CSE 4005 DATA WAREHOUSING AND DATA MINING LAB PROJECT REPORT

SLOT: L5

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PROJECT TITLE: LOAN APPROVAL PREDICTION

Abstract

With the enhancement in the banking sector lots of people are applying for bank loans but the bank has its limited assets which it has to grant to limited people only, so finding out to whom the loan can be granted which will be a safer option for the bank is a typical process. So in this project reducing this risk factor behind selecting the safe person so as to save lots of bank efforts and assets is done. This is done by mining the Big Data of the previous records of the people to whom the loan was granted before and on the basis of these records/experiences the machine was trained using the machine learning model which give the most accurate result. The main objective of this project is to predict whether assigning the loan to particular person will be safe or not. This project is divided into four sections (i)Data Collection (ii)Data Preprocessing (iii)Data Visualization (iv) model training and results.

Introduction

Distribution of the loans is the core business part of almost every banks. The main portion the bank's assets comes directly came from the profit earned from the loans distributed by the banks. The prime objective in banking environment is to invest their assets in safe hands where it is. Today many banks/financial companies approves loan after a regress process of verification and validation but still there is no surety whether the chosen applicant is the deserving right applicant out of all applicants. Through this system we can predict whether that particular applicant is safe or not and the whole process of validation of features is automated by machine learning technique.

Loan Prediction is very helpful for employee of banks as well as for the applicant also.The Loan Prediction System can automatically calculate the weight of each features taking part in loan processing and on new test data same features are processed with respect to their associated weight .A time limit can be set for the applicant to check whether his/her loan can be sanctioned or not. Loan Prediction System allows jumping to specific application so that it can be check on priority basis.

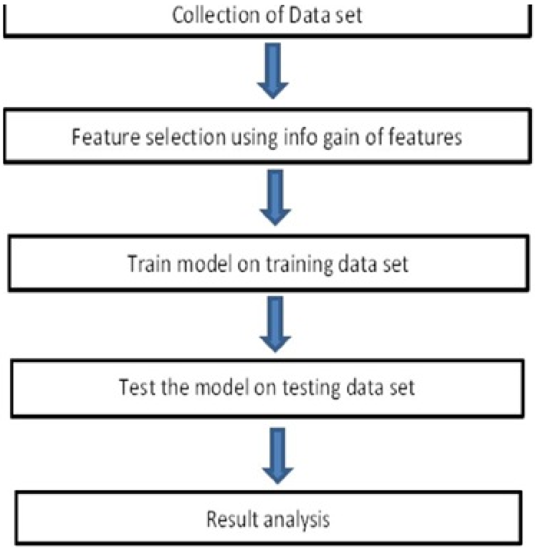
Problem Statement

Dream Housing Finance company deals in all home loans. They have presence across all urban, semi urban and rural areas. Customer first apply for home loan after that company validates the customer eligibility for loan. Company wants to automate the loan eligibility process (real time) based on customer detail provided while filling online application form. These details are Gender, Marital Status, Education, Number of Dependents, Income, Loan Amount, Credit History and others. To automate this process, they have given a problem to identify the customers segments, those are eligible for loan amount so that they can specifically target these customers.

This is a standard supervised classification task.A classification problem where we have to predict whether a loan would be approved or not. Below is the dataset attributes with description.

Variable	Description
Loan_ID	Unique Loan ID
Gender	Male/ Female
Married	Applicant married (Y/N)
Dependents	Number of dependents
Education	Applicant Education (Graduate/ Under Graduate)
Self_Employed	Self employed (Y/N)
ApplicantIncome	Applicant income
CoapplicantIncome	Coapplicant income
LoanAmount	Loan amount in thousands
Loan_Amount_Term	Term of loan in months
Credit_History	credit history meets guidelines
Property_Area	Urban/ Semi Urban/ Rural
Loan_Status	Loan approved (Y/N)

Architecture



Implementation In Python

Import Modules

In [61]:

```
import numpy as np
from numpy import percentile
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Load Dataset

In [62]:

```
df=pd.read csv('Loan Data.csv')
```

In [63]:

```
df
```

Out[63]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Are
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.0	1.0	Urba
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0	1.0	Rur
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0	1.0	Urba
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0	1.0	Urba
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0	1.0	Urba
...	...	...	...	...	...	...	...	...	...	...	...	.
976	LP002971	Male	Yes	3+	Not Graduate	Yes	4009	1777.0	113.0	360.0	1.0	Urba
977	LP002975	Male	Yes	0	Graduate	No	4158	709.0	115.0	360.0	1.0	Urba
978	LP002980	Male	No	0	Graduate	No	3250	1993.0	126.0	360.0	NaN	Semiurba
979	LP002986	Male	Yes	0	Graduate	No	5000	2393.0	158.0	360.0	1.0	Rur
980	LP002989	Male	No	0	Graduate	Yes	9200	0.0	98.0	180.0	1.0	Rur

981 rows × 13 columns

In [64]:

```
df.info() #get info about dataset
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 981 entries, 0 to 980
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            981 non-null    object
 1   Gender             957 non-null    object
 2   Married            978 non-null    object
 3   Dependents         956 non-null    object
 4   Education          981 non-null    object
```

```
 5   Self_Employed      926 non-null    object
 6   ApplicantIncome    981 non-null    int64
 7   CoapplicantIncome  981 non-null    float64
 8   LoanAmount         954 non-null    float64
 9   Loan_Amount_Term   961 non-null    float64
 10  Credit_History     902 non-null    float64
 11  Property_Area      981 non-null    object
 12  Loan_Status        614 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 99.8+ KB
```

In [65]:

```
df.describe() #get the statistic info about the numerical columns
```

Out[65]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	981.000000	981.000000	954.000000	961.000000	902.000000
mean	5179.795107	1601.916330	142.511530	342.201873	0.835920
std	5695.104533	2718.772806	77.421743	65.100602	0.370553
min	0.000000	0.000000	9.000000	6.000000	0.000000
25%	2875.000000	0.000000	100.000000	360.000000	1.000000
50%	3800.000000	1110.000000	126.000000	360.000000	1.000000
75%	5516.000000	2365.000000	162.000000	360.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.000000	1.000000

DataPreprocessing

fill missing values

In [66]:

```
df.isna().sum() #check the total number of na values
```

Out[66]:

```
Loan_ID                0
Gender                24
Married                3
Dependents            25
Education              0
Self_Employed         55
ApplicantIncome        0
CoapplicantIncome      0
LoanAmount            27
Loan_Amount_Term      20
Credit_History        79
Property_Area          0
Loan_Status          367
dtype: int64
```

In [67]:

```
df.isnull().sum()
#(df.iloc[:,1:13] == 0).sum() #find zeros in all the columns
```

Out[67]:

```
Loan_ID                0
Gender                24
Married                3
Dependents            25
Education              0
Self_Employed         55
ApplicantIncome        0
CoapplicantIncome      0
LoanAmount            27
Loan_Amount_Term      20
Credit_History        79
Property_Area          0
Loan_Status          367
dtype: int64
```

In [68]:

```
df['LoanAmount']=df['LoanAmount'].fillna(df['LoanAmount'].median())
df['Credit_History']=df['Credit_History'].fillna(df['Credit_History'].mode().iloc[0])
df['Loan_Amount_Term']=df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].median())
```

In [69]:

```
for i in df.columns: #fill na values with median values
    if (df[i].dtype=='object'):
        df[i]=df[i].fillna(df[i].mode().iloc[0])
```

Label Encoding

In [70]:

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

In [71]:

```
lb_make= LabelEncoder() #recode the catergorical values
df['Gender']=lb_make.fit_transform(df.Gender)# 1male 0 female
df['Married']=lb_make.fit_transform(df.Married)

df['Education']=lb_make.fit_transform(df.Education)
df['Self_Employed']=lb_make.fit_transform(df.Self_Employed)

df['Property_Area']=lb_make.fit_transform(df.Property_Area)
#df['Property_Area']=df['Property_Area'].replace({"Urban": 1, "Rural": 2,"Semiurban": 3}, inplace=True)
df['Loan_Status']=lb_make.fit_transform(df.Loan_Status)
```

In [72]:

```
df['Dependents']=df['Dependents'].str.replace(r'\D', '')# remove extra characters
df.Dependents=pd.to_numeric(df.Dependents)
```

In [73]:

```
df.drop('Loan_ID',axis=1,inplace=True)#drop loan id
```

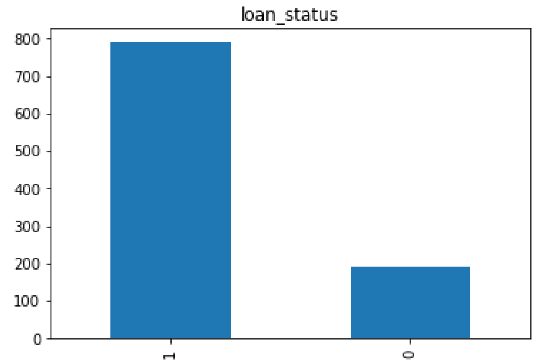
Visualization

In [74]:

```
df['Loan_Status'].value_counts(normalize=True)   #normalization
df['Loan_Status'].value_counts().plot.bar(title='loan_status')
```

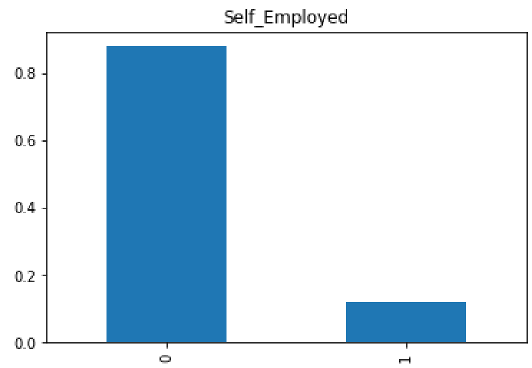
Out[74]:

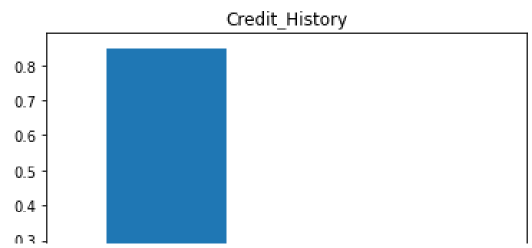
```
<matplotlib.axes._subplots.AxesSubplot at 0x1664e06ea08>
```

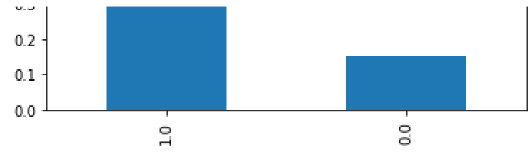


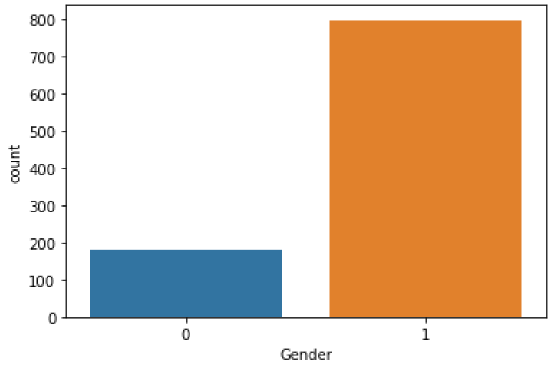
In [126]:

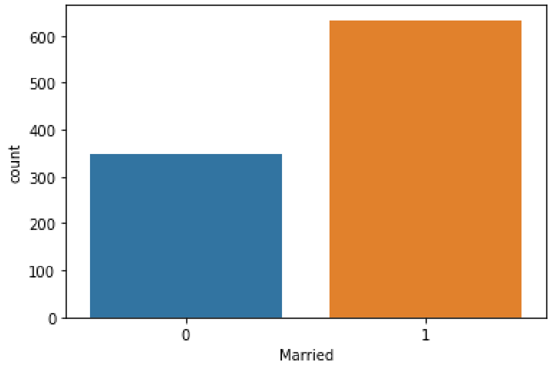
```
df['Self_Employed'].value_counts(normalize=True).plot.bar(title='Self_Employed')
plt.show()
df['Credit_History'].value_counts(normalize=True).plot.bar(title='Credit_History')
plt.show()

sns.countplot(df['Gender'])
plt.show()
sns.countplot(df['Married'])
plt.show()
sns.countplot(df['Dependents'])
plt.show()
sns.countplot(df['Property_Area'])
```

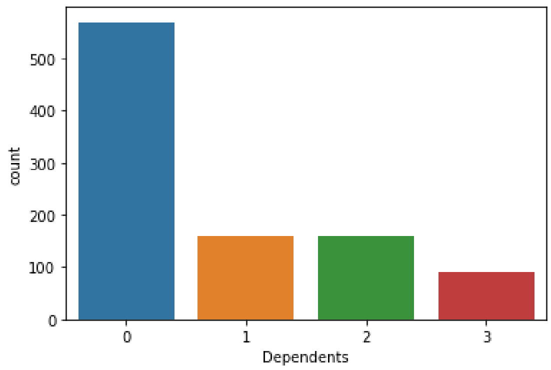






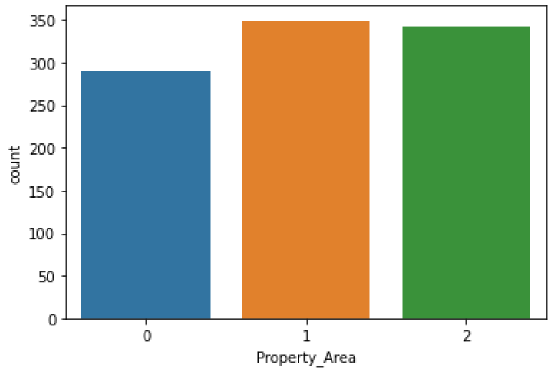






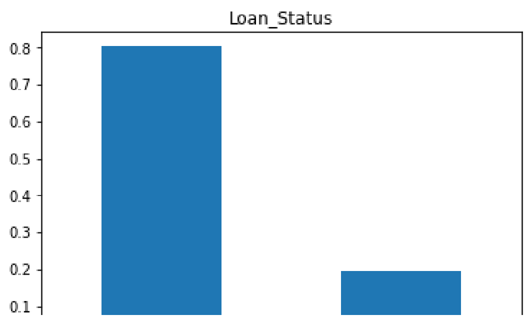
Out[126]:

<matplotlib.axes._subplots.AxesSubplot at 0x1664fa93f08>



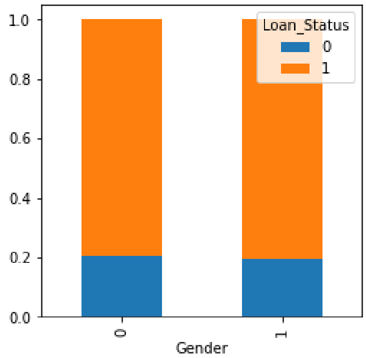
In [76]:

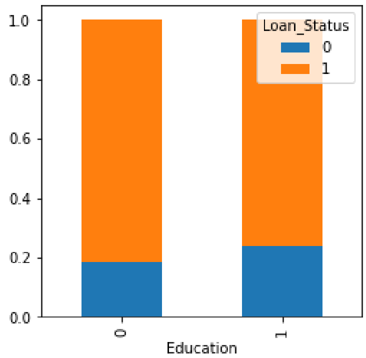
```
df['Loan_Status'].value_counts(normalize=True).plot.bar( title='Loan_Status')
plt.show()
```

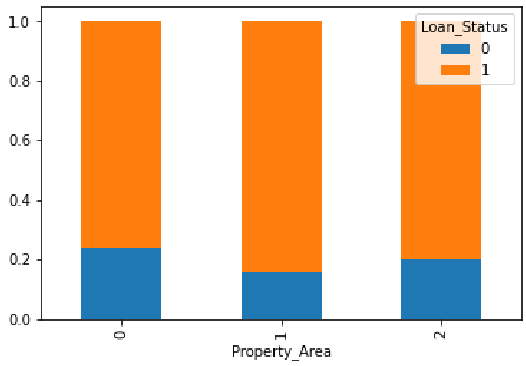


In [124]:

```
Gender=pd.crosstab(df['Gender'],df['Loan_Status'])
Gender.div(Gender.sum(1).astype(float), axis=0).plot(kind='bar',stacked=True,figsize=(4,4))
plt.show()
Education=pd.crosstab(df['Education'],df['Loan_Status'])
Education.div(Education.sum(1).astype(float), axis=0).plot(kind='bar',stacked=True,figsize=(4,4))
plt.show()
Property_Area.div(Property_Area.sum(1).astype(float), axis=0).plot(kind='bar',stacked=True)
plt.show()
```







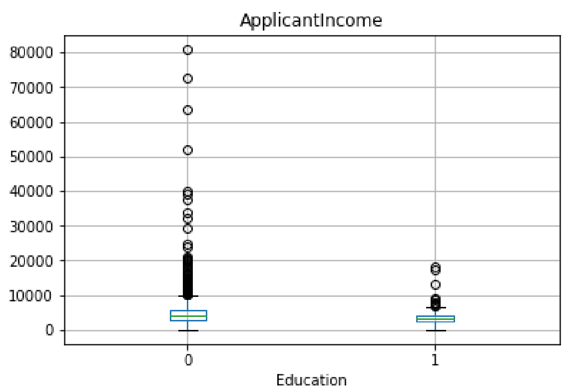
Outlier Detection

In [78]:

```
df.boxplot(column='ApplicantIncome', by = 'Education')
plt.suptitle('')
```

Out[78]:

```
Text(0.5, 0.98, '')
```

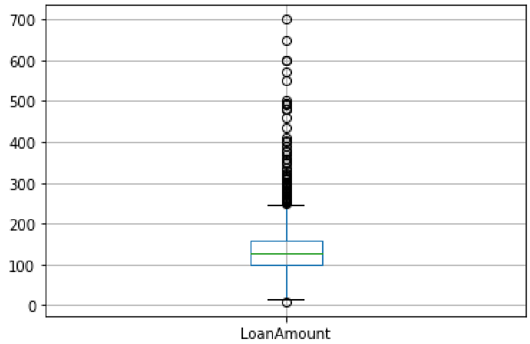


In [79]:

```
df.boxplot('LoanAmount')
```

Out[79]:

<matplotlib.axes._subplots.AxesSubplot at 0x1664f492e48>

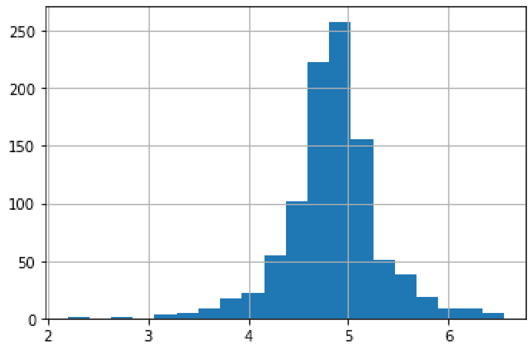


In [80]:

```
df['LoanAmount_log']=np.log(df['LoanAmount'])
df['LoanAmount log'].hist(bins=20)
```

Out[80]:

<matplotlib.axes._subplots.AxesSubplot at 0x1664f50c408>



Log Transformation

In [81]:

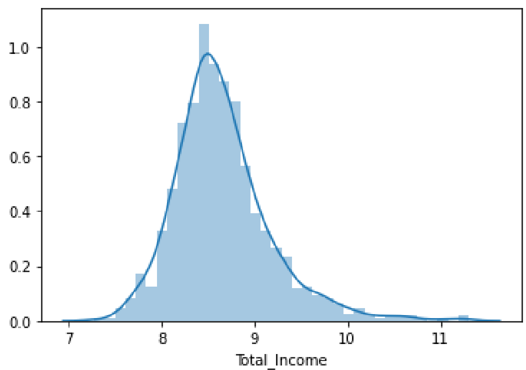
```
df['LoanAmount log']=np.log(df['LoanAmount'])
```

In [82]:

```
df['Total_Income']=df['ApplicantIncome']+df['CoapplicantIncome']
sns.distplot(np.log(df['Total Income']))
```

Out[82]:

<matplotlib.axes._subplots.AxesSubplot at 0x1664f5b1608>

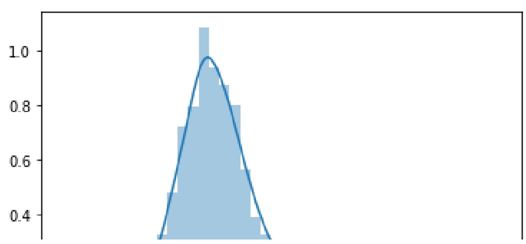


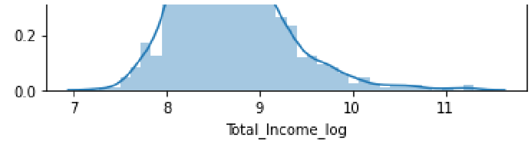
In [83]:

```
df['Total_Income_log'] = np.log(df['Total_Income'])
sns.distplot(df['Total Income log'])
```

Out[83]:

<matplotlib.axes._subplots.AxesSubplot at 0x1664f389f48>





In [84]:

```
df.corr()
```

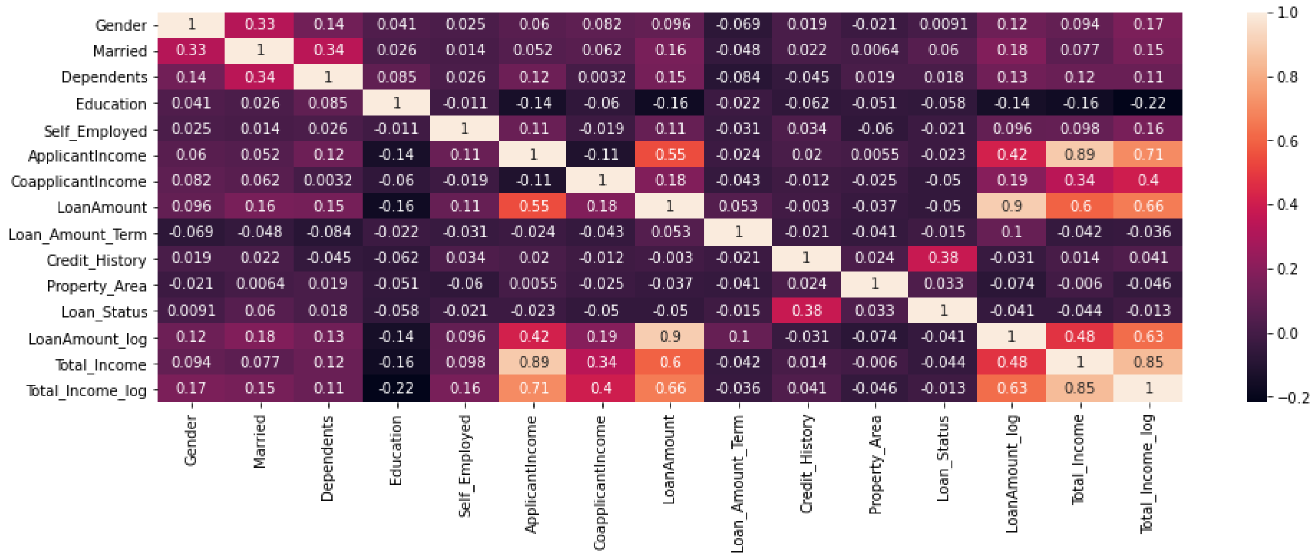
Out[84]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Prope
Gender	1.000000	0.327012	0.139248	0.040649	0.024719	0.060444	0.082428	0.095866	-0.069058	0.018627	-(
Married	0.327012	1.000000	0.344291	0.026211	0.013666	0.052126	0.061606	0.155463	-0.047505	0.021738	(
Dependents	0.139248	0.344291	1.000000	0.084894	0.026241	0.122136	0.003223	0.149722	-0.084190	-0.045335	(
Education	0.040649	0.026211	0.084894	1.000000	-0.010848	-0.138909	-0.060380	-0.163174	-0.021575	-0.062416	-(
Self_Employed	0.024719	0.013666	0.026241	-0.010848	1.000000	0.113106	-0.018861	0.107061	-0.031451	0.034485	-(
ApplicantIncome	0.060444	0.052126	0.122136	-0.138909	0.113106	1.000000	-0.114247	0.546241	-0.023823	0.020201	(
CoapplicantIncome	0.082428	0.061606	0.003223	-0.060380	-0.018861	-0.114247	1.000000	0.179327	-0.042750	-0.011531	-(
LoanAmount	0.095866	0.155463	0.149722	-0.163174	0.107061	0.546241	0.179327	1.000000	0.052775	-0.003005	-(
Loan_Amount_Term	-0.069058	-0.047505	-0.084190	-0.021575	-0.031451	-0.023823	-0.042750	0.052775	1.000000	-0.021495	-(
Credit_History	0.018627	0.021738	-0.045335	-0.062416	0.034485	0.020201	-0.011531	-0.003005	-0.021495	1.000000	(
Property_Area	-0.020801	0.006372	0.018639	-0.050685	-0.059678	0.005513	-0.024921	-0.036888	-0.041144	0.024342	'
Loan_Status	0.009116	0.059570	0.018397	-0.057680	-0.021323	-0.023077	-0.050084	-0.049868	-0.015291	0.380696	(
LoanAmount_log	0.123055	0.180598	0.134937	-0.143129	0.096043	0.417236	0.193742	0.901467	0.104715	-0.030598	-(
Total_Income	0.094346	0.077085	0.116923	-0.158577	0.098419	0.893847	0.343317	0.597357	-0.041817	0.013894	-(
Total_Income_log	0.167323	0.151465	0.112517	-0.215370	0.157912	0.707843	0.402275	0.663366	-0.035838	0.040516	-(

Corelation Matrix

In [85]:

```
plt.figure(figsize = (16,5))

#ax = sns.heatmap(df1.iloc[:, 1:6:], annot=True, linewidths=.5)
ax=sns.heatmap(df.corr(),annot=True)
```



Model Training

In [86]:

```
from sklearn.model_selection import train_test_split
from sklearn import metrics,preprocessing
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score,confusion_matrix, classification_report
from sklearn.metrics import accuracy_score,roc_auc_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

In [87]:

```
X=df.drop(['Loan_Status','LoanAmount_log','Total_Income','Total_Income_log'],axis=1)
```

```python
#X=df[['Credit_Histo']]
y=df[['Loan_Status']]
```

In [88]:

```python
X
```

Out[88]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area
0	1	0	0	0	0	5849	0.0	126.0	360.0	1.0	2
1	1	1	1	0	0	4583	1508.0	128.0	360.0	1.0	0
2	1	1	0	0	1	3000	0.0	66.0	360.0	1.0	2
3	1	1	0	1	0	2583	2358.0	120.0	360.0	1.0	2
4	1	0	0	0	0	6000	0.0	141.0	360.0	1.0	2
...	...	...	...	...	...	...	...	...	...	...	...
976	1	1	3	1	1	4009	1777.0	113.0	360.0	1.0	2
977	1	1	0	0	0	4158	709.0	115.0	360.0	1.0	2
978	1	0	0	0	0	3250	1993.0	126.0	360.0	1.0	1
979	1	1	0	0	0	5000	2393.0	158.0	360.0	1.0	0
980	1	0	0	0	1	9200	0.0	98.0	180.0	1.0	0

981 rows × 11 columns

In [89]:

```python
y
```

Out[89]:

	Loan_Status
0	1
1	0
2	1
3	1
4	1
...	...
976	1
977	1
978	1
979	1
980	1

981 rows × 1 columns

In [90]:

```python
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=42)
```

In [91]:

```python
X_train
```

Out[91]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area
572	1	1	2	0	0	16666	0.0	275.0	360.0	1.0	2
849	1	0	0	0	0	2231	2774.0	176.0	360.0	0.0	2
906	1	0	0	1	0	3271	0.0	90.0	360.0	1.0	0
432	1	0	0	0	0	12876	0.0	405.0	360.0	1.0	1
228	1	1	0	0	0	4758	0.0	158.0	480.0	1.0	1
...	...	...	...	...	...	...	...	...	...	...	...
106	1	1	2	0	0	11417	1126.0	225.0	360.0	1.0	2
270	0	0	0	0	0	3237	0.0	30.0	360.0	1.0	2
860	1	1	2	0	1	5000	2166.0	150.0	360.0	1.0	2
435	0	1	0	0	0	10047	0.0	126.0	240.0	1.0	1
102	1	1	0	0	0	13650	0.0	126.0	360.0	1.0	2

686 rows × 11 columns

In [92]:

```python
X_test
```

Out[92]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area
789	1	1	2	0	0	4912	4614.0	160.0	360.0	1.0	0
497	1	1	0	0	0	4625	2857.0	111.0	12.0	1.0	2
139	1	1	2	1	0	4200	1430.0	129.0	360.0	1.0	0
570	1	1	1	0	0	3417	1750.0	186.0	360.0	1.0	2
66	1	0	0	1	0	3200	2254.0	126.0	180.0	0.0	2
...	...	...	...	...	...	...	...	...	...	...	...
758	1	1	2	0	1	10890	0.0	260.0	12.0	1.0	0
567	1	1	3	0	0	3400	2500.0	123.0	360.0	0.0	0
916	0	0	0	0	1	14987	0.0	177.0	360.0	1.0	0
889	1	1	3	0	0	2773	1497.0	108.0	360.0	1.0	1
521	1	0	0	0	0	2500	0.0	55.0	360.0	1.0	1

295 rows × 11 columns

In [93]:

```
y_train
```

Out[93]:

	Loan_Status
572	1
849	1
906	1
432	1
228	1
...	...
106	1
270	1
860	1
435	1
102	1

686 rows × 1 columns

In [94]:

```
y_test
```

Out[94]:

	Loan_Status
789	1
497	1
139	0
570	1
66	0
...	...
758	1
567	0
916	1
889	1
521	1

295 rows × 1 columns

Logistic Regression

In [95]:

```
lm=LogisticRegression(random_state=10)
lm.fit(X_train,y_train)
ypred=lm.predict(X_test)

print(ypred)
```

```
[1 1 1 1 0 1 1 0 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1
 1 1 1 0 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

```
 1 1 1 1 1 1 1 0 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1]
```

In [96]:

```
df
```

Out[96]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_St
0	1	0	0	0	0	5849	0.0	126.0	360.0	1.0	2	
1	1	1	1	0	0	4583	1508.0	128.0	360.0	1.0	0	
2	1	1	0	0	1	3000	0.0	66.0	360.0	1.0	2	
3	1	1	0	1	0	2583	2358.0	120.0	360.0	1.0	2	
4	1	0	0	0	0	6000	0.0	141.0	360.0	1.0	2	
...	...	...	...	...	...	...	...	...	...	...	...	
976	1	1	3	1	1	4009	1777.0	113.0	360.0	1.0	2	
977	1	1	0	0	0	4158	709.0	115.0	360.0	1.0	2	
978	1	0	0	0	0	3250	1993.0	126.0	360.0	1.0	1	
979	1	1	0	0	0	5000	2393.0	158.0	360.0	1.0	0	
980	1	0	0	0	1	9200	0.0	98.0	180.0	1.0	0	

981 rows × 15 columns

In [97]:

```
print(classification report(y test, ypred))
```

```
              precision    recall  f1-score   support

           0       0.71      0.19      0.30        63
           1       0.82      0.98      0.89       232

    accuracy                           0.81       295
   macro avg       0.76      0.58      0.60       295
weighted avg       0.79      0.81      0.76       295
```

In [98]:

```
accuracy score(y test,ypred)
```

Out[98]:

```
0.8101694915254237
```

In [99]:

```
confusion matrix(y test,ypred)
```

Out[99]:

```
array([[ 12,  51],
       [  5, 227]], dtype=int64)
```

In [100]:

```
f1 score(y test,ypred)
```

Out[100]:

```
0.8901960784313726
```

Decision Tree

In [101]:

```
tree_clf=DecisionTreeClassifier() #decison tree algorithm
tree clf.fit(X train,y train)
```

Out[101]:

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=None, max_features=None, 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, presort='deprecated',
                       random_state=None, splitter='best')
```

In [102]:

```
ypred_tree=tree_clf.predict(X_test)
print(ypred tree)
```

```
[1 1 1 1 0 1 1 0 1 1 1 1 1 1 0 1 0 1 1 1 1 1 1 1 0 0 1 1 1 1 0 1 1 1 1 1 1
 1 1 0 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 0 0 1 1 1 1
 0 0 0 1 1 0 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 0 1 1 0 1 1 1 1 1 0
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 0 1 0 1 1 1 1 1 1 1 0 1 1 0
 1 1 1 0 1 1 1 1 1 1 1 0 1 1 1 1 1 0 1 1 1 1 0 0 1 1 0 1 1 0 1 0 0 1 1 1 1
```

```
 1 1 1 1 1 1 1 0 1 1 0 1 1 1 1 1 1 1 0 1 1 1 0 1 1 1 1 1 1 1 1 1 0 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 0 1 0 1 1 1 1 1 1 1 1 1 1 0 1 1
 0 1 0 1 0 0 1 1 1 1 1 0 1 1 1 1 1 1 1 0 1 1 1 1 0 0 1 1 1 1 1 1 1 1 1 1]
```

In [103]:

```python
accuracy score(y test,ypred tree)
```

Out[103]:

```
0.7559322033898305
```

In [104]:

```python
f1 score(y test,ypred tree)
```

Out[104]:

```
0.8487394957983194
```

In [105]:

```python
print(classification report(y test, ypred tree))
```

```
              precision    recall  f1-score   support

           0       0.41      0.33      0.37        63
           1       0.83      0.87      0.85       232

    accuracy                           0.76       295
   macro avg       0.62      0.60      0.61       295
weighted avg       0.74      0.76      0.75       295
```

Random forest Algorithm

In [106]:

```python
forest=RandomForestClassifier() #random forest
forest.fit(X_train,y_train)
ypred_f=forest.predict(X_test)
print(ypred f)
```

```
[1 1 1 1 0 1 1 0 1 0 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 0 1 1 0
 1 1 1 0 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1
 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 0 0 1 1 1 1 1 1 1 1 1 1]
```

In [107]:

```python
accuracy score(y test,ypred f)
```

Out[107]:

```
0.8
```

In [108]:

```python
f1 score(y test,ypred f)
```

Out[108]:

```
0.8836291913214991
```

In [109]:

```python
print(classification report(y test, ypred f))
```

```
              precision    recall  f1-score   support

           0       0.60      0.19      0.29        63
           1       0.81      0.97      0.88       232

    accuracy                           0.80       295
   macro avg       0.71      0.58      0.59       295
weighted avg       0.77      0.80      0.76       295
```

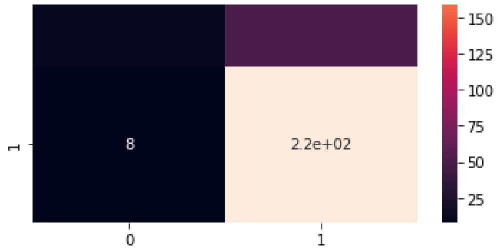
Confusion Matrix

In [114]:

```python
cm = confusion_matrix(y_test, ypred_f)
cm
sns.heatmap(cm, annot=True)
```

Out[114]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1664f632108>
```



Support Vector Machine

In [116]:

```
from sklearn.svm import SVC
svc_m=SVC()
svc_m.fit(X_train,y_train)
```

Out[116]:

```
SVC(C=1.0, break_ties=False, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='scale', kernel='rbf',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
```

In [117]:

```
yp=svc_m.predict(X_test)
```

In [118]:

```
accuracy_score(y_test,yp)
```

Out[118]:

```
0.7864406779661017
```

In [119]:

```
f1_score(y_test,yp)
```

Out[119]:

```
0.8804554079696395
```

Conclusion

The Data Mining process started from data cleaning and preprocessing, Missing value imputations, then Visualization and finally model building and evaluation. The best accuracy on the test set is 0.8101 for logistic regression,0.7559 for decsion tree,0.80 for random forest and 0.786 for svm. This brings some of the following insights about approval. Applicants with Credit history not passing fails to get approved, Probably because that they have a probability of a not paying back. Most of the Time, Applicants with high income sanctioning low amount is to more likely get approved which make sense, more likely to pay back their loans. Some basic characteristic gender and marital status seems not to be taken into consideration by the company.