



ASSIGNMENT

DATA PREPROCESSING

AATHIL TA

B16o345CS

AKARSH JOICE

B16o148CS

DATA SET SELECTION:

We have selected the dataset of a bank for giving loans to their customers. The data has 615 rows and 13 columns. The attributes of the dataset are Gender, Marital Status, Education, Number of Dependents, Income, Loan Amount, Credit History, and others.

Among all industries, financial domain has the most extensive use of analytics & data science methods. This data set would help us to get enough hold of working on data sets from banking companies, what challenges are faced, what strategies are used, which variables influence the outcome etc . we can make use of this dataset to automate loan allotting process, we can identify the customers segments, those are eligible for loan amount so that they can specifically target these customers.

All the attributes are skewed ,so it's better to choose median as central measure,since we choose median as central measure,its better to use IQR or MAD(median Average Deviation).KDE plot is a better choice for visualizing since we have no idea on distribution of attributes.

Measures of Central Deviation

October 13, 2019

```
[1]: import seaborn as sns  
import matplotlib.pyplot as plt
```

```
[2]: import pandas as pd  
dframe = pd.read_csv("loan_data_set.csv")
```

```
[3]: dframe= pd.read_csv("loan_data_set.csv")  
dframe.ApplicantIncome.fillna(dframe.mean(),inplace=True) #by mean  
print(dframe.ApplicantIncome.head())
```

```
0    5849  
1    4583  
2    3000  
3    2583  
4    6000  
Name: ApplicantIncome, dtype: int64
```

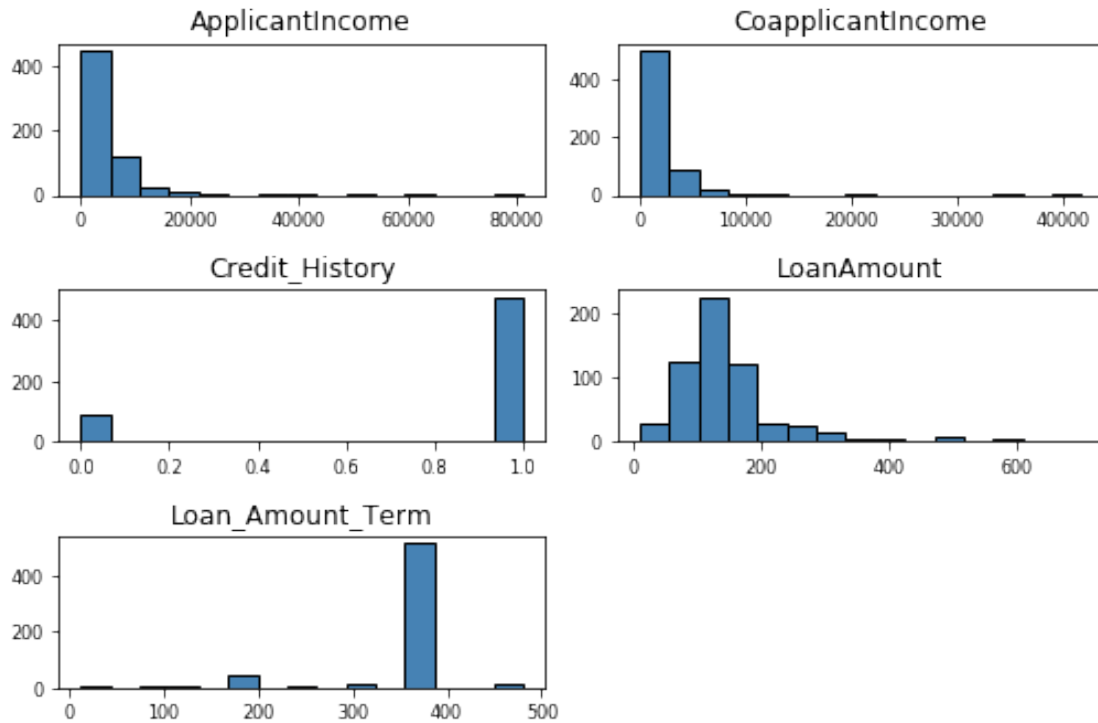
```
[4]: dframe.mean()
```

```
[4]: ApplicantIncome    5403.459283  
CoapplicantIncome    1621.245798  
LoanAmount           146.412162  
Loan_Amount_Term      342.000000  
Credit_History        0.842199  
dtype: float64
```

```
[5]: dframe.median()
```

```
[5]: ApplicantIncome    3812.5  
CoapplicantIncome    1188.5  
LoanAmount           128.0  
Loan_Amount_Term      360.0  
Credit_History        1.0  
dtype: float64
```

```
[6]: dframe.hist(bins=15, color='steelblue', edgecolor='black', linewidth=1.0,  
                xlabelsize=8, ylabelsize=8, grid=False)  
plt.tight_layout(rect=(0, 0, 1.2, 1.2))
```



```
[7]: df.dropna(inplace=True)
df.describe()
```

```
[7]:
```

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term \
count	480.000000	480.000000	480.000000	480.000000
mean	5364.231250	1581.093583	144.735417	342.050000
std	5668.251251	2617.692267	80.508164	65.212401
min	150.000000	0.000000	9.000000	36.000000
25%	2898.750000	0.000000	100.000000	360.000000
50%	3859.000000	1084.500000	128.000000	360.000000
75%	5852.500000	2253.250000	170.000000	360.000000
max	81000.000000	33837.000000	600.000000	480.000000


```

Credit_History
count      480.000000
mean        0.854167
std         0.353307
min         0.000000
25%         1.000000
50%         1.000000
75%         1.000000
max         1.000000

```

```
[8]: df.std()
```

```
[8]: ApplicantIncome      5668.251251  
     CoapplicantIncome    2617.692267  
     LoanAmount           80.508164  
     Loan_Amount_Term      65.212401  
     Credit_History        0.353307  
     dtype: float64
```

```
[ ]:
```

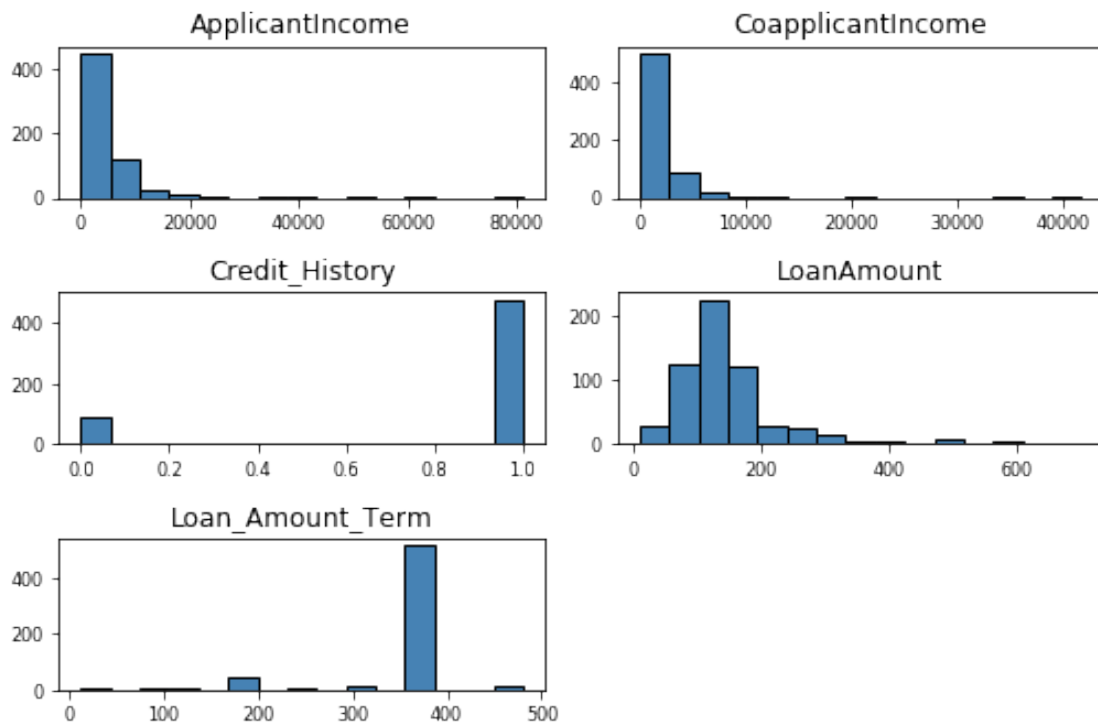
visualization: python

October 13, 2019

```
[1]: import pandas as pd
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import matplotlib as mpl
import numpy as np
import seaborn as sns

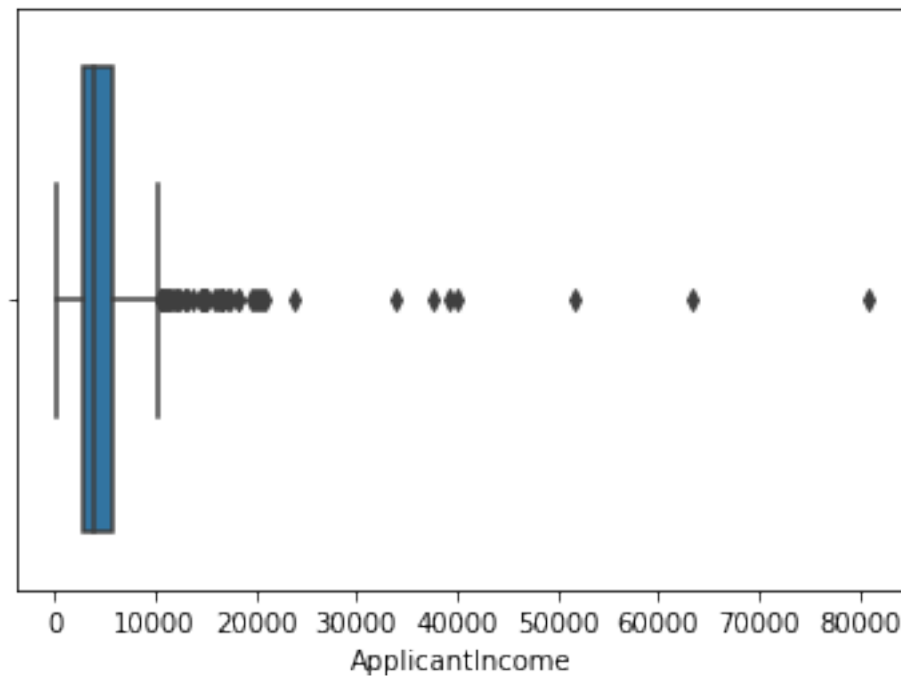
[2]: df = pd.read_csv("loan_data_set.csv")

[3]: df.hist(bins=15, color='steelblue', edgecolor='black', linewidth=1.0,
            xlabelsize=8, ylabelsize=8, grid=False)
plt.tight_layout(rect=(0, 0, 1.2, 1.2))
```

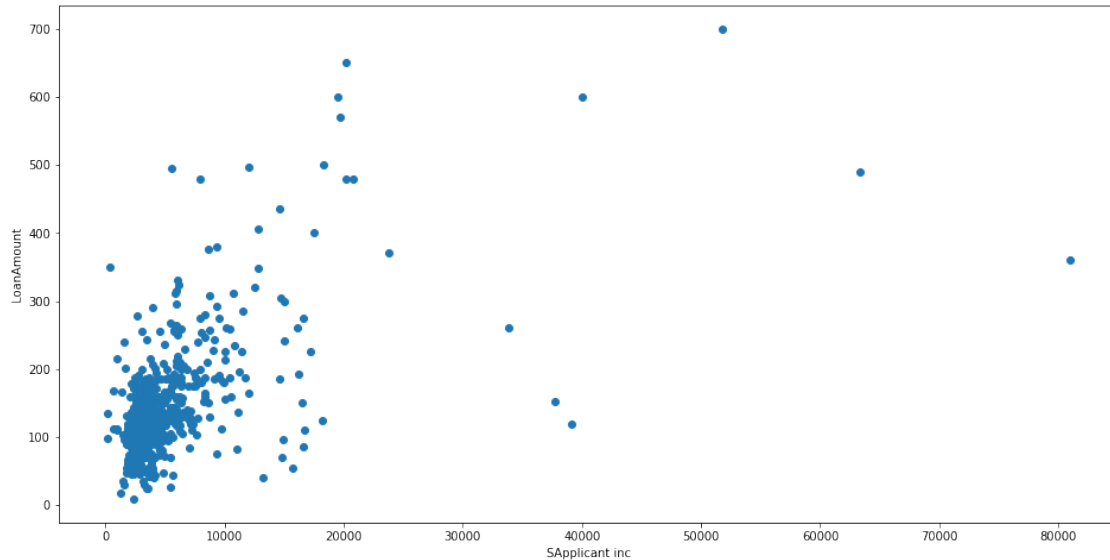


```
[4]: #outliers...  
sns.boxplot(x=df['ApplicantIncome'])
```

```
[4]: <matplotlib.axes._subplots.AxesSubplot at 0x1a18fac710>
```



```
[5]: fig, ax = plt.subplots(figsize=(16,8))  
ax.scatter(df['ApplicantIncome'], df['LoanAmount'])  
ax.set_xlabel('SApplicant inc')  
ax.set_ylabel('LoanAmount')  
plt.show()
```

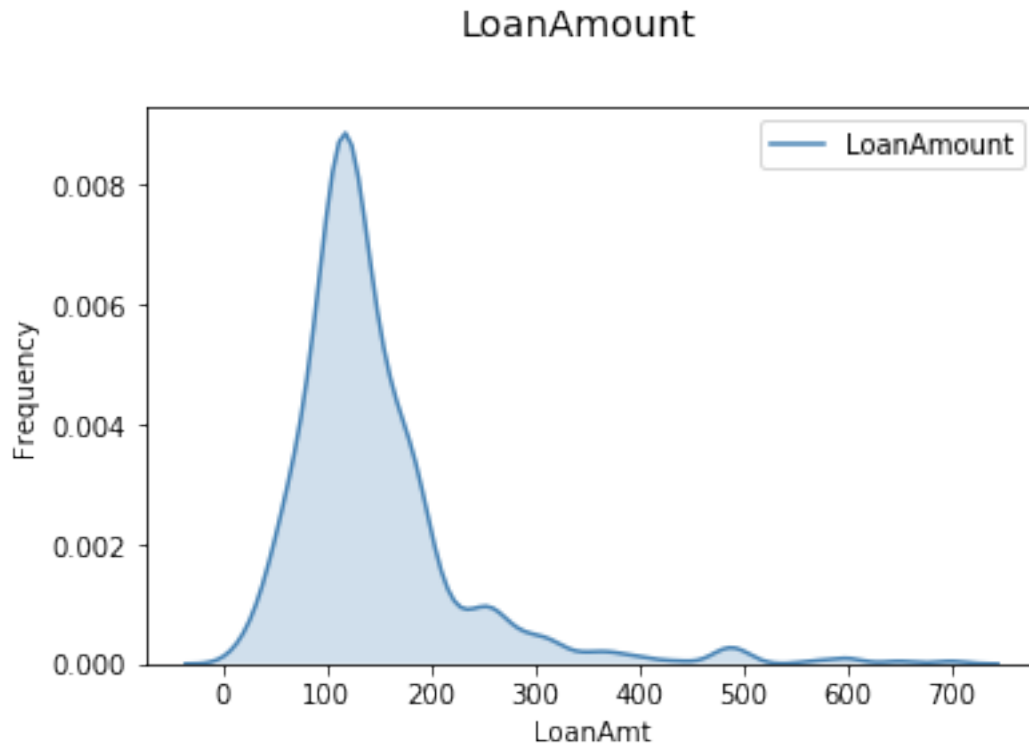



```
[6]: fig = plt.figure(figsize = (6, 4))
title = fig.suptitle("LoanAmt", fontsize=14)
fig.subplots_adjust(top=0.85, wspace=0.3)

ax1 = fig.add_subplot(1,1, 1)
ax1.set_xlabel("LoanAmt")
ax1.set_ylabel("Frequency")
sns.kdeplot(df['LoanAmount'], ax=ax1, shade=True, color='steelblue')
```

```
/Users/cluelessidiot/anaconda3/lib/python3.7/site-
packages/statsmodels/nonparametric/kde.py:447: RuntimeWarning: invalid value
encountered in greater
  X = X[np.logical_and(X > clip[0], X < clip[1])] # won't work for two columns.
/Users/cluelessidiot/anaconda3/lib/python3.7/site-
packages/statsmodels/nonparametric/kde.py:447: RuntimeWarning: invalid value
encountered in less
  X = X[np.logical_and(X > clip[0], X < clip[1])] # won't work for two columns.
```

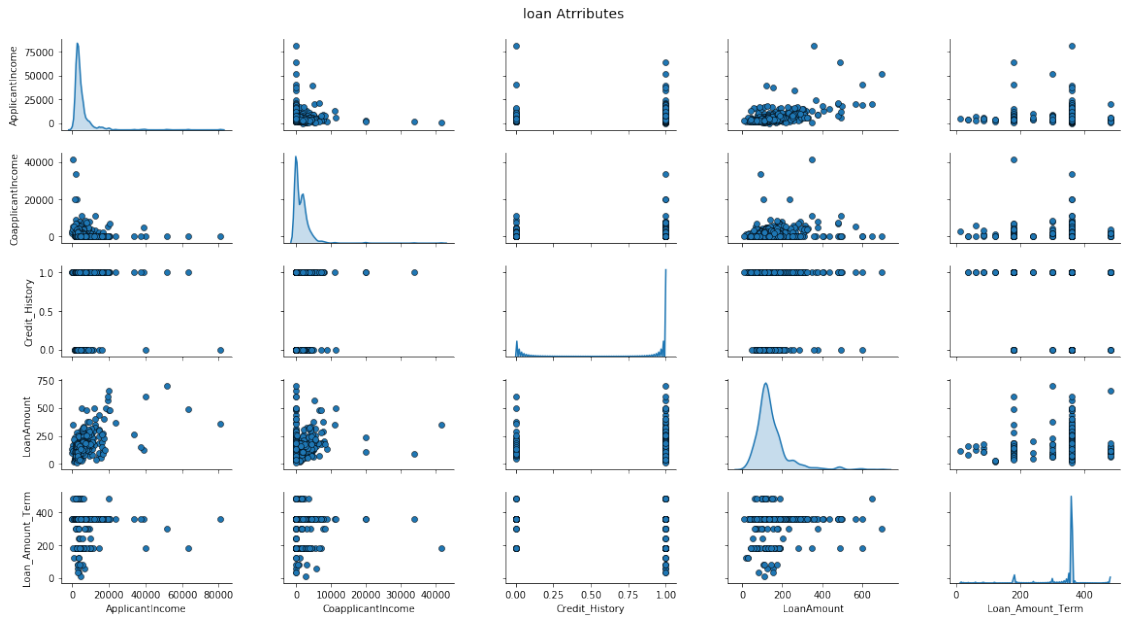
```
[6]: <matplotlib.axes._subplots.AxesSubplot at 0x1a199557b8>
```



```
[7]: # Pair-wise Scatter Plots
cols = ['ApplicantIncome', 'CoapplicantIncome', 'Credit_History',
        'LoanAmount', 'Loan_Amount_Term']
pp = sns.pairplot(df[cols], size=1.8, aspect=1.8,
                  plot_kws=dict(edgecolor="k", linewidth=0.5),
                  diag_kind="kde", diag_kws=dict(shade=True))

fig = pp.fig
fig.subplots_adjust(top=0.93, wspace=0.3)
t = fig.suptitle('loan Attributes', fontsize=14)
```

```
/Users/cluelessidiot/anaconda3/lib/python3.7/site-
packages/seaborn/axisgrid.py:2065: UserWarning: The `size` parameter has been
renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```



[]:

Removing Noise

October 13, 2019

```
[1]: import pandas as pd
df = pd.read_csv("loan_data_set.csv")
#print (df.head())

[16]: #replacing all missing values by mean
#df.fillna(df.mean(),inplace=True)
#print (df.head())
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(15,8))
#sns.distplot(df.column_name, bins =30)

pmd=df
total=pmd.isnull().sum()
percent=(pmd.isnull().sum()/pmd.isnull().count())
missingData=pd.concat([total,percent],axis=1,keys=['Total','Percent'])
print (missingData)
f, ax = plt.subplots(figsize=(15, 6))
plt.xticks(rotation='90')
sns.barplot(x=missingData.index, y=missingData['Percent'])
plt.xlabel('Features', fontsize=15)
plt.ylabel('Percent of missing values', fontsize=15)
plt.title('Percent missing data by feature', fontsize=15)
missingData.head()
```

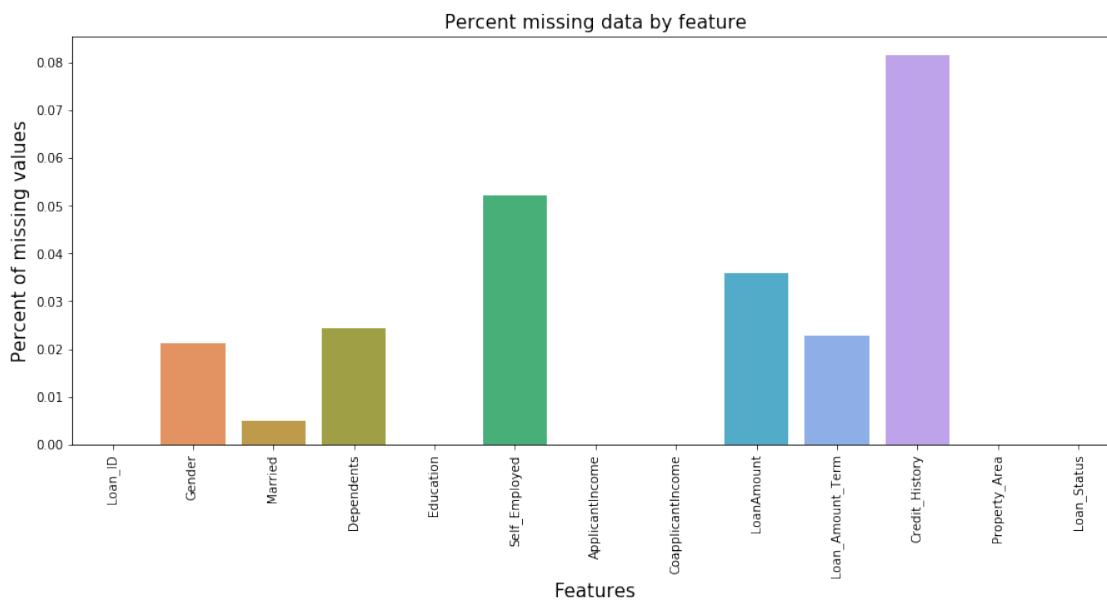
	Total	Percent
Loan_ID	0	0.000000
Gender	13	0.021173
Married	3	0.004886
Dependents	15	0.024430
Education	0	0.000000
Self_Employed	32	0.052117
ApplicantIncome	0	0.000000
CoapplicantIncome	0	0.000000
LoanAmount	22	0.035831
Loan_Amount_Term	14	0.022801
Credit_History	50	0.081433

Property_Area	0	0.000000
Loan_Status	0	0.000000

```
[16]:
```

	Total	Percent
Loan_ID	0	0.000000
Gender	13	0.021173
Married	3	0.004886
Dependents	15	0.024430
Education	0	0.000000

<Figure size 1080x576 with 0 Axes>



```
[3]: #data cleaning
#method 1->ignore the data row containing missing values..
dframe= pd.read_csv("loan_data_set.csv")
print(dframe['LoanAmount'].head())
dframe.isnull().count()
dframe.dropna(inplace=True)
print (dframe['LoanAmount'].head())
#dframe.count()
```

```
0      NaN
1    128.0
2     66.0
3    120.0
4    141.0
Name: LoanAmount, dtype: float64
```

```
1    128.0
2     66.0
3    120.0
4    141.0
5    267.0
Name: LoanAmount, dtype: float64
```

[4]: *#for back fill*

```
dframe= pd.read_csv("loan_data_set.csv")
dframe.fillna(method='bfill',inplace=True)#for forward-fill
print(dframe['LoanAmount'].head())
dframe.fillna(method='ffill',inplace=True)#forbackward fill
```

```
0    128.0
1    128.0
2     66.0
3    120.0
4    141.0
Name: LoanAmount, dtype: float64
```

[5]: *#replace with constant*

```
dframe= pd.read_csv("loan_data_set.csv")
dframe.LoanAmount.fillna(99,inplace=True)
print(dframe['LoanAmount'].head())
```

```
0     99.0
1    128.0
2     66.0
3    120.0
4    141.0
Name: LoanAmount, dtype: float64
```

[6]:

```
dframe= pd.read_csv("loan_data_set.csv")
dframe.LoanAmount.fillna(dframe.LoanAmount.mean(),inplace=True)#by mean
print(dframe.LoanAmount.head())
```

```
0    146.412162
1    128.000000
2     66.000000
3    120.000000
4    141.000000
Name: LoanAmount, dtype: float64
```

[7]:

```
dframe= pd.read_csv("loan_data_set.csv")
dframe.LoanAmount.fillna(dframe.LoanAmount.median(),inplace=True)#by median
```

```
print(dframe.LoanAmount.head())
```

```
0    128.0
1    128.0
2     66.0
3    120.0
4    141.0
Name: LoanAmount, dtype: float64
```

```
[9]: #now we are gonna insert mean values but within +- standard deviation
import numpy as np
dframe= pd.read_csv("loan_data_set.csv")
LoanAmountAverage=dframe['LoanAmount'].mean()
LoanAmountStd=dframe['LoanAmount'].std()
LoanAmountNullCt=dframe['LoanAmount'].isnull().sum();
LoanAmountNullRl=np.random.
    ↳randint(LoanAmountAverage-LoanAmountStd,LoanAmountAverage+LoanAmountStd,size=LoanAmountNullCt)
dframe['LoanAmount'][np.isnan(dframe['LoanAmount'])]=LoanAmountNullRl
print(dframe.LoanAmount.head())
dframe['LoanAmount'] = dframe['LoanAmount'].astype(int)
```

```
0     69.0
1    128.0
2     66.0
3    120.0
4    141.0
Name: LoanAmount, dtype: float64
```

/Users/cluelessidiot/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:8: 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#indexing-view-versus-copy>

```
[10]: from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from numpy import nan
```

```
[11]: df= pd.read_csv("loan_data_set.csv")
imp = IterativeImputer(max_iter=10, random_state=0)
imp.fit(df[['CoapplicantIncome','LoanAmount']])
IterativeImputer(add_indicator=False, estimator=None,
                  imputation_order='ascending', initial_strategy='mean',
                  max_iter=10, max_value=None, min_value=None,
                  missing_values=nan, n_nearest_features=None,
```

```
random_state=0, sample_posterior=False, tol=0.001,  
verbose=0)
```

```
[11]: IterativeImputer(add_indicator=False, estimator=None,  
      imputation_order='ascending', initial_strategy='mean',  
      max_iter=10, max_value=None, min_value=None,  
      missing_values=nan, n_nearest_features=None, random_state=0,  
      sample_posterior=False, tol=0.001, verbose=0)
```

```
[12]: #print (df.head())  
dq=imp.transform(df[['CoapplicantIncome', 'LoanAmount']])
```

```
[13]: print (dq)
```

```
[[  0.         137.85795547]  
 [1508.         128.         ]  
 [  0.          66.         ]  
 ...  
 [ 240.         253.         ]  
 [  0.         187.         ]  
 [  0.         133.         ]]
```

```
[ ]:
```

```
[ ]:
```


Data Reduction

October 13, 2019

```
[1]: import pandas as pd
df = pd.read_csv("loan_data_set.csv")
#print (df.head())

[2]: from sklearn.preprocessing import StandardScaler
dframe= pd.read_csv("loan_data_set.csv")
dframe.LoanAmount.fillna(dframe.LoanAmount.median(),inplace=True) #by median
dframe.Loan_Amount_Term.fillna(dframe.Loan_Amount_Term.median(),inplace=True) #by
↳median
import matplotlib.pyplot as plt

[3]: features_for_pca=['ApplicantIncome','LoanAmount','CoapplicantIncome','Loan_Amount_Term']

[23]: # Separating out the features
x = dframe.loc[:, features_for_pca].values
#print (x)
y = dframe.loc[:,['Loan_Status']].values
print (x)
x = StandardScaler().fit_transform(x)
print (x)
#normalization..... of selected attributes
```

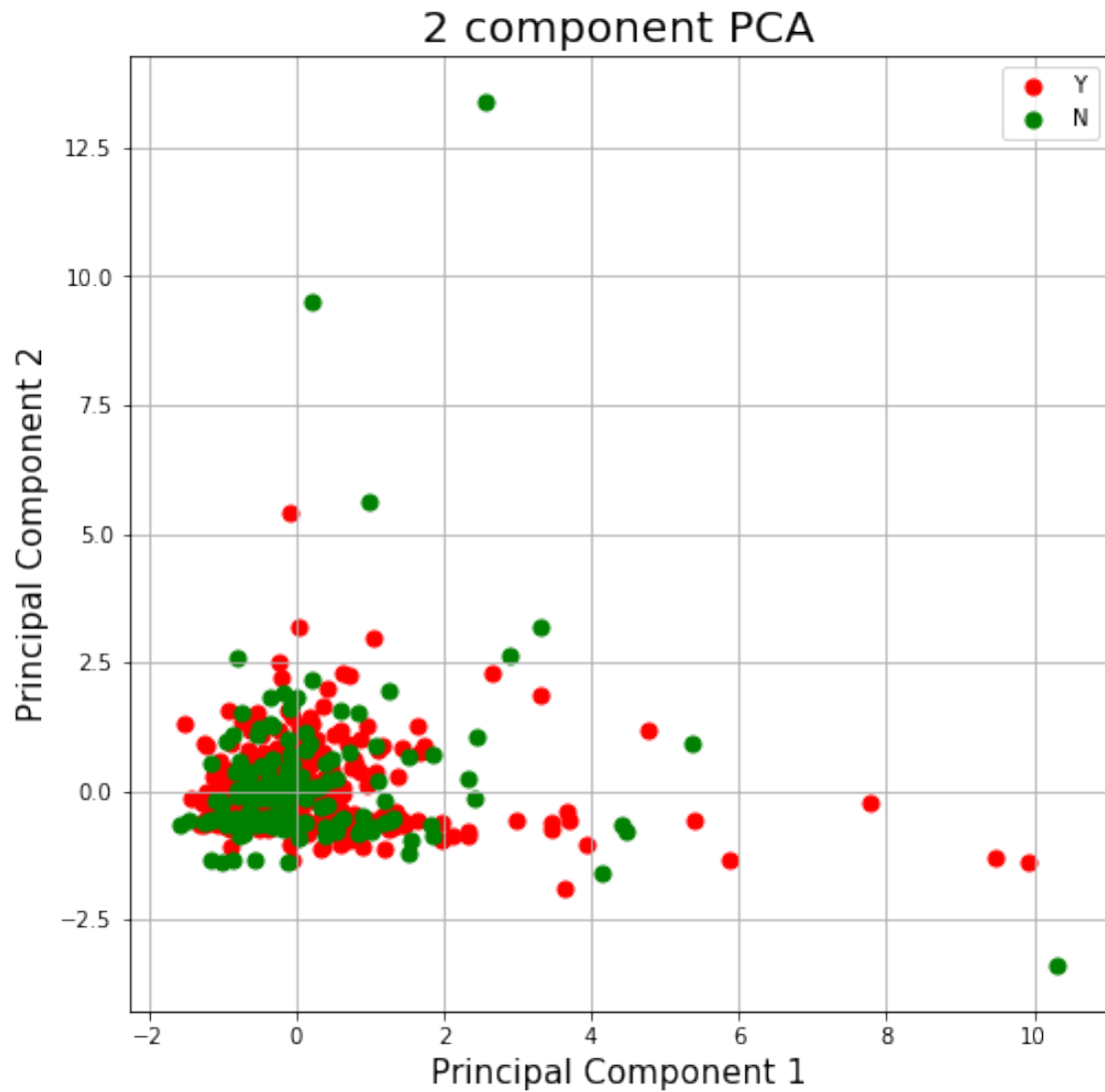
```
[[5849.  128.    0.  360.]
 [4583.  128. 1508.  360.]
 [3000.   66.    0.  360.]
 ...
 [8072.  253.  240.  360.]
 [7583.  187.    0.  360.]
 [4583.  133.    0.  360.]]
[[ 0.07299082 -0.21124125 -0.55448733  0.2732313 ]
 [-0.13441195 -0.21124125 -0.03873155  0.2732313 ]
 [-0.39374734 -0.94899647 -0.55448733  0.2732313 ]
 ...
 [ 0.43717437  1.27616847 -0.47240418  0.2732313 ]
 [ 0.35706382  0.49081614 -0.55448733  0.2732313 ]
 [-0.13441195 -0.15174486 -0.55448733  0.2732313 ]]
```

```
[24]: from sklearn.decomposition import PCA
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(x)

principalDf = pd.DataFrame(data = principalComponents, columns = ['principal_
→component 1', 'principal component 2'])
#print (principalDf)

[6]: finalDf = pd.concat([principalDf, df[['Loan_Status']]], axis = 1)
#print (finalDf)

[7]: fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 component PCA', fontsize = 20)
targets = ['Y','N']
colors = ['r', 'g', 'b']
for target, color in zip(targets,colors):
    indicesToKeep = finalDf['Loan_Status'] == target
    ax.scatter(finalDf.loc[indicesToKeep, 'principal component 1'], finalDf.
→loc[indicesToKeep, 'principal component 2'], c = color, s = 50)
ax.legend(targets)
ax.grid()
```



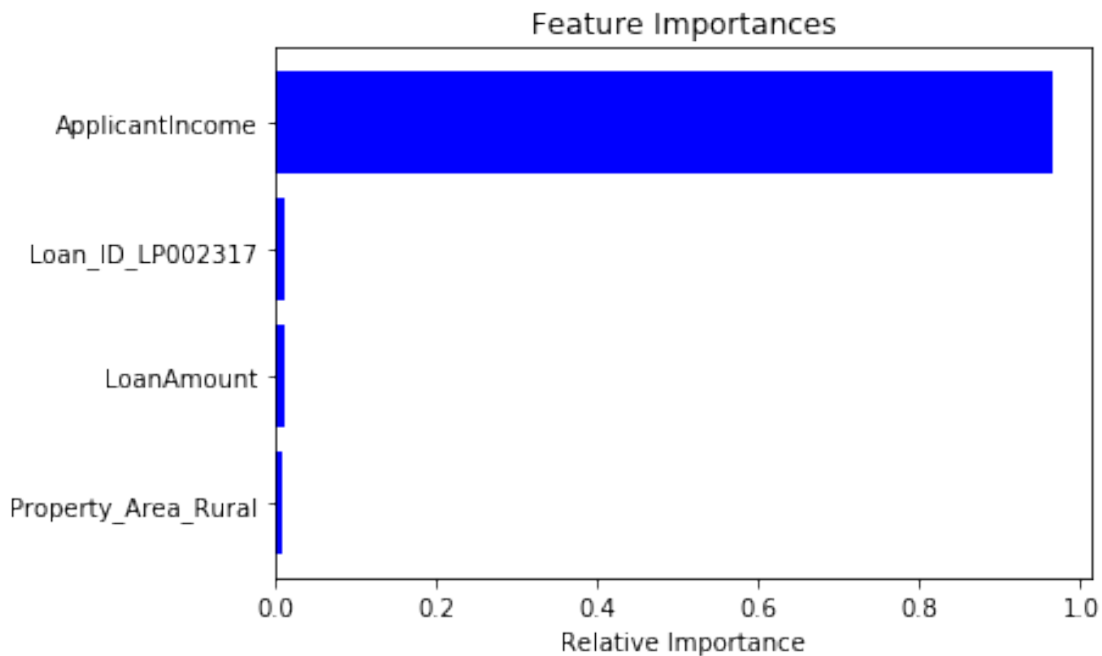
```
[13]: from sklearn.ensemble import RandomForestRegressor
import numpy as np
df = pd.read_csv("loan_data_set.csv")
qf=pd.read_csv("loan_data_set.csv")

df.dropna(inplace=True)
conv_dict={'N':1., 'Y':2}
df['Loan_Status']=df.Loan_Status.apply(conv_dict.get)
#df=df.drop([ 'LoanAmount'], axis=0)
#df.LoanAmount.fillna(df.LoanAmount.median(),inplace=True)#by median
model = RandomForestRegressor(random_state=1, max_depth=3)
df=pd.get_dummies(df)
model.fit(df,df.ApplicantIncome)
```

```
/Users/cluelessidiot/anaconda3/lib/python3.7/site-
packages/sklearn/ensemble/forest.py:245: FutureWarning: The default value of
n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

```
[13]: RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=3,
                             max_features='auto', max_leaf_nodes=None,
                             min_impurity_decrease=0.0, min_impurity_split=None,
                             min_samples_leaf=1, min_samples_split=2,
                             min_weight_fraction_leaf=0.0, n_estimators=10,
                             n_jobs=None, oob_score=False, random_state=1, verbose=0,
                             warm_start=False)
```

```
[14]: features = df.columns
importances = model.feature_importances_
indices = np.argsort(importances)[-4:] # top 10 features
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='b', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



```
[15]: df=pd.read_csv("loan_data_set.csv")
df.corr()
```

```
[15]:
```

	ApplicantIncome	CoapplicantIncome	LoanAmount	\
ApplicantIncome	1.000000	-0.116605	0.570909	

CoapplicantIncome	-0.116605	1.000000	0.188619
LoanAmount	0.570909	0.188619	1.000000
Loan_Amount_Term	-0.045306	-0.059878	0.039447
Credit_History	-0.014715	-0.002056	-0.008433

	Loan_Amount_Term	Credit_History
ApplicantIncome	-0.045306	-0.014715
CoapplicantIncome	-0.059878	-0.002056
LoanAmount	0.039447	-0.008433
Loan_Amount_Term	1.000000	0.001470
Credit_History	0.001470	1.000000

[16]: *#from above table ,correleation of .5 greater either one attributes is selected*

```
[18]: from sklearn.feature_selection import f_regression
df=pd.read_csv("loan_data_set.csv")
qf=df[['ApplicantIncome','CoapplicantIncome','LoanAmount','Loan_Amount_Term','Credit_History'],'
df=df[['ApplicantIncome','CoapplicantIncome','LoanAmount','Loan_Amount_Term','Credit_History']]
conv_dict={'N':1, 'Y':2}
qf['Loan_Status']=qf.Loan_Status.apply(conv_dict.get)
df.dropna(inplace=True)
qf.dropna(inplace=True)
ffs = f_regression(df,qf.Loan_Status)
```

```
[19]: variable = [ ]
for i in range(0,len(df.columns)-1):
    print (ffs[0][i])
    if ffs[0][i] >=.4:
        variable.append(df.columns[i])
```

```
0.02079342985136059
0.9923690484110282
0.7085056246888057
0.4314605380860428
```

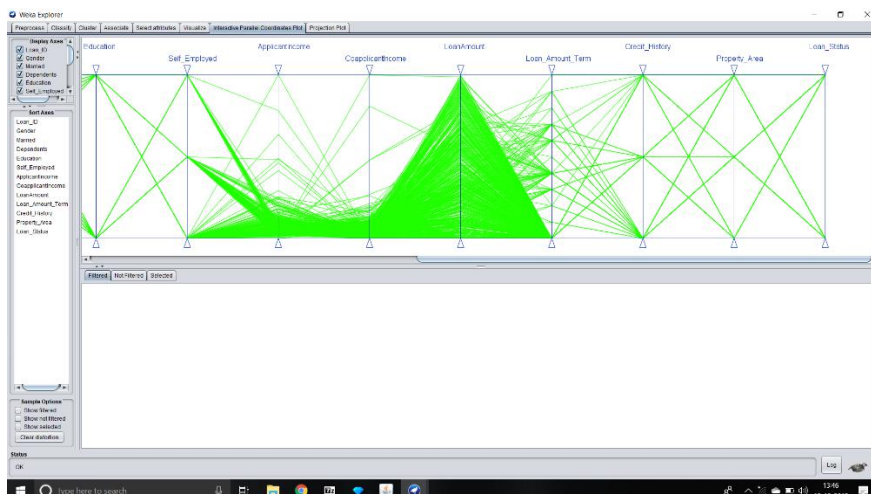
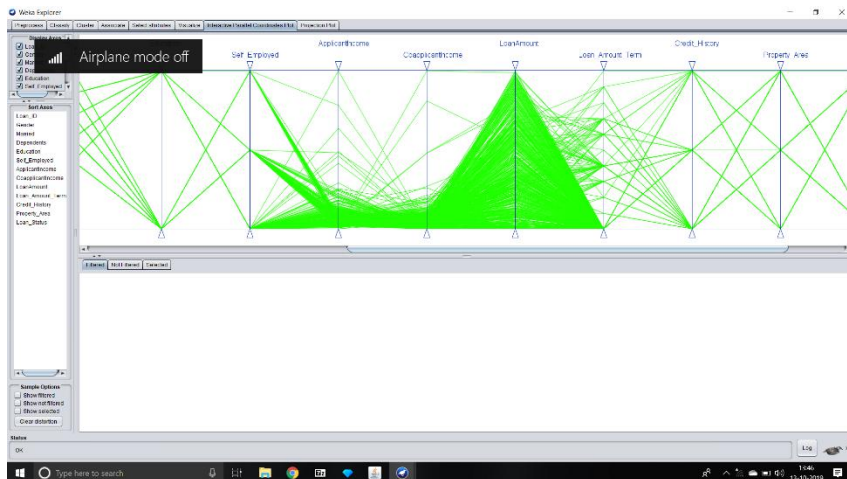
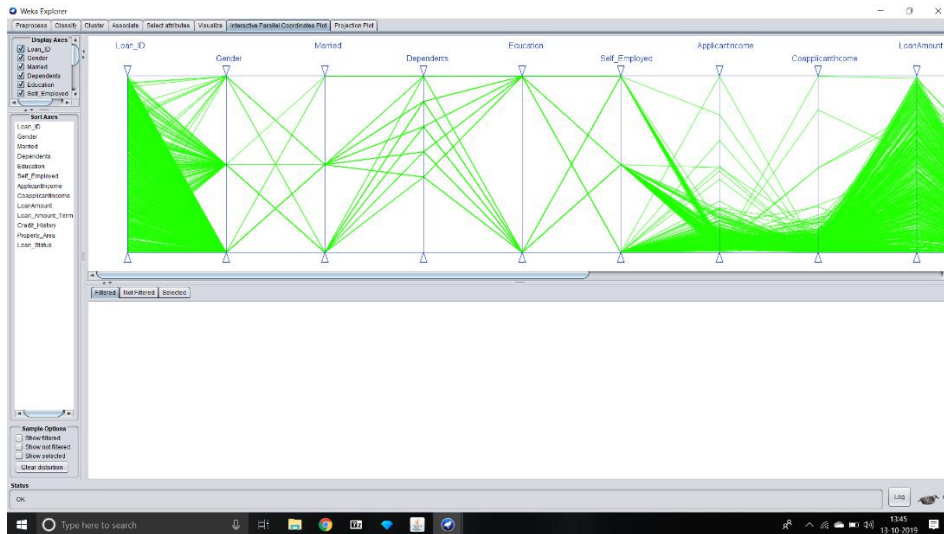
```
[20]: print (variable)
```

```
['CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Term']
```

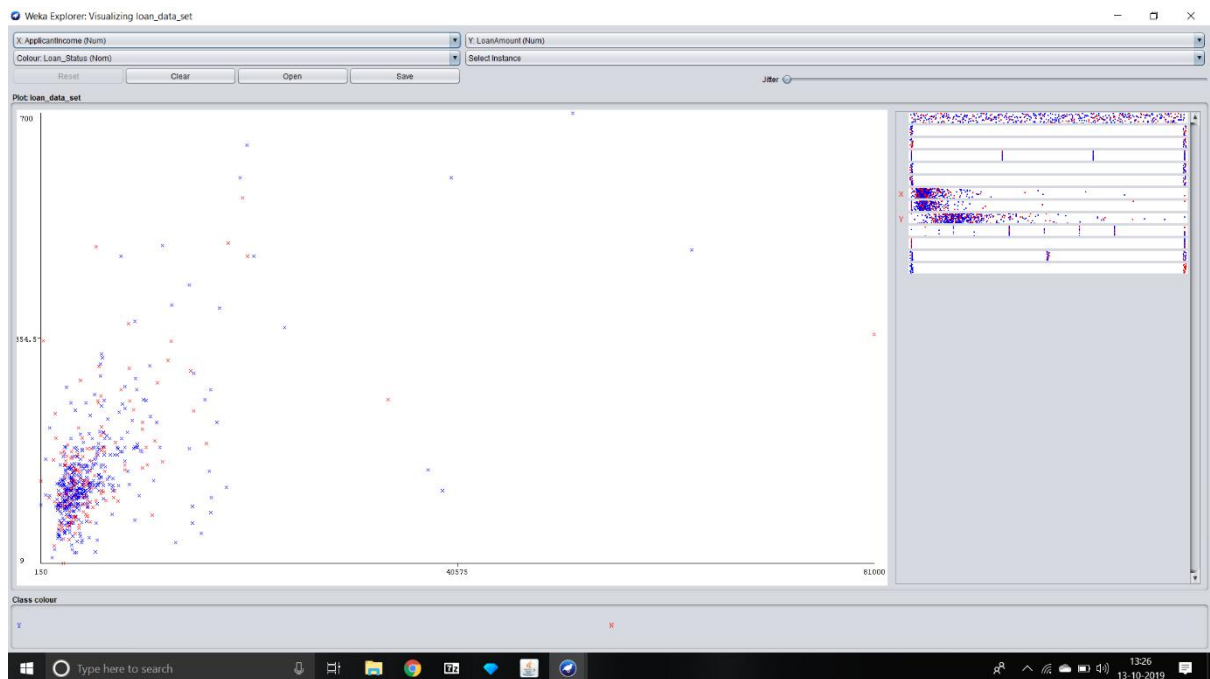
```
[ ]:
```

DATA VISUALISATION:

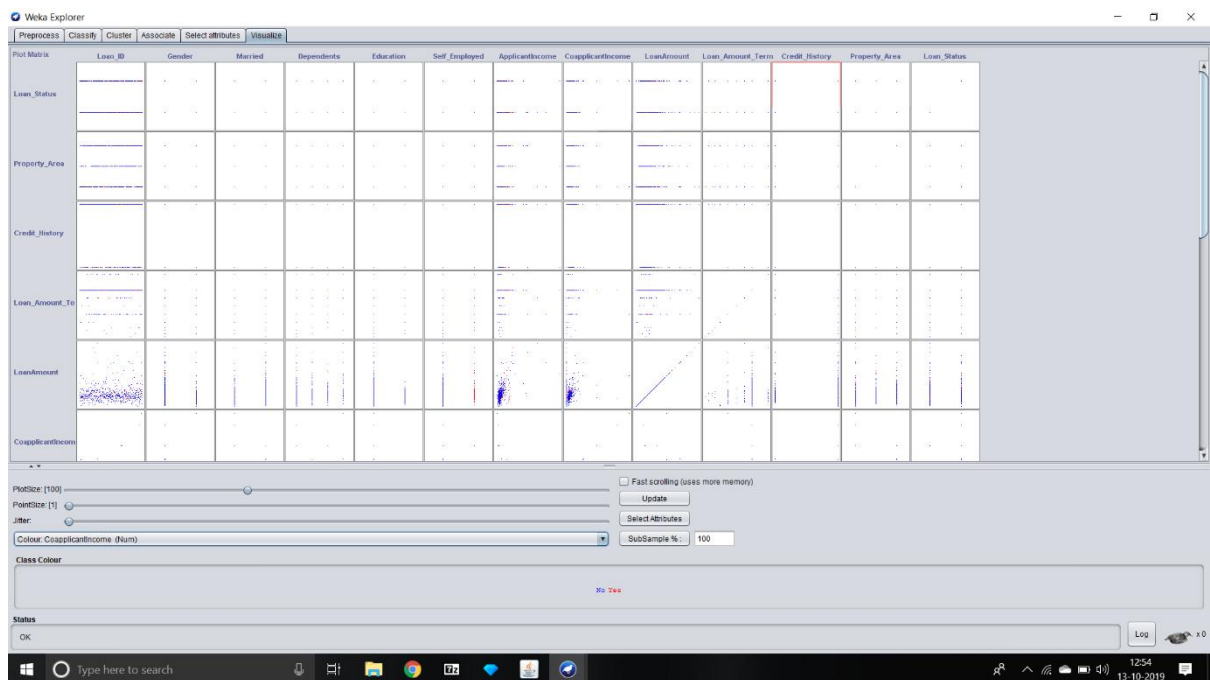
1. PARALLEL COORDINATES:



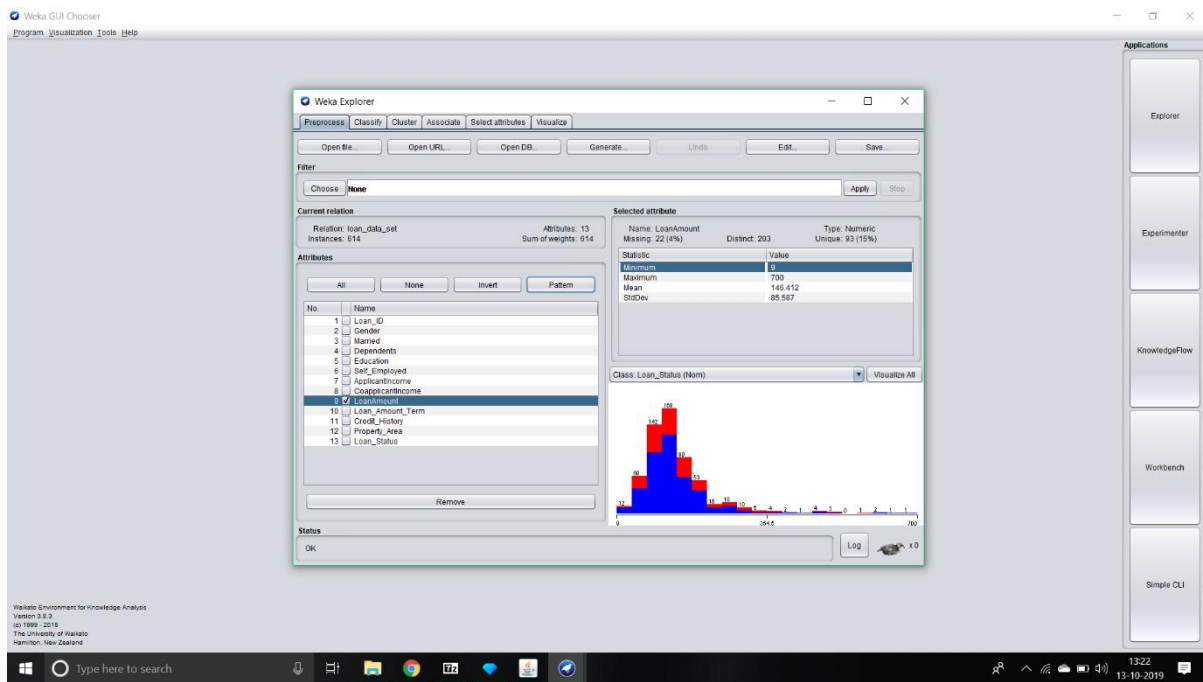
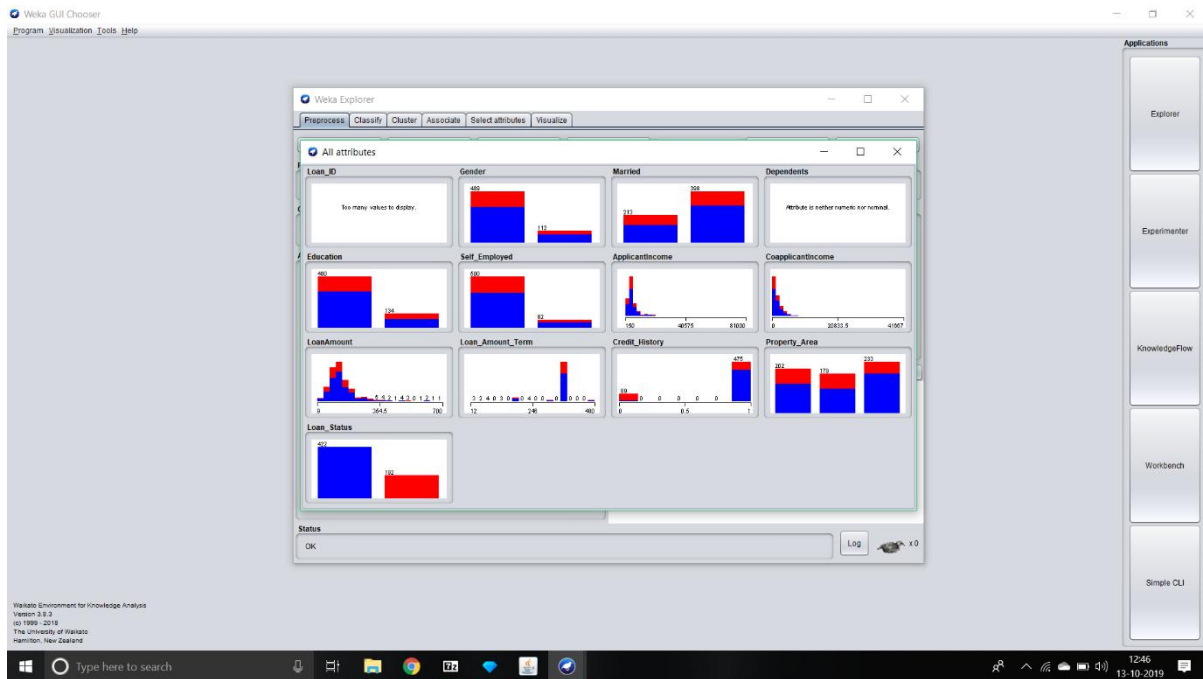
2. SCATTER PLOT:



3. SCATTER MATRIX:



4.HISTOGRAM:



DATA PREPROCESSING:

1. BEFORE REPLACE MISSING WITH MEAN

The screenshot shows the Weka Explorer interface with the 'ReplaceMissingValues' filter selected in the 'Filter' pane. The 'Current relation' is 'loan_data_set' with 614 instances. The 'Attributes' list on the left includes: 1. loan_ID, 2. Gender, 3. Married, 4. Dependents, 5. Education, 6. Self_Employed, 7. ApplicantIncome, 8. CoapplicantIncome, 9. LoanAmount, 10. Loan_Amount_Term, 11. Credit_History, 12. Property_Area, and 13. Loan_Status. The 'Viewer' window displays the first 13 attributes for 614 instances, showing a mix of nominal and numerical data.

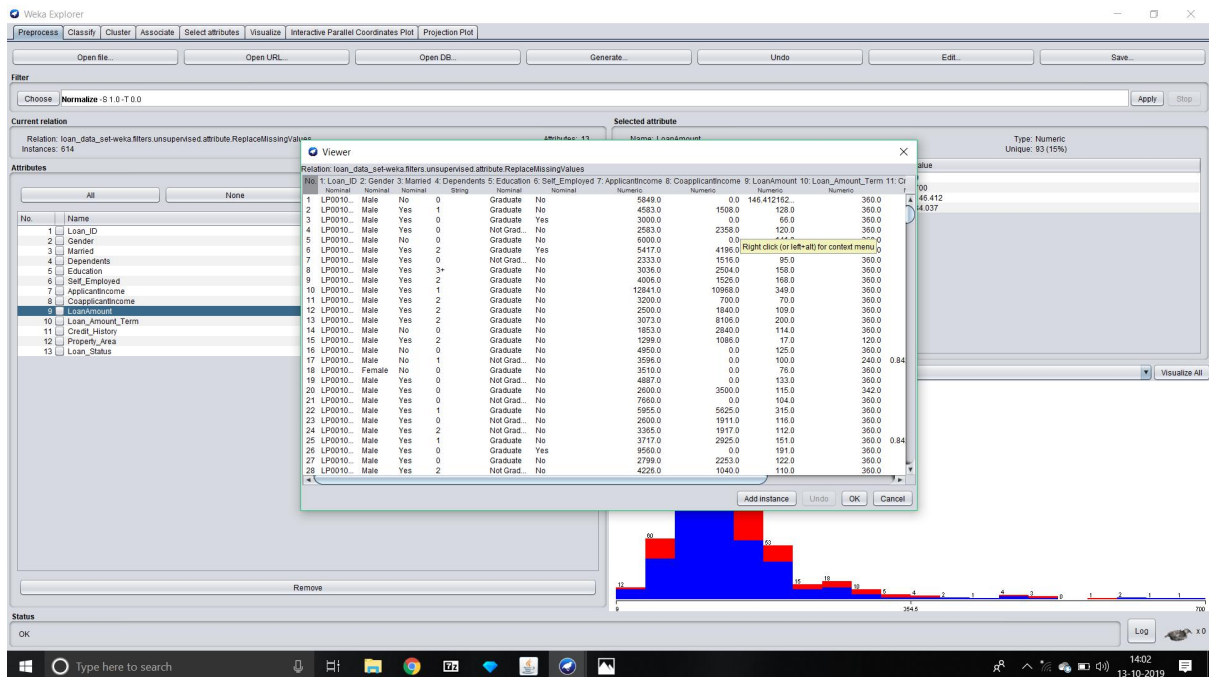
No.	Name	Type	Value
1	loan_ID	Nominal	No
2	Gender	Nominal	Male
3	Married	Nominal	Yes
4	Dependents	Nominal	No
5	Education	Nominal	Graduate
6	Self_Employed	Nominal	No
7	ApplicantIncome	Nominal	5849.0
8	CoapplicantIncome	Nominal	0.0
9	LoanAmount	Nominal	1284.0
10	Loan_Amount_Term	Nominal	360.0
11	Credit_History	Nominal	Yes
12	Property_Area	Nominal	Urban
13	Loan_Status	Nominal	Y

REPLACE MISSING WITH MEAN

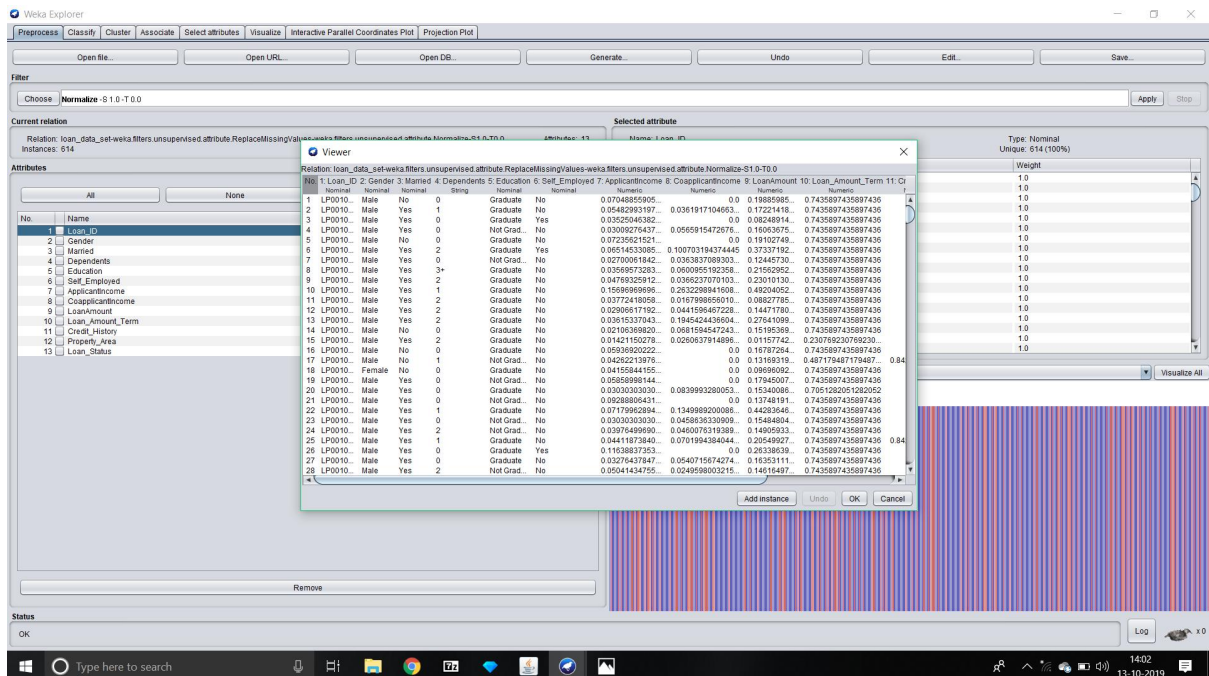
The screenshot shows the Weka Explorer interface with the 'ReplaceMissingValues' filter selected in the 'Filter' pane. The 'Current relation' is 'loan_data_set' with 614 instances. The 'Attributes' list on the left includes: 1. loan_ID, 2. Gender, 3. Married, 4. Dependents, 5. Education, 6. Self_Employed, 7. ApplicantIncome, 8. CoapplicantIncome, 9. LoanAmount, 10. Loan_Amount_Term, 11. Credit_History, 12. Property_Area, and 13. Loan_Status. The 'Viewer' window displays the first 13 attributes for 614 instances, showing a mix of nominal and numerical data. Some values are highlighted in blue, indicating missing values that have been replaced with the mean.

No.	Name	Type	Value
1	loan_ID	Nominal	No
2	Gender	Nominal	Male
3	Married	Nominal	Yes
4	Dependents	Nominal	No
5	Education	Nominal	Graduate
6	Self_Employed	Nominal	No
7	ApplicantIncome	Nominal	5849.0
8	CoapplicantIncome	Nominal	0.0
9	LoanAmount	Nominal	1284.0
10	Loan_Amount_Term	Nominal	360.0
11	Credit_History	Nominal	Yes
12	Property_Area	Nominal	Urban
13	Loan_Status	Nominal	Y

2. Before Normalizing



After Normalizing



3. Before preprocessing

The screenshot shows the OpenRefine web application interface. The top navigation bar includes 'OpenRefine loan_data_set.csv', 'Open', 'Export', and 'Help' buttons. Below the navigation bar, the 'Facet / Filter' panel on the left contains a 'Using facets and filters' section with instructions and a link to 'Watch these screencasts'. The main data table displays 614 rows of loan records. The columns are: Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, LoanAmount, Loan_Amount_T, Credit_History, Property_Area, and Loan_Status. The table shows a variety of loan types, including 'Rural', 'Urban', and 'Semiurban'. The bottom status bar indicates the file is 'loan_data_set.csv' and shows the system time as 09:55 on 11-10-2019.

Removing tuple with missing values(loan_amount)

The screenshot shows the OpenRefine web application interface after removing rows with missing values in the 'LoanAmount' column. The top navigation bar is the same as the previous screenshot. The 'Facet / Filter' panel on the left now includes a 'LoanAmount' facet, which is currently set to 'All'. The main data table displays 592 rows of loan records. The columns are the same as in the previous screenshot. The bottom status bar indicates the file is 'loan_data_set.csv' and shows the system time as 10:34 on 11-10-2019.