Importing Libraries

```
# 'os' module provides functions for interacting with the operating system
import os

# 'Numpy' is used for mathematical operations on large, multi-dimensional arrays and matrices
import numpy as np

# 'Pandas' is used for data manipulation and analysis
import pandas as pd

# 'Matplotlib' is a data visualization library for 2D and 3D plots, built on numpy
from matplotlib import pyplot as plt
%matplotlib inline

# 'Seaborn' is based on matplotlib; used for plotting statistical graphics
import seaborn as sns

# to suppress warnings
import warnings
warnings.filterwarnings("ignore")
```

Importing and Exploration of the dataset

```
# loading the data and setting the unique client_id as the index::

df = pd.read_csv('/content/loans.csv', index_col = 'client_id')
```

```
# showing the first 5 rows of the dataset:
df.head()
```

client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate
46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15
46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25
46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68
46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24
46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13

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```
# To check the Dimensions of the dataset:
df.shape
```

```
(443, 7)
```

```
# Checking the info of the data:
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 443 entries, 46109 to 26945
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   loan_type    443 non-null    object
 1   loan_amount  443 non-null    int64
 2   repaid       443 non-null    int64
 3   loan_id      443 non-null    int64
 4   loan_start   443 non-null    object
 5   loan_end     443 non-null    object
 6   rate         443 non-null    float64
dtypes: float64(1), int64(3), object(3)
memory usage: 27.7+ KB
```

Checking the datatypes of the columns

```
df.dtypes
```

	0
loan_type	object
loan_amount	int64
repaid	int64
loan_id	int64
loan_start	object
loan_end	object
rate	float64

dtype: object

Converting the data types of columns

- loan_id to object
- repaid to category dtype
- loan_start and loan_end to date type

```
# loan_id:

df['loan_id'] = df['loan_id'].astype('object')

# repaid:

df['repaid'] = df['repaid'].astype('category')
```

```
# loan_start:

df['loan_start'] = pd.to_datetime(df['loan_start'], format = '%Y-%m-%d')


# loan_end:

df['loan_end'] = pd.to_datetime(df['loan_end'], format = '%Y-%m-%d')
```

Checking the datatypes again:

```
df.dtypes
```

	0
loan_type	object
loan_amount	int64
repaid	category
loan_id	object
loan_start	datetime64[ns]
loan_end	datetime64[ns]
rate	float64

dtype: object

Summary Statistics of the data

```
# Summary Statistics for Numerical data:
df.describe()
```

	loan_amount	loan_start	loan_end	rate
count	443.000000	443	443	443.000000
mean	7982.311512	2007-08-02 12:56:53.092550912	2009-08-23 11:35:37.246049536	3.217156
min	559.000000	2000-01-26 00:00:00	2001-08-02 00:00:00	0.010000
25%	4232.500000	2003-10-19 00:00:00	2005-09-12 12:00:00	1.220000
50%	8320.000000	2007-03-10 00:00:00	2009-03-19 00:00:00	2.780000
75%	11739.000000	2011-07-31 00:00:00	2013-09-11 12:00:00	4.750000
max	14971.000000	2014-11-11 00:00:00	2017-05-07 00:00:00	12.620000
std	4172.891992	NaN	NaN	2.397168

```
# Summary Statistics for Categorical data:
df.describe(exclude=[np.number])
```

	loan_type	repaid	loan_id	loan_start	loan_end
count	443	443.0	443.0	443	443
unique	4	2.0	443.0	NaN	NaN
top	home	1.0	10243.0	NaN	NaN
freq	121	237.0	1.0	NaN	NaN
mean	NaN	NaN	NaN	2007-08-02 12:56:53.092550912	2009-08-23 11:35:37.246049536
min	NaN	NaN	NaN	2000-01-26 00:00:00	2001-08-02 00:00:00
25%	NaN	NaN	NaN	2003-10-19 00:00:00	2005-09-12 12:00:00
50%	NaN	NaN	NaN	2007-03-10 00:00:00	2009-03-19 00:00:00
75%	NaN	NaN	NaN	2011-07-31 00:00:00	2013-09-11 12:00:00
max	NaN	NaN	NaN	2014-11-11 00:00:00	2017-05-07 00:00:00

Missing Values

```
# use isnull().sum() to check for missing values
df.isnull().sum()
```

	0
loan_type	0
loan_amount	0
repaid	0
loan_id	0
loan_start	0
loan_end	0
rate	0

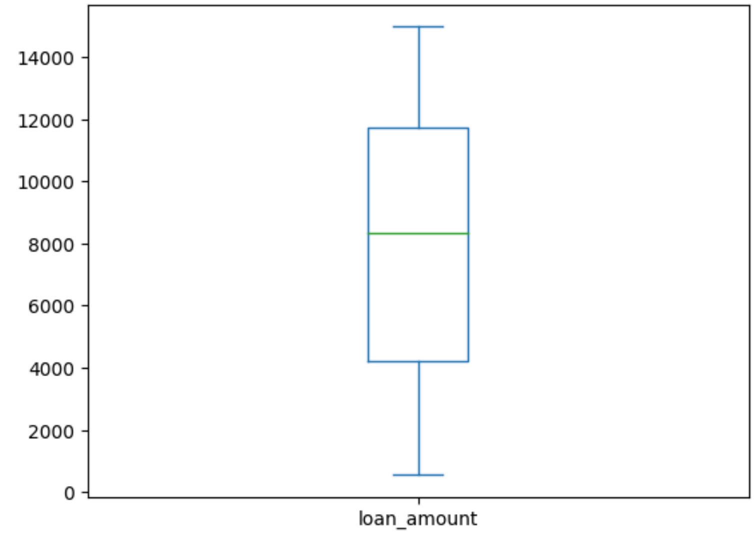
dtype: int64

There are no missing values in the data.

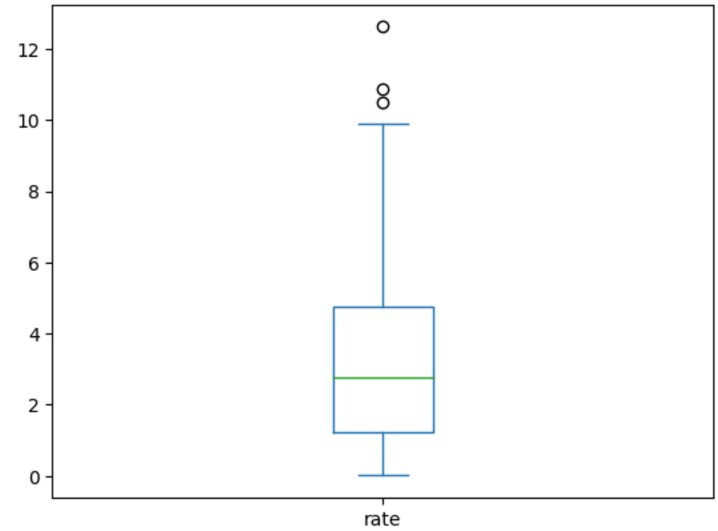
Outliers Treatment

To check presence of outlier, we plot box plot.

```
# For loan_amount
df['loan_amount'].plot(kind='box')
plt.show()
```




```
# For rate
df['rate'].plot(kind='box')
plt.show()
```



We can see that there are no outliers in the loan_amount column and some outliers are present in the rate column. To treat for outliers can either cap the values or transform the data. I Shall demonstrate both the approaches here.

Transformation

SQRT transformation

```
df['SQRT_RATE'] = df['rate']**0.5
```

```
df['sqrt_rate'] = np.sqrt(df['rate'])
```

```
df.head()
```

client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate	SQRT_RATE	sqrt_rate
46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15	1.466288	1.466288
46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25	1.118034	1.118034
46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68	0.824621	0.824621
46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24	1.113553	1.113553
46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13	1.769181	1.769181

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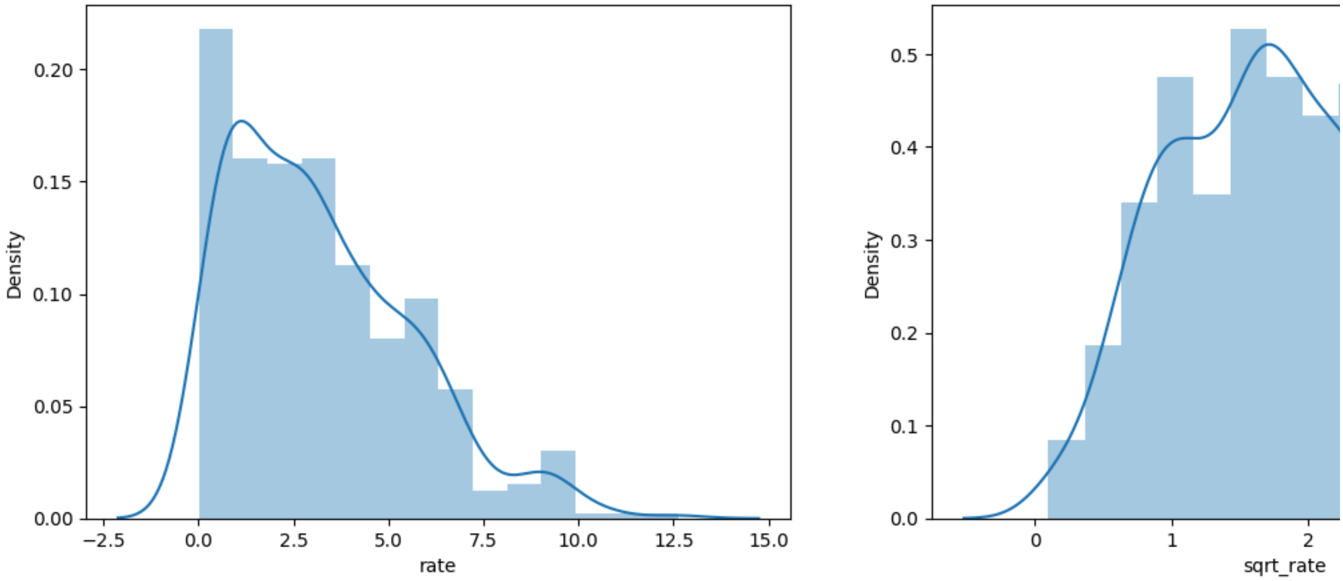
```
#checking the skewness, kurtosis between the original and transformed data:
print("The skewness of the original data is {}".format(df.rate.skew()))
print('The skewness of the SQRT transformed data is {}'.format(df.SQRT_RATE.skew()))

print('')

print("The kurtosis of the original data is {}".format(df.rate.kurt()))
print("The kurtosis of the SQRT transformed data is {}".format(df.SQRT_RATE.kurt()))
```

```
The skewness of the original data is 0.884204614329943
The skewness of the SQRT transformed data is 0.04964154055528862

The kurtosis of the original data is 0.42437165143736433
The kurtosis of the SQRT transformed data is -0.6318437642052039
```

```
# plotting the distribution

fig, axes = plt.subplots(1,2, figsize=(15,5))
sns.distplot(df['rate'], ax=axes[0])
sns.distplot(df['sqrt_rate'], ax=axes[1])

plt.show()
```



Result:

The Rate column was right skewed earlier. The skewness and kurtosis as reduced significantly. The transformed SQRT rate, on the right graph resembles normal distribution now.

Log Transformation

```
df['Log Rate'] = np.log(df['rate'])
```

```
df.head()
```

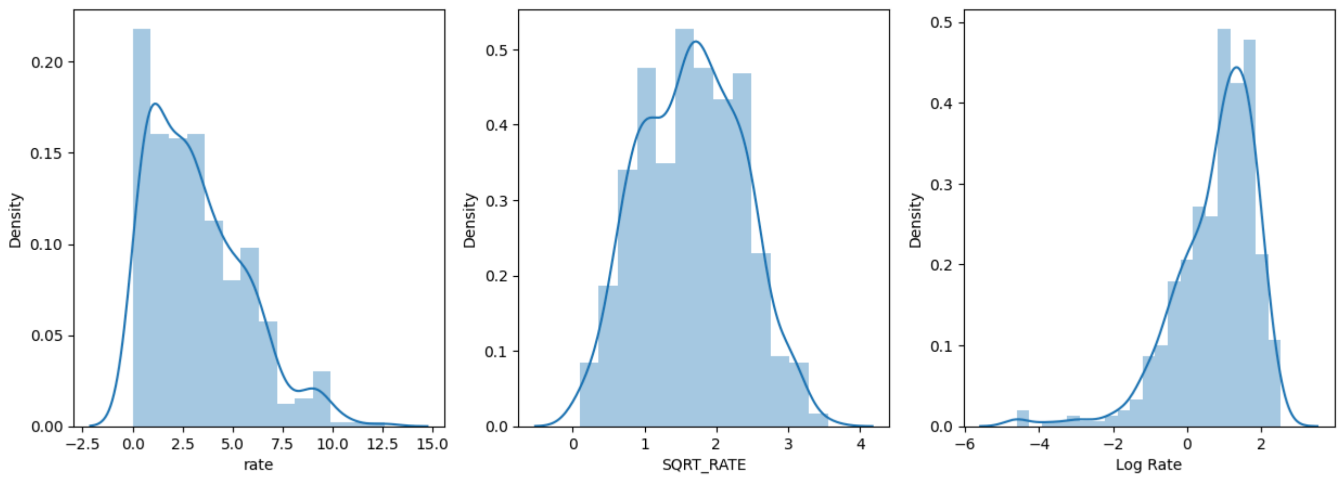
	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate	SQRT_RATE	sqrt_rate	Log Rate
client_id										
46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15	1.466288	1.466288	0.765468
46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25	1.118034	1.118034	0.223144
46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68	0.824621	0.824621	-0.385662
46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24	1.113553	1.113553	0.215111
46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13	1.769181	1.769181	1.141033

Next steps: View recommended plots New interactive sheet

```
print("The skewness of the original data is {}".format(df.rate.skew()))
print('The skewness of the SQRT transformed data is {}'.format(df.SQRT_RATE.skew()))
print("The skewnss of the LOG transformed data is {}".format(df['Log Rate'].skew()))

print('')


print("The kurtosis of the original data is {}".format(df.rate.kurt()))
print("The kurtosis of the SQRT transformed data is {}".format(df.SQRT_RATE.kurt()))
print("The kurtosis of the LOG transformed data is {}".format(df['Log Rate'].kurt()))
```

```
The skewness of the original data is 0.884204614329943
The skewness of the SQRT transformed data is 0.04964154055528862
The skewnss of the LOG transformed data is -1.5943217626331552

The kurtosis of the original data is 0.42437165143736433
The kurtosis of the SQRT transformed data is -0.6318437642052039
The kurtosis of the LOG transformed data is 4.157026150198228
```

```
# plot the graph:

fig, axes = plt.subplots(1,3,figsize=(15,5))

sns.distplot(df['rate'], ax=axes[0])
sns.distplot(df['SQRT_RATE'], ax=axes[1])
sns.distplot(df['Log Rate'], ax=axes[2])

plt.show()
```



Inference:

Log Transformation made the rate left skewed and more peaked.

However, Log transformation is more closer to 0 and hence is more normal. Though it heavily maniupulates the data.

In our case, square root transformation is more suitable.#

```
## Using Lambda function :

df['LOG_Rate'] = df['rate'].apply(lambda x:np.log(x))
```

```
df.head()
```

	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate	SQRT_RATE	sqrt_rate	Log Rate	LOG_Rate
client_id											
46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15	1.466288	1.466288	0.765468	0.765468
46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25	1.118034	1.118034	0.223144	0.223144
46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68	0.824621	0.824621	-0.385662	-0.385662

Next steps: View recommended plots New interactive sheet

There are other transformations available also called BoxCox. There is an inbuilt function in Sci-kit Learn library called PowerTransformer for this which can also be called to transform the data.

Outliers Treatment using Capping Approach

Z-Score approach to treat Outliers:

All the values above 3 standard deviation and below -3 standard deviation are outliers and can be removed

```
# loading the dataset and setting client id as index

df1 = pd.read_csv('loans.csv', index_col = 'client_id')
df1.head()
```

	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate
client_id							
46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15
46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25
46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68
46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24
46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13

Next steps: View recommended plots New interactive sheet

```
# loan_id:

df1['loan_id'] = df1['loan_id'].astype('object')

# repaid:

df1['repaid'] = df1['repaid'].astype('category')
```

```
# loan_start:

df1['loan_start'] = pd.to_datetime(df1['loan_start'], format = '%Y-%m-%d')


# loan_end:

df1['loan_end'] = pd.to_datetime(df1['loan_end'], format = '%Y-%m-%d')
```

```
# 'SciPy' is used to perform scientific computations
import scipy.stats as stats
```

Using SciPy Library to calculate the Z-Score:

```
# Creating new variable with Z-score of each record:
df1['ZR'] = stats.zscore(df1['rate'])
```

```
df.head()
```

	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate	SQRT_RATE	sqrt_rate	Log Rate	LOG_Rate
client_id											
46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15	1.466288	1.466288	0.765468	0.765468
46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25	1.118034	1.118034	0.223144	0.223144
46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68	0.824621	0.824621	-0.385662	-0.385662

Next steps: View recommended plots New interactive sheet

```
# Combined Lower limit and Upper limit:

df1[(df1['ZR']<-3) | (df1['ZR']>3)]
```

	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate	ZR
client_id								
41480	credit	2947	1	10302	2005-11-10	2008-03-16	10.49	3.037362
48177	other	6318	0	10224	2003-02-02	2005-05-08	10.89	3.204415
49624	home	8133	1	10312	2009-03-14	2011-03-21	12.62	3.926916

```
# count of outliers:

df1[(df1['ZR']<-3) | (df1['ZR']>3)].shape[0]
```

```
3
```

```
### Cleaned Data: without outliers so z>-3 and z< +3

df2= df1[(df1['ZR']>-3) & (df1['ZR']<3)].reset_index()
df2.head()
```

	client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate	ZR
0	46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15	-0.445677
1	46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25	-0.821544
2	46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68	-1.059594
3	46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24	-0.825721
4	46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13	-0.036399

Next steps: View recommended plots New interactive sheet

```
df1.shape
```

```
(443, 8)
```

```
df2.shape
```

```
(440, 9)
```

Interpretation:

A crude way to know whether the outliers have been removed or not is to check the dimensions of the data. From the above output, we can see that the dimensions are reduced that implies outliers are removed.

```
df3 = df2.copy()
```

```
df3.drop(columns = ['ZR'], inplace=True)
df3.head()
```

	client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate
0	46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15
1	46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25
2	46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68
3	46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24
4	46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13

Next steps: View recommended plots New interactive sheet

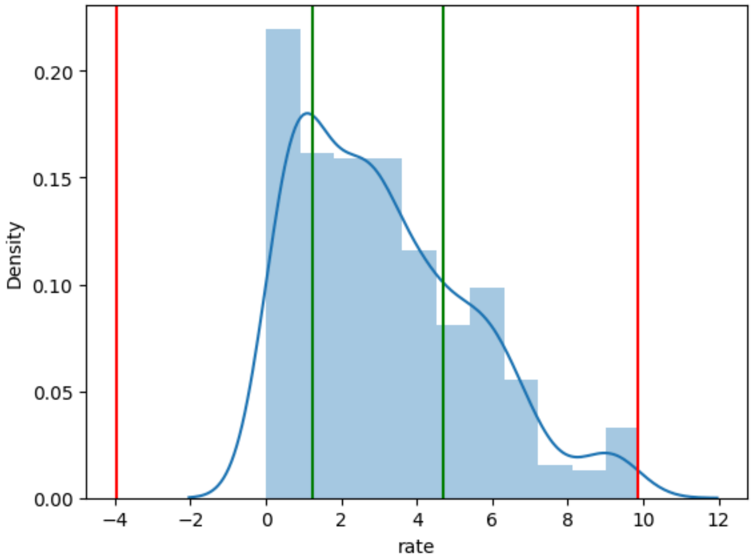
IQR Method to treat Outliers:

All the values below Q1 - 1.5IQR and values above Q3 + 1.5IQR are outliers and can be removed.

```
# finding the Quantiles:

Q1 = df3.rate.quantile(0.25)
Q2 = df3.rate.quantile(0.50)
Q3 = df3.rate.quantile(0.75)

# IQR : Inter-Quartile Range

IQR = Q3 - Q1

# Lower Limit:
LC = Q1 - (1.5*IQR)

# Upper Limit:
UC = Q3 + (1.5*IQR)

display(LC)
display(UC)
```

```
-3.9762499999999994
9.87375
```

```
## Plot

sns.distplot(df3.rate)
plt.axvline(UC, color='r')
plt.axvline(LC, color ='r')
plt.axvline(Q1, color='g')
plt.axvline(Q3, color='g')
plt.show()
```




```
# Find count of Outliers wrt IQR

df3[(df3.rate<LC) | (df3.rate>UC)].reset_index(drop=True)
```

	client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate
0	39505	cash	11647	1	11928	2003-07-28	2005-12-24	9.91

```
df3[(df3.rate<LC) | (df3.rate>UC)].shape[0]
```

1

```
## Store the clean data wrt IQR:

df4 = df3[(df3.rate>LC) & (df3.rate<UC)]
df4.head()
```

	client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate
0	46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15
1	46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25
2	46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68
3	46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24
4	46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13

Next steps: View recommended plots New interactive sheet

```
df3.shape
```

(440, 8)

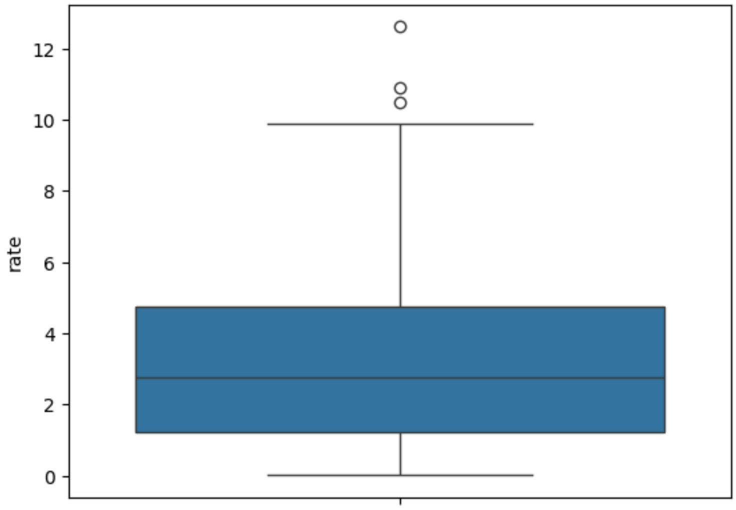
```
df4.shape
```

(439, 8)

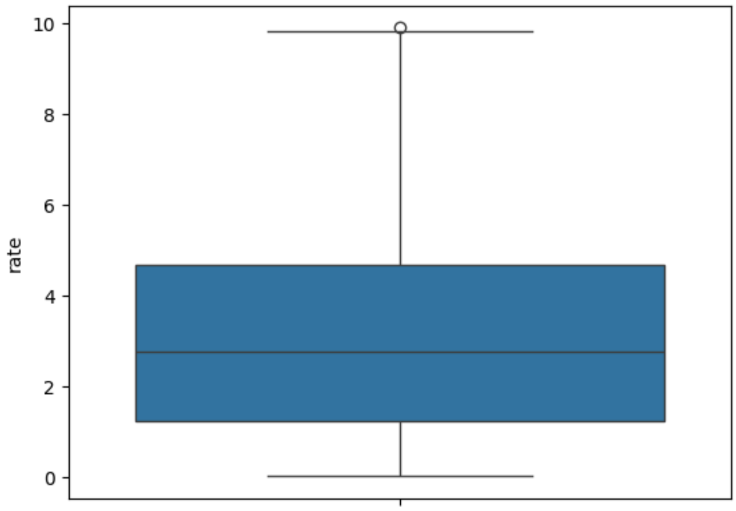
Interpretation:

A crude way to know whether the outliers have been removed or not is to check the dimensions of the data. From the above output, we can see that the dimensions are reduced that implies outliers are removed.

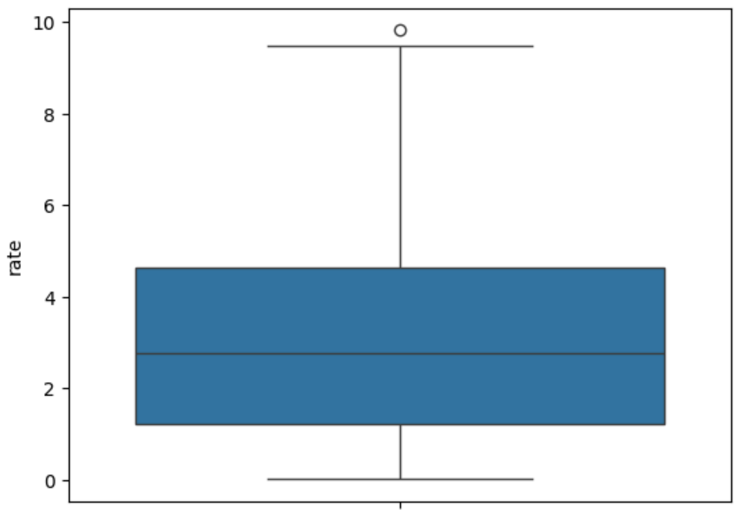
```
## Box Plot for rate--- based on IQR Method

sns.boxplot(df1.rate)
plt.show()
```




```
# Box Plot for rate --- based on Z-score cleaned data

sns.boxplot(df2.rate)
plt.show()
```




```
# Box Plot for rate --- based on IQR cleaned data

sns.boxplot(df4.rate)
plt.show()
```



Scaling the Numerical Features

There are two ways to scale the data:

Standardization (Z-Score)
Normalization: Min Max Scalar Both can by done manually as well as have in-built functions in sklearn. Will demonstrate both.

Standardization (Z-Score) Scales the data using the formula (x-mean)/standard deviation

Manually:

```
# for Rate :
avg_rate = df3['rate'].mean()
avg_rate
```

```
3.161818181818182
```

```
std_rate = df3['rate'].std()
std_rate
```

```
2.3079474188229154
```

```
# Step 1 : transform using Z-score
df3['Z_Score_Rate'] = (df3['rate'] - avg_rate)/std_rate
```

```
df3.head()
```

	client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate	Z_Score_Rate
0	46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15	-0.438406
1	46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25	-0.828363
2	46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68	-1.075336
3	46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24	-0.832696
4	46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13	-0.013786

Next steps: View recommended plots New interactive sheet

```
# checking if the skewness and kurtosis post scaling or not:

# For Rate:

print("The skewness for the original data is {}.".format(df3.rate.skew()))
print("The kurtosis for the original data is {}.".format(df3.rate.kurt()))

print('')

print("The skewness for the Zscore Scaled column is {}.".format(df3.Z_Score_Rate.skew()))
print("The kurtosis for the Zscore Scaled columns is {}.".format(df3.Z_Score_Rate.kurt()))
```

```
The skewness for the original data is 0.7594062707815686.
The kurtosis for the original data is -0.05964248048746912.

The skewness for the Zscore Scaled column is 0.7594062707815691.
The kurtosis for the Zscore Scaled columns is -0.05964248048746823.
```

```
# For Loan_amount:
avg_LA = df3['loan_amount'].mean()
avg_LA
```

```
7997.195454545455
```

```
std_LA = df3['loan_amount'].std()
std_LA
```

```
4179.435966237437
```

```
# Step 1 : transform using Z-score
df3['Z_Score_LA'] = (df3['loan_amount'] - avg_LA)/std_LA
```

```
df.head()
```

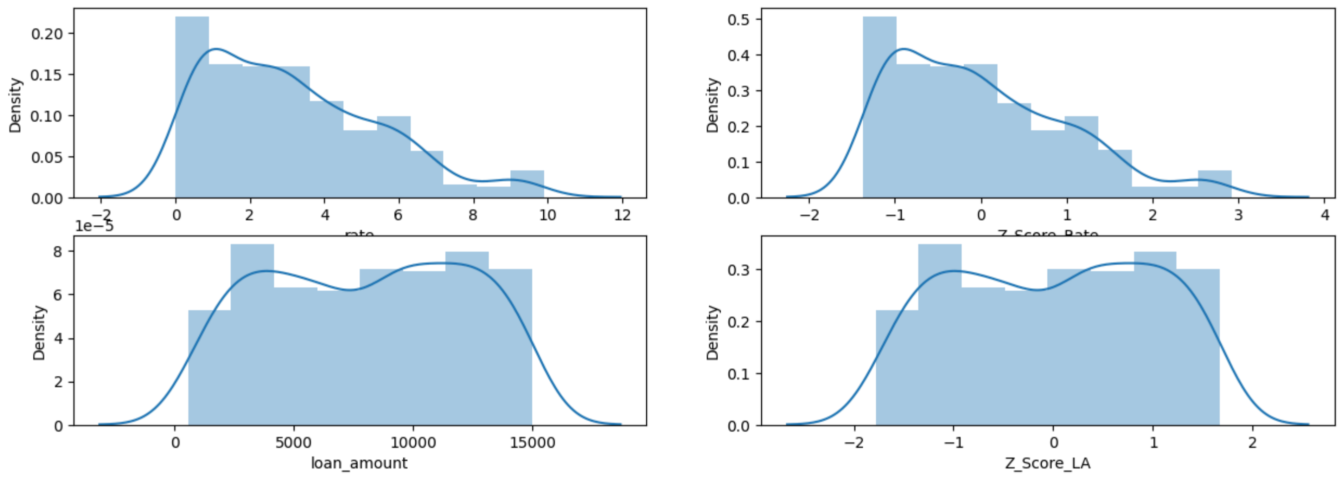
client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate	SQRT_RATE	sqrt_rate	Log Rate	LOG_Rate
46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15	1.466288	1.466288	0.765468	0.765468
46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25	1.118034	1.118034	0.223144	0.223144
46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68	0.824621	0.824621	-0.385662	-0.385662

Next steps: View recommended plots New interactive sheet

```
# checking if the skewness and kurtosis post scaling or not:

# For Loan_amount:

print("The skewness for the original data is {}.".format(df3.loan_amount.skew()))
print("The kurtosis for the original data is {}.".format(df3.loan_amount.kurt()))

print('')

print("The skewness for the Zscore Scaled column is {}.".format(df3.Z_Score_LA.skew()))
print("The kurtosis for the Zscore Scaled columns is {}.".format(df3.Z_Score_LA.kurt()))
```

```
The skewness for the original data is -0.04678765472024289.
The kurtosis for the original data is -1.2354309429278456.

The skewness for the Zscore Scaled column is -0.04678765472024289.
The kurtosis for the Zscore Scaled columns is -1.2354309429278456.
```

```
# Distribution of the columns

fig, axes = plt.subplots(2,2, figsize=(15,5))

sns.distplot(df3['rate'], ax=axes[0,0])
sns.distplot(df3['Z_Score_Rate'], ax=axes[0,1])
sns.distplot(df3['loan_amount'], ax=axes[1,0])
sns.distplot(df3['Z_Score_LA'], ax=axes[1,1])


plt.show()
```



The only difference between the two curves is of the Range on the x-axis. The impact of scaling on data is: Skewness, Kurtosis and Distribution all remain same.

The need for Scaling is :

Comparison between variables is easier
Computation power is more efficient and less time consuming.

```
# Loans data:

df4 = df3.copy()
df4.drop(columns = ['Z_Score_Rate'], inplace=True)
df4.head()
```

```
from sklearn.preprocessing import StandardScaler
```

```
df4_num = df[['loan_amount','rate']]
df4_num.head()
```

	loan_amount	rate
client_id		
46109	13672	2.15
46109	9794	1.25
46109	12734	0.68
46109	12518	1.24
46109	14049	3.13

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```
SS = StandardScaler()

scaled_x = SS.fit_transform(df4_num)
scaled_x
```

```
[-1.67850552e+00, -1.09500455e+00],
[-6.92703253e-01,  7.44570327e-01],
[ 1.47471692e-01,  1.73017856e+00],
[-1.61037006e+00,  2.75754986e+00],
[ 1.10088552e+00, -9.59362558e-01],
[-5.33641006e-01, -5.58437173e-01],
[-4.87770528e-02,  2.50697150e+00],
```

Normalization: Min Max Scalar

Scales the data using the formula (x - min)/(max - min)

Manually:

```
# ForeRate:
min_rate = df4.rate.min()
min_rate
```

```
0.01
```

```
max_rate = df4.rate.max()
max_rate
```

```
9.82
```

```
df4['Min_Max_R'] = (df4['rate'] - min_rate)/ (max_rate - min_rate)
```

```
# checking if the skewness and kurtosis post scaling or not:

# For Rate:

print("The skewness for the original data is {}.".format(df4.rate.skew()))
print("The skewness for the Zscore Scaled column is {}.".format(df3.Z_Score_Rate.skew()))
print("The skewness for the Min Max Scaled Data is {}.".format(df4.Min_Max_R.skew()))


print('')

print("The kurtosis for the original data is {}.".format(df4.rate.kurt()))
print("The kurtosis for the Zscore Scaled columns is {}.".format(df3.Z_Score_Rate.kurt()))
print("The kurtosis for the Min Max Scaled Data is {}.".format(df4.Min_Max_R.kurt()))
```

```
The skewness for the original data is 0.7427101742731893.
The skewness for the Zscore Scaled column is 0.7594062707815691.
The skewness for the Min Max Scaled Data is 0.7427101742731892.

The kurtosis for the original data is -0.10284962185127.
The kurtosis for the Zscore Scaled columns is -0.05964248048746823.
The kurtosis for the Min Max Scaled Data is -0.10284962185127133.
```

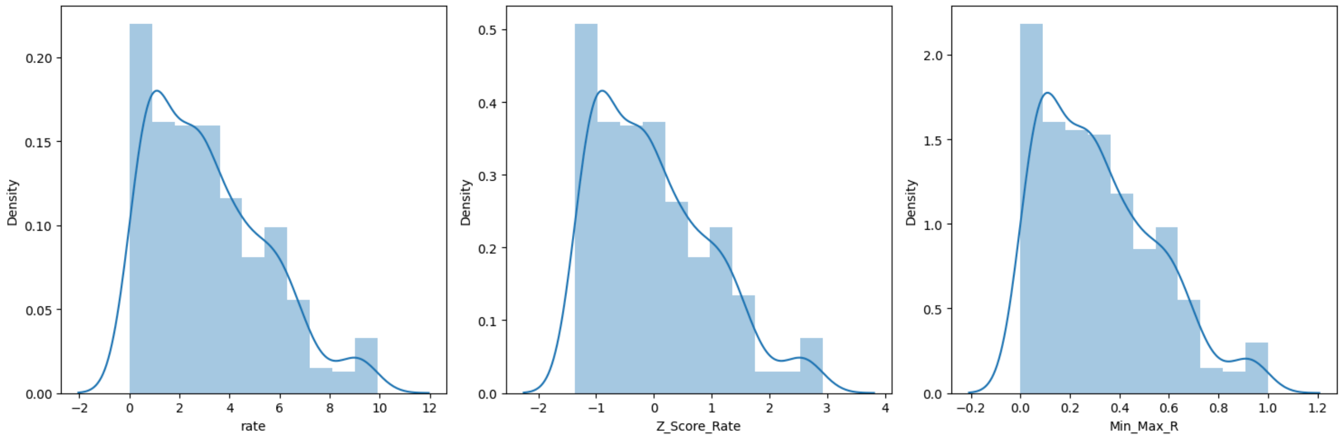
```
# Distribution of the columns

# For Rate

fig, axes = plt.subplots(1,3, figsize=(15,5))

sns.distplot(df3['rate'], ax=axes[0])
sns.distplot(df3['Z_Score_Rate'], ax=axes[1])
sns.distplot(df4['Min_Max_R'], ax=axes[2])

plt.tight_layout()
plt.show()
```




```
# For Loan_amount:
min_LA = df4.loan_amount.min()
min_LA
```

```
559
```

```
max_LA = df4.loan_amount.max()
max_LA
```

```
14971
```

```
df4['Min_Max_LA'] = (df4['loan_amount'] - min_LA)/ (max_LA - min_LA)
```

```
# checking if the skewness and kurtosis post scaling or not:

# For Rate:

print("The skewness for the original data is {}.".format(df4.loan_amount.skew()))
print("The skewness for the Zscore Scaled column is {}.".format(df3.Z_Score_LA.skew()))
print("The skewness for the Min Max Scaled Data is {}.".format(df4.Min_Max_LA.skew()))


print('')

print("The kurtosis for the original data is {}.".format(df4.loan_amount.kurt()))
print("The kurtosis for the Zscore Scaled columns is {}.".format(df3.Z_Score_LA.kurt()))
print("The kurtosis for the Min Max Scaled Data is {}.".format(df4.Min_Max_LA.kurt()))
```

```
The skewness for the original data is -0.04238992284864244.
The skewness for the Zscore Scaled column is -0.04678765472024289.
The skewness for the Min Max Scaled Data is -0.04238992284864285.

The kurtosis for the original data is -1.2349794881482345.
The kurtosis for the Zscore Scaled columns is -1.2354309429278456.
The kurtosis for the Min Max Scaled Data is -1.2349794881482352.
```

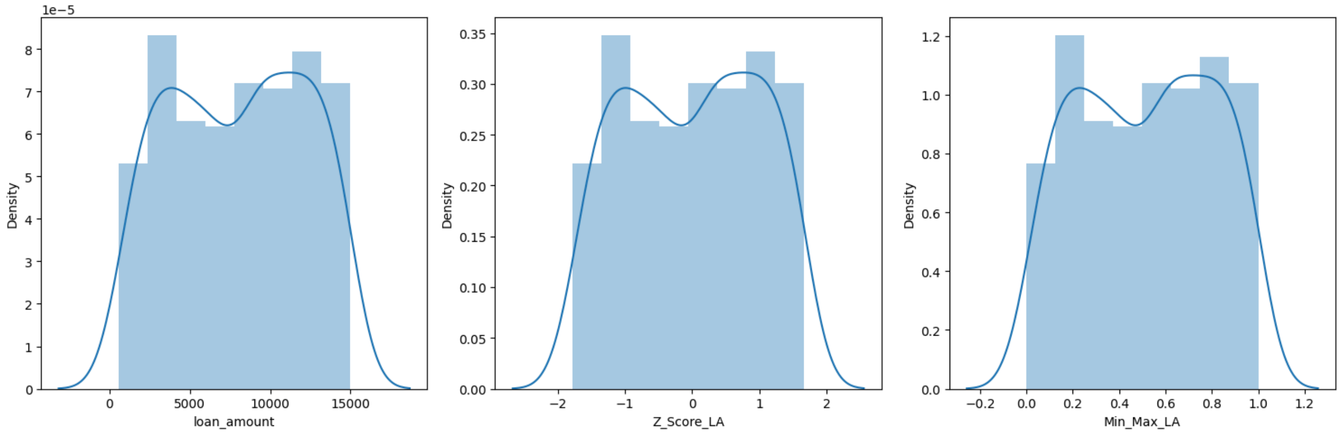
```
# Distribution of the columns

# For Loan_Amount

fig, axes = plt.subplots(1,3, figsize=(15,5))

sns.distplot(df3['loan_amount'], ax=axes[0])
sns.distplot(df3['Z_Score_LA'], ax=axes[1])
sns.distplot(df4['Min_Max_LA'], ax=axes[2])

plt.tight_layout()
plt.show()
```



By Sklearn:

```
from sklearn.preprocessing import MinMaxScaler
```

```
MS = MinMaxScaler()

MinMaxScaled = MS.fit_transform(df4_num)
MinMaxScaled
```

```
[8.34512906e-01, 1.77636796e-01],
[9.97987788e-01, 1.53053132e-01],
[2.96280877e-02, 4.67882633e-02],
[3.14737719e-01, 3.95717684e-01],
[5.57729670e-01, 5.82870738e-01],
[4.93338884e-02, 7.77954005e-01],
[8.33472107e-01, 7.21649485e-02],
[3.60741049e-01, 1.48295004e-01],
[5.00971413e-01, 7.30372720e-01],
```

Few things to keep in mind: With Scaling all three - Skewness, Kurtosis and distribution remain same so there is no impact on outliers as well.

Encoding the Categorical Features

There are two ways to encode the categorical data into dummyvariables. Using:

pd.get_dummies
sklearn's in-built function of OneHotEncoder and LabelEncoder

```
# Loans data:

df_loans = df3.copy()
```

```
df_loans.drop(columns = ['Z_Score_Rate'], inplace=True)
df_loans.drop(columns = ['Z_Score_LA'], inplace=True)
```

```
df_loans.head()
```

	client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate
0	46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15
1	46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25
2	46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68
3	46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24
4	46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13

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```
df_loans.dtypes
```

	0
client_id	int64
loan_type	object
loan_amount	int64
repaid	category
loan_id	object
loan_start	datetime64[ns]
loan_end	datetime64[ns]
rate	float64

dtype: object

```
# Repaid is also a categoriy columns and creating dummies for loan_type
df_loans.repaid.head()
```

	repaid
0	0
1	0
2	1
3	1
4	1

dtype: category

1.pd.get_dummies approach:

```
dummy_cat = pd.get_dummies(df_loans['loan_type'], drop_first = True)
dummy_cat.head()

# drop_first = True drops the first column for each feature
```

	credit	home	other
0	False	True	False
1	True	False	False
2	False	True	False
3	False	False	False
4	True	False	False

2.OneHot Encoding

```
from sklearn.preprocessing import OneHotEncoder
```

```
OE_tips = OneHotEncoder(drop ='first').fit(df_loans[['loan_type']])
OE_tips.categories_
```

```
[array(['cash', 'credit', 'home', 'other'], dtype=object)]
```

3. Label Encoding

```
from sklearn.preprocessing import LabelEncoder
```

```
LE = LabelEncoder()

LE_tips = LE.fit(df_loans[['loan_type']])
```

```
LE_tips.classes_
```

```
array(['cash', 'credit', 'home', 'other'], dtype=object)
```

```
# transform any new values to Dummy variables via Label Encoder
LE_tips.transform(['other', 'cash', 'home', 'credit'])
```

```
array([3, 0, 2, 1])
```

```
# Inverse transform to get original values from the dummy variables:
LE_tips.inverse_transform([1,2,3,0])
```

```
array(['credit', 'home', 'other', 'cash'], dtype=object)
```

Creating new Derived Features

We can use the loan_start and loan_end features to calculate the tenure of the loan

```
import datetime as dt
```

```
df_loans['loan_tenure'] =  df_loans['loan_end'] - df_loans['loan_start']
```

```
df_loans.head()
```

	client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate	loan_tenure
0	46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15	613 days
1	46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25	635 days
2	46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68	519 days
3	46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24	879 days
4	46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13	684 days

Next steps: View recommended plots New interactive sheet

```
df_loans.dtypes
```

	0
client_id	int64
loan_type	object
loan_amount	int64
repaid	category
loan_id	object
loan_start	datetime64[ns]
loan_end	datetime64[ns]
rate	float64
loan_tenure	timedelta64[ns]

dtype: object

The number of days in the tenure are currently in TimeDelta, we want it integer hence will do the conversion as follows:

```
df_loans['loan_tenure'] = df_loans['loan_tenure'].dt.days
df_loans['loan_tenure']
```

	loan_tenure
0	613
1	635
2	519
3	879
4	684
...	...
435	928
436	511
437	948
438	633
439	638

440 rows × 1 columns

dtype: int64

```
## Tenure in number of Years:

df_loans['loan_tenure'] = df_loans['loan_tenure']/365
df_loans['loan_tenure']
```

	loan_tenure
0	1.679452
1	1.739726
2	1.421918
3	2.408219
4	1.873973
...	...
435	2.542466
436	1.400000
437	2.597260
438	1.734247

Training and Testing data

dtype: float64

```
from sklearn.model_selection import train_test_split
```

```
## Splitting for X and Y variables:

Y = df_loans['loan_amount']
X = df_loans.drop('loan_amount', axis=1)
```

```
# Independent Variable

X.head()
```

	client_id	loan_type	repaid	loan_id	loan_start	loan_end	rate	loan_tenure
0	46109	home	0	10243	2002-04-16	2003-12-20	2.15	1.679452
1	46109	credit	0	10984	2003-10-21	2005-07-17	1.25	1.739726
2	46109	home	1	10990	2006-02-01	2007-07-05	0.68	1.421918
3	46109	cash	1	10596	2010-12-08	2013-05-05	1.24	2.408219
4	46109	credit	1	11415	2010-07-07	2012-05-21	3.13	1.873973

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```
# Dependent or Target Variable

Y.head()
```

	loan_amount
0	13672
1	9794
2	12734
3	12518
4	14049