[92]:
```
df.groupby('SeriousDlqin2yrs')['age'].agg(['count','mean'])
```

[92]:

SeriousDlqin2yrs	count	mean
0	139974	52.567834
1	10026	45.869040

[93]:
```
df['age'].groupby(df.SeriousDlqin2yrs).mean().plot(kind='bar', color=['blue',␣
↪'green'])
```

[93]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae9e9fac8>
```



Delinquent cusomters are younger than non-delinquent customers.

let's now explore the relationship in detail by categorising age. To categorise the variable, we will choose 25, 50 and 75 percentile as cutoffs.

[94]:
```
df['age'].describe()
```

[94]:
```
count    150000.000000
mean         52.120087
std          14.389418
min          18.000000
25%          41.000000
50%          52.000000
75%          63.000000
max          80.000000
Name: age, dtype: float64
```

[95]:
```
def cat_ruul(ruul):
    if ruul <41:
        return 1
    elif 41<= ruul <52:
```

```
        return 2
    elif 52<= ruul <63:
        return 3
    else:
        return 4
```

[96]:
```
df['age_cat'] = df['age'].apply(cat_ruul)
df.head(3)
```

[96]:

	ID	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	DebtRatio	MonthlyIncome	NumberOfOpenCreditLinesAndLoans	NumberRealEstateLoansOrLines	NumberOfDependents	ruul_cat	age_cat
0	1	1	0.766127	45	0.802982	9120.0	13	5	2.0	4	2
1	2	0	0.957151	40	0.121876	2600.0	4	0	1.0	4	1
2	3	0	0.658180	38	0.085113	3042.0	2	0	0.0	4	1

[97]:
```
# lets check if the categorization was done correctly
df.groupby('age_cat')['age'].agg(['min','max'])
```

[97]:

age_cat	min	max
1	18	40
2	41	51
3	52	62
4	63	80

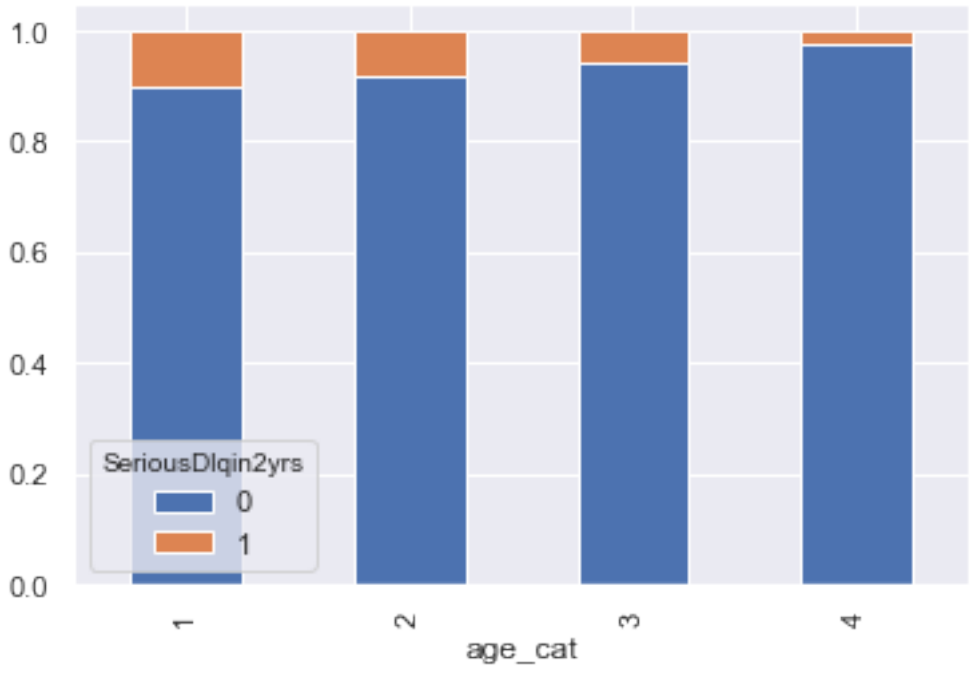
[98]:
```
pd.crosstab(df.SeriousDlqin2yrs, df.age_cat, normalize='columns')
```

[98]:

age_cat	1	2	3	4
SeriousDlqin2yrs				
0	0.896458	0.918115	0.942146	0.973347
1	0.103542	0.081885	0.057854	0.026653

[99]:
```
sb=pd.crosstab(df.age_cat, df.SeriousDlqin2yrs, normalize=0)
sb.plot.bar(stacked=True)
```

[99]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae7366c48>
```



Plot shows that there are more proportion of delinquents in the category of youngest age. Delinquency decreases as age increases uniformly.

[100]:
```
df2=pd.crosstab(df.SeriousDlqin2yrs, df.age_cat)
chi2_contingency(df2)
```

[100]:
```
(1930.9900919630384,
 0.0,
 3,
 array([[32751.11652, 36079.69824, 35711.10004, 35432.0852 ],
        [ 2345.88348,  2584.30176,  2557.89996,  2537.9148 ]]))
```

chi-square test establish that there is significant dependency between age and delinquency;

1.10 SeriousDlqin2yrs vs DebtRatio

Easiest approach is to compare the means of DebtRatio by two categories of SeriousDlqin2yrs

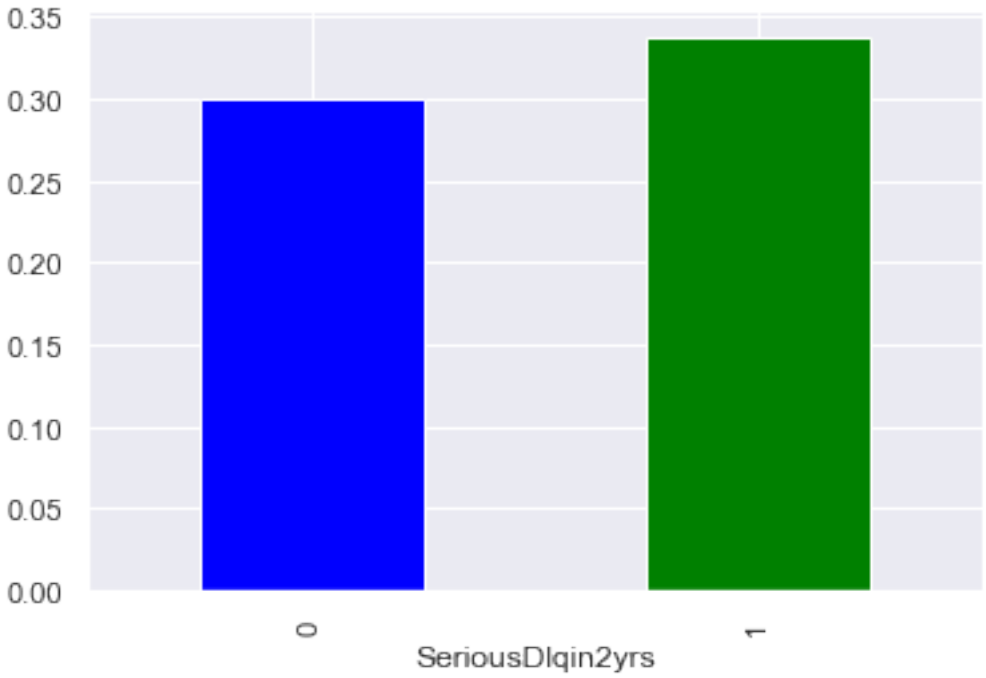
[101]:
```
df.groupby('SeriousDlqin2yrs')['DebtRatio'].agg(['count','mean'])
```

[101]:

SeriousDlqin2yrs	count	mean
0	139974	0.300645
1	10026	0.337519

[102]:
```
df['DebtRatio'].groupby(df.SeriousDlqin2yrs).mean().plot(kind='bar',␣
↪color=['blue', 'green'])
```

[102]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae73e9748>
```



Delinquent customers got higher debtratio compared to non-delinquent customers.

let's now explore the relationship in detail by categorising DebtRatio. To categorise the variable, we will choose 25, 50 and 75 percentile as cutoffs.

[103]:
```
df['DebtRatio'].describe()
```

[103]:
```
count    150000.000000
mean          0.303109
std           0.226290
min           0.000000
25%           0.126122
50%           0.274252
75%           0.438325
max           1.000000
Name: DebtRatio, dtype: float64
```

[104]:
```
def cat_ruul(ruul):
    if ruul <0.13:
        return 1
```

```
    elif 0.13<= ruul <0.27:
        return 2
    elif 0.27<= ruul <0.43:
        return 3
    else:
        return 4
```

[105]:
```
df['DebtRatio_cat'] = df['DebtRatio'].apply(cat_ruul)
df.head(3)
```

[105]:

	ID	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	DebtRatio	MonthlyIncome	NumberOfOpenCreditLinesAndLoans	NumberRealEstateLoansOrLines	NumberOfDependents	ruul_cat	age_cat	DebtRatio_cat
0	1	1	0.766127	45	0.802982	9120.0	13	5	2.0	4	2	4
1	2	0	0.957151	40	0.121876	2600.0	4	0	1.0	4	1	1
2	3	0	0.658180	38	0.085113	3042.0	2	0	0.0	4	1	1

[106]:
```
# lets check if the categorization was done correctly
df.groupby('DebtRatio_cat')['DebtRatio'].agg(['min','max'])
```

[106]:

DebtRatio_cat	min	max
1	0.000000	0.129995
2	0.130008	0.269990
3	0.270009	0.429991
4	0.430011	1.000000

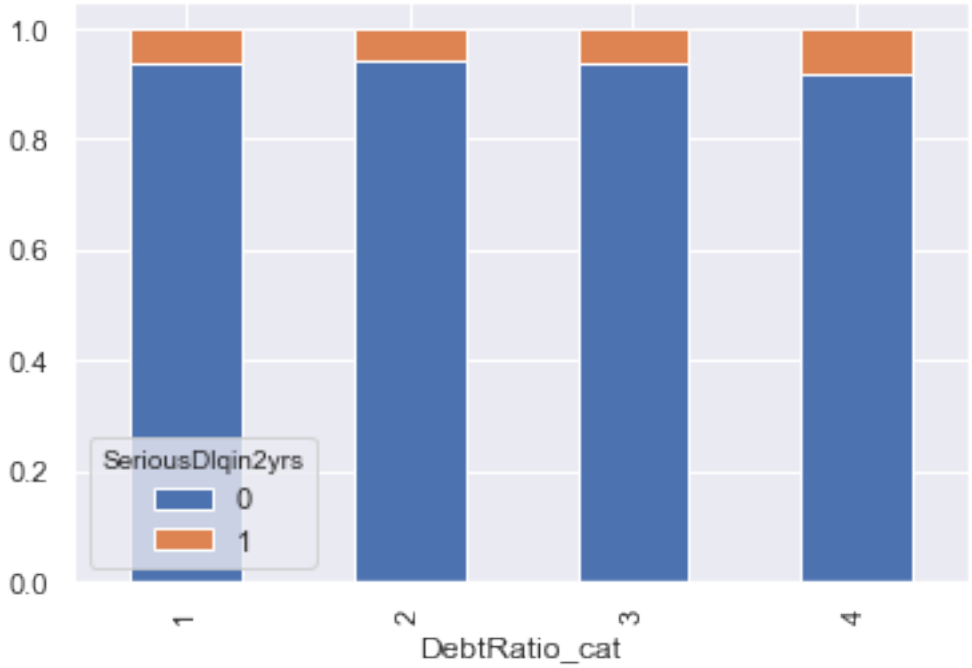
[107]:
```
pd.crosstab(df.SeriousDlqin2yrs, df.DebtRatio_cat, normalize='columns')
```

[107]:

SeriousDlqin2yrs \ DebtRatio_cat	1	2	3	4
0	0.939219	0.939605	0.938991	0.915813
1	0.060781	0.060395	0.061009	0.084187

[108]:
```
sb=pd.crosstab(df.DebtRatio_cat, df.SeriousDlqin2yrs, normalize=0)
sb.plot.bar(stacked=True)
```

[108]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae8ffb508>
```



As expected it shows that there are more delinquents in the category of highest DebtRatio.

[109]:
```
df2=pd.crosstab(df.SeriousDlqin2yrs, df.DebtRatio_cat)
chi2_contingency(df2)
```

[109]:
```
(254.86642993657873,
 5.7976020035809566e-55,
 3,
 array([[35726.0306 , 33219.56284, 34582.9096 , 36445.49696],
        [ 2558.9694 ,  2379.43716,  2477.0904 ,  2610.50304]]))
```

Chi-square test establish that there is significant dependency between DebtRatio and delinquency.

1.11 SeriousDlqin2yrs vs MonthlyIncome

Simplest approach is to compare the means of MonthlyIncome by two categories of SeriousDlqin2yrs

[110]:
```
df.groupby('SeriousDlqin2yrs')['MonthlyIncome'].agg(['count','mean'])
```

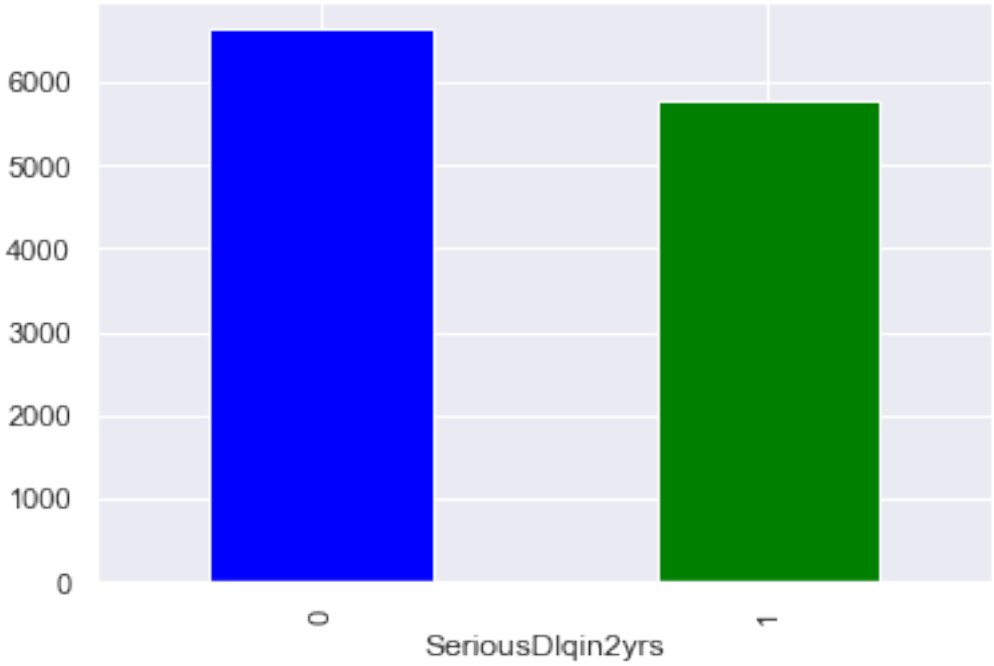
[110]:

SeriousDlqin2yrs	count	mean

```
0                 139974  6635.519196
1                  10026  5776.572910
```

[111]:
```
df['MonthlyIncome'].groupby(df.SeriousDlqin2yrs).mean().plot(kind='bar',␣
↪color=['blue', 'green'])
```

[111]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae906aa08>
```



Delinquent cusomters got lower MonthlyIncome compared to non-delinquent customers.

let's now explore the relationship in detail by categorising MonthlyIncome. To categorise the variable, we will choose 25, 50 and 75 percentile as cutoffs.

[112]:
```
df['MonthlyIncome'].describe()
```

[112]:
```
count    150000.000000
mean       6578.107227
std        4286.321398
min        1000.000000
25%        3600.000000
50%        5500.000000
75%        8333.000000
max       25000.000000
Name: MonthlyIncome, dtype: float64
```

[113]:
```
def cat_ruul(ruul):
    if ruul <3600:
        return 1
    elif 3600<= ruul <5500:
        return 2
    elif 5500<= ruul <8333:
        return 3
    else:
        return 4
```

[114]:
```
df['MonthlyIncome_cat'] = df['MonthlyIncome'].apply(cat_ruul)
df.head(3)
```

[114]:

	ID	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	DebtRatio	MonthlyIncome	NumberOfOpenCreditLinesAndLoans	NumberRealEstateLoansOrLines	NumberOfDependents	ruul_cat	age_cat	DebtRatio_cat	MonthlyIncome_cat
0	1	1	0.766127	45	0.802982	9120.0	13	5	2.0	4	2	4	4
1	2	0	0.957151	40	0.121876	2600.0	4	0	1.0	4	1	1	1
2	3	0	0.658180	38	0.085113	3042.0	2	0	0.0	4	1	1	1

[115]:
```
# lets check if the categorization was done correctly
df.groupby('MonthlyIncome_cat')['MonthlyIncome'].agg(['min','max'])
```

[115]:

MonthlyIncome_cat	min	max
1	1000.0	3599.0
2	3600.0	5499.0
3	5500.0	8332.0
4	8333.0	25000.0

[116]:
```
pd.crosstab(df.SeriousDlqin2yrs, df.MonthlyIncome_cat, normalize='columns')
```

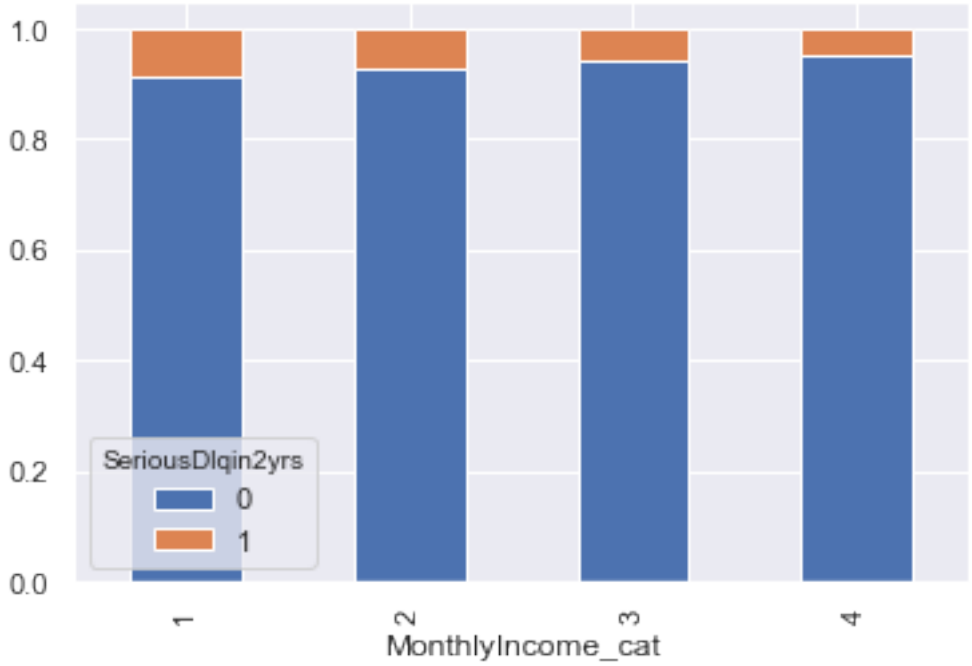
[116]:

MonthlyIncome_cat	1	2	3	4
SeriousDlqin2yrs				

```
0                   0.912834  0.926565  0.940627  0.951984
1                   0.087166  0.073435  0.059373  0.048016
```

[117]:
```
sb=pd.crosstab(df.MonthlyIncome_cat, df.SeriousDlqin2yrs, normalize=0)
sb.plot.bar(stacked=True)
```

[117]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae90f87c8>
```



As expected it shows that there are less delinquents in the category of highest MonthlyIncome.

[118]:
```
df2=pd.crosstab(df.SeriousDlqin2yrs, df.MonthlyIncome_cat)
chi2_contingency(df2)
```

[118]:
```
(524.3515592410665,
 2.518157324733066e-113,
 3,
 array([[34974.8368 , 33953.95976, 35441.4168 , 35603.78664],
        [ 2505.1632 ,  2432.04024,  2538.5832 ,  2550.21336]]))
```

Chi-square test establish that there is significant dependency between MonthlyIncome and delinquency;

1.12 SeriousDlqin2yrs vs NumberOfOpenCreditLinesAndLoans

Simplest approach is to compare the means of NumberOfOpenCreditLinesAndLoans by two categories of SeriousDlqin2yrs

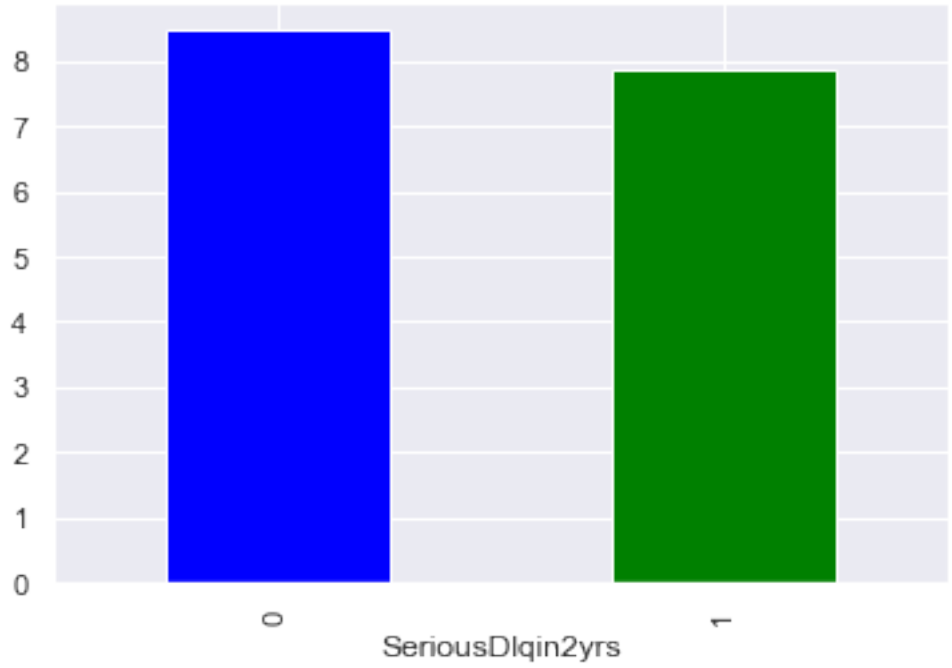
[119]:
```
df.groupby('SeriousDlqin2yrs')['NumberOfOpenCreditLinesAndLoans'].
↪agg(['count','mean'])
```

[119]:

SeriousDlqin2yrs	count	mean
0	139974	8.480196
1	10026	7.860762

[120]:
```
df['NumberOfOpenCreditLinesAndLoans'].groupby(df.SeriousDlqin2yrs).mean().
↪plot(kind='bar', color=['blue', 'green'])
```

[120]: <matplotlib.axes._subplots.AxesSubplot at 0x22ae911a348>



Delinquent cusomters got lower NumberOfOpenCreditLinesAndLoans compared to non-delinquent customers.

let's now explore the relationship in detail by categorising NumberOfOpenCreditLinesAndLoans. To categorise the variable, we will choose 25, 50 and 75 percentile as cutoffs.

[121]:
```
df['NumberOfOpenCreditLinesAndLoans'].describe()
```

[121]:
```
count    150000.000000
mean          8.438793
std           5.070728
min           0.000000
25%           5.000000
```

```
50%           8.000000
75%          11.000000
max          30.000000
Name: NumberOfOpenCreditLinesAndLoans, dtype: float64
```

[122]:
```
def cat_ruul(ruul):
    if ruul <5:
        return 1
    elif 5<= ruul <8:
        return 2
    elif 8<= ruul <11:
        return 3
    else:
        return 4
```

[123]:
```
df['NOCLL_Cat'] = df['NumberOfOpenCreditLinesAndLoans'].apply(cat_ruul)
df.head(3)
```

[123]:

	ID	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	DebtRatio	MonthlyIncome	NumberOfOpenCreditLinesAndLoans	NumberRealEstateLoansOrLines	NumberOfDependents	ruul_cat	age_cat	DebtRatio_cat	MonthlyIncome_cat	NOCLL_Cat
0	1	1	0.766127	45	0.802982	9120.0	13	5	2.0	4	2	4	4	4
1	2	0	0.957151	40	0.121876	2600.0	4	0	1.0	4	1	1	1	1
2	3	0	0.658180	38	0.085113	3042.0	2	0	0.0	4	1	1	1	1

[124]:
```
df.groupby('NOCLL_Cat')['NumberOfOpenCreditLinesAndLoans'].agg(['min','max'])
```

[124]:

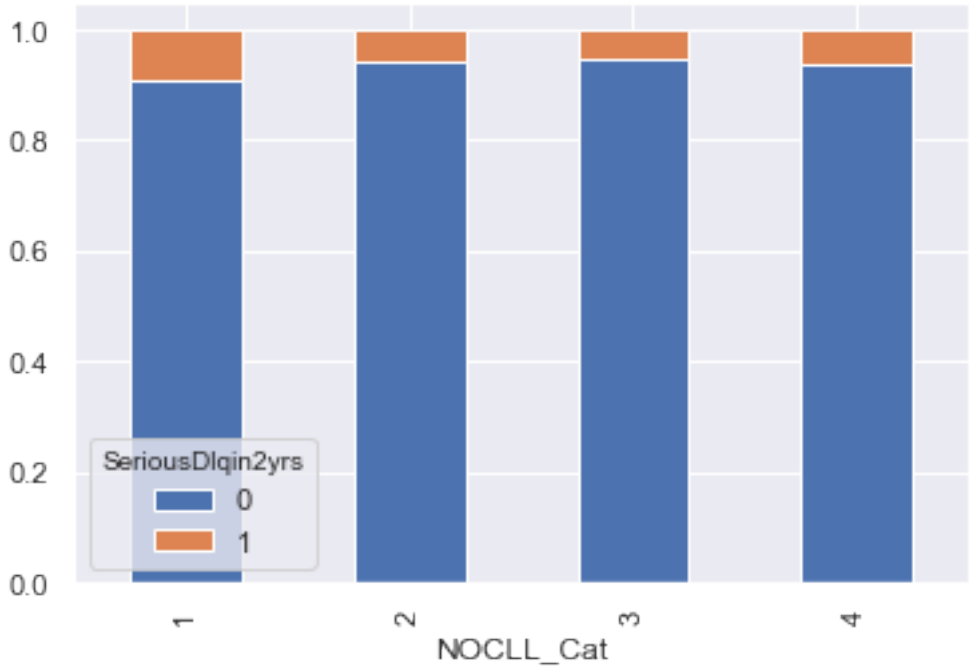
NOCLL_Cat	min	max
1	0	4
2	5	7
3	8	10
4	11	30

[125]:
```
pd.crosstab(df.SeriousDlqin2yrs, df.NOCLL_Cat, normalize='columns')
```

[125]:
```
NOCLL_Cat                1         2         3         4
SeriousDlqin2yrs
0                 0.907811  0.941694  0.945023  0.935852
1                 0.092189  0.058306  0.054977  0.064148
```

[126]:
```
sb=pd.crosstab(df.NOCLL_Cat, df.SeriousDlqin2yrs, normalize=0)
sb.plot.bar(stacked=True)
```

[126]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae90bf4c8>
```



As expected it shows that there are more delinquents in the category of lowest NumberOfOpenCreditLinesAndLoans.

[127]:
```
df2=pd.crosstab(df.SeriousDlqin2yrs, df.NOCLL_Cat)
chi2_contingency(df2)
```

[127]:
```
(473.89910137342736,
 2.1617934485230027e-102,
 3,
 array([[31409.23244, 37130.4364 , 31299.11956, 40135.2116 ],
        [ 2249.76756,  2659.5636 ,  2241.88044,  2874.7884 ]]))
```

Chi-square test establish that there is significant dependency between NumberOfOpenCreditLinesAndLoans and delinquency;

1.12.1 SeriousDlqin2yrs vs NumberRealEstateLoansOrLines

Simplest approach is to compare the means of NumberRealEstateLoansOrLines by two categories of SeriousDlqin2yrs

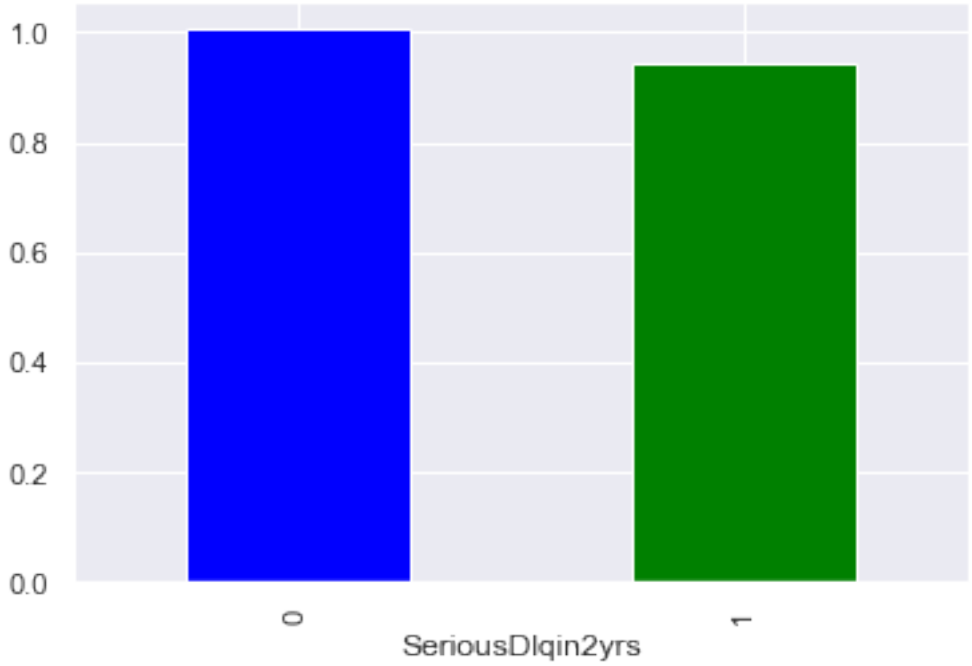
[128]:
```
df.groupby('SeriousDlqin2yrs')['NumberRealEstateLoansOrLines'].
↪agg(['count','mean'])
```

[128]:

SeriousDlqin2yrs	count	mean
0	139974	1.006808
1	10026	0.942051

[129]:
```
df['NumberRealEstateLoansOrLines'].groupby(df.SeriousDlqin2yrs).mean().
↪plot(kind='bar', color=['blue', 'green'])
```

[129]: <matplotlib.axes._subplots.AxesSubplot at 0x22ae920df08>



Delinquent cusomters got lower NumberRealEstateLoansOrLines compared to non-delinquent customers.

let's now explore the relationship in detail by categorising NumberRealEstateLoansOrLines. To categorise the variable, we will choose 25, 50 and 75 percentile as cutoffs.

[130]:
```
df['NumberRealEstateLoansOrLines'].describe()
```

[130]:
```
count    150000.000000
mean          1.002480
std           1.020301
min           0.000000
25%           0.000000
50%           1.000000
75%           2.000000
max           5.000000
Name: NumberRealEstateLoansOrLines, dtype: float64
```

[131]:
```
def cat_ruul(ruul):
    if ruul <=0:
        return 1
    elif 0< ruul <=1:
        return 2
    elif 1< ruul <=2:
        return 3
    else:
        return 4
```

[132]:
```
df['NRELL_Cat'] = df['NumberRealEstateLoansOrLines'].apply(cat_ruul)
df.head(3)
```

[132]:

	ID	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	DebtRatio	MonthlyIncome	NumberOfOpenCreditLinesAndLoans	NumberRealEstateLoansOrLines	NumberOfDependents	ruul_cat	age_cat	DebtRatio_cat	MonthlyIncome_cat	NOCLL_Cat	NRELL_Cat
0	1	1	0.766127	45	0.802982	9120.0	13	5	2.0	4	2	4	4	4	4
1	2	0	0.957151	40	0.121876	2600.0	4	0	1.0	4	1	1	1	1	1
2	3	0	0.658180	38	0.085113	3042.0	2	0	0.0	4	1	1	1	1	1

[133]:
```
# lets check if the categorization was done correctly
df.groupby('NRELL_Cat')['NumberRealEstateLoansOrLines'].agg(['min','max'])
```

[133]:

NRELL_Cat	min	max
1	0	0
2	1	1
3	2	2
4	3	5

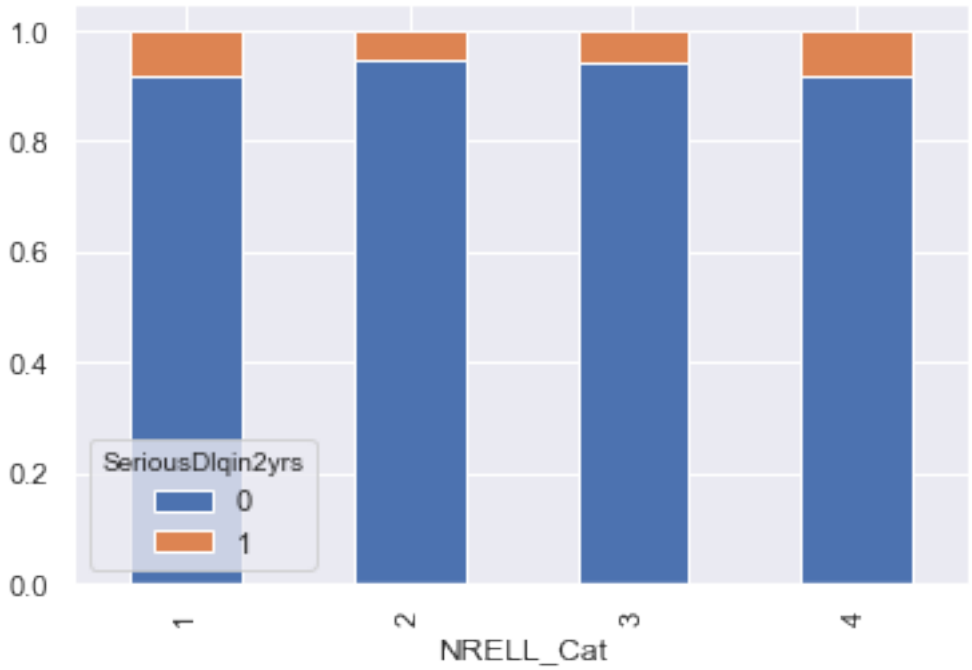
[134]:
```
pd.crosstab(df.SeriousDlqin2yrs, df.NRELL_Cat, normalize='columns')
```

[134]:

SeriousDlqin2yrs \ NRELL_Cat	1	2	3	4
0	0.916851	0.947495	0.944007	0.915494
1	0.083149	0.052505	0.055993	0.084506

[135]:
```
sb=pd.crosstab(df.NRELL_Cat, df.SeriousDlqin2yrs, normalize=0)
sb.plot.bar(stacked=True)
```

[135]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae9c40e88>
```



As expected it shows that there are more delinquents in the category of lowest NumberRealEstateLoansOrLines.

[136]:
```
df2=pd.crosstab(df.SeriousDlqin2yrs, df.NRELL_Cat)
chi2_contingency(df2)
```

[136]:
```
(521.3188180426857,
 1.1438773309834148e-112,
 3,
 array([[52432.39408, 48839.72808, 29415.06952,  9286.80832],
        [ 3755.60592,  3498.27192,  2106.93048,   665.19168]]))
```

chi-square test establish that there is significant dependency between NumberRealEstateLoansOrLines and delinquency;

1.13 SeriousDlqin2yrs vs NumberOfDependents

Simplest approach is to compare the means of NumberOfDependents by two categories of SeriousDlqin2yrs

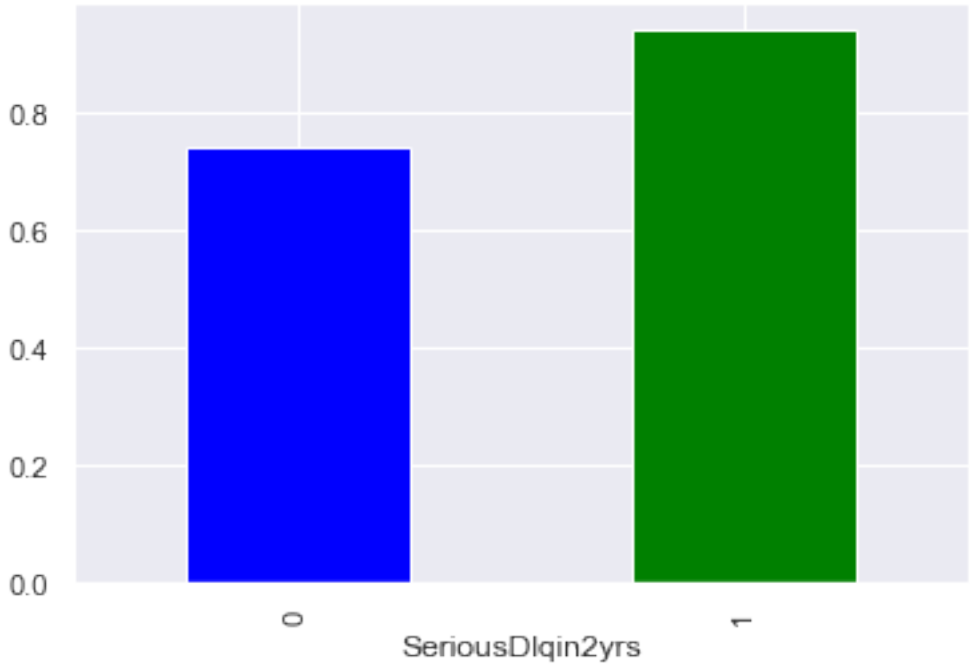
[137]:
```
df.groupby('SeriousDlqin2yrs')['NumberOfDependents'].agg(['count','mean'])
```

[137]:

SeriousDlqin2yrs	count	mean
0	139974	0.741159
1	10026	0.940555

[138]:
```
df['NumberOfDependents'].groupby(df.SeriousDlqin2yrs).mean().plot(kind='bar',␣
↪color=['blue', 'green'])
```

[138]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae8f60588>
```



Delinquent cusomters got higher NumberOfDependents compared to non-delinquent customers.

let's now explore the relationship in detail by categorising NumberOfDependents. To categorise the variable, we will choose 25, 50 and 75 percentile as cutoffs.

[139]:
```
df['NumberOfDependents'].describe()
```

[139]:
```
count    150000.000000
mean          0.754487
std           1.101377
min           0.000000
25%           0.000000
50%           0.000000
75%           1.000000
max           5.000000
Name: NumberOfDependents, dtype: float64
```

[140]:
```
def cat_ruul(ruul):
    if ruul <=0:
        return 1
    elif 0< ruul <=1:
        return 2
    elif 1< ruul <=2:
        return 3
    else:
        return 4
```

[141]:
```
df['NOD_Cat'] = df['NumberOfDependents'].apply(cat_ruul)
df.head(3)
```

[141]:

	ID	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	DebtRatio	\
0	1	1	0.766127	45	0.802982	
1	2	0	0.957151	40	0.121876	
2	3	0	0.658180	38	0.085113	

	MonthlyIncome	NumberOfOpenCreditLinesAndLoans	\
0	9120.0	13	
1	2600.0	4	
2	3042.0	2	

	NumberRealEstateLoansOrLines	NumberOfDependents	ruul_cat	age_cat	\
0	5	2.0	4	2	
1	0	1.0	4	1	
2	0	0.0	4	1	

	DebtRatio_cat	MonthlyIncome_cat	NOCLL_Cat	NRELL_Cat	NOD_Cat
0	4	4	4	4	3
1	1	1	1	1	2

```
2              1                   1          1          1         1
```

[142]:
```
# lets check if the categorization was done correctly
df.groupby('NOD_Cat')['NumberOfDependents'].agg(['min','max'])
```

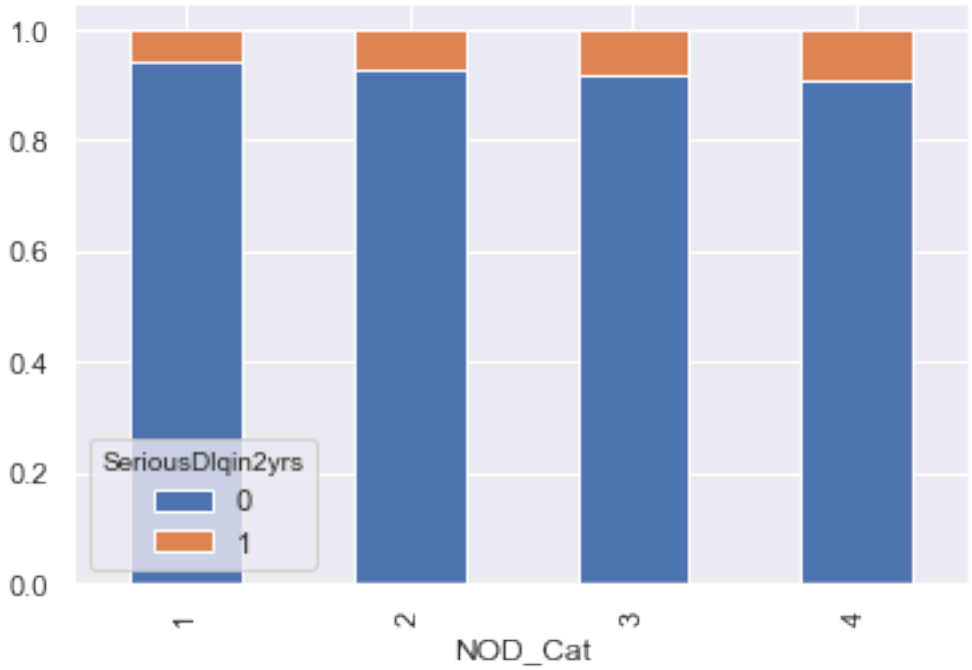
[142]:
```
         min  max
NOD_Cat
1        0.0  0.0
2        1.0  1.0
3        2.0  2.0
4        3.0  5.0
```

[143]:
```
pd.crosstab(df.SeriousDlqin2yrs, df.NOD_Cat, normalize='columns')
```

[143]:
```
NOD_Cat                 1        2         3         4
SeriousDlqin2yrs
0                0.941697  0.92732  0.919681  0.908779
1                0.058303  0.07268  0.080319  0.091221
```

[144]:
```
sb=pd.crosstab(df.NOD_Cat, df.SeriousDlqin2yrs, normalize=0)
sb.plot.bar(stacked=True)
```

[144]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22ae8e77bc8>
```



As expected it shows that there are more delinquents in the category of highest NumberOfDepen-

dents.

[145]:
```
df2=pd.crosstab(df.SeriousDlqin2yrs, df.NOD_Cat)
chi2_contingency(df2)
```

[145]:
```
(307.8359012512757,
 2.0034894537531076e-66,
 3,
 array([[83260.26784, 25241.978  , 18705.1922 , 12766.56196],
        [ 5963.73216,  1808.022  ,  1339.8078 ,   914.43804]]))
```

chi-square test establish that there is significant dependency between NumberOfDependents and delinquency;

This discussion provided an overview of EDA. Ideally this should result in a professional presentation. The Charts created can be copied and pasted into the presentation software or the summarised values can be used to create charts. Each of this analyses should be supported with conclusions.

[ ]:

[ ]: