In [1]: 1 import pandas as pd
In [2]: 1 data=pd.read\_csv("/home/placement/Downloads/Titanic Dataset.csv")
In [3]: 1 data.describe()

Out[3]:

	Passengerld	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

```
In [4]:
            data.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 891 entries, 0 to 890
        Data columns (total 12 columns):
             Column
                           Non-Null Count
                                           Dtype
              -----
                                            _ _ _ _
             PassengerId 891 non-null
                                           int64
             Survived
                           891 non-null
                                           int64
         1
         2
             Pclass
                           891 non-null
                                           int64
         3
                           891 non-null
                                           obiect
             Name
         4
             Sex
                           891 non-null
                                           obiect
          5
             Age
                           714 non-null
                                           float64
                           891 non-null
         6
             SibSp
                                           int64
                                           int64
         7
             Parch
                           891 non-null
         8
             Ticket
                           891 non-null
                                           obiect
          9
             Fare
                           891 non-null
                                           float64
             Cabin
                           204 non-null
         10
                                           obiect
         11 Embarked
                           889 non-null
                                           obiect
        dtypes: float64(2), int64(5), object(5)
        memory usage: 83.7+ KB
In [5]:
          1 list(data)
Out[5]: ['PassengerId',
          'Survived',
          'Pclass',
          'Name',
          'Sex',
          'Age',
          'SibSp',
          'Parch',
          'Ticket',
          'Fare',
          'Cabin',
          'Embarked']
```

```
1 data.isna().sum()#no.of null values
In [6]:
Out[6]: PassengerId
                         0
        Survived
                         0
        Pclass
                         0
        Name
        Sex
                         0
                       177
        Age
        SibSp
                         0
        Parch
                         0
        Ticket
                         0
        Fare
                         0
        Cabin
                       687
        Embarked
                         2
        dtype: int64
In [7]:
         datal=data.drop(['Cabin','Name','PassengerId','Ticket','SibSp','Parch'],axis=1)#deleting columns
```

In [8]: 1 data1

Out[8]:

	Survived	Pclass	Sex	Age	Fare	Embarked
0	0	3	male	22.0	7.2500	S
1	1	1	female	38.0	71.2833	С
2	1	3	female	26.0	7.9250	S
3	1	1	female	35.0	53.1000	S
4	0	3	male	35.0	8.0500	S
886	0	2	male	27.0	13.0000	S
887	1	1	female	19.0	30.0000	S
888	0	3	female	NaN	23.4500	S
889	1	1	male	26.0	30.0000	С
890	0	3	male	32.0	7.7500	Q

891 rows × 6 columns

```
In [9]: 1 data1.isna().sum()#finding null values
```

Out[9]: Survived 0
Pclass 0
Sex 0
Age 177
Fare 0
Embarked 2
dtype: int64

In [10]: 1 data1.shape#no of rows and columns

Out[10]: (891, 6)

In [11]: 1 data1['Sex']=data1['Sex'].map({'male':1,'female':0})#assinging 1 to male and 0 to female using map

In [12]: 1 data1

Out[12]:

	Survived	Pclass	Sex	Age	Fare	Embarked
0	0	3	1	22.0	7.2500	S
1	1	1	0	38.0	71.2833	С
2	1	3	0	26.0	7.9250	S
3	1	1	0	35.0	53.1000	S
4	0	3	1	35.0	8.0500	S
•••						
886	0	2	1	27.0	13.0000	S
887	1	1	0	19.0	30.0000	S
888	0	3	0	NaN	23.4500	S
889	1	1	1	26.0	30.0000	С
890	0	3	1	32.0	7.7500	Q

891 rows × 6 columns

In [13]: 1 datal=datal.fillna(datal.mean())#fill null values using mean

/snap/jupyter/6/lib/python3.7/site-packages/ipykernel\_launcher.py:1: FutureWarning: Dropping of nuisance co lumns in DataFrame reductions (with 'numeric\_only=None') is deprecated; in a future version this will raise TypeError. Select only valid columns before calling the reduction.

"""Entry point for launching an IPython kernel.

In [14]: 1 data1

Out[14]:

	Survived	Pclass	Sex	Age	Fare	Embarked
0	0	3	1	22.000000	7.2500	S
1	1	1	0	38.000000	71.2833	С
2	1	3	0	26.000000	7.9250	S
3	1	1	0	35.000000	53.1000	S
4	0	3	1	35.000000	8.0500	S
886	0	2	1	27.000000	13.0000	S
887	1	1	0	19.000000	30.0000	S
888	0	3	0	29.699118	23.4500	S
889	1	1	1	26.000000	30.0000	С
890	0	3	1	32.000000	7.7500	Q

891 rows × 6 columns

In [15]: 1 data1.isna().sum()

Out[15]: Survived 0
Pclass 0
Sex 0
Age 0
Fare 0
Embarked 2
dtype: int64

In [16]:

data2=pd.get\_dummies(data1)#where the pclass it shows"1" other pclass it shows "0" data2

Out[16]:

	Survived	Pclass	Sex	Age	Fare	Embarked_C	Embarked_Q	Embarked_S
0	0	3	1	22.000000	7.2500	0	0	1
1	1	1	0	38.000000	71.2833	1	0	0
2	1	3	0	26.000000	7.9250	0	0	1
3	1	1	0	35.000000	53.1000	0	0	1
4	0	3	1	35.000000	8.0500	0	0	1
886	0	2	1	27.000000	13.0000	0	0	1
887	1	1	0	19.000000	30.0000	0	0	1
888	0	3	0	29.699118	23.4500	0	0	1
889	1	1	1	26.000000	30.0000	1	0	0
890	0	3	1	32.000000	7.7500	0	1	0

891 rows × 8 columns

In [17]:

1 x=data2.drop(['Survived'],axis=1)#deleting churn

In [18]: 1 x

Out[18]:

	Pclass	Sex	Age	Fare	Embarked_C	Embarked_Q	Embarked_S
0	3	1	22.000000	7.2500	0	0	1
1	1	0	38.000000	71.2833	1	0	0
2	3	0	26.000000	7.9250	0	0	1
3	1	0	35.000000	53.1000	0	0	1
4	3	1	35.000000	8.0500	0	0	1
886	2	1	27.000000	13.0000	0	0	1
887	1	0	19.000000	30.0000	0	0	1
888	3	0	29.699118	23.4500	0	0	1
889	1	1	26.000000	30.0000	1	0	0
890	3	1	32.000000	7.7500	0	1	0

891 rows × 7 columns

```
In [20]: 1 y=data['Survived']
In [21]: 1 from sklearn.model_selection import train_test_split
2 x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.33,random_state=42)
```

```
In [22]: 1 x.head(5)
```

Out[22]:

	Pclass	Sex	Age	Fare	Embarked_C	Embarked_Q	Embarked_S
0	3	1	22.0	7.2500	0	0	1
1	1	0	38.0	71.2833	1	0	0
2	3	0	26.0	7.9250	0	0	1
3	1	0	35.0	53.1000	0	0	1
4	3	1	35.0	8.0500	0	0	1

```
In [23]:
          1 from sklearn.model selection import GridSearchCV #GridSearchCV is for parameter tuning
          2 from sklearn.ensemble import RandomForestClassifier
             cls=RandomForestClassifier()
          4 | n estimators=[25,50,75,100,125,150,175,200] #number of decision trees in the forest, default = 100
          5 criterion=['gini', 'entropy'] #criteria for choosing nodes default = 'gini'
             max depth=[3,5,10] #maximum number of nodes in a tree default = None (it will go till all possible nodes
             parameters={'n estimators': n estimators,'criterion':criterion,'max depth':max depth} #this will undergd
          8 RFC cls = GridSearchCV(cls, parameters)
          9 RFC cls.fit(x train, y train)
Out[23]: GridSearchCV(estimator=RandomForestClassifier(),
                      param grid={'criterion': ['gini', 'entropy'],
                                   'max depth': [3, 5, 10],
                                  'n estimators': [25, 50, 75, 100, 125, 150, 175, 200]})
In [24]:
          1 RFC cls.best params
Out[24]: {'criterion': 'gini', 'max depth': 5, 'n estimators': 200}
          1 | cls=RandomForestClassifier(n_estimators=175,criterion='entropy',max_depth=10)
In [25]:
```

```
1 cls.fit(x train,y train)
In [26]:
Out[26]: RandomForestClassifier(criterion='entropy', max depth=10, n estimators=175)
          1 rfy pred=cls.predict(x test)
In [27]:
In [28]:
          1 rfy pred
Out[28]: array([0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1,
                0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1,
                0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
                1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0,
                0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1,
                0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0,
                0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0,
                1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0,
                0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1,
                0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0,
                0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0,
                1, 0, 1, 1, 0, 0, 1, 1, 0])
In [29]:
          1 from sklearn.metrics import confusion matrix
          2 confusion matrix(y test,rfy pred)
Out[29]: array([[149, 26],
                [ 35, 85]])
In [30]:
          1 from sklearn.metrics import accuracy score
          2 accuracy score(y test,rfy pred)#EFFICENCY OF THE CONFUSION MATRIX
Out[30]: 0.7932203389830509
In [ ]:
```