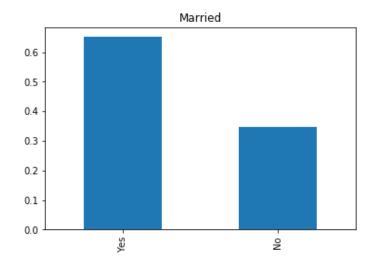
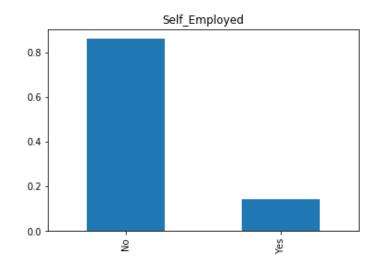
```
In [1]:
         import pandas as pd
         import numpy as np
                                                 # For mathematical calculations
         import seaborn as sns
                                                 # For data visualization
         import matplotlib.pyplot as plt
                                                 # For plotting graphs
         %matplotlib inline
         import warnings
                                                 # To ignore any warnings
 In [2]: warnings.filterwarnings("ignore")
         train = pd.read_csv("C:/Users/Admin/Desktop/ML/train_u6lujuX_CVtuZ9i.csv")
 In [3]:
 In [4]:
         test = pd.read_csv("C:/Users/Admin/Desktop/ML/test_Y3wMUE5_7gLdaTN.csv")
 In [5]:
         train_original=train.copy()
 In [6]:
         test_original=test.copy()
 In [7]:
         train.columns
 Out[7]: Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
                'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmoun
         t',
                'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Statu
         s'],
               dtype='object')
 In [8]: test.columns
 Out[8]: Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
                 'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmoun
         t',
                 'Loan_Amount_Term', 'Credit_History', 'Property_Area'],
               dtype='object')
 In [9]: | train.dtypes
 Out[9]: Loan ID
                                object
         Gender
                                object
         Married
                                object
         Dependents
                                object
         Education
                                object
         Self_Employed
                                object
                                int64
         ApplicantIncome
         CoapplicantIncome
                              float64
         LoanAmount
                              float64
         Loan_Amount_Term
                               float64
         Credit_History
                              float64
         Property_Area
                               object
         Loan_Status
                               object
         dtype: object
In [10]: train.shape, test.shape
Out[10]: ((614, 13), (368, 12))
```

```
In [11]: | train['Loan_Status'].value_counts()
Out[11]: Y
               422
               192
         Name: Loan_Status, dtype: int64
In [12]: # Normalize can be set to True to print proportions instead of number
          train['Loan_Status'].value_counts(normalize=True)
Out[12]: Y
               0.687296
               0.312704
         Name: Loan_Status, dtype: float64
In [13]:
         train['Loan_Status'].value_counts().plot.bar()
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0xcf30150>
          400
          350
          300
          250
          200
          150
          100
           50
            0
In [14]: train['Gender'].value_counts(normalize=True).plot.bar(figsize=(20,10), tit
         le= 'Gender')
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0xdfbfa10>
          0.8
          0.7
          0.6
          0.5
          0.4
          0.3
          0.1
                              Male
In [15]:
         train['Married'].value_counts(normalize=True).plot.bar(title= 'Married')
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0xe029c10>
```



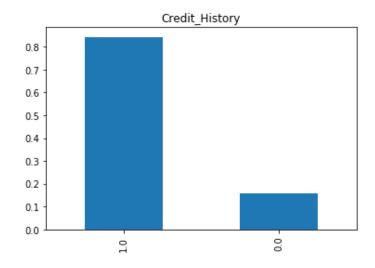
In [16]: train['Self_Employed'].value_counts(normalize=True).plot.bar(title= 'Self_
Employed')

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0xe46b810>

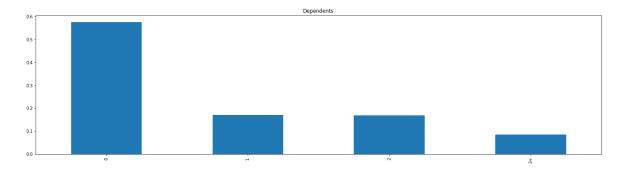


In [17]: train['Credit_History'].value_counts(normalize=True).plot.bar(title= 'Cred
it_History')

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0xe05eff0>

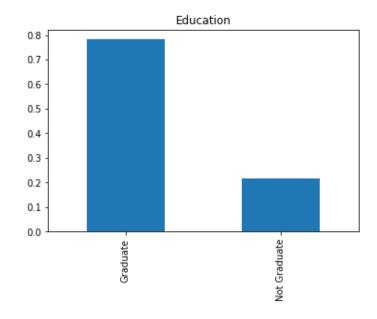


Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0xe0a7a30>



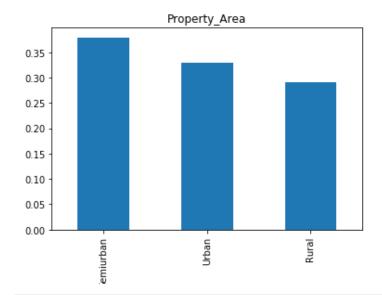
In [19]: train['Education'].value_counts(normalize=True).plot.bar(title= 'Educatio
n')

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0xe0e1cf0>

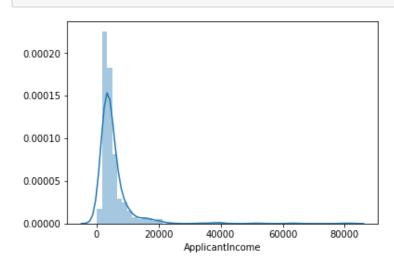


In [20]: train['Property_Area'].value_counts(normalize=True).plot.bar(title= 'Prope
 rty_Area')

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0xe401750>

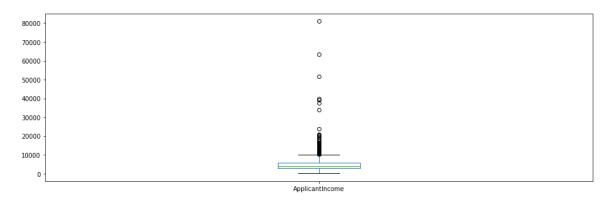


In [21]: sns.distplot(train['ApplicantIncome']);



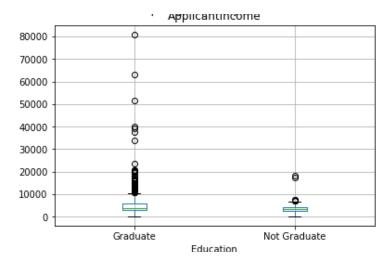
In [22]: train['ApplicantIncome'].plot.box(figsize=(16,5))

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0xe1a6370>

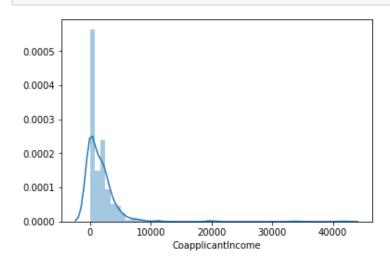


```
In [23]: train.boxplot(column='ApplicantIncome', by = 'Education')
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0xe1e1fb0>

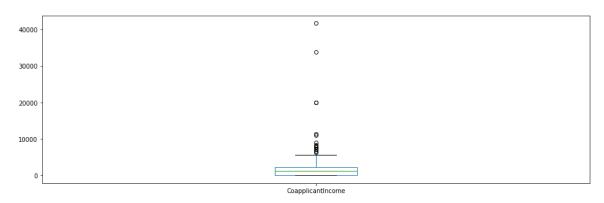


In [24]: sns.distplot(train['CoapplicantIncome']);

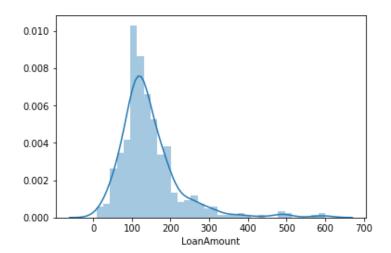


In [25]: train['CoapplicantIncome'].plot.box(figsize=(16,5))

Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0xe155810>

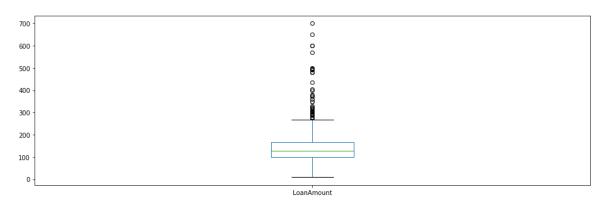


```
In [26]: df=train.dropna()
sns.distplot(df['LoanAmount']);
```



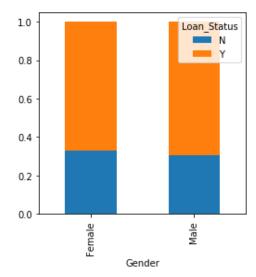
In [27]: train['LoanAmount'].plot.box(figsize=(16,5))

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0xea5ad10>



In [28]: Gender=pd.crosstab(train['Gender'], train['Loan_Status'])
 Gender.div(Gender.sum(1).astype(float), axis=0).plot(kind="bar", stacked=T
 rue, figsize=(4,4))

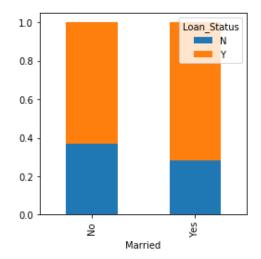
Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0xe184ab0>



In [29]: Married=pd.crosstab(train['Married'],train['Loan_Status'])
 Married.div(Married.sum(1).astype(float), axis=0).plot(kind="bar", stacked
 =True, figsize=(4,4))

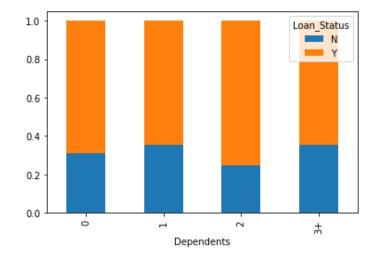
Out[20]: smathlatlik avan subblata Avancubalat at Ovabodboo

vuc[29]. <macptotttp.axes._supptots.axesSupptot at vxeb2tb5v>

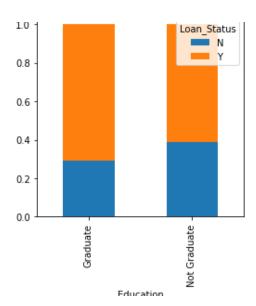


In [30]: Dependents=pd.crosstab(train['Dependents'], train['Loan_Status'])
 Dependents.div(Dependents.sum(1).astype(float), axis=0).plot(kind="bar", s
 tacked=True)

Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0xeb5f930>

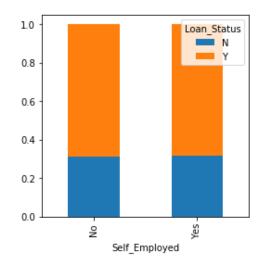


Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0xebae2d0>



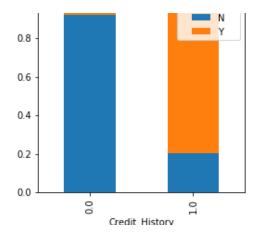
In [32]: Self_Employed=pd.crosstab(train['Self_Employed'], train['Loan_Status'])
 Self_Employed.div(Self_Employed.sum(1).astype(float), axis=0).plot(kind="b
 ar", stacked=True, figsize=(4,4))

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0xebe9430>



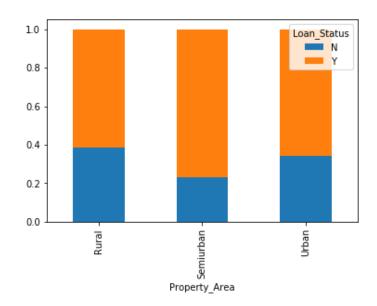
In [33]: Credit_History=pd.crosstab(train['Credit_History'], train['Loan_Status'])
 Credit_History.div(Credit_History.sum(1).astype(float), axis=0).plot(kind=
"bar", stacked=True, figsize=(4,4))

Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0xec43290>



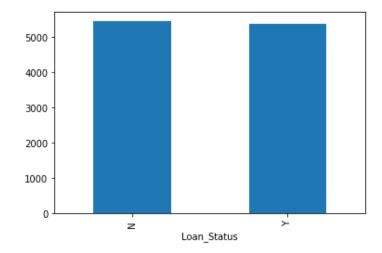
In [34]: Property_Area=pd.crosstab(train['Property_Area'], train['Loan_Status'])
 Property_Area.div(Property_Area.sum(1).astype(float), axis=0).plot(kind="b
 ar", stacked=True)

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0xedbc750>



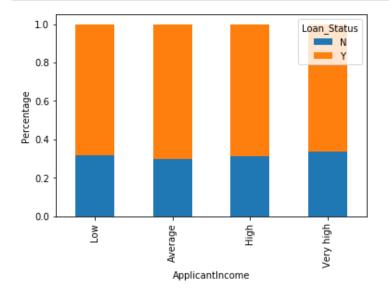
In [35]: train.groupby('Loan_Status')['ApplicantIncome'].mean().plot.bar()

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0xedf7e90>

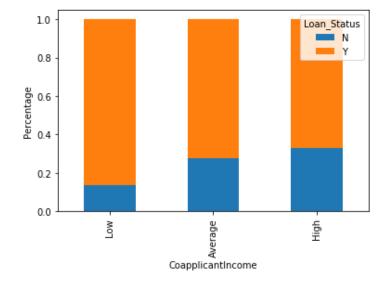


```
In [36]: bins=[0,2500,4000,6000,81000]
group=['Low','Average','High', 'Very high']
```

In [37]: Income_bin=pd.crosstab(train['Income_bin'], train['Loan_Status'])
 Income_bin.div(Income_bin.sum(1).astype(float), axis=0).plot(kind="bar", s
 tacked=True)
 plt.xlabel('ApplicantIncome')
 P = plt.ylabel('Percentage')

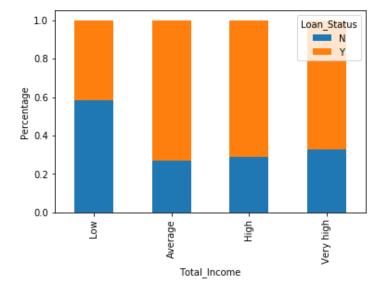


In [38]: bins=[0,1000,3000,42000]
 group=['Low','Average','High']
 train['Coapplicant_Income_bin']=pd.cut(train['CoapplicantIncome'],bins,lab
 els=group)
 Coapplicant_Income_bin=pd.crosstab(train['Coapplicant_Income_bin'],train[
 'Loan_Status'])
 Coapplicant_Income_bin.div(Coapplicant_Income_bin.sum(1).astype(float), ax
 is=0).plot(kind="bar", stacked=True)
 plt.xlabel('CoapplicantIncome')
 P = plt.ylabel('Percentage')

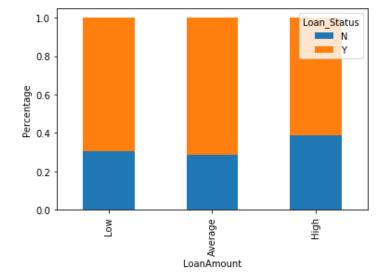


```
In [39]: train['Total_Income']=train['ApplicantIncome']+train['CoapplicantIncome']
bins=[0,2500,4000,6000,81000]
group=['Low','Average','High', 'Very high']
train['Total_Income_bin']=pd.cut(train['Total_Income'],bins,labels=group)
Total_Income_bin=pd.crosstab(train['Total_Income_bin'],train['Loan_Status']
```

```
])
Total_Income_bin.div(Total_Income_bin.sum(1).astype(float), axis=0).plot(k
ind="bar", stacked=True)
plt.xlabel('Total_Income')
P = plt.ylabel('Percentage')
```

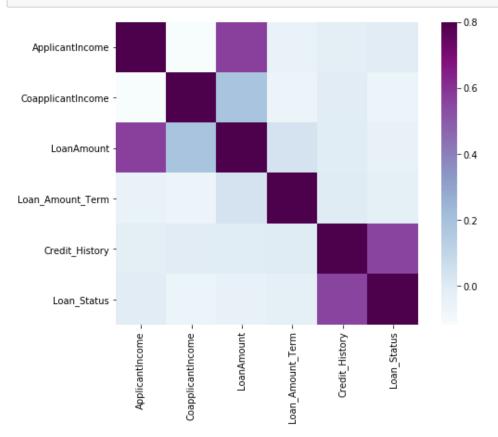


In [40]: bins=[0,100,200,700]
 group=['Low','Average','High']
 train['LoanAmount_bin']=pd.cut(train['LoanAmount'],bins,labels=group)
 LoanAmount_bin=pd.crosstab(train['LoanAmount_bin'],train['Loan_Status'])
 LoanAmount_bin.div(LoanAmount_bin.sum(1).astype(float), axis=0).plot(kind= "bar", stacked=True)
 plt.xlabel('LoanAmount')
 P = plt.ylabel('Percentage')



```
In [42]: matrix = train.corr()
f, ax = plt.subplots(figsize=(9, 6))
```

sns.heatmap(matrix, vmax=.8, square=True, cmap="BuPu");



In [43]: train.isnull().sum()

```
Out[43]: Loan_ID
                                0
         Gender
                                13
         Married
                                 3
                                15
         Dependents
         Education
                                0
                                32
         Self_Employed
         ApplicantIncome
                                0
         CoapplicantIncome
                                0
         LoanAmount
                                22
                                14
         Loan_Amount_Term
         Credit_History
                                50
                                0
         Property_Area
                                 0
         Loan_Status
         dtype: int64
```

In [44]: train['Gender'].fillna(train['Gender'].mode()[0], inplace=True)
 train['Married'].fillna(train['Married'].mode()[0], inplace=True)
 train['Dependents'].fillna(train['Dependents'].mode()[0], inplace=True)
 train['Self_Employed'].fillna(train['Self_Employed'].mode()[0], inplace=True)
 train['Credit_History'].fillna(train['Credit_History'].mode()[0], inplace=True)

```
In [45]: train['Loan_Amount_Term'].value_counts()
```

```
Out[45]: 360.0 512
180.0 44
480.0 15
300.0 13
84.0 4
```

```
240.0
         120.0
                     3
                     2
         36.0
         60.0
                     2
         12.0
                     1
         Name: Loan_Amount_Term, dtype: int64
In [46]: train['Loan_Amount_Term'].fillna(train['Loan_Amount_Term'].mode()[0], inpl
         ace=True)
In [47]:
         train['LoanAmount'].fillna(train['LoanAmount'].median(), inplace=True)
In [48]:
         train.isnull().sum()
Out[48]: Loan_ID
                               0
         Gender
                               0
         Married
                               0
         Dependents
                               0
         Education
                               0
         Self_Employed
                               0
         ApplicantIncome
                               0
         CoapplicantIncome
                               0
         LoanAmount
                               0
         Loan_Amount_Term
                               0
         Credit_History
                               0
         Property_Area
                               0
         Loan_Status
                               0
         dtype: int64
In [49]:
         test['Gender'].fillna(train['Gender'].mode()[0], inplace=True)
         test['Dependents'].fillna(train['Dependents'].mode()[0], inplace=True)
         test['Self_Employed'].fillna(train['Self_Employed'].mode()[0], inplace=Tru
         e)
         test['Credit_History'].fillna(train['Credit_History'].mode()[0], inplace=T
         rue)
         test['Loan_Amount_Term'].fillna(train['Loan_Amount_Term'].mode()[0], inpla
         ce=True)
         test['LoanAmount'].fillna(train['LoanAmount'].median(), inplace=True)
In [50]: | test.isnull().sum()
Out[50]: Loan_ID
                               0
         Gender
                               0
         Married
                               0
         Dependents
                               0
         Education
                               0
         Self_Employed
                               0
         ApplicantIncome
                               0
         CoapplicantIncome
                               0
         LoanAmount
                               0
         Loan_Amount_Term
                               0
         Credit_History
                               0
         Property_Area
                               0
         dtype: int64
In [51]:
         train['LoanAmount_log'] = np.log(train['LoanAmount'])
         train['LoanAmount_log'].hist(bins=20)
         test['LoanAmount_log'] = np.log(test['LoanAmount'])
```

4

```
140
120
100
80
60
40
20
0
2 3 4 5 6
```

```
In [52]: train=train.drop('Loan_ID', axis=1)
         test=test.drop('Loan_ID', axis=1)
In [53]: X = train.drop('Loan_Status',1)
         y = train.Loan_Status
In [54]: X=pd.get_dummies(X)
         train=pd.get_dummies(train)
         test=pd.get_dummies(test)
In [55]: from sklearn.model_selection import train_test_split
         x_train, x_cv, y_train, y_cv = train_test_split(X,y, test_size =0.3)
In [56]: from sklearn.linear_model import LogisticRegression
         from sklearn.metrics import accuracy_score
         model = LogisticRegression()
         model.fit(x_train, y_train)
Out[56]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=Tru
         e,
                   intercept_scaling=1, max_iter=100, multi_class='warn',
                   n_jobs=None, penalty='12', random_state=None, solver='warn',
                   tol=0.0001, verbose=0, warm_start=False)
In [57]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=Tru
         e,
                            intercept_scaling=1, max_iter=100, multi_class='ovr', n
         _jobs=1,
                            penalty='12', random_state=1, solver='liblinear', tol=
         0.0001,
                            verbose=0, warm_start=False)
Out[57]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=Tru
                   intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                   penalty='12', random_state=1, solver='liblinear', tol=0.0001,
```

verbose=0, warm_start=False)

ion set and calculate its accuracy.

ions are by calculating the accuracy.

In [58]: pred_cv = model.predict(x_cv) #Let's predict the Loan_Status for validat

#Let us calculate how accurate our predict

Out[50]. W 2801801801803

In [59]: accuracy_score(y_cv,pred_cv)

```
OUC[OO]: 0'LOSTOSTOSTOSTOSC
         pred_test = model.predict(test) #Let's make predictions for the test datas
In [60]:
         et.
         submission=pd.read_csv("C:/Users/Admin/Desktop/ML/Sample_Submission_ZAuT18
In [61]:
         0_FK3zQHh.csv")
In [62]: submission['Loan_Status']=pred_test
         submission['Loan_ID']=test_original['Loan_ID']
In [63]: submission['Loan_Status'].replace(0, 'N',inplace=True)
         submission['Loan_Status'].replace(1, 'Y',inplace=True)
         pd.DataFrame(submission, columns=['Loan_ID', 'Loan_Status']).to_csv('logist
In [64]:
         ic.csv')
         logistic= pd.read_csv("logistic.csv")
         logistic.columns
Out[64]: Index(['Unnamed: 0', 'Loan_ID', 'Loan_Status'], dtype='object')
In [65]: print(logistic)
              Unnamed: 0
                          Loan_ID Loan_Status
         0
                       0 LP001015
                                             Ν
                                             Υ
         1
                       1 LP001015
         2
                       2 LP001022
                                             Υ
         3
                       3 LP001031
                                             Υ
         4
                       4 LP001035
                                             Υ
         5
                       5 LP001051
                                             Υ
         6
                       6 LP001054
                                             Υ
         7
                       7 LP001055
                                             Υ
         8
                       8 LP001056
                                             Ν
         9
                       9 LP001059
                                             Υ
         10
                                             Υ
                      10 LP001067
         11
                      11 LP001078
                                             Υ
                      12 LP001082
                                             Υ
         12
         13
                      13 LP001083
                                             Υ
                      14 LP001094
         14
                                             Ν
         15
                      15 LP001096
                                             Υ
                                             Υ
         16
                      16 LP001099
                                             Υ
         17
                      17 LP001105
         18
                      18 LP001107
                                             Υ
                      19 LP001108
                                             Υ
         19
         20
                      20 LP001115
                                             Υ
         21
                      21 LP001121
                                             Υ
         22
                      22 LP001124
                                             Υ
                      23 LP001128
                                             Υ
         23
         24
                      24 LP001135
                                             Υ
         25
                                             Υ
                      25 LP001149
                      26 LP001153
         26
                                             N
                      27 LP001163
         27
                                             Υ
         28
                      28 LP001169
                                             Υ
         29
                      29 LP001174
                                             Υ
                     338 LP002856
         338
                                             Υ
         339
                     339 LP002857
                                             Υ
                     340 LP002858
         340
                                             N
         341
                     341 LP002860
                                             Υ
         342
                     342 LP002867
                                             Υ
```

```
344
                     344 LP002870
                                              Υ
                     345 LP002876
                                              Υ
         345
         346
                     346 LP002878
                                              Υ
         347
                     347 LP002879
                                              Ν
         348
                     348 LP002885
                                              Υ
         349
                     349 LP002890
                                              Υ
         350
                     350 LP002891
                                              Υ
                                              Υ
         351
                     351 LP002899
         352
                     352 LP002901
                                              Υ
                     353 LP002907
         353
                                              Υ
         354
                     354 LP002920
                                              Υ
         355
                     355 LP002921
                                              N
         356
                     356 LP002932
                                              Υ
         357
                     357 LP002935
                                              Υ
                     358 LP002952
                                              Υ
         358
         359
                     359 LP002954
                                              Υ
                                              Υ
         360
                     360 LP002962
         361
                     361 LP002965
                                              Υ
         362
                     362 LP002969
                                              Υ
         363
                     363 LP002971
                                              Υ
                                              Υ
         364
                     364 LP002975
                                              Υ
         365
                     365 LP002980
                     366 LP002986
         366
                                              Υ
         367
                     367 LP002989
         [368 rows x 3 columns]
In [66]:
         from sklearn.model_selection import StratifiedKFold
In [67]:
         i=1
         kf = StratifiedKFold(n_splits=5, random_state=1, shuffle=True)
         for train_index, test_index in kf.split(X,y):
             print('\n{} of kfold {}'.format(i,kf.n_splits))
             xtr,xvl = X.loc[train_index],X.loc[test_index]
             ytr,yvl = y[train_index],y[test_index]
             model = LogisticRegression(random_state=1)
             model.fit(xtr, ytr)
             pred_test = model.predict(xvl)
             score = accuracy_score(yv1, pred_test)
             print('accuracy_score', score)
             i+=1
             pred_test = model.predict(test)
             pred=model.predict_proba(xvl)[:,1]
         1 of kfold 5
         accuracy_score 0.7983870967741935
         2 of kfold 5
         accuracy_score 0.8306451612903226
         3 of kfold 5
         accuracy_score 0.8114754098360656
         4 of kfold 5
         accuracy_score 0.7950819672131147
         5 of kfold 5
         accuracy_score 0.8278688524590164
In [68]: | train['Total_Income']=train['ApplicantIncome']+train['CoapplicantIncome']
```

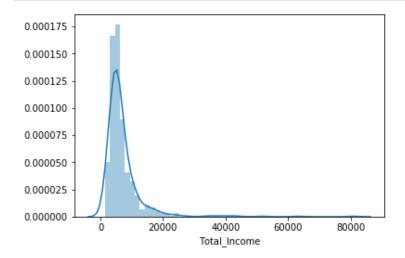
Υ

343

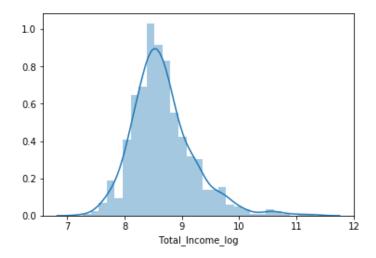
343 LP002869

```
test['Total_Income']=test['ApplicantIncome']+test['CoapplicantIncome']
```

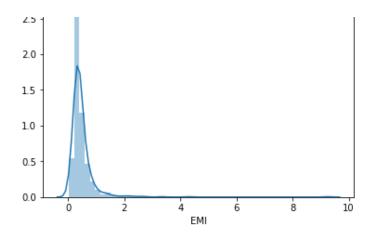
```
In [69]: sns.distplot(train['Total_Income']);
```

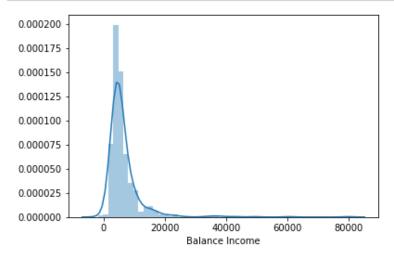


```
In [70]: train['Total_Income_log'] = np.log(train['Total_Income'])
  test['Total_Income_log'] = np.log(test['Total_Income'])
  sns.distplot(train['Total_Income_log']);
```



```
In [71]: train['EMI']=train['LoanAmount']/train['Loan_Amount_Term']
    test['EMI']=test['LoanAmount']/test['Loan_Amount_Term']
    sns.distplot(train['EMI']);
```





```
In [74]: X = train.drop('Loan_Status',1)
y = train.Loan_Status  # Save target variable in separate da
taset
```

```
In [75]:
    i=1
    kf = StratifiedKFold(n_splits=5, random_state=1, shuffle=True)
    for train_index, test_index in kf.split(X,y):
        print('\n{} of kfold {}'.format(i,kf.n_splits))
        xtr,xvl = X.loc[train_index],X.loc[test_index]
        ytr,yvl = y[train_index],y[test_index]

        model = LogisticRegression(random_state=1)
        model.fit(xtr, ytr)
        pred_test = model.predict(xvl)
        score = accuracy_score(yvl,pred_test)
        print('accuracy_score',score)
        i+=1
        pred_test = model.predict(test)
        pred=model.predict_proba(xvl)[:,1]
```

```
1 of kfold 5
         accuracy_score 0.8064516129032258
         2 of kfold 5
         accuracy_score 0.8306451612903226
         3 of kfold 5
         accuracy_score 0.7786885245901639
         4 of kfold 5
         accuracy_score 0.7868852459016393
         5 of kfold 5
         accuracy_score 0.819672131147541
In [76]: submission['Loan_Status']=pred_test # filling Loan_Status with predictions
         submission['Loan_ID']=test_original['Loan_ID'] # filling Loan_ID with test
         Loan ID
         # replacing 0 and 1 with N and Y
         submission['Loan_Status'].replace(0, 'N',inplace=True)
         submission['Loan_Status'].replace(1, 'Y',inplace=True)
         # Converting submission file to .csv format
         pd.DataFrame(submission, columns=['Loan_ID', 'Loan_Status']).to_csv('Log2.c
         sv')
In [77]: from sklearn import tree
In [78]: i=1
         kf = StratifiedKFold(n_splits=5, random_state=1, shuffle=True)
         for train_index, test_index in kf.split(X,y):
             print('\n{} of kfold {}'.format(i,kf.n_splits))
             xtr,xvl = X.loc[train_index],X.loc[test_index]
             ytr,yvl = y[train_index],y[test_index]
             model = tree.DecisionTreeClassifier(random_state=1)
             model.fit(xtr, ytr)
             pred_test = model.predict(xvl)
             score = accuracy_score(yvl,pred_test)
             print('accuracy_score', score)
             pred_test = model.predict(test)
         1 of kfold 5
         accuracy_score 0.7258064516129032
         2 of kfold 5
         accuracy_score 0.7419354838709677
         3 of kfold 5
         accuracy_score 0.7049180327868853
         4 of kfold 5
         accuracy_score 0.680327868852459
         5 of kfold 5
         accuracy_score 0.7049180327868853
In [79]: | submission['Loan_Status']=pred_test
                                                       # filling Loan_Status with
          predictions
         submission['Loan_ID']=test_original['Loan_ID'] # filling Loan_ID with test
         Loan_ID
```

```
# replacing 0 and 1 with N and Y
         submission['Loan_Status'].replace(0, 'N',inplace=True)
         submission['Loan_Status'].replace(1, 'Y',inplace=True)
         # Converting submission file to .csv format
         pd.DataFrame(submission, columns=['Loan_ID', 'Loan_Status']).to_csv('Decisi
         on Tree.csv')
In [80]: from sklearn.ensemble import RandomForestClassifier
In [81]: i=1
         kf = StratifiedKFold(n_splits=5, random_state=1, shuffle=True)
         for train_index, test_index in kf.split(X,y):
             print('\n{} of kfold {}'.format(i,kf.n_splits))
             xtr,xvl = X.loc[train_index],X.loc[test_index]
             ytr,yvl = y[train_index],y[test_index]
             model = RandomForestClassifier(random_state=1, max_depth=10)
             model.fit(xtr, ytr)
             pred_test = model.predict(xvl)
             score = accuracy_score(yvl,pred_test)
             print('accuracy_score', score)
             i+=1
             pred_test = model.predict(test)
         1 of kfold 5
         accuracy_score 0.8225806451612904
         2 of kfold 5
         accuracy_score 0.8145161290322581
         3 of kfold 5
         accuracy_score 0.7377049180327869
         4 of kfold 5
         accuracy_score 0.7295081967213115
         5 of kfold 5
         accuracy_score 0.8114754098360656
         importances=pd.Series(model.feature_importances_, index=X.columns)
In [82]:
         importances.plot(kind='barh', figsize=(12,8))
Out[82]: <matplotlib.axes._subplots.AxesSubplot at 0x536f6b0>
```

Balance Income -

