Titanic data challenge

The goal is to predict whether or not a passenger survived based on attributes such as their age, sex, passenger class, where they embarked and so on.

First, login to Kaggle competition to download train.csv and test.csv. Save them to the titanic directory.

We first split the training data into training and validation sets. You can use cross validation as well.

Train the following three classifers:

- Logistic regression
- SVM
- KNN classifier

Report the features of each model, the confusion matrix, classification summary, and AUC.

Select the best model and use it to predict the test set. Submit your predictions in the test set.

In [1]:
```
import pandas as pd
import numpy as np
```

In [2]:
```
%cd /Users/Cloris/Downloads
```

```
/Users/Cloris/Downloads
```

In [3]:
```
titanic = pd.read_csv('train.csv', header = 0, dtype={'Age': np.float64})
titanic.tail()
```

Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.45	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.75	NaN	Q

Performing Data Cleaning and Analysis

1. Understanding meaning of each column: Data Dictionary: Variable Description

Survived - Survived (1) or died (0) Pclass - Passenger's class (1 = 1st, 2 = 2nd, 3 = 3rd) Name - Passenger's name Sex - Passenger's sex Age - Passenger's age SibSp - Number of siblings/spouses aboard Parch - Number of parents/children aboard (Some children travelled only with a nanny, therefore parch=0 for them.) Ticket - Ticket number Fare - Fare Cabin - Cabin Embarked - Port of embarkation (C = Cherbourg, Q = Queenstown, S = Southampton)

1. Analysing which columns are completely useless in predicting the survival and deleting them Note - Don't just delete the columns because you are not finding it useful. Or focus is not on deleting the columns. Our focus is on analysing how each column is affecting the result or the prediction and in accordance with that deciding whether to keep the column or to delete the column or fill the null values of the column by some values and if yes, then what values.

In [4]:
```
titanic.describe()
```

Out[4]:

	PassengerId	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 [5]:
```
#Name column can never decide survival of a person, hence we can safely delete it
del titanic["Name"]
titanic.head()
```

Out[5]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	male	35.0	0	0	373450	8.0500	NaN	S

In [6]:
```
del titanic["Ticket"]
titanic.head()
```

Out[6]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Cabin	Embarked
0	1	0	3	male	22.0	1	0	7.2500	NaN	S
1	2	1	1	female	38.0	1	0	71.2833	C85	C
2	3	1	3	female	26.0	0	0	7.9250	NaN	S
3	4	1	1	female	35.0	1	0	53.1000	C123	S
4	5	0	3	male	35.0	0	0	8.0500	NaN	S

In [7]:
```
del titanic["Fare"]
titanic.head()
```

Out[7]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Cabin	Embarked
0	1	0	3	male	22.0	1	0	NaN	S
1	2	1	1	female	38.0	1	0	C85	C
2	3	1	3	female	26.0	0	0	NaN	S
3	4	1	1	female	35.0	1	0	C123	S
4	5	0	3	male	35.0	0	0	NaN	S

In [8]:
```
del titanic['Cabin']
titanic.head()
```

Out[8]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Embarked
0	1	0	3	male	22.0	1	0	S
1	2	1	1	female	38.0	1	0	C
2	3	1	3	female	26.0	0	0	S
3	4	1	1	female	35.0	1	0	S
4	5	0	3	male	35.0	0	0	S

In [9]:
```
# Changing Value for "Male, Female" string values to numeric values , male=1 and female=2
def getNumber(str):
    if str=="male":
        return 1
    else:
        return 2
titanic["Gender"]=titanic["Sex"].apply(getNumber)
#We have created a new column called "Gender" and
#filling it with values 1,2 based on the values of sex column
titanic.head()
```

Out[9]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Embarked	Gender
0	1	0	3	male	22.0	1	0	S	1
1	2	1	1	female	38.0	1	0	C	2
2	3	1	3	female	26.0	0	0	S	2
3	4	1	1	female	35.0	1	0	S	2
4	5	0	3	male	35.0	0	0	S	1

In [10]:
```
#Deleting Sex column, since no use of it now
del titanic["Sex"]
titanic.head()
```

Out[10]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Embarked	Gender
0	1	0	3	22.0	1	0	S	1
1	2	1	1	38.0	1	0	C	2
2	3	1	3	26.0	0	0	S	2
3	4	1	1	35.0	1	0	S	2
4	5	0	3	35.0	0	0	S	1

In [11]:
```
titanic.isnull().sum()
```

Out[11]:
```
PassengerId      0
Survived         0
Pclass           0
Age            177
SibSp            0
Parch            0
Embarked         2
Gender           0
dtype: int64
```

Fill the null values of the Age column. Fill mean Survived age(mean age of the survived people) in the column where the person has survived and mean not Survived age (mean age of the people who have not survived) in the column where person has not survived

In [12]:
```
meanS= titanic[titanic.Survived==1].Age.mean()
meanS
```

Out[12]:
```
28.343689655172415
```

Creating a new "Age" column , filling values in it with a condition if goes True then given values (here meanS) is put in place of last values else nothing happens, simply the values are copied from the "Age" column of the dataset

In [13]:
```
titanic["age"]=np.where(pd.isnull(titanic.Age) & titanic["Survived"]==1   ,meanS, titanic["Age"])
titanic.head()
```

Out[13]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Embarked	Gender	age
0	1	0	3	22.0	1	0	S	1	22.0
1	2	1	1	38.0	1	0	C	2	38.0
2	3	1	3	26.0	0	0	S	2	26.0
3	4	1	1	35.0	1	0	S	2	35.0
4	5	0	3	35.0	0	0	S	1	35.0

In [14]:
```
titanic.isnull().sum()
```

Out[14]:
```
PassengerId      0
Survived         0
Pclass           0
Age            177
SibSp            0
Parch            0
Embarked         2
Gender           0
age            125
dtype: int64
```

In [15]:
```
# Finding the mean age of "Not Survived" people
meanNS=titanic[titanic.Survived==0].Age.mean()
meanNS
```

Out[15]:
```
30.62617924528302
```

In [16]:
```
titanic.age.fillna(meanNS,inplace=True)
titanic.head()
```

Out[16]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Embarked	Gender	age
0	1	0	3	22.0	1	0	S	1	22.0
1	2	1	1	38.0	1	0	C	2	38.0
2	3	1	3	26.0	0	0	S	2	26.0
3	4	1	1	35.0	1	0	S	2	35.0
4	5	0	3	35.0	0	0	S	1	35.0

In [17]:
```
titanic.isnull().sum()
```

Out[17]:
```
PassengerId      0
Survived         0
Pclass           0
Age            177
SibSp            0
Parch            0
Embarked         2
Gender           0
age              0
dtype: int64
```

In [18]:
```
del titanic['Age']
titanic.head()
```

Out[18]:

	PassengerId	Survived	Pclass	SibSp	Parch	Embarked	Gender	age
0	1	0	3	1	0	S	1	22.0
1	2	1	1	1	0	C	2	38.0
2	3	1	3	0	0	S	2	26.0
3	4	1	1	1	0	S	2	35.0
4	5	0	3	0	0	S	1	35.0

We want to check if "Embarked" column is is important for analysis or not, that is whether survival of the person depends on the Embarked column value or not

In [19]:
```
# Finding the number of people who have survived
# given that they have embarked or boarded from a particular port

survivedQ = titanic[titanic.Embarked == 'Q'][titanic.Survived == 1].shape[0]
survivedC = titanic[titanic.Embarked == 'C'][titanic.Survived == 1].shape[0]
survivedS = titanic[titanic.Embarked == 'S'][titanic.Survived == 1].shape[0]
print(survivedQ)
print(survivedC)
print(survivedS)
```

```
30
93
217
/var/folders/k6/4rd3w0v91_74v64t4lpg4ysr0000gn/T/ipykernel_66136/3300902897.py:4: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  survivedQ = titanic[titanic.Embarked == 'Q'][titanic.Survived == 1].shape[0]
/var/folders/k6/4rd3w0v91_74v64t4lpg4ysr0000gn/T/ipykernel_66136/3300902897.py:5: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  survivedC = titanic[titanic.Embarked == 'C'][titanic.Survived == 1].shape[0]
/var/folders/k6/4rd3w0v91_74v64t4lpg4ysr0000gn/T/ipykernel_66136/3300902897.py:6: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  survivedS = titanic[titanic.Embarked == 'S'][titanic.Survived == 1].shape[0]
```

In [20]:
```
survivedQ = titanic[titanic.Embarked == 'Q'][titanic.Survived == 0].shape[0]
survivedC = titanic[titanic.Embarked == 'C'][titanic.Survived == 0].shape[0]
survivedS = titanic[titanic.Embarked == 'S'][titanic.Survived == 0].shape[0]
print(survivedQ)
print(survivedC)
print(survivedS)
```

```
47
75
427
/var/folders/k6/4rd3w0v91_74v64t4lpg4ysr0000gn/T/ipykernel_66136/3240960939.py:1: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  survivedQ = titanic[titanic.Embarked == 'Q'][titanic.Survived == 0].shape[0]
/var/folders/k6/4rd3w0v91_74v64t4lpg4ysr0000gn/T/ipykernel_66136/3240960939.py:2: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  survivedC = titanic[titanic.Embarked == 'C'][titanic.Survived == 0].shape[0]
/var/folders/k6/4rd3w0v91_74v64t4lpg4ysr0000gn/T/ipykernel_66136/3240960939.py:3: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  survivedS = titanic[titanic.Embarked == 'S'][titanic.Survived == 0].shape[0]
```

As there are significant changes in the survival rate based on which port the passengers aboard the ship. We cannot delete the whole embarked column(It is useful). Now the Embarked column has some null values in it and hence we can safely say that deleting some rows from total rows will not affect the result. So rather than trying to fill those null values with some vales. We can simply remove them.

In [21]:
```
titanic.dropna(inplace=True)
titanic.head()
```

Out[21]:

	PassengerId	Survived	Pclass	SibSp	Parch	Embarked	Gender	age
0	1	0	3	1	0	S	1	22.0
1	2	1	1	1	0	C	2	38.0
2	3	1	3	0	0	S	2	26.0
3	4	1	1	1	0	S	2	35.0
4	5	0	3	0	0	S	1	35.0

In [22]:
```
titanic.isnull().sum()
```

Out[22]:
```
PassengerId    0
Survived       0
Pclass         0
SibSp          0
Parch          0
Embarked       0
Gender         0
age            0
dtype: int64
```

In [23]:
```
#Renaming "age" and "gender" columns
titanic.rename(columns={'age':'Age'}, inplace=True)
```

```
titanic.head()
```

Out[23]:

	PassengerId	Survived	Pclass	SibSp	Parch	Embarked	Gender	Age
0	1	0	3	1	0	S	1	22.0
1	2	1	1	1	0	C	2	38.0
2	3	1	3	0	0	S	2	26.0
3	4	1	1	1	0	S	2	35.0
4	5	0	3	0	0	S	1	35.0

In [24]:
```
titanic.rename(columns={'Gender':'Sex'}, inplace=True)
titanic.head()
```

Out[24]:

	PassengerId	Survived	Pclass	SibSp	Parch	Embarked	Sex	Age
0	1	0	3	1	0	S	1	22.0
1	2	1	1	1	0	C	2	38.0
2	3	1	3	0	0	S	2	26.0
3	4	1	1	1	0	S	2	35.0
4	5	0	3	0	0	S	1	35.0

In [25]:
```
def getS(str):
    if str=="S":
        return 1
    else:
        return 0
titanic["S"]=titanic["Embarked"].apply(getS)
def getQ(str):
    if str=="Q":
        return 1
    else:
        return 0
titanic["Q"]=titanic["Embarked"].apply(getQ)
def getC(str):
    if str=="C":
        return 1
    else:
        return 0
titanic["C"]=titanic["Embarked"].apply(getC)
titanic.head()
```

Out[25]:

	PassengerId	Survived	Pclass	SibSp	Parch	Embarked	Sex	Age	S	Q	C
0	1	0	3	1	0	S	1	22.0	1	0	0
1	2	1	1	1	0	C	2	38.0	0	0	1
2	3	1	3	0	0	S	2	26.0	1	0	0
3	4	1	1	1	0	S	2	35.0	1	0	0
4	5	0	3	0	0	S	1	35.0	1	0	0

In [26]:
```
del titanic['Embarked']
titanic.head()
```

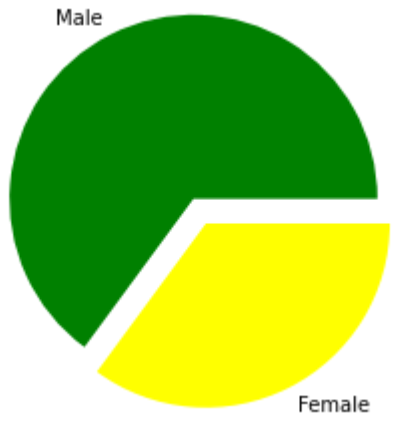
Out[26]:

	PassengerId	Survived	Pclass	SibSp	Parch	Sex	Age	S	Q	C
0	1	0	3	1	0	1	22.0	1	0	0
1	2	1	1	1	0	2	38.0	0	0	1
2	3	1	3	0	0	2	26.0	1	0	0
3	4	1	1	1	0	2	35.0	1	0	0
4	5	0	3	0	0	1	35.0	1	0	0

In [27]:
```
#Drawing a pie chart for number of males and females aboard
import matplotlib.pyplot as plt
from matplotlib import style

males = (titanic['Sex'] == 1).sum()
#Summing up all the values of column gender with a
#condition for male and similary for females
females = (titanic['Sex'] == 2).sum()
print(males)
print(females)
p = [males, females]
plt.pie(p,    #giving array
       labels = ['Male', 'Female'], #Correspndingly giving labels
       colors = ['green', 'yellow'],   # Corresponding colors
       explode = (0.15, 0),    #How much the gap should me there between the pies
       startangle = 0)  #what start angle should be given
plt.axis('equal')
plt.show()
```

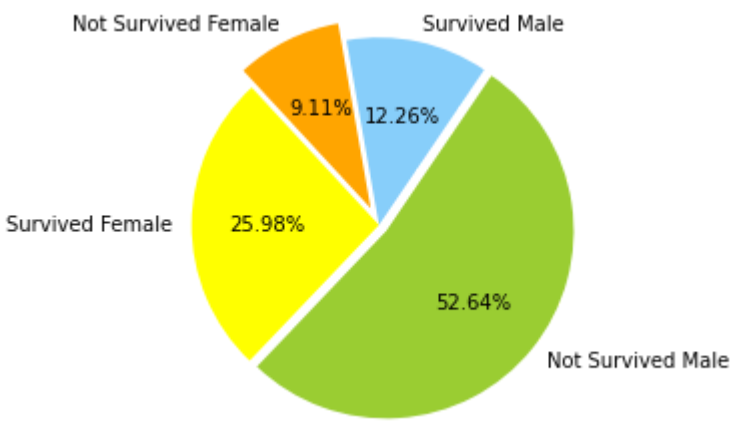
```
577
312
```



In [28]:
```
# More Precise Pie Chart
MaleS=titanic[titanic.Sex==1][titanic.Survived==1].shape[0]
print(MaleS)
MaleN=titanic[titanic.Sex==1][titanic.Survived==0].shape[0]
print(MaleN)
FemaleS=titanic[titanic.Sex==2][titanic.Survived==1].shape[0]
print(FemaleS)
FemaleN=titanic[titanic.Sex==2][titanic.Survived==0].shape[0]
print(FemaleN)
```

```
109
468
231
81
/var/folders/k6/4rd3w0v91_74v64t4lpg4ysr0000gn/T/ipykernel_66136/3105620411.py:2: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  MaleS=titanic[titanic.Sex==1][titanic.Survived==1].shape[0]
/var/folders/k6/4rd3w0v91_74v64t4lpg4ysr0000gn/T/ipykernel_66136/3105620411.py:4: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  MaleN=titanic[titanic.Sex==1][titanic.Survived==0].shape[0]
/var/folders/k6/4rd3w0v91_74v64t4lpg4ysr0000gn/T/ipykernel_66136/3105620411.py:6: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  FemaleS=titanic[titanic.Sex==2][titanic.Survived==1].shape[0]
/var/folders/k6/4rd3w0v91_74v64t4lpg4ysr0000gn/T/ipykernel_66136/3105620411.py:8: UserWarning: Boolean Series key will
be reindexed to match DataFrame index.
  FemaleN=titanic[titanic.Sex==2][titanic.Survived==0].shape[0]
```

In [29]:
```
chart=[MaleS,MaleN,FemaleS,FemaleN]
colors=['lightskyblue','yellowgreen','Yellow','Orange']
labels=["Survived Male","Not Survived Male","Survived Female","Not Survived Female"]
explode=[0,0.05,0,0.1]
plt.pie(chart,labels=labels,colors=colors,explode=explode,startangle=100,counterclock=False,autopct="%.2f%%")
plt.axis("equal")
plt.show()
```



In [30]:
```
test_data = pd.read_csv("test.csv")
test_data.head()
```

Out[30]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S

The data is already split into a training set and a test set. We need to preprocess the test data in the same step as we have done for the training data.

In [31]:
```
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  418 non-null    int64  
 1   Pclass       418 non-null    int64  
 2   Name         418 non-null    object 
 3   Sex          418 non-null    object 
 4   Age          332 non-null    float64
 5   SibSp        418 non-null    int64  
 6   Parch        418 non-null    int64  
 7   Ticket       418 non-null    object 
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object 
 10  Embarked     418 non-null    object 
dtypes: float64(2), int64(4), object(5)
memory usage: 36.0+ KB
```

In [32]:
```
#Name column can never decide survival of a person, hence we can safely delete it
del test_data["Name"]
del test_data["Ticket"]
del test_data["Fare"]
del test_data['Cabin']
test_data.head()
```

Out[32]:

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Embarked
0	892	3	male	34.5	0	0	Q
1	893	3	female	47.0	1	0	S
2	894	2	male	62.0	0	0	Q
3	895	3	male	27.0	0	0	S
4	896	3	female	22.0	1	1	S

In [33]:
```
# Changing Value for "Male, Female" string values to numeric values , male=1 and female=2
def getNumber(str):
    if str=="male":
        return 1
    else:
        return 2
test_data["Gender"]=test_data["Sex"].apply(getNumber)
#We have created a new column called "Gender" and
#filling it with values 1,2 based on the values of sex column
test_data.head()
#Deleting Sex column, since no use of it now
del test_data["Sex"]
test_data.head()
```

Out[33]:

	PassengerId	Pclass	Age	SibSp	Parch	Embarked	Gender
0	892	3	34.5	0	0	Q	1
1	893	3	47.0	1	0	S	2
2	894	2	62.0	0	0	Q	1
3	895	3	27.0	0	0	S	1
4	896	3	22.0	1	1	S	2

In [34]:
```
test_data.isnull().sum()
```

Out[34]:
```
PassengerId     0
Pclass          0
Age            86
SibSp           0
Parch           0
Embarked        0
Gender          0
dtype: int64
```

In [35]:
```
# fill age
meanAge=test_data.Age.mean()
test_data.Age.fillna(meanAge,inplace=True)
```

In [36]:
```
test_data.head()
```

Out[36]:

	PassengerId	Pclass	Age	SibSp	Parch	Embarked	Gender
0	892	3	34.5	0	0	Q	1
1	893	3	47.0	1	0	S	2
2	894	2	62.0	0	0	Q	1
3	895	3	27.0	0	0	S	1
4	896	3	22.0	1	1	S	2

In [37]:
```
titanic.isnull().sum()
```

Out[37]:
```
PassengerId    0
Survived       0
Pclass         0
SibSp          0
Parch          0
Sex            0
Age            0
S              0
Q              0
C              0
dtype: int64
```

In [38]:
```
test_data.rename(columns={'Gender':'Sex'}, inplace=True)
def getS(str):
    if str=="S":
        return 1
    else:
        return 0
test_data["S"]=test_data["Embarked"].apply(getS)
def getQ(str):
    if str=="Q":
        return 1
    else:
        return 0
test_data["Q"]=test_data["Embarked"].apply(getQ)
def getC(str):
    if str=="C":
        return 1
    else:
        return 0
test_data["C"]=test_data["Embarked"].apply(getC)
del test_data['Embarked']
```

In [39]:
```
test_data.head()
```

Out[39]:

	PassengerId	Pclass	Age	SibSp	Parch	Sex	S	Q	C
0	892	3	34.5	0	0	1	0	1	0
1	893	3	47.0	1	0	2	1	0	0
2	894	2	62.0	0	0	1	0	1	0
3	895	3	27.0	0	0	1	1	0	0
4	896	3	22.0	1	1	2	1	0	0

Split the data into training and validation sets

In [40]:
```
from sklearn.model_selection import train_test_split
```

In [41]:
```
X = titanic[['PassengerId','Pclass','Age','SibSp','Parch','Sex','S','Q','C']]
y = titanic["Survived"]
```

In [42]:
```
X_train, X_validate, y_train, y_validate = train_test_split(X,y,test_size = 0.3, random_state = 101)
```

Logistic Regression

In [43]:
```
from sklearn.linear_model import LogisticRegression
logmodel= LogisticRegression()
logmodel.fit(X_train,y_train)
```

```
/Users/Cloris/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_logistic.py:814: ConvergenceWarning: lbf
gs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[43]:
```
LogisticRegression()
```

In [44]:
```
logpredictions = logmodel.predict(X_validate)
```

Evaluation: Classification summary, Confusion Metric and AUC

In [45]:
```
from sklearn.metrics import classification_report
print(classification_report(y_validate,logpredictions))
from sklearn.metrics import confusion_matrix
print(confusion_matrix(y_validate,logpredictions))
tn, fp, fn, tp = confusion_matrix(y_validate,logpredictions).ravel()
(tn, fp, fn, tp)
from sklearn.metrics import roc_auc_score
print('AUC-ROC score:', roc_auc_score(y_validate,logpredictions))
```

```
              precision    recall  f1-score   support

           0       0.83      0.91      0.87       163
           1       0.84      0.70      0.76       104

    accuracy                           0.83       267
   macro avg       0.83      0.81      0.82       267
weighted avg       0.83      0.83      0.83       267

[[149  14]
 [ 31  73]]
AUC-ROC score: 0.808016753185465
```

SVM

In [46]:
```
from sklearn.svm import SVC
```

In [47]:
```
svc_model = SVC()
```

In [48]:
```
svc_model.fit(X_train,y_train)
```

Out[48]:
```
SVC()
```

In [49]:
```
SVMpredictions = svc_model.predict(X_validate)
```

Evaluation: Classification summary, Confusion Metric and AUC

In [50]:
```
print(classification_report(y_validate,SVMpredictions))
print(confusion_matrix(y_validate,SVMpredictions))
print('AUC-ROC score:', roc_auc_score(y_validate,SVMpredictions))
```

```
              precision    recall  f1-score   support

           0       0.61      1.00      0.76       163
           1       0.00      0.00      0.00       104

    accuracy                           0.61       267
   macro avg       0.31      0.50      0.38       267
weighted avg       0.37      0.61      0.46       267

[[163   0]
 [104   0]]
AUC-ROC score: 0.5
/Users/Cloris/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarnin
g: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/Cloris/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarnin
g: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/Cloris/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarnin
g: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

KNN

Standardize the variables

In [51]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X)
```

Out[51]:
```
StandardScaler()
```

In [52]:
```
scaled_festures = scaler.transform(X)
df_feat = pd.DataFrame(scaled_festures,columns = ['PassengerId','Pclass','Age','SibSp','Parch','Sex','S','Q','C'])
df_feat.head()
```

Out[52]:

	PassengerId	Pclass	Age	SibSp	Parch	Sex	S	Q	C
0	-1.732505	0.825209	-0.594028	0.431350	-0.474326	-0.735342	0.616794	-0.307941	-0.482711
1	-1.728611	-1.572211	0.639592	0.431350	-0.474326	1.359911	-1.621287	-0.307941	2.071634
2	-1.724718	0.825209	-0.285623	-0.475199	-0.474326	1.359911	0.616794	-0.307941	-0.482711
3	-1.720825	-1.572211	0.408289	0.431350	-0.474326	1.359911	0.616794	-0.307941	-0.482711
4	-1.716931	0.825209	0.408289	-0.475199	-0.474326	-0.735342	0.616794	-0.307941	-0.482711

Train, Validation split

In [53]:
```
Xk_train, Xk_validate, yk_train,yk_validate = train_test_split(scaled_festures,
                                                            titanic['Survived'],test_size = 0.3, random_state = 101)
```

In [54]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [55]:
```
knn = KNeighborsClassifier(n_neighbors = 1)
```

In [56]:
```
knn.fit(Xk_train,yk_train)
```

Out[56]:
```
KNeighborsClassifier(n_neighbors=1)
```

In [57]:
```
KNNpredictions = knn.predict(Xk_validate)
```

Evaluation: Classification summary, Confusion Metric and AUC

In [58]:
```
print(classification_report(yk_validate,KNNpredictions))
print(confusion_matrix(yk_validate,KNNpredictions))
print('AUC-ROC score:', roc_auc_score(yk_validate,KNNpredictions))
```

```
              precision    recall  f1-score   support

           0       0.78      0.87      0.82       163
           1       0.75      0.62      0.68       104

    accuracy                           0.77       267
   macro avg       0.77      0.75      0.75       267
weighted avg       0.77      0.77      0.77       267

[[141  22]
 [ 39  65]]
AUC-ROC score: 0.7450153374233129
```

From the evaluation, we would choose logistic regression model to predict the survival for test data

In [59]:
```
predictions = logmodel.predict(test_data)
```

In [60]:
```
test_data['Precitions'] = predictions
```

In [61]:
```
test_data.describe()
```

Out[61]:

	PassengerId	Pclass	Age	SibSp	Parch	Sex	S	Q	C	Precitions
count	418.000000	418.000000	418.000000	418.000000	418.000000	418.000000	418.000000	418.000000	418.000000	418.000000
mean	1100.500000	2.265550	30.272590	0.447368	0.392344	1.363636	0.645933	0.110048	0.244019	0.389952
std	120.810458	0.841838	12.634534	0.896760	0.981429	0.481622	0.478803	0.313324	0.430019	0.488324
min	892.000000	1.000000	0.170000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000
25%	996.250000	1.000000	23.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000
50%	1100.500000	3.000000	30.272590	0.000000	0.000000	1.000000	1.000000	0.000000	0.000000	0.000000
75%	1204.750000	3.000000	35.750000	1.000000	0.000000	2.000000	1.000000	0.000000	0.000000	1.000000
max	1309.000000	3.000000	76.000000	8.000000	9.000000	2.000000	1.000000	1.000000	1.000000	1.000000