```
In []:
         import numpy as np
         import pandas as pd
         import seaborn as sns
         import matplotlib.pyplot as plt
         %matplotlib inline
In [ ]: train_data = pd.read_csv("../data/train_u6lujuX_CVtuZ9i.csv")
         train data.head()
Out[]:
             Loan ID Gender Married
                                      Dependents
                                                   Education Self_Employed Applicant_Income
         0 LP001002
                                                                                       5849
                                                0
                                                    Graduate
                        Male
                                   No
                                                                        No
          1 LP001003
                                                1
                                                    Graduate
                                                                                       4583
                        Male
                                  Yes
                                                                        No
           LP001005
                        Male
                                  Yes
                                                0
                                                    Graduate
                                                                       Yes
                                                                                       3000
                                                         Not
           LP001006
                        Male
                                                0
                                                                                        2583
                                  Yes
                                                                        No
                                                    Graduate
           LP001008
                        Male
                                   No
                                                0
                                                    Graduate
                                                                        No
                                                                                       6000
         print(train_data.shape)
In [ ]:
         (614, 13)
         train_data.describe()
Out[]:
                Applicant_Income
                                 Coapplicant_Income
                                                     Loan_Amount Loan_Amount_Term
                                                                                      Credit
                      614.000000
                                         614.000000
                                                       592.000000
                                                                           600.00000
         count
                                                                                         564
         mean
                    5403.459283
                                         1621.245798
                                                        146.412162
                                                                           342.00000
           std
                     6109.041673
                                        2926.248369
                                                        85.587325
                                                                             65.12041
                      150.000000
                                           0.000000
                                                         9.000000
                                                                             12.00000
           min
                                                       100.000000
                                                                           360.00000
          25%
                     2877.500000
                                           0.000000
          50%
                     3812.500000
                                        1188.500000
                                                       128.000000
                                                                           360.00000
          75%
                    5795.000000
                                                       168.000000
                                                                           360.00000
                                        2297.250000
           max
                    81000.000000
                                       41667.000000
                                                       700.000000
                                                                           480.00000
In []:
         # variable types
         train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
        RangeIndex: 614 entries, 0 to 613
        Data columns (total 13 columns):
         #
             Column
                                 Non-Null Count Dtype
             Loan_ID
                                 614 non-null
         0
                                                 object
         1
             Gender
                                 601 non-null
                                                 object
         2
             Married
                                 611 non-null
                                                 object
                                 599 non-null
         3
             Dependents
                                                 object
                                 614 non-null
         4
             Education
                                                 object
         5
                                582 non-null
             Self_Employed
                                                 object
             Applicant_Income 614 non-null
Coapplicant_Income 614 non-null
Loan Amount 592 non-null
         6
                                                 int64
         7
                                                 float64
         8
                                                 float64
         9
             Loan_Amount_Term
                                 600 non-null float64
         10 Credit_History
                                 564 non-null float64
         11 Property_Area
                                 614 non-null
                                                 object
         12 Loan_Status
                                 614 non-null
                                                 object
        dtypes: float64(4), int64(1), object(8)
        memory usage: 62.5+ KB
In [ ]: # count missing values per col
        def missing values(df):
            a = num_null_values = df.isnull().sum()
            return a
In []: missing_values(train_data)
Out[]: Loan_ID
                               0
        Gender
                              13
                               3
        Married
                              15
        Dependents
        Education
                               0
        Self_Employed
                              32
                               0
        Applicant_Income
        Coapplicant_Income
                               0
        Loan Amount
                              22
        Loan_Amount_Term
                              14
        Credit_History
                              50
        Property_Area
                               0
        Loan_Status
        dtype: int64
In [ ]: # drop cols, mutate df in place
        # Dependents col includes 3+ value, which makes processing complicated -
```

train\_data.drop(["Loan\_ID","Dependents"], axis=1, inplace=True)

In [ ]: train\_data

:[]:		Gender	Married	Education	Self_Employed	Applicant_Income	Coapplicant_Income
	0	Male	No	Graduate	No	5849	0.0
	1	Male	Yes	Graduate	No	4583	1508.C
	2	Male	Yes	Graduate	Yes	3000	0.0
	3	Male	Yes	Not Graduate	No	2583	2358.0
	4	Male	No	Graduate	No	6000	0.0
	•••	•••					
6	609	Female	No	Graduate	No	2900	0.0
(	610	Male	Yes	Graduate	No	4106	0.0
	611	Male	Yes	Graduate	No	8072	240.0
(	612	Male	Yes	Graduate	No	7583	0.0
•	613	Female	No	Graduate	Yes	4583	0.0
6′	14 ro	ws × 11 (	columns				

```
In [ ]: ### Dealing with null values [ categorical ] ###
        cols = train_data[["Gender", "Married", "Self_Employed"]]
        for i in cols:
            # fill missing values with mode of column, e.g. replace missing gende
            train_data[i].fillna(train_data[i].mode().iloc[0], inplace=True)
In [ ]: # no more missing values for categorical features
        train data.isnull().sum()
Out[]: Gender
                               0
        Married
                               0
        Education
        Self Employed
                               0
        Applicant_Income
                               0
        Coapplicant_Income
                               0
        Loan_Amount
                              22
        Loan_Amount_Term
                              14
                              50
        Credit History
        Property_Area
                               0
        Loan_Status
                               0
        dtype: int64
In [ ]: ## Dealing with Numerical Values missing_data ##
        n_cols = train_data[["Loan_Amount", "Loan_Amount_Term", "Credit_History"]
        for i in n cols:
            # fill missing numerical values with mean of feature
            train_data[i].fillna(train_data[i].mean(axis=0), inplace=True)
In [ ]: ### Visualization ###
        def bar_chart(col):
```

Approved = train\_data[train\_data["Loan\_Status"] == "Y"] [col].value\_coun Disapproved = train\_data[train\_data["Loan\_Status"] == "N"] [col].value\_c

print(Approved)

```
print(Disapproved)

df1 = pd.DataFrame([Approved, Disapproved])

df1.index = ["Approved", "Disapproved"]

df1.plot(kind="bar")
```

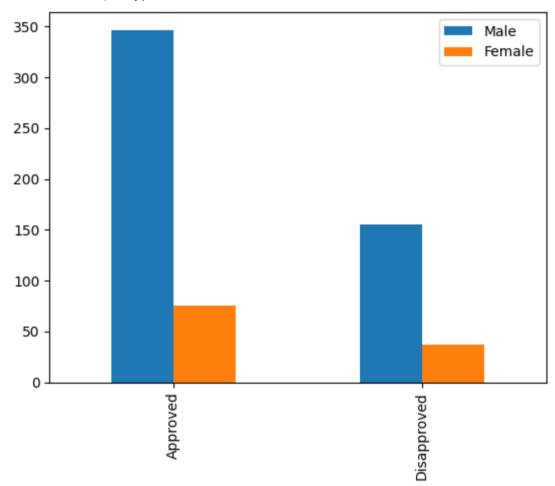
## In [ ]: bar\_chart("Gender")

Male 347 Female 75

Name: Gender, dtype: int64

Male 155 Female 37

Name: Gender, dtype: int64



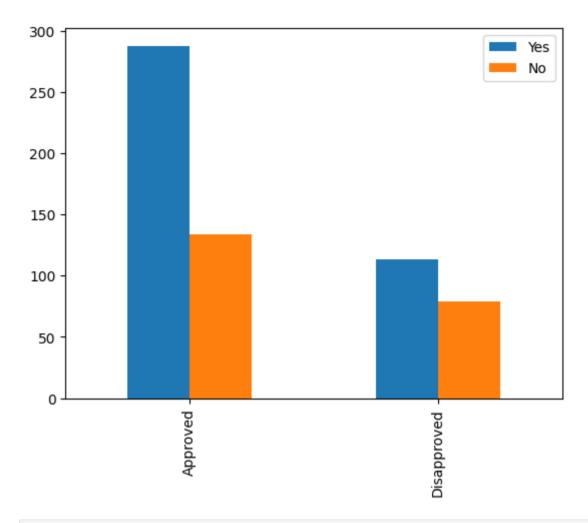
## In [ ]: bar\_chart("Married")

Yes 288 No 134

Name: Married, dtype: int64

Yes 113 No 79

Name: Married, dtype: int64



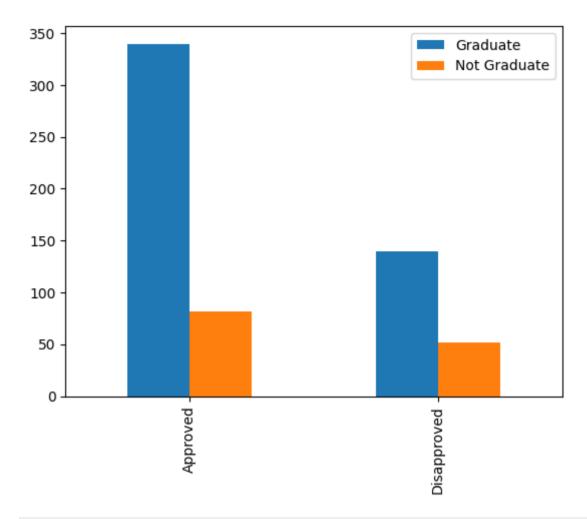
## In [ ]: bar\_chart("Education")

Graduate 340 Not Graduate 82

Name: Education, dtype: int64

Graduate 140 Not Graduate 52

Name: Education, dtype: int64



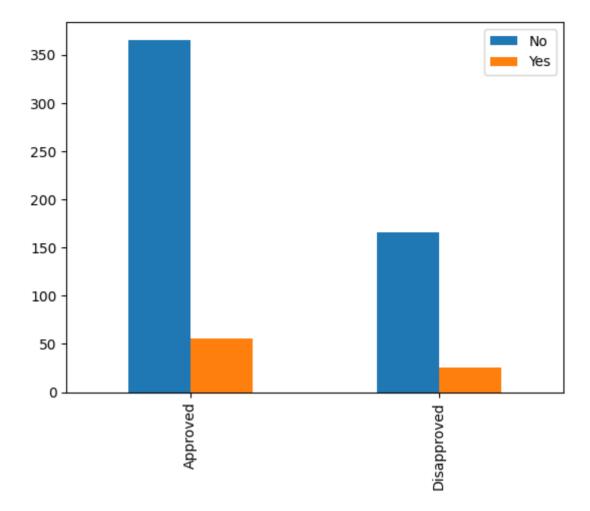
## In [ ]: bar\_chart("Self\_Employed")

No 366 Yes 56

Name: Self\_Employed, dtype: int64

No 166 Yes 26

Name: Self\_Employed, dtype: int64



In []: from sklearn.preprocessing import OrdinalEncoder

ord\_enc = OrdinalEncoder()
# encode categories into numbers so machine can understand
train\_data[["Gender", 'Married', 'Education', 'Self\_Employed', 'Property\_Area
train\_data.head()

Out[]:		Gender	Married	Education	Self_Employed	Applicant_Income	Coapplicant_Income
	0	1.0	0.0	0.0	0.0	5849	0.0
	1	1.0	1.0	0.0	0.0	4583	1508.0
	2	1.0	1.0	0.0	1.0	3000	0.0
	3	1.0	1.0	1.0	0.0	2583	2358.0
	4	1.0	0.0	0.0	0.0	6000	0.0

In [ ]: train\_data[["Gender",'Married','Education','Self\_Employed','Property\_Area

In [ ]: train\_data

Out[]:		Gender	Married	Education	Self_Employed	Applicant_Income	Coapplicant_Income
	0	1	0	0	0	5849	0.0
	1	1	1	0	0	4583	1508.C
	2	1	1	0	1	3000	0.0
	3	1	1	1	0	2583	2358.0
	4	1	0	0	0	6000	0.0
	•••	•••	•••				
	609	0	0	0	0	2900	0.0
	610	1	1	0	0	4106	0.0
	611	1	1	0	0	8072	240.0
	612	1	1	0	0	7583	0.0
	613	0	0	0	1	4583	0.0

614 rows × 11 columns

```
In [ ]: from sklearn.model_selection import train_test_split
        # remove target variable from feature set
        X = train_data.drop("Loan_Status", axis=1)
        # store target variable in y
        y = train data["Loan Status"]
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
        print(X_train.shape)
        print(y_train.shape)
        print(X test.shape)
        print(y_test.shape)
        (491, 10)
        (491,)
        (123, 10)
        (123,)
In [ ]: from sklearn.naive_bayes import GaussianNB
        # data follows normal distribution
        qfc = GaussianNB()
        # learn what kind of features result in which kind of loan statuses
        gfc.fit(X_train, y_train)
        # run against X_test
        pred1 = gfc.predict(X_test)
In [ ]: from sklearn.metrics import precision_score, recall_score, accuracy_score
        # why use precision and recall? when dataset is imbalanced
        def loss(y_true, y_pred):
            # how many correct TP / TP+FP
            pre = precision_score(y_true, y_pred)
            # how many correct TP / TP+FN
            rec = recall_score(y_true, y_pred)
            acc = accuracy_score(y_true, y_pred)
```

```
print('precision', pre)
            print('recall', rec)
            print('accuracy', acc)
In [ ]: loss(y_test, pred1)
        precision 0.792079207921
        recall 0.9523809523809523
        accuracy 0.7967479674796748
In [ ]: from sklearn.svm import SVC
        from sklearn.model_selection import GridSearchCV
        # defining parameter range
        param_grid = {
          'C': [0.1, 1, 10, 100, 1000],
          'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
          'kernel': ['rbf']
        }
        grid = GridSearchCV(SVC(), param_grid, refit=True, verbose=3)
        grid.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 25 candidates, totalling 125 fits
[CV 1/5] END ......C=0.1, gamma=1, kernel=rbf;, score=0.687 total time
   0.0s
[CV 2/5] END ......C=0.1, gamma=1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END ......C=0.1, gamma=1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END ......C=0.1, gamma=1, kernel=rbf;, score=0.694 total time
   0.0s
[CV 5/5] END ......C=0.1, gamma=1, kernel=rbf;, score=0.694 total time
   0.0s
[CV 1/5] END .....C=0.1, gamma=0.1, kernel=rbf;, score=0.687 total time
   0.0s
[CV 2/5] END ......C=0.1, gamma=0.1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END .....C=0.1, gamma=0.1, kernel=rbf;, score=0.684 total time
   0.05
[CV 4/5] END .....C=0.1, gamma=0.1, kernel=rbf;, score=0.694 total time
   0.0s
[CV 5/5] END .....C=0.1, gamma=0.1, kernel=rbf;, score=0.694 total time
   0.0s
[CV 1/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.687 total time
   0.0s
[CV 2/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.694 total time
   0.0s
[CV 5/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.694 total time
   0.0s
[CV 1/5] END ....C=0.1, gamma=0.001, kernel=rbf;, score=0.687 total time
   0.0s
[CV 2/5] END ....C=0.1, gamma=0.001, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END ....C=0.1, gamma=0.001, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END ....C=0.1, gamma=0.001, kernel=rbf;, score=0.694 total time
   0.0s
[CV 5/5] END ....C=0.1, gamma=0.001, kernel=rbf;, score=0.694 total time
   0.0s
[CV 1/5] END ...C=0.1, gamma=0.0001, kernel=rbf;, score=0.687 total time
   0.0s
[CV 2/5] END ...C=0.1, gamma=0.0001, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END ...C=0.1, gamma=0.0001, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END ...C=0.1, gamma=0.0001, kernel=rbf;, score=0.694 total time
    0.0s
[CV 5/5] END ...C=0.1, gamma=0.0001, kernel=rbf;, score=0.694 total time
   0.0s
[CV 1/5] END .....C=1, gamma=1, kernel=rbf;, score=0.687 total time
   0.0s
[CV 2/5] END ......C=1, gamma=1, kernel=rbf;, score=0.684 total time
[CV 3/5] END ......C=1, gamma=1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END ......C=1, gamma=1, kernel=rbf;, score=0.694 total time
[CV 5/5] END ......C=1, gamma=1, kernel=rbf;, score=0.694 total time
```

```
0.0s
[CV 1/5] END ......C=1, gamma=0.1, kernel=rbf;, score=0.697 total time
   0.0s
[CV 2/5] END ......C=1, gamma=0.1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END ......C=1, gamma=0.1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END ......C=1, gamma=0.1, kernel=rbf;, score=0.694 total time
   0.0s
[CV 5/5] END ......C=1, gamma=0.1, kernel=rbf;, score=0.704 total time
   0.0s
[CV 1/5] END ......C=1, gamma=0.01, kernel=rbf;, score=0.697 total time
   0.0s
[CV 2/5] END ......C=1, gamma=0.01, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END ......C=1, gamma=0.01, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END ......C=1, gamma=0.01, kernel=rbf;, score=0.684 total time
   0.0s
[CV 5/5] END ......C=1, gamma=0.01, kernel=rbf;, score=0.704 total time
   0.0s
[CV 1/5] END .....C=1, gamma=0.001, kernel=rbf;, score=0.687 total time
   0.0s
[CV 2/5] END .....C=1, gamma=0.001, kernel=rbf;, score=0.673 total time
   0.0s
[CV 3/5] END .....C=1, gamma=0.001, kernel=rbf;, score=0.704 total time
   0.0s
[CV 4/5] END .....C=1, gamma=0.001, kernel=rbf;, score=0.663 total time
   0.0s
[CV 5/5] END .....C=1, gamma=0.001, kernel=rbf;, score=0.714 total time
   0.0s
[CV 1/5] END .....C=1, gamma=0.0001, kernel=rbf;, score=0.646 total time
   0.0s
[CV 2/5] END .....C=1, gamma=0.0001, kernel=rbf;, score=0.653 total time
   0.0s
[CV 3/5] END .....C=1, gamma=0.0001, kernel=rbf;, score=0.633 total time
   0.0s
[CV 4/5] END .....C=1, gamma=0.0001, kernel=rbf;, score=0.663 total time
   0.0s
[CV 5/5] END .....C=1, gamma=0.0001, kernel=rbf;, score=0.673 total time
   0.0s
[CV 1/5] END .......C=10, gamma=1, kernel=rbf;, score=0.697 total time
   0.0s
[CV 2/5] END ......C=10, gamma=1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END ......C=10, gamma=1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END ......C=10, gamma=1, kernel=rbf;, score=0.694 total time
   0.0s
[CV 5/5] END .......C=10, gamma=1, kernel=rbf;, score=0.704 total time
   0.0s
[CV 1/5] END ......C=10, gamma=0.1, kernel=rbf;, score=0.697 total time
   0.0s
[CV 2/5] END ......C=10, gamma=0.1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END ......C=10, gamma=0.1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END ......C=10, gamma=0.1, kernel=rbf;, score=0.694 total time
[CV 5/5] END ......C=10, gamma=0.1, kernel=rbf;, score=0.704 total time
```

```
0.0s
[CV 1/5] END .....C=10, gamma=0.01, kernel=rbf;, score=0.697 total time
   0.0s
[CV 2/5] END .....C=10, gamma=0.01, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END .....C=10, gamma=0.01, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END .....C=10, gamma=0.01, kernel=rbf;, score=0.673 total time
   0.0s
[CV 5/5] END .....C=10, gamma=0.01, kernel=rbf;, score=0.704 total time
   0.0s
[CV 1/5] END .....C=10, gamma=0.001, kernel=rbf;, score=0.677 total time
   0.0s
[CV 2/5] END .....C=10, gamma=0.001, kernel=rbf;, score=0.653 total time
   0.0s
[CV 3/5] END .....C=10, gamma=0.001, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END .....C=10, gamma=0.001, kernel=rbf;, score=0.663 total time
   0.0s
[CV 5/5] END .....C=10, gamma=0.001, kernel=rbf;, score=0.714 total time
   0.0s
[CV 1/5] END ....C=10, qamma=0.0001, kernel=rbf;, score=0.616 total time
   0.0s
[CV 2/5] END ....C=10, gamma=0.0001, kernel=rbf;, score=0.622 total time
   0.0s
[CV 3/5] END ....C=10, gamma=0.0001, kernel=rbf;, score=0.622 total time
   0.0s
[CV 4/5] END ....C=10, gamma=0.0001, kernel=rbf;, score=0.622 total time
   0.0s
[CV 5/5] END ....C=10, gamma=0.0001, kernel=rbf;, score=0.663 total time
   0.0s
[CV 1/5] END ......C=100, gamma=1, kernel=rbf;, score=0.697 total time
   0.0s
[CV 2/5] END ......C=100, gamma=1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END ......C=100, gamma=1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END ......C=100, gamma=1, kernel=rbf;, score=0.694 total time
   0.0s
[CV 5/5] END ......C=100, gamma=1, kernel=rbf;, score=0.704 total time
   0.0s
[CV 1/5] END .....C=100, gamma=0.1, kernel=rbf;, score=0.697 total time
   0.0s
[CV 2/5] END ......C=100, gamma=0.1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END .....C=100, gamma=0.1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END .....C=100, gamma=0.1, kernel=rbf;, score=0.694 total time
   0.0s
[CV 5/5] END .....C=100, gamma=0.1, kernel=rbf;, score=0.704 total time
   0.0s
[CV 1/5] END .....C=100, gamma=0.01, kernel=rbf;, score=0.697 total time
   0.0s
[CV 2/5] END .....C=100, gamma=0.01, kernel=rbf;, score=0.684 total time
[CV 3/5] END .....C=100, gamma=0.01, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END .....C=100, gamma=0.01, kernel=rbf;, score=0.673 total time
[CV 5/5] END .....C=100, gamma=0.01, kernel=rbf;, score=0.704 total time
```

```
0.0s
[CV 1/5] END ....C=100, gamma=0.001, kernel=rbf;, score=0.677 total time
   0.05
[CV 2/5] END ....C=100, gamma=0.001, kernel=rbf;, score=0.653 total time
   0.0s
[CV 3/5] END ....C=100, gamma=0.001, kernel=rbf;, score=0.694 total time
   0.0s
[CV 4/5] END ....C=100, gamma=0.001, kernel=rbf;, score=0.673 total time
   0.0s
[CV 5/5] END ....C=100, gamma=0.001, kernel=rbf;, score=0.714 total time
   0.0s
[CV 1/5] END ...C=100, gamma=0.0001, kernel=rbf;, score=0.606 total time
   0.0s
[CV 2/5] END ...C=100, gamma=0.0001, kernel=rbf;, score=0.592 total time
   0.0s
[CV 3/5] END ...C=100, gamma=0.0001, kernel=rbf;, score=0.582 total time
   0.05
[CV 4/5] END ...C=100, gamma=0.0001, kernel=rbf;, score=0.622 total time
   0.0s
[CV 5/5] END ...C=100, gamma=0.0001, kernel=rbf;, score=0.673 total time
   0.0s
[CV 1/5] END ......C=1000, gamma=1, kernel=rbf;, score=0.697 total time
   0.0s
[CV 2/5] END ......C=1000, gamma=1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END ......C=1000, gamma=1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END ......C=1000, gamma=1, kernel=rbf;, score=0.694 total time
   0.0s
[CV 5/5] END ......C=1000, gamma=1, kernel=rbf;, score=0.704 total time
   0.0s
[CV 1/5] END .....C=1000, gamma=0.1, kernel=rbf;, score=0.697 total time
   0.0s
[CV 2/5] END .....C=1000, gamma=0.1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END .....C=1000, gamma=0.1, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END .....C=1000, gamma=0.1, kernel=rbf;, score=0.694 total time
   0.0s
[CV 5/5] END .....C=1000, gamma=0.1, kernel=rbf;, score=0.704 total time
   0.0s
[CV 1/5] END ....C=1000, gamma=0.01, kernel=rbf;, score=0.697 total time
   0.0s
[CV 2/5] END ....C=1000, gamma=0.01, kernel=rbf;, score=0.684 total time
   0.0s
[CV 3/5] END ....C=1000, gamma=0.01, kernel=rbf;, score=0.684 total time
   0.0s
[CV 4/5] END ....C=1000, gamma=0.01, kernel=rbf;, score=0.673 total time
   0.0s
[CV 5/5] END ....C=1000, gamma=0.01, kernel=rbf;, score=0.704 total time
   0.0s
[CV 1/5] END ...C=1000, gamma=0.001, kernel=rbf;, score=0.677 total time
   0.0s
[CV 2/5] END ...C=1000, gamma=0.001, kernel=rbf;, score=0.653 total time
[CV 3/5] END ...C=1000, gamma=0.001, kernel=rbf;, score=0.694 total time
   0.0s
[CV 4/5] END ...C=1000, gamma=0.001, kernel=rbf;, score=0.673 total time
[CV 5/5] END ...C=1000, gamma=0.001, kernel=rbf;, score=0.714 total time
```

```
0.0s
        [CV 1/5] END ..C=1000, gamma=0.0001, kernel=rbf;, score=0.606 total time
            0.0s
        [CV 2/5] END ..C=1000, gamma=0.0001, kernel=rbf;, score=0.582 total time
            0.0s
        [CV 3/5] END ..C=1000, gamma=0.0001, kernel=rbf;, score=0.592 total time
            0.0s
        [CV 4/5] END ..C=1000, gamma=0.0001, kernel=rbf;, score=0.622 total time
            0.0s
        [CV 5/5] END ..C=1000, gamma=0.0001, kernel=rbf;, score=0.673 total time
            0.0s
Out[]: | GridSearchCV
         ▶ estimator: SVC
               ▶ SVC
In [ ]: grid.best_params_
Out[]: {'C': 1, 'gamma': 0.1, 'kernel': 'rbf'}
In [ ]: svc = SVC(C= 0.1, gamma= 1, kernel= 'rbf')
        svc.fit(X_train, y_train)
        pred2 = svc.predict(X_test)
        loss(y test,pred2)
        precision 0.6829268292682927
        recall 1.0
        accuracy 0.6829268292682927
In [ ]: from xgboost import XGBClassifier
        xgb = XGBClassifier(learning rate=0.1,
         n estimators=1000,
         max_depth=3,
         min_child_weight=1,
         gamma=0,
         subsample=0.8,
         colsample bytree=0.8,
         objective= 'binary:logistic',
         nthread=4,
         scale_pos_weight=1,
         seed=27)
        xgb.fit(X_train, y_train)
        pred3 = xgb.predict(X_test)
        loss(y_test, pred3)
        precision 0.8152173913043478
        recall 0.8928571428571429
        accuracy 0.7886178861788617
       from sklearn.tree import DecisionTreeClassifier
        from sklearn.model selection import RandomizedSearchCV
        def randomized_search(params, runs=20, clf=DecisionTreeClassifier(random_
            rand_clf = RandomizedSearchCV(clf, params, n_iter=runs, cv=5, n_jobs=
            rand_clf.fit(X_train, y_train)
            best_model = rand_clf.best_estimator_
```

```
# Extract best score
            best_score = rand_clf.best_score_
            # Print best score
            print("Training score: {:.3f}".format(best_score))
            # Predict test set labels
            y_pred = best_model.predict(X_test)
            # Compute accuracy
            accuracy = accuracy_score(y_test, y_pred)
            # Print accuracy
            print('Test score: {:.3f}'.format(accuracy))
            return best_model
In [ ]: | randomized_search(params={'criterion':['entropy', 'gini'],
                                       'splitter':['random', 'best'],
                                   'min_weight_fraction_leaf':[0.0, 0.0025, 0.005,
                                   'min_samples_split':[2, 3, 4, 5, 6, 8, 10],
                                   'min_samples_leaf':[1, 0.01, 0.02, 0.03, 0.04],
                                   'min_impurity_decrease':[0.0, 0.0005, 0.005, 0.
                                   'max_leaf_nodes':[10, 15, 20, 25, 30, 35, 40, 4
                                   'max features':[0.95, 0.90, 0.85, 0.80, 0.75, 0
                                   'max_depth': [None, 2,4,6,8],
                                   'min weight fraction leaf': [0.0, 0.0025, 0.005,
                                  })
        Training score: 0.811
        Test score: 0.805
Out[]: ▼
                                DecisionTreeClassifier
        DecisionTreeClassifier(criterion='entropy', max_depth=2, max_feat
        ures=0.95,
                                 min samples leaf=0.04, min samples split=
        6,
                                 random state=2)
In [ ]: ds = DecisionTreeClassifier(max_depth=8, max_features=0.9, max_leaf_nodes
                               min_impurity_decrease=0.05, min_samples_leaf=0.02,
                               min_samples_split=10, min_weight_fraction_leaf=0.0
                                random state=2, splitter='random')
        ds.fit(X_train, y_train)
        pred4 =ds.predict(X test)
        loss(y_test, pred4)
        precision 0.7830188679245284
        recall 0.9880952380952381
        accuracy 0.8048780487804879
In [ ]: from sklearn.ensemble import RandomForestClassifier
        randomized search(params={
                                  'min_samples_leaf':[1,2,4,6,8,10,20,30],
                                   'min_impurity_decrease':[0.0, 0.01, 0.05, 0.10,
                                   'max_features':[0.8, 0.7, 0.6, 0.5, 0.4],
```