In [48]:
```
#Building a predictive loan prediction model based on the customer profile using  machine learning algorithm .

# 1.Sample description about the datast.
             # LoanAmount : Loan amount in thousands of dollars
            # Loan_Amount_Term : Term of loan in months
            # Credit_History : Credit history meets guidelines yes or no
            # Property_Area : Urban/ Semi Urban/ Rural
           # Loan_Status : Loan approved (Y/N) this is the target variable

#Activities:
#Task 1: Data Preprocessing
#Task 2: Handling missing values with the mode of column value if the percentage of null value is greater than
#Task 3: Encoding: Handling Catagroical Columns.
#Task 4: Feature scaling  using Standardization
#Task 5: Apply oversampling for balancing dependant variables.
#Task 6: Split both train and test data
#Task 7: K-fold cross validation for improving the performance of our model for unseen data
#Task 8: Model Building  using logistic regression,SVM,Decision tree classifier and random forest clasffication
#task 9: Hyperparameter tuning
#task 10: Evaluation
```

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sn
import matplotlib.pyplot as plt
import warnings
warnings.simplefilter(action="ignore", category=FutureWarning)
pd.options.mode.chained_assignment = None # To omit default='warnings'
```

In [2]:
```
#reading the data and checking of the first row of data
loan=pd.read_csv('loan_data.csv')
loan.head()
```

Out[2]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Terr
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.

In [3]:
```
#Checking of null values in percentage
loan.isnull().sum()*100/loan.shape[0]
```

Out[3]:
```
Loan_ID              0.000000
Gender               2.117264
Married              0.488599
Dependents           2.442997
Education            0.000000
Self_Employed        5.211726
ApplicantIncome      0.000000
CoapplicantIncome    0.000000
LoanAmount           3.583062
Loan_Amount_Term     2.280130
Credit_History       8.143322
Property_Area        0.000000
Loan_Status          0.000000
dtype: float64
```

In [4]:
```
loan.columns
```

Out[4]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [6]:
```
#Selection of columns with having <5% of null values
column=['Gender', 'Married', 'Dependents','LoanAmount','Loan_Amount_Term']
```

In [7]:
```
#Droping null values
loan.dropna(subset=column,inplace=True)
```

In [8]:
```
loan['Self_Employed'].mode()
```

Out[8]:
```
0    No
Name: Self_Employed, dtype: object
```

In [9]:
```
#Taking the mode value for columns with having >5% of null values
loan['Self_Employed']=loan['Self_Employed'].fillna(loan['Self_Employed'].mode()[0])
loan['Credit_History']=loan['Credit_History'].fillna(loan['Credit_History'].mode()[0])
```

In [10]:
```
#Checking of null values after cleaning
loan.isnull().sum()*100/loan.shape[0]
```

Out[10]:
```
Loan_ID              0.0
Gender               0.0
Married              0.0
Dependents           0.0
Education            0.0
Self_Employed        0.0
ApplicantIncome      0.0
CoapplicantIncome    0.0
LoanAmount           0.0
Loan_Amount_Term     0.0
Credit_History       0.0
Property_Area        0.0
Loan_Status          0.0
dtype: float64
```

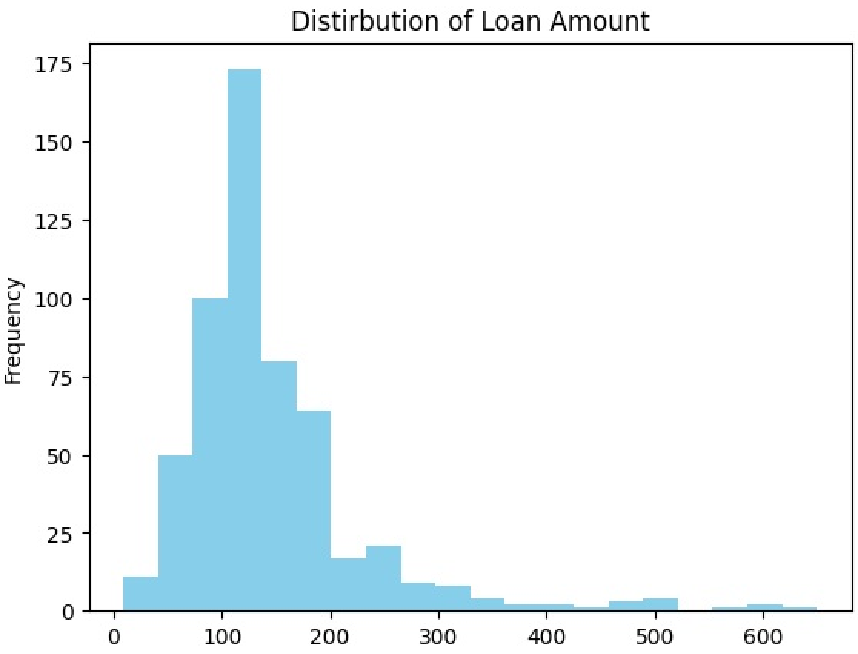
In [11]:
```
#checking of duplicate records
loan.duplicated().any()
#It returns false value so that the data set has no duplicate values
```

Out[11]:
```
False
```

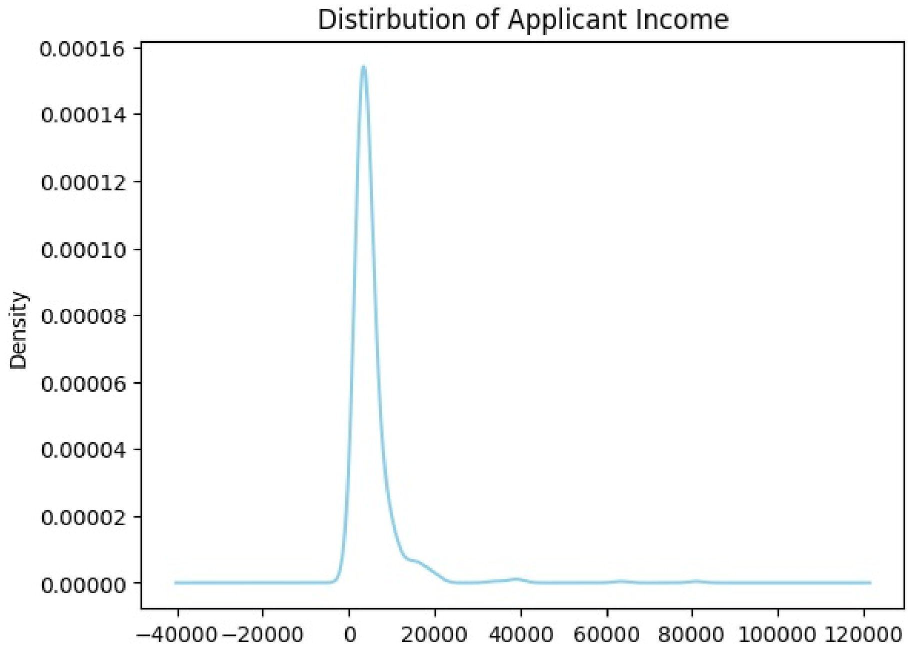
In [12]:
```
#Total instance of data after pre-processing
loan.shape
```

Out[12]:
```
(553, 13)
```

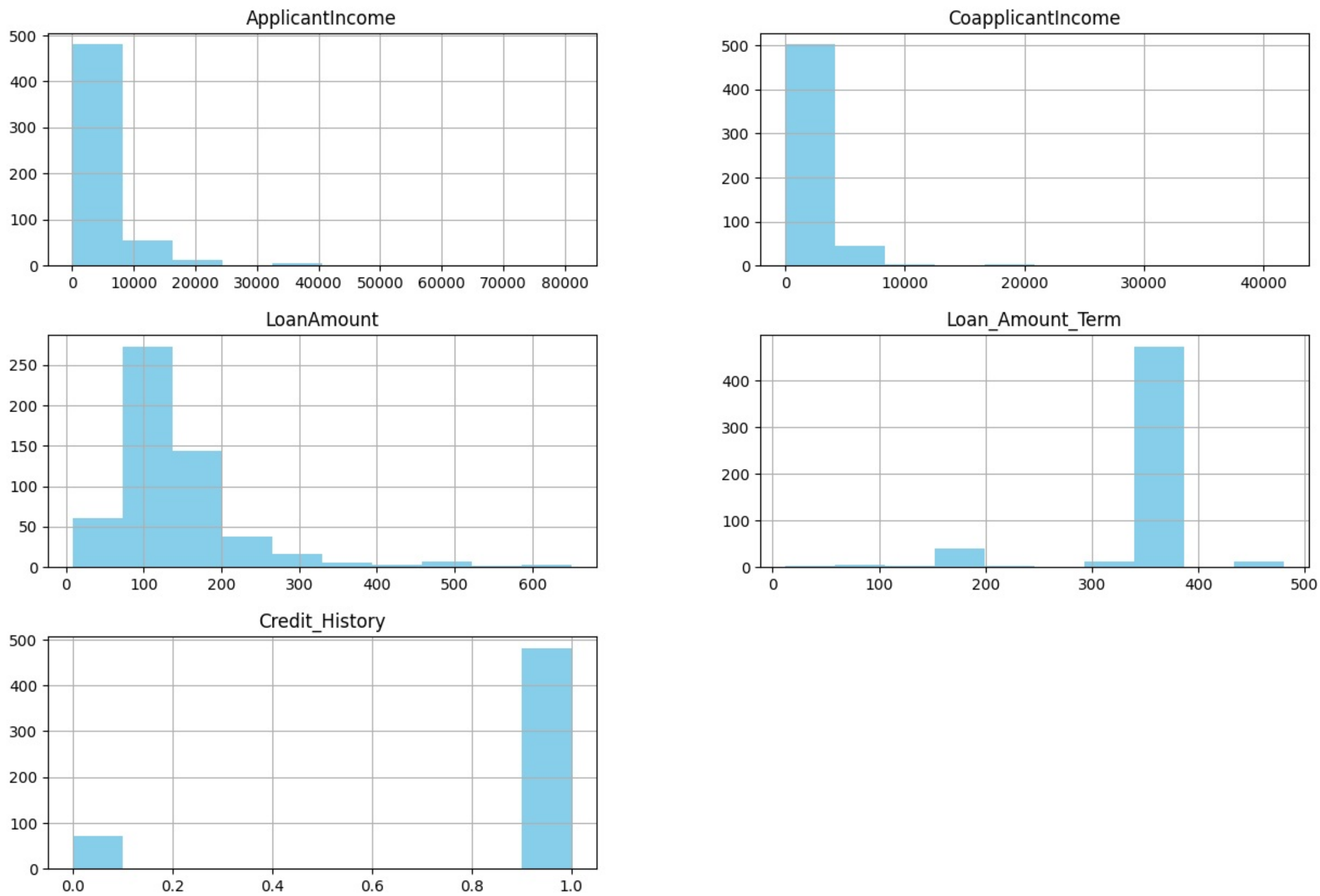
In [31]:
```
#Checking the distirbution of data for some features
loan['LoanAmount'].plot(kind='hist',bins=20,color='skyblue',title="Distirbution of Loan Amount")
plt.show()
```



In [29]:
```
loan['ApplicantIncome'].plot(kind='kde',color='skyblue',title="Distirbution of Applicant Income")
plt.show()
#Its clear that many loan applicant customer has an income of less than 20000$
```



In [40]:
```
#Visualizing the distribution for all columns
loan.hist(figsize=(15,10),color='skyblue')
plt.show()
```



2. Handling Catagorical columns

In [13]:
```
#Removing unwanted column
loan.drop('Loan_ID',axis=1,inplace=True)
```

In [14]:
```
loan.sample(3)
```

Out[14]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit
404	Female	No	0	Graduate	Yes	7441	0.0	194.0	360.0	
269	Female	No	1	Graduate	No	2876	1560.0	90.0	360.0	
411	Male	Yes	0	Graduate	No	6256	0.0	160.0	360.0	

In [15]:
```
#Replacing '3+' by '4'
```

```
In [15]: #Replacing '3+' by '4'
loan['Dependents']=loan['Dependents'].apply(lambda x:'4'if x=='3+' else x)
```

```
In [16]: loan['Dependents'].unique()
```

```
Out[16]: array(['1', '0', '2', '4'], dtype=object)
```

```
In [17]: loan.columns
```

```
Out[17]: Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
       'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

```
In [18]: #Getting dummies values for catagorical data to get dummies numerical value
loan['Gender']=loan['Gender'].astype('category').cat.codes
loan['Married']=loan['Married'].astype('category').cat.codes
loan['Education']=loan['Education'].astype('category').cat.codes
loan['Self_Employed']=loan['Self_Employed'].astype('category').cat.codes
loan['Property_Area']=loan['Property_Area'].astype('category').cat.codes
loan['Loan_Status']=loan['Loan_Status'].astype('category').cat.codes
```

```
In [19]: #Thew new data after getting dummies value
loan.head(2)
```

Out[19]:

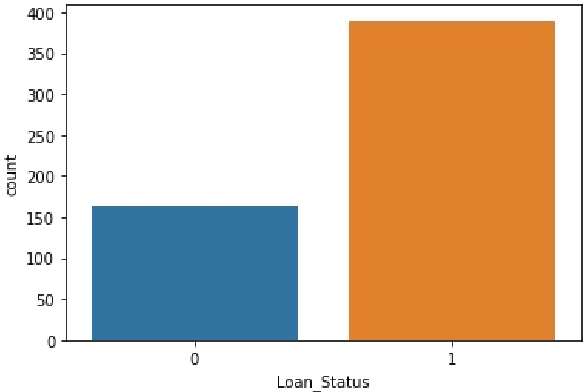
	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_H
1	1	1	1	0	0	4583	1508.0	128.0	360.0	
2	1	1	0	0	1	3000	0.0	66.0	360.0	

```
In [20]: #Oversampling – Duplicating samples from the minority class
#Balancing the data based on target variable
loan['Loan_Status'].value_counts()
```

```
Out[20]: 1    389
0    164
Name: Loan_Status, dtype: int64
```

```
In [21]: sn.countplot(loan['Loan_Status'])
plt.show()
```

```
/usr/local/lib/python3.9/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as
a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argum
ents without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```




```
In [22]: #Store feature matrix in X and target in vector y
X=loan.drop('Loan_Status',axis=1)
Y=loan['Loan_Status']
```

```
In [23]: # instantiating the random over sampler
from imblearn.over_sampling import RandomOverSampler
from collections import Counter
ros = RandomOverSampler()
# resampling X, y
X_resampling, Y_resampling = ros.fit_resample(X, Y)
```

```
In [24]: X=X_resampling
Y=Y_resampling
print(Counter(Y))
```

```
Counter({0: 389, 1: 389})
```

3. Feature Scaling(Standardization)

```
In [25]: #Columns to be standardaized
cols=['ApplicantIncome','CoapplicantIncome','LoanAmount','Loan_Amount_Term']
```

In [26]:
```
#Scaling using Standrdization
from sklearn.preprocessing import StandardScaler
st=StandardScaler()
X[cols]=st.fit_transform(X[cols])
```

In [27]:
```
#Standardized result
X.head(5)
```

Out[27]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_H
0	1	1	1	0	0	-0.137708	-0.072302	-0.231354	0.274535	
1	1	1	0	0	1	-0.371603	-0.492544	-0.965103	0.274535	
2	1	1	0	1	0	-0.433217	0.164573	-0.326031	0.274535	
3	1	0	0	0	0	0.071661	-0.492544	-0.077503	0.274535	
4	1	1	2	0	1	-0.014480	0.676778	1.413664	0.274535	

4. Split the dataset into traning and test and apply K-fold cross validation

In [28]:
```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
import numpy as np
```

In [29]:
```
model_df={}
def model_val(model,X,Y):
  X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.2,random_state=42)
  model.fit(X_train,Y_train)
  Y_pred=model.predict(X_test)
  print(f'{model} accuracy is {accuracy_score(Y_test,Y_pred)}')

  score=cross_val_score(model,X,Y,cv=5)
  print(f'{model} average cross val is {np.mean(score)}')
  model_df[model]=round(np.mean(score)*100,2)
```

In [30]:
```
#Using LogisticRegression
from sklearn.linear_model import LogisticRegression
model1=LogisticRegression()
model_val(model1,X,Y)
```

```
LogisticRegression() accuracy is 0.7051282051282052
LogisticRegression() average cross val is 0.705616211745244
```

In [31]:
```
model_df
```

Out[31]:
```
{LogisticRegression(): 70.56}
```

In [32]:
```
#Using SVC
from sklearn import svm
model2=svm.SVC()
model_val(model2,X,Y)
```

```
SVC() accuracy is 0.717948717948718
SVC() average cross val is 0.7262200165425974
```

In [33]:
```
#Using Decesion Tree classifier
from sklearn.tree import DecisionTreeClassifier
model3=DecisionTreeClassifier()
model_val(model3,X,Y)
```

```
DecisionTreeClassifier() accuracy is 0.8782051282051282
DecisionTreeClassifier() average cross val is 0.852183622828784
```

In [34]:
```
#using RandomForest Classifier
from sklearn.ensemble import RandomForestClassifier
model4=RandomForestClassifier()
model_val(model4,X,Y)
```

```
RandomForestClassifier() accuracy is 0.8846153846153846
RandomForestClassifier() average cross val is 0.907460711331679
```

In [35]:
```
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.2,random_state=42)
model4.fit(X_train,Y_train)
Y_pred=model4.predict(X_test)
from sklearn.metrics import confusion_matrix , classification_report
print(classification_report(Y_test,Y_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.88      0.88        76
           1       0.89      0.89      0.89        80

    accuracy                           0.88       156
   macro avg       0.88      0.88      0.88       156
weighted avg       0.88      0.88      0.88       156
```

In [36]:
```python
model_df
# Hence RandomForestClassifier  is the best classfication algorithm for this dataset
```

Out[36]:
```
{LogisticRegression(): 70.56,
 SVC(): 72.62,
 DecisionTreeClassifier(): 85.22,
 RandomForestClassifier(): 90.75}
```

5.Hyperparameter tuning

In [37]:
```python
#Obtaining optimal model by changing parameters
#Using randomized search CV
```

In [66]:
```python
from sklearn.model_selection import RandomizedSearchCV
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 100, stop = 500, num = 10)]
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 110, num = 11)]
max_depth.append(None)
# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               }
random_grid
```

Out[66]:
```
{'n_estimators': [100, 144, 188, 233, 277, 322, 366, 411, 455, 500],
 'max_features': ['auto', 'sqrt'],
 'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, None]}
```

In [67]:
```python
# Use the random grid to search for best hyperparameters
from sklearn.ensemble import RandomForestClassifier
# First create the base model to tune
rf = RandomForestClassifier()
# Random search of parameters, using 5 fold cross validation,
# search across 100 different combinations, and use all available cores
rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid,n_iter = 200,cv = 5,random_sta
# Fit the random search model
rf_random.fit(X_train,Y_train)
```

Out[67]:
```
▸ RandomizedSearchCV
▸ estimator: RandomForestClassifier
  ▸ RandomForestClassifier
```

In [68]:
```python
#Evalutaing the model
# Selecting the optimal model
best_random = rf_random.best_estimator_
```

In [69]:
```python
Y_pred2=best_random.predict(X_test)
accuracy_score(Y_test,Y_pred2)
```

Out[69]:
```
0.8782051282051282
```

In [70]:
```python
print(classification_report(Y_test,Y_pred2))
```

```
              precision    recall  f1-score   support

           0       0.88      0.87      0.87        76
           1       0.88      0.89      0.88        80

    accuracy                           0.88       156
   macro avg       0.88      0.88      0.88       156
weighted avg       0.88      0.88      0.88       156
```

In [3]:
```python
# Unfortunetly,The hyperparameter tuning result is less accurant than the normal one.
```