titanic

September 3, 2023

1 Problem :

2 Question and problem definition

Knowing from a training set of samples listing passengers who survived or did not survive the Titanic disaster, can our model determine based on a given test dataset not containing the survival information, if these passengers in the test dataset survived or not.

On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers and crew. Translated 32% survival rate. One of the reasons that the shipwreck led to such loss of life was that there were not enough lifeboats for the passengers and crew. Although there was some element of luck involved in surviving the sinking, some groups of people were more likely to survive than others, such as women, children, and the upper-class. FA titanic data. Perform Classification on the attached data using all the possible algorithms. Perform cross validation to narrow down to the best model. On that best model evaluate it using precision and recall scores

[1]:
```
# lets import the important libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
titanic = pd.read_csv('train.csv')
titanic.head()
```

[2]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
```

```
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

[3]:
```
# check the shape, column and description of the data set
titanic.shape
```

[3]:
```
(891, 12)
```

[4]:
```
titanic.columns
```

[4]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

[5]:
```
titanic.describe()
```

[5]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

Interpretation: * the age group that was on titanic ship was on an average 42 to 80.

[6]:
```
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

[7]:
```
titanic.describe(include=['O'])
```

[7]:

	Name	Sex	Ticket	Cabin	Embarked
count	891	891	891	204	889
unique	891	2	681	147	3
top	Braund, Mr. Owen Harris	male	347082	B96 B98	S
freq	1	577	7	4	644

[8]:
```
# EDA: lets find the null values:
```

[9]:
```
titanic.isna().sum(axis=0)
```

[9]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

[10]:
```
#.For age column lets put the mean of age and hence it will be filling from the␣
↪description data mean =29.699118
```

```
titanic['Age']= titanic['Age'].fillna(np.mean(titanic['Age']))
```

[11]:
```
# lets check the null value if null remains
titanic.isna().sum()
```

[11]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

[12]:
```
titanic['Age'].isna().sum()
```

[12]:
```
0
```

[13]:
```
titanic['Age'].unique()
```

[13]:
```
array([22.        , 38.        , 26.        , 35.        , 29.69911765,
       54.        ,  2.        , 27.        , 14.        ,  4.        ,
       58.        , 20.        , 39.        , 55.        , 31.        ,
       34.        , 15.        , 28.        ,  8.        , 19.        ,
       40.        , 66.        , 42.        , 21.        , 18.        ,
        3.        ,  7.        , 49.        , 29.        , 65.        ,
       28.5       ,  5.        , 11.        , 45.        , 17.        ,
       32.        , 16.        , 25.        ,  0.83      , 30.        ,
       33.        , 23.        , 24.        , 46.        , 59.        ,
       71.        , 37.        , 47.        , 14.5       , 70.5       ,
       32.5       , 12.        ,  9.        , 36.5       , 51.        ,
       55.5       , 40.5       , 44.        ,  1.        , 61.        ,
       56.        , 50.        , 36.        , 45.5       , 20.5       ,
       62.        , 41.        , 52.        , 63.        , 23.5       ,
        0.92      , 43.        , 60.        , 10.        , 64.        ,
       13.        , 48.        ,  0.75      , 53.        , 57.        ,
       80.        , 70.        , 24.5       ,  6.        ,  0.67      ,
       30.5       ,  0.42      , 34.5       , 74.        ])
```

Interpretation: we can see that the null values have been filled with the mean values

[14]:
```python
# Lets do for Embrked, filled with the mean value=
titanic['Cabin'].unique()
```

[14]:
```
array([nan, 'C85', 'C123', 'E46', 'G6', 'C103', 'D56', 'A6',
       'C23 C25 C27', 'B78', 'D33', 'B30', 'C52', 'B28', 'C83', 'F33',
       'F G73', 'E31', 'A5', 'D10 D12', 'D26', 'C110', 'B58 B60', 'E101',
       'F E69', 'D47', 'B86', 'F2', 'C2', 'E33', 'B19', 'A7', 'C49', 'F4',
       'A32', 'B4', 'B80', 'A31', 'D36', 'D15', 'C93', 'C78', 'D35',
       'C87', 'B77', 'E67', 'B94', 'C125', 'C99', 'C118', 'D7', 'A19',
       'B49', 'D', 'C22 C26', 'C106', 'C65', 'E36', 'C54',
       'B57 B59 B63 B66', 'C7', 'E34', 'C32', 'B18', 'C124', 'C91', 'E40',
       'T', 'C128', 'D37', 'B35', 'E50', 'C82', 'B96 B98', 'E10', 'E44',
       'A34', 'C104', 'C111', 'C92', 'E38', 'D21', 'E12', 'E63', 'A14',
       'B37', 'C30', 'D20', 'B79', 'E25', 'D46', 'B73', 'C95', 'B38',
       'B39', 'B22', 'C86', 'C70', 'A16', 'C101', 'C68', 'A10', 'E68',
       'B41', 'A20', 'D19', 'D50', 'D9', 'A23', 'B50', 'A26', 'D48',
       'E58', 'C126', 'B71', 'B51 B53 B55', 'D49', 'B5', 'B20', 'F G63',
       'C62 C64', 'E24', 'C90', 'C45', 'E8', 'B101', 'D45', 'C46', 'D30',
       'E121', 'D11', 'E77', 'F38', 'B3', 'D6', 'B82 B84', 'D17', 'A36',
       'B102', 'B69', 'E49', 'C47', 'D28', 'E17', 'A24', 'C50', 'B42',
       'C148'], dtype=object)
```

[15]:
```python
# lets fill the null value in the cabin with zero
titanic['Cabin']= titanic['Cabin'].fillna(0)
```

[16]:
```python
titanic.isna().sum()
```

[16]:
```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Cabin          0
Embarked       2
dtype: int64
```

3 Assumption from the above datset:

Before going ahead for data preprocessing, we have further concluded some assumption based on data cleaning and description of our titanic: * # colinearity: * we have seen that cabin can droped as it contains 687 null values which indicates that it doesnot have passengers inside which can impact our model accuracy, hence we can drop it. * Name column again has unique features whic can impact a regularization of overfitting or laziness in the model for prediction. * Ticket column also we can drop as it has alot of duplicate data of ranges and further it can be biased with our survival of passengers as the model prediction. * PassengerID can also be dropped as it doesnot impact the survival of passengers.

[17]:
```
# dropping for final data set before training and testing for model prediction
final_data =titanic.drop(['PassengerId','Name','Ticket','Cabin'],axis=1)
```

[18]:
```
final_data.head()
```

[18]:

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

Interpretation:Now our data set is ready for training and testing the survival chekc of the passengers.

[19]:
```
#Lets Do the exploratory Data Analysis.
#lets use preprocessing label encoder to convert the categorical into numerical␣
↪data of column Sex and Embarked

from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
```

[20]:
```
le=LabelEncoder()
```

[21]:
```
titanic['Sex'].unique()
```

[21]:
```
array(['male', 'female'], dtype=object)
```

[22]:
```
titanic['Embarked'].unique()
```

[22]:
```
array(['S', 'C', 'Q', nan], dtype=object)
```

[23]:
```
final_data['Sex']= le.fit_transform(final_data['Sex'])
```

[24]:
```
final_data.head()
```

[24]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	1	22.0	1	0	7.2500	S
1	1	1	0	38.0	1	0	71.2833	C
2	1	3	0	26.0	0	0	7.9250	S
3	1	1	0	35.0	1	0	53.1000	S
4	0	3	1	35.0	0	0	8.0500	S

[25]:
```
final_data['Embarked']= le.fit_transform(final_data['Embarked'])
```

[26]:
```
final_data.head()
```

[26]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	1	22.0	1	0	7.2500	2
1	1	1	0	38.0	1	0	71.2833	0
2	1	3	0	26.0	0	0	7.9250	2
3	1	1	0	35.0	1	0	53.1000	2
4	0	3	1	35.0	0	0	8.0500	2

[27]:
```
final_data['Embarked'].unique()
```

[27]:
```
array([2, 0, 1, 3])
```

[28]:
```
final_data.isnull().sum()
```

[28]:
```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
```

[29]:
```
# lets check he correlation between pclass and survived.
final_data[['Pclass','Survived']].groupby(['Pclass'],as_index= False).mean().
↪sort_values(by='Survived',ascending=False)
```

[29]:

	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

Interpretation: we can see that 62% first class passengers survived, second class =47% and more brutal impact on the third class =24% who survived.

[30]:
```
#Similarly lets check for gender  and survival factors
final_data[['Sex','Survived']].groupby(['Sex'],as_index= False).mean().
↪sort_values(by='Survived',ascending=False)
```

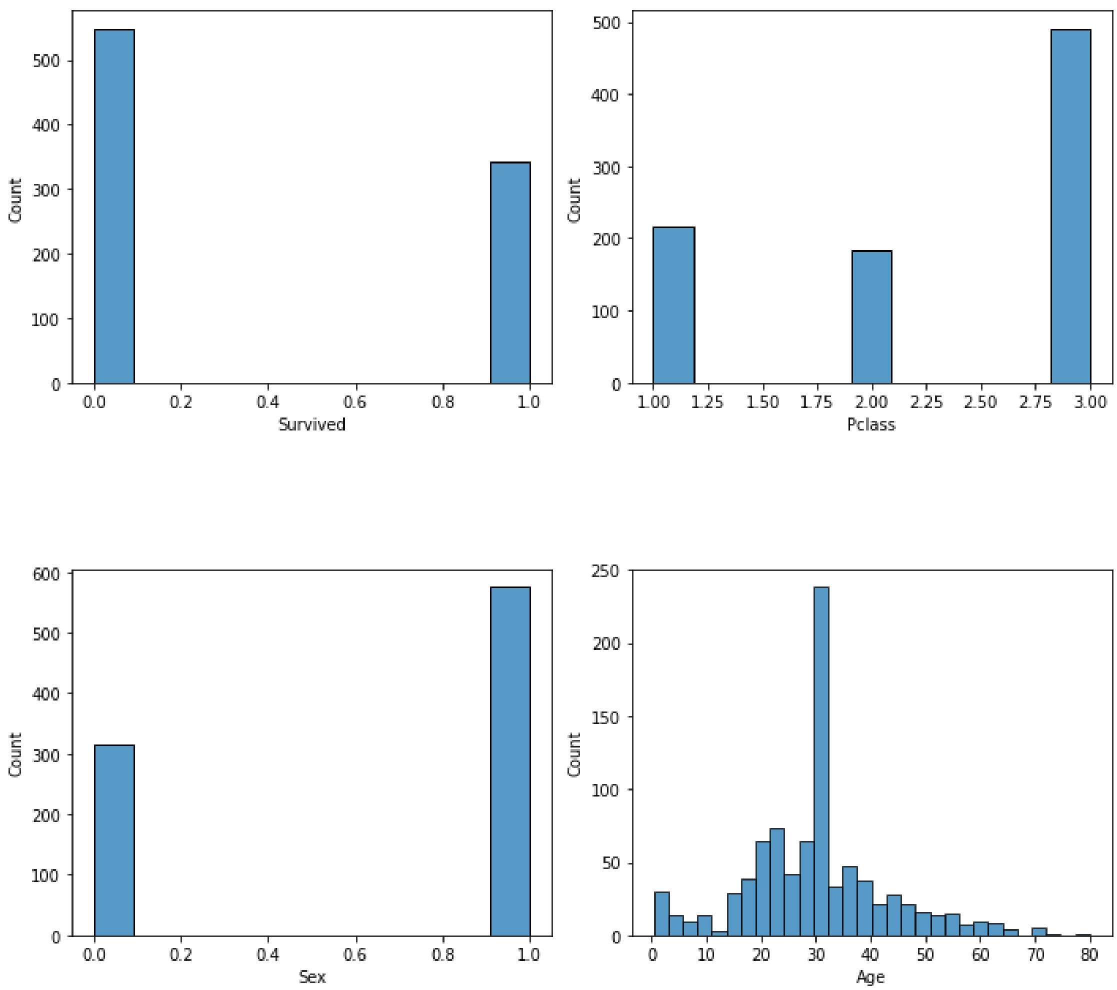
[30]:

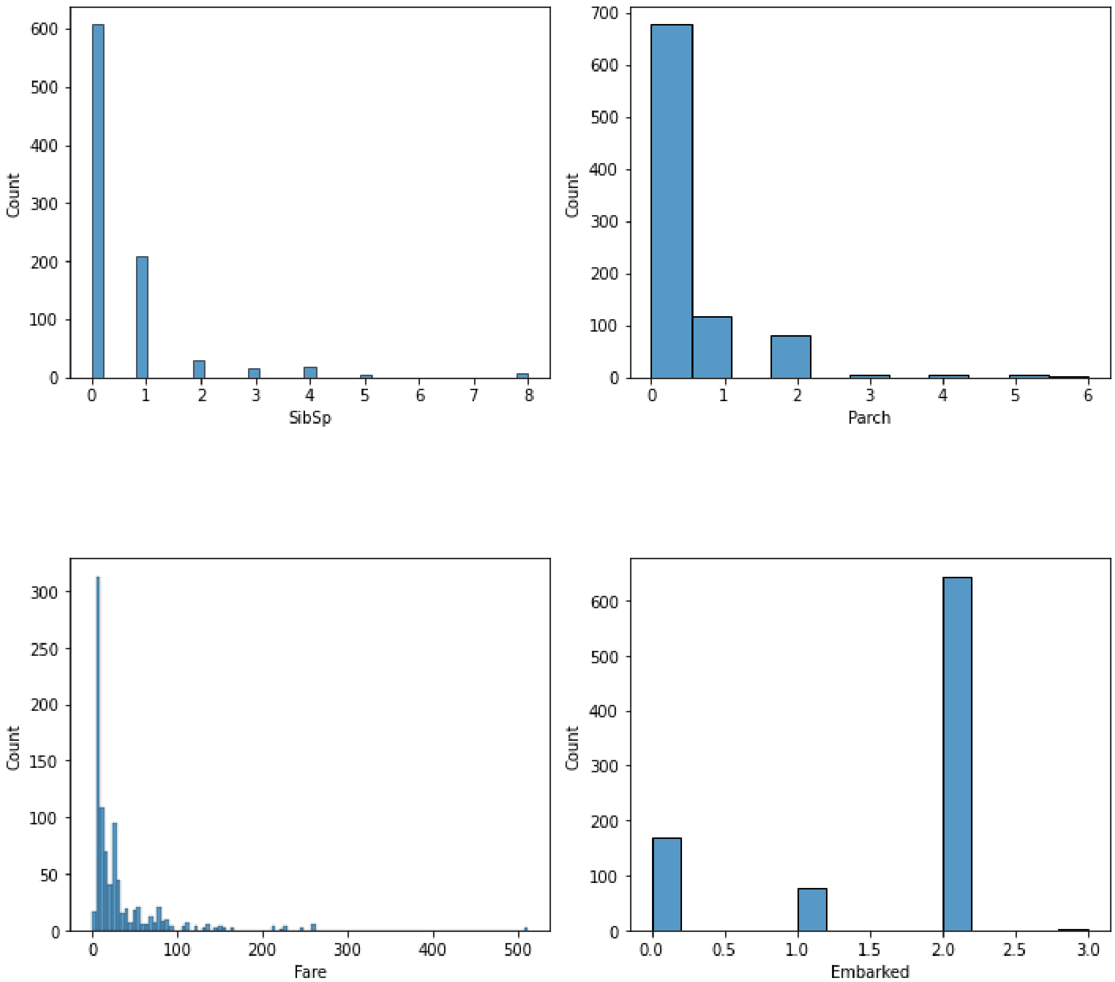
	Sex	Survived
0	0	0.742038
1	1	0.188908

Interpretation: male =74% and females=18% who survived in the targic titanic collapsed.

4 Analyze by visualizing the data

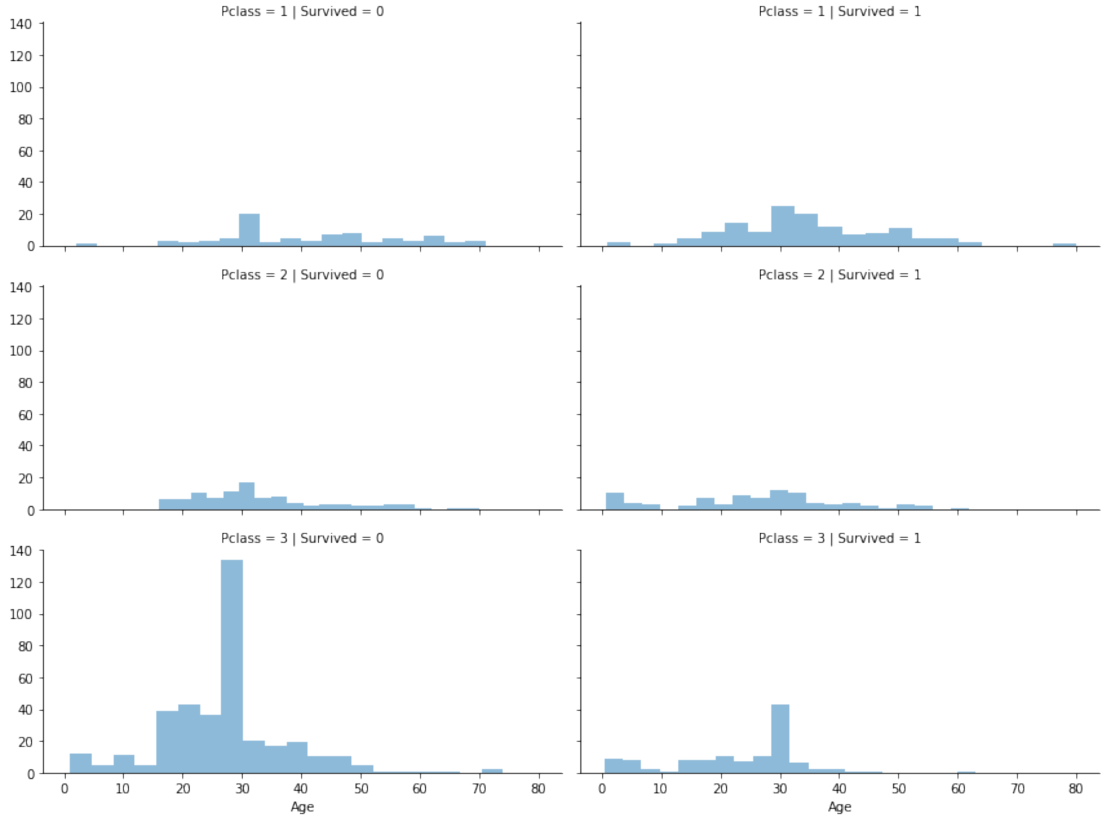
[31]:
```
import seaborn as sns

num_cols = ['Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare','Embarked']

for i in range(0,len(num_cols),2):
        plt.figure(figsize=(10,4))
        plt.subplot(121)
        sns.histplot(final_data[num_cols[i]], kde=False)
        plt.subplot(122)
        sns.histplot(final_data[num_cols[i+1]], kde=False)
        plt.tight_layout()
        plt.show()
```





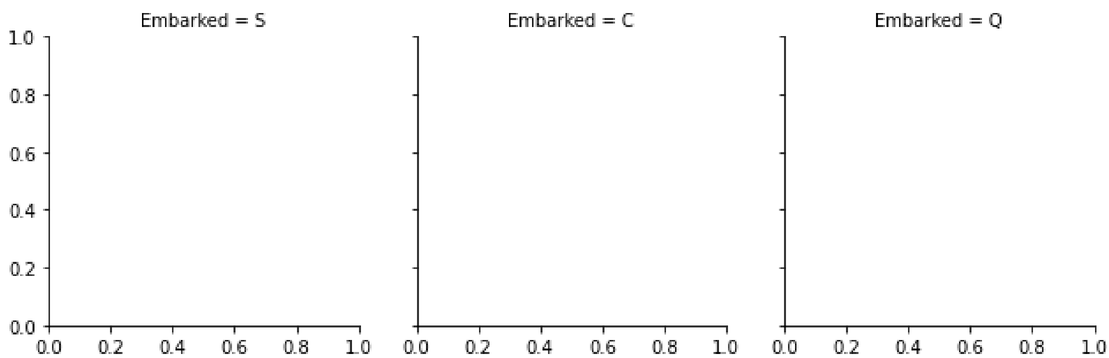
Interpretation: The survival rates in each category * Survived :300 above passenger survived * Age:survival rate was pretty more in the range between 30-40 * Pclass: first class passengers survived in higher range as compared to third class passengers * Fare: who has given more fare has higher chances of priority survival * Embarked:S has higher chances of survival * Sex:Make survives more as compared to female.

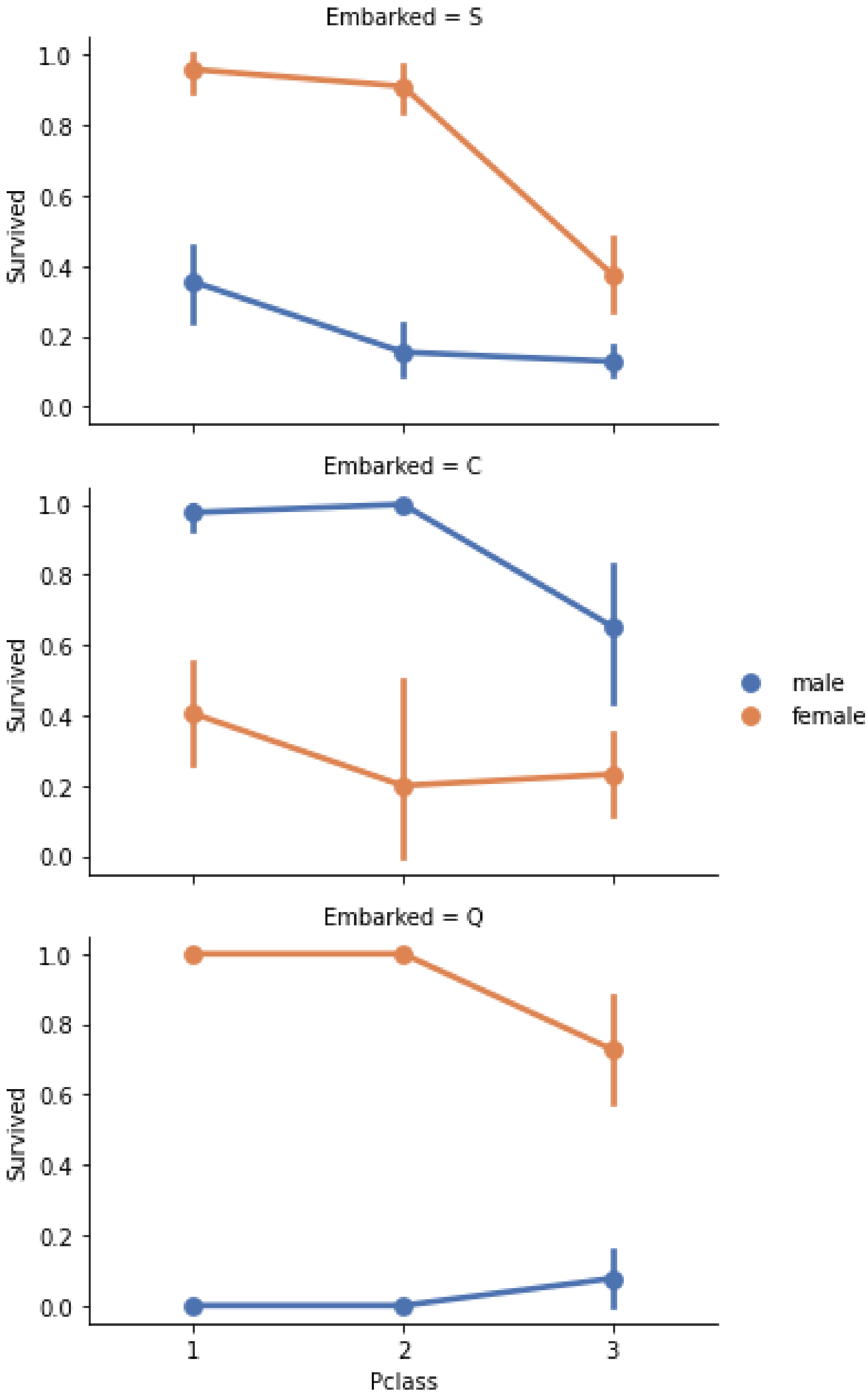
[32]:
```
#Lets try depth of visualization of passengers in class and survival of␣
 ↪passenger
grid_titanic =sns.FacetGrid(titanic,col='Survived',row='Pclass',aspect=2)
grid_titanic.map(plt.hist, 'Age', alpha=.5, bins=20)
grid_titanic.add_legend();
```



[33]:
```
grid_embarked = sns.FacetGrid(titanic, col='Embarked')
grid_embarked = sns.FacetGrid(titanic, row='Embarked', aspect=1.6)
grid_embarked.map(sns.pointplot, 'Pclass', 'Survived', 'Sex', palette='deep')
grid_embarked.add_legend()
```

[33]: <seaborn.axisgrid.FacetGrid at 0x7f037f5222f0>





Embarked = S
Embarked = C
Embarked = Q
Survived
1.0
0.8
0.6
0.4
0.2
0.0
1
2
3
Pclass
male
female

[34]:
```
plt.boxplot(final_data)
```

[34]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f037e94e020>,
  <matplotlib.lines.Line2D at 0x7f037e94ca60>,
  <matplotlib.lines.Line2D at 0x7f037e94f100>,
  <matplotlib.lines.Line2D at 0x7f037e94f3a0>,
  <matplotlib.lines.Line2D at 0x7f037e9803a0>,
  <matplotlib.lines.Line2D at 0x7f037e980640>,
  <matplotlib.lines.Line2D at 0x7f037e981600>,
  <matplotlib.lines.Line2D at 0x7f037e9818a0>,
  <matplotlib.lines.Line2D at 0x7f037e982860>,
  <matplotlib.lines.Line2D at 0x7f037e982b00>,
  <matplotlib.lines.Line2D at 0x7f037e983ac0>,
  <matplotlib.lines.Line2D at 0x7f037e983d60>,
  <matplotlib.lines.Line2D at 0x7f037e7c0d60>,
  <matplotlib.lines.Line2D at 0x7f037e7c1000>,
  <matplotlib.lines.Line2D at 0x7f037e7c1e10>,
  <matplotlib.lines.Line2D at 0x7f037e7c20b0>],
 'caps': [<matplotlib.lines.Line2D at 0x7f037e94e440>,
  <matplotlib.lines.Line2D at 0x7f037e94e6e0>,
  <matplotlib.lines.Line2D at 0x7f037e94f640>,
  <matplotlib.lines.Line2D at 0x7f037e94f8e0>,
  <matplotlib.lines.Line2D at 0x7f037e9808e0>,
  <matplotlib.lines.Line2D at 0x7f037e980b80>,
  <matplotlib.lines.Line2D at 0x7f037e981b40>,
  <matplotlib.lines.Line2D at 0x7f037e981de0>,
  <matplotlib.lines.Line2D at 0x7f037e982da0>,
  <matplotlib.lines.Line2D at 0x7f037e983040>,
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  <matplotlib.lines.Line2D at 0x7f037e7c02e0>,
  <matplotlib.lines.Line2D at 0x7f037e7c12a0>,
  <matplotlib.lines.Line2D at 0x7f037e7c13c0>,
  <matplotlib.lines.Line2D at 0x7f037e7c2350>,
  <matplotlib.lines.Line2D at 0x7f037e7c25f0>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f037e94dd80>,
  <matplotlib.lines.Line2D at 0x7f037e94ee60>,
  <matplotlib.lines.Line2D at 0x7f037e980100>,
  <matplotlib.lines.Line2D at 0x7f037e981360>,
  <matplotlib.lines.Line2D at 0x7f037e9825c0>,
  <matplotlib.lines.Line2D at 0x7f037e983820>,
  <matplotlib.lines.Line2D at 0x7f037e7c0ac0>,
  <matplotlib.lines.Line2D at 0x7f037e7c1b70>],
 'medians': [<matplotlib.lines.Line2D at 0x7f037e94e980>,
  <matplotlib.lines.Line2D at 0x7f037e94fb80>,
  <matplotlib.lines.Line2D at 0x7f037e980e20>,
```

```
 <matplotlib.lines.Line2D at 0x7f037e982080>,
 <matplotlib.lines.Line2D at 0x7f037e9832e0>,
 <matplotlib.lines.Line2D at 0x7f037e7c0580>,
 <matplotlib.lines.Line2D at 0x7f037e7c1630>,
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'fliers': [<matplotlib.lines.Line2D at 0x7f037e94ebc0>,
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 <matplotlib.lines.Line2D at 0x7f037e9810c0>,
 <matplotlib.lines.Line2D at 0x7f037e982320>,
 <matplotlib.lines.Line2D at 0x7f037e983580>,
 <matplotlib.lines.Line2D at 0x7f037e7c0820>,
 <matplotlib.lines.Line2D at 0x7f037e7c18d0>,
 <matplotlib.lines.Line2D at 0x7f037e7c2b30>],
'means': []}
```
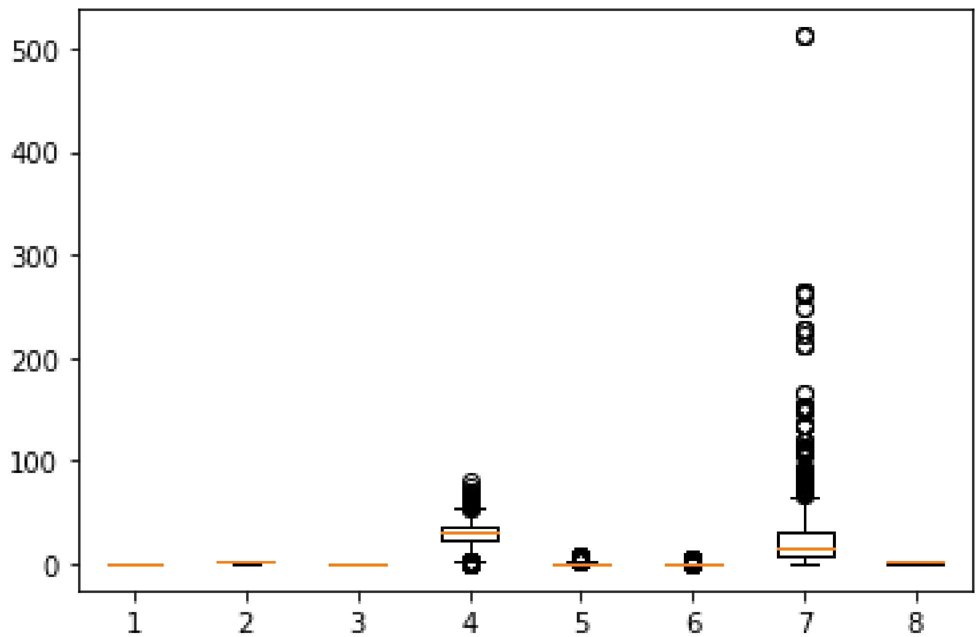



[59]:
```
# lets import machine learning models
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold, cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB␣
↪,BernoulliNB,ComplementNB,CategoricalNB,MultinomialNB
```

```
from sklearn.model_selection import train_test_split,KFold,cross_val_score
from sklearn.metrics import classification_report,␣
↪f1_score,accuracy_score,precision_score,confusion_matrix
from sklearn.preprocessing import StandardScaler
```

[36]:
```
final_data.columns
```

[36]:
```
Index(['Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare',
       'Embarked'],
      dtype='object')
```

[37]:
```
x= final_data.drop('Survived',axis=1)
y= final_data['Survived']
```

[38]:
```
x.head()
```

[38]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	3	1	22.0	1	0	7.2500	2
1	1	0	38.0	1	0	71.2833	0
2	3	0	26.0	0	0	7.9250	2
3	1	0	35.0	1	0	53.1000	2
4	3	1	35.0	0	0	8.0500	2

[39]:
```
y
```

[39]:
```
0      0
1      1
2      1
3      1
4      0
      ..
886    0
887    1
888    0
889    1
890    0
Name: Survived, Length: 891, dtype: int64
```

[40]:
```
# lets split the data in train ans test set
x_train,x_test,y_train,y_test= train_test_split(x,y,test_size=0.3)
```

[41]:
```
print("the x_train shape", x_train.shape)
print("the y_train shape", y_train.shape)

print("the x_test shape", x_test.shape)
print("the y_test shape", y_test.shape)
```

```
the x_train shape (623, 7)
the y_train shape (623,)
the x_test shape (268, 7)
the y_test shape (268,)
```

[42]:
```
y.info()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 891 entries, 0 to 890
Series name: Survived
Non-Null Count  Dtype
--------------  -----
891 non-null    int64
dtypes: int64(1)
memory usage: 7.1 KB
```

[43]:
```
sc= StandardScaler()
```

[44]:
```
x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
```

[45]:
```
classifier = LogisticRegression(random_state=0, solver="liblinear")
classifier.fit(x_train, y_train)
```

[45]:
```
LogisticRegression(random_state=0, solver='liblinear')
```

[46]:
```
y_pred = classifier.predict(x_test)
```

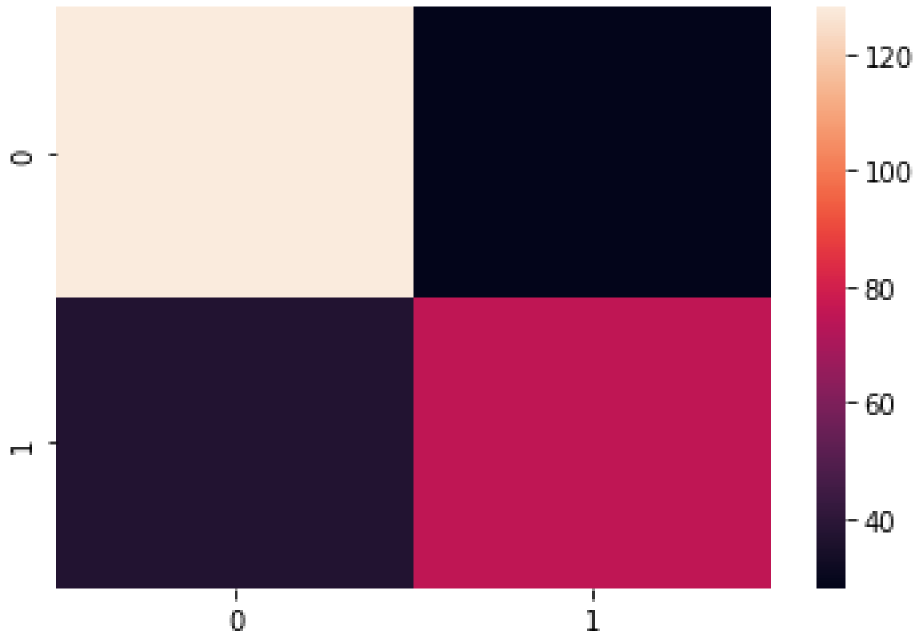
[47]:
```
# confusion matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy score:",accuracy)
```

```
[[128  28]
 [ 37  75]]
Accuracy score: 0.7574626865671642
```

with the help of logisticRegression the accuracy socre is 76%

[48]:
```
# plot the heatmap
sns.heatmap(cm)
```

[48]:
```
<AxesSubplot: >
```



[57]:
```
classification_models = []
classification_models.append(('Logistic Regression',␣
 ↪LogisticRegression(solver="liblinear")))
classification_models.append(('K Nearest Neighbor',␣
 ↪KNeighborsClassifier(n_neighbors=5, metric="minkowski",p=2)))
classification_models.append(('Kernel SVM using rbf', SVC(kernel =␣
 ↪'rbf',gamma='scale')))
classification_models.append(('Naive Bayes', GaussianNB()))
classification_models.append(('Decision Tree', DecisionTreeClassifier(criterion␣
 ↪= "entropy")))
classification_models.append(('Random Forest',␣
 ↪RandomForestClassifier(n_estimators=100, criterion="entropy")))
```

[58]:
```
for name, model in classification_models:
  kfold = KFold(n_splits=10, random_state=(7), shuffle=(True))
  result = cross_val_score(model, x, y, cv=kfold, scoring='accuracy')
  print("%s: Mean Accuracy = %.2f%% - SD Accuracy = %.2f%%" % (name, result.
 ↪mean()*100, result.std()*100))
```

```
Logistic Regression: Mean Accuracy = 79.24% - SD Accuracy = 4.24%
K Nearest Neighbor: Mean Accuracy = 70.25% - SD Accuracy = 6.20%
Kernel SVM using rbf: Mean Accuracy = 67.44% - SD Accuracy = 5.70%
Naive Bayes: Mean Accuracy = 78.56% - SD Accuracy = 4.40%
Decision Tree: Mean Accuracy = 78.57% - SD Accuracy = 3.49%
Random Forest: Mean Accuracy = 81.60% - SD Accuracy = 5.96%
```

[54]:
```
# lets try again for kernel:kernel{'linear', 'poly', 'rbf', 'sigmoid',␣
↪'precomputed'}
# decision tree creterion:{gini,logloss}
classification_models = []
classification_models.append(('Logistic Regression',␣
↪LogisticRegression(solver="liblinear")))
classification_models.append(('K Nearest Neighbor',␣
↪KNeighborsClassifier(n_neighbors=5, metric="minkowski",p=2)))
classification_models.append(('Kernel SVM using poly', SVC(kernel =␣
↪'poly',gamma='scale')))
classification_models.append(('Naive Bayes', GaussianNB()))
classification_models.append(('Decision Tree using Gini',␣
↪DecisionTreeClassifier(criterion = "gini")))
classification_models.append(('Decision Tree using LogLoss',␣
↪DecisionTreeClassifier(criterion = "log_loss")))
classification_models.append(('Random Forest using Gini',␣
↪RandomForestClassifier(n_estimators=100, criterion="gini")))
classification_models.append(('Random Forest using LogLoss',␣
↪RandomForestClassifier(n_estimators=100, criterion="log_loss")))
```

[55]:
```
for name, model in classification_models:
  kfold = KFold(n_splits=10, random_state=(7), shuffle=(True))
  result = cross_val_score(model, x, y, cv=kfold, scoring='accuracy')
  print("%s: Mean Accuracy = %.2f%% - SD Accuracy = %.2f%%" % (name, result.
↪mean()*100, result.std()*100))
```

```
Logistic Regression: Mean Accuracy = 79.24% - SD Accuracy = 4.24%
K Nearest Neighbor: Mean Accuracy = 70.25% - SD Accuracy = 6.20%
Kernel SVM using poly: Mean Accuracy = 64.53% - SD Accuracy = 6.43%
Naive Bayes: Mean Accuracy = 78.56% - SD Accuracy = 4.40%
Decision Tree using Gini: Mean Accuracy = 77.67% - SD Accuracy = 4.33%
Decision Tree using LogLoss: Mean Accuracy = 79.12% - SD Accuracy = 3.12%
Random Forest using Gini: Mean Accuracy = 80.92% - SD Accuracy = 5.32%
Random Forest using LogLoss: Mean Accuracy = 81.37% - SD Accuracy = 5.66%
```

[60]:
```
classification_models = []
classification_models.append(('Naive Bayes', GaussianNB()))
classification_models.append(('Naive Bayes', BernoulliNB()))
classification_models.append(('Naive Bayes', ComplementNB()))
classification_models.append(('Naive Bayes', ComplementNB()))
classification_models.append(('Naive Bayes', CategoricalNB()))
classification_models.append(('Naive Bayes', MultinomialNB()))
```

[61]:
```
for name, model in classification_models:
  kfold = KFold(n_splits=10, random_state=(7), shuffle=(True))
  result = cross_val_score(model, x, y, cv=kfold, scoring='accuracy')
```

```
print("%s: Mean Accuracy = %.2f%% - SD Accuracy = %.2f%%" % (name, result.
↪mean()*100, result.std()*100))
```

```
Naive Bayes: Mean Accuracy = 78.56% - SD Accuracy = 4.40%
Naive Bayes: Mean Accuracy = 78.68% - SD Accuracy = 4.37%
Naive Bayes: Mean Accuracy = 68.68% - SD Accuracy = 4.70%
Naive Bayes: Mean Accuracy = 68.68% - SD Accuracy = 4.70%
Naive Bayes: Mean Accuracy = nan% - SD Accuracy = nan%
Naive Bayes: Mean Accuracy = 68.68% - SD Accuracy = 4.70%
```

[ ]:

```

```

5 Observation:

- Logistic Regression: Logistic Regression is a useful model to run early in the workflow. Logistic regression measures the relationship between the categorical dependent variable (feature) and one or more independent variables (features) by estimating probabilities using a logistic function, which is the cumulative logistic distribution. (Reference Wikipedia.)
- Logistic Regression: Mean Accuracy = 79.24% - SD Accuracy = 4.24%
- K Nearest Neighbour: In pattern recognition, the k-Nearest Neighbors algorithm (or k-NN for short) is a non-parametric method used for classification and regression. A sample is classified by a majority vote of its neighbors, with the sample being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor. Reference Wikipedia.
- K Nearest Neighbor: Mean Accuracy = 70.25% - SD Accuracy = 6.20%
- SVM: we model using Support Vector Machines which are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training samples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new test samples to one category or the other, making it a non-probabilistic binary linear classifier. Reference Wikipedia.
- Kernel SVM using rbf: Mean Accuracy = 67.44% - SD Accuracy = 5.70%
- Kernel SVM using poly: Mean Accuracy = 64.53% - SD Accuracy = 6.43%
- Decision Tree Classifier: This model uses a decision tree as a predictive model which maps features (tree branches) to conclusions about the target value (tree leaves). Tree models where the target variable can take a finite set of values are called classification trees; in these tree structures, leaves represent class labels and branches represent conjunctions of features that lead to those class labels. Decision trees where the target variable can take continuous values (typically real numbers) are called regression trees. Reference Wikipedia.
- Decision Tree: Mean Accuracy = 78.57% - SD Accuracy = 3.49%
- Decision Tree using Gini: Mean Accuracy = 77.67% - SD Accuracy = 4.33%
- Decision Tree using LogLoss: Mean Accuracy = 79.12% - SD Accuracy = 3.12%

- Random Forest Tree Classifier: The next model Random Forests is one of the most popular. Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees (n_estimators=100) at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Reference Wikipedia.
- Random Forest using Gini: Mean Accuracy = 80.92% - SD Accuracy = 5.32%
- Random Forest using LogLoss: Mean Accuracy = 81.37% - SD Accuracy = 5.66%
- Random Forest: Mean Accuracy = 81.60% - SD Accuracy = 5.96%
- Navie Bayes: In machine learning, naive Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong (naive) independence assumptions between the features. Naive Bayes classifiers are highly scalable, requiring a number of parameters linear in the number of variables (features) in a learning problem. (Reference Wikipedia.)
- Naive Bayes: Mean Accuracy = 78.56% - SD Accuracy = 4.40%
- Naive Bayes: Mean Accuracy = 78.68% - SD Accuracy = 4.37%
- Naive Bayes: Mean Accuracy = 68.68% - SD Accuracy = 4.70%
- Naive Bayes: Mean Accuracy = 68.68% - SD Accuracy = 4.70%
- Naive Bayes: Mean Accuracy = nan% - SD Accuracy = nan%
- Naive Bayes: Mean Accuracy = 68.68% - SD Accuracy = 4.70%

6 Conclusion:

- KNeighbour classifier works well as compared to svc and but was worst than logistic regression.
- amongst decision tree and random forest, for this dataset random forest works pretty great here with an accuracy 81%
- Naive bayes works moderately here as accuracy ranges as compared to random forest and logistic regression is very less.

6.1 Hence for titanic survival dataset random forest, logisitc regression and decision tree classifier.

-Zeba Khan

[ ]:
```

```