Titanic_survival_prediction

May 30, 2024

Predicting Survival From Titanic Crash

1 Objective : Titanic Crash Survived Classification

2 Exploratory Data Analysis (EDA) - Python

3 Insights - Patterns

4 Classification (Using the ML)

5 1. Load Python Modules

[45]:
```
#  Use Python's import statement to load modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
import warnings
warnings.filterwarnings('ignore', category=FutureWarning)

from tabulate import tabulate

from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import LabelEncoder


from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression

from sklearn.naive_bayes import CategoricalNB
from sklearn.naive_bayes import GaussianNB

from sklearn.svm import SVC

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier


from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier

from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from imblearn.over_sampling import SMOTE
```

6 2. Read the Dataset from CSV file - Using Pandas

[46]:
```
file_path=r"Titanic_Dataset.csv"
titanic_df = pd.read_csv(file_path)
titanic_df.head()
```

[46]:
```
   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
```

[47]:
```
#drop - sensitive - non imp columns
titanic_df.drop(['PassengerId','Name','Ticket'],axis=1,inplace=True)
titanic_df.head()
```

[47]:
```
   Survived  Pclass     Sex   Age  SibSp  Parch     Fare Cabin Embarked
0         0       3    male  22.0      1      0   7.2500   NaN        S
1         1       1  female  38.0      1      0  71.2833   C85        C
2         1       3  female  26.0      0      0   7.9250   NaN        S
3         1       1  female  35.0      1      0  53.1000  C123        S
4         0       3    male  35.0      0      0   8.0500   NaN        S
```

7 3. Basic Inspection on given dataset

[48]:
```
def basic_inspection_dataset(table):
    """Generates a basic inspection dataset from the given table."""

    print("top 5 rows - using head")
    print(table.head())
    print()

    print("bottom 5 rows using tail")
    print(table.tail())
    print()

    print("numbers of samples and columns")
    print(table.shape)
    print()

    print("numbers of samples ")
```

```
    print(len(table))
    print()

    print("numbers of entries in the data frame")
    print(table.size)
    print()

    print("Columns Names")
    print(table.columns)
    print()

    print("Columns dtypes")
    print(table.dtypes)
    print()

    print("Dataframe info")
    print(table.info())
    print()

    print()
    print("check the missing value in each column")
    print(table.isnull().sum())

    print()
    print("check the missing value in each column")
    print(table.isna().sum())

basic_inspection_dataset(titanic_df)
```

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

bottom 5 rows using tail
     Survived  Pclass     Sex   Age  SibSp  Parch   Fare Cabin Embarked
886         0       2    male  27.0      0      0  13.00   NaN        S
887         1       1  female  19.0      0      0  30.00   B42        S
888         0       3  female   NaN      1      2  23.45   NaN        S
889         1       1    male  26.0      0      0  30.00  C148        C
890         0       3    male  32.0      0      0   7.75   NaN        Q

numbers of samples and columns
(891, 9)
```

```
numbers of samples
891

numbers of entries in the data frame
8019

Columns Names
Index(['Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare', 'Cabin',
       'Embarked'],
      dtype='object')

Columns dtypes
Survived      int64
Pclass        int64
Sex          object
Age         float64
SibSp         int64
Parch         int64
Fare        float64
Cabin        object
Embarked     object
dtype: object

Dataframe info
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 9 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Survived  891 non-null    int64
 1   Pclass    891 non-null    int64
 2   Sex       891 non-null    object
 3   Age       714 non-null    float64
 4   SibSp     891 non-null    int64
 5   Parch     891 non-null    int64
 6   Fare      891 non-null    float64
 7   Cabin     204 non-null    object
 8   Embarked  889 non-null    object
dtypes: float64(2), int64(4), object(3)
memory usage: 62.8+ KB
None


check the missing value in each column
Survived      0
Pclass        0
Sex           0
Age         177
```

```
SibSp         0
Parch         0
Fare          0
Cabin       687
Embarked      2
dtype: int64

check the missing value in each column
Survived      0
Pclass        0
Sex           0
Age         177
SibSp         0
Parch         0
Fare          0
Cabin       687
Embarked      2
dtype: int64
```

[49]:
```python
#drop - due to huge null values and non imp features
titanic_df.drop(['Cabin','Embarked'],axis=1,inplace=True)
titanic_df.head()
```

[49]:

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

8 4. Handling Missing Values - Cat - Variables

[50]:
```python
# No Missing Values - I am skipping this section
titanic_df.isnull().sum()
```

[50]:
```
Survived      0
Pclass        0
Sex           0
Age         177
SibSp         0
Parch         0
Fare          0
dtype: int64
```

[51]:
```python
## conver to cat - object data type
titanic_df["Pclass"]=titanic_df["Pclass"].astype("object")
titanic_df["Survived"]=titanic_df["Survived"].astype("object")
```

```
titanic_df["SibSp"]=titanic_df["SibSp"].astype("object")
titanic_df["Parch"]=titanic_df["Parch"].astype("object")
```

[52]:
```
titanic_df.dtypes
```

[52]:
```
Survived     object
Pclass       object
Sex          object
Age         float64
SibSp        object
Parch        object
Fare        float64
dtype: object
```

9 5. Categorical- Variable - Analysis -Using Pipeline

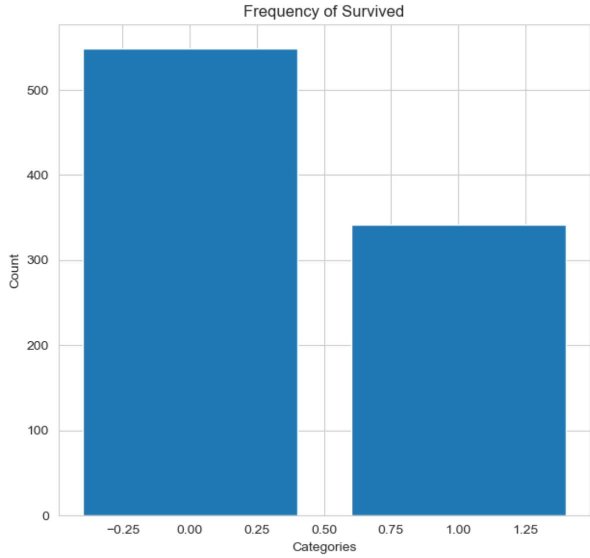
[53]:
```
class BarPieChartTransformer(BaseEstimator, TransformerMixin):
    def __init__(self):
        pass

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        df=X.copy()
        cat_cols = df.select_dtypes(include='object').columns
        for cat_name in cat_cols:
            value_counts = df[cat_name].value_counts().reset_index()
            # Rename the columns
            value_counts.columns = ['Class', 'Frequency']

            # Print the result as a table
            print(f"{cat_name} frequency table")
            print(tabulate(value_counts, headers='keys', tablefmt='pretty'))

            # Calculate relative frequency
            total_count = value_counts['Frequency'].sum()
            value_counts['Relative Frequency %'] =␣
↪round((value_counts['Frequency'] / total_count)*100,2)

            # Print the result as a table
            print(f"{cat_name} Relative frequency table")
            print(tabulate(value_counts, headers='keys', tablefmt='pretty'))

            # Extract the values and index from value counts
            value_counts = df[cat_name].value_counts()
```

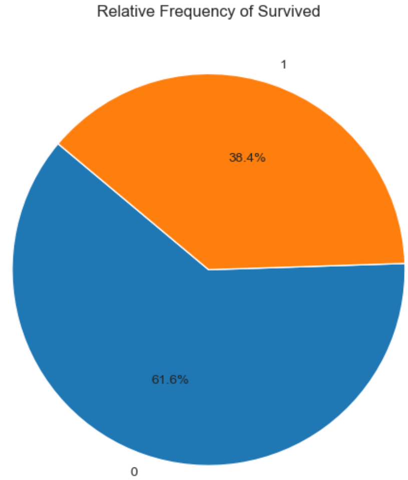
```
            values = value_counts.values
            labels = value_counts.index

            fig, axs = plt.subplots(1, 2, figsize=(12, 6))  # 1 row, 2 columns
            # Create a bar graph
            axs[0].bar(labels, values)
            axs[0].set_title(f'Frequency of {cat_name}')
            axs[0].set_xlabel('Categories')  # Set x-label
            axs[0].set_ylabel('Count')       # Set y-label

            axs[1].pie(value_counts.values, labels=value_counts.index,␣
↪autopct='%1.1f%%', startangle=140)
            axs[1].set_title(f'Relative Frequency of {cat_name}')
            plt.tight_layout()
            # Show the plot
            plt.show()
```

[54]:

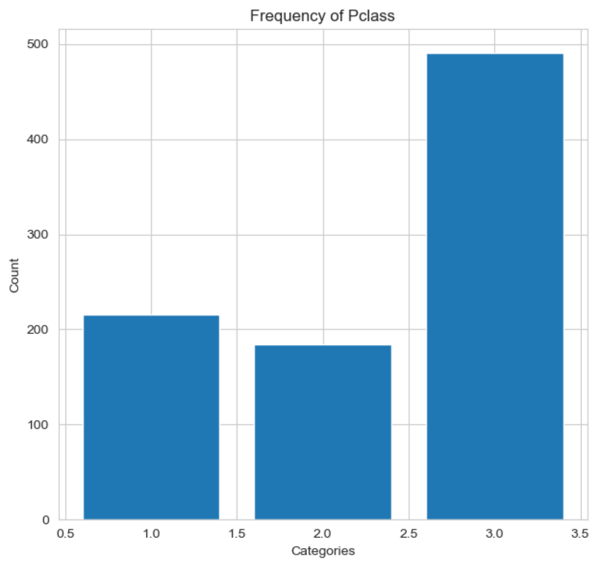
```
pipeline_cat_var = Pipeline([
    ('bar_pie_chart', BarPieChartTransformer())
])


# Fit and transform your data using the pipeline
processed_data = pipeline_cat_var.fit_transform(titanic_df)
```

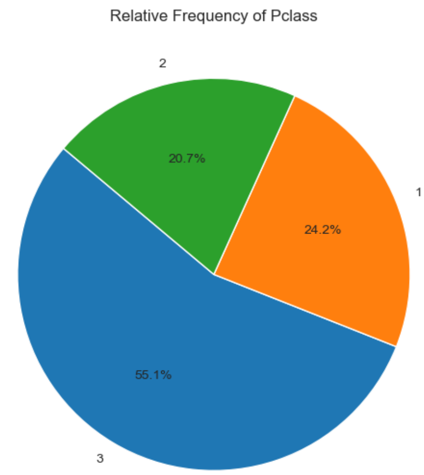
```
Survived frequency table
+---+-------+-----------+
|   | Class | Frequency |
+---+-------+-----------+
| 0 |   0   |    549    |
| 1 |   1   |    342    |
+---+-------+-----------+
Survived Relative frequency table
+---+-------+-----------+----------------------+
|   | Class | Frequency | Relative Frequency % |
+---+-------+-----------+----------------------+
| 0 |  0.0  |   549.0   |        61.62         |
| 1 |  1.0  |   342.0   |        38.38         |
+---+-------+-----------+----------------------+
```






```
Pclass frequency table
+---+-------+-----------+
|   | Class | Frequency |
+---+-------+-----------+
| 0 |   3   |    491    |
| 1 |   1   |    216    |
| 2 |   2   |    184    |
+---+-------+-----------+
Pclass Relative frequency table
+---+-------+-----------+----------------------+
|   | Class | Frequency | Relative Frequency % |
+---+-------+-----------+----------------------+
| 0 |  3.0  |   491.0   |        55.11         |
| 1 |  1.0  |   216.0   |        24.24         |
| 2 |  2.0  |   184.0   |        20.65         |
+---+-------+-----------+----------------------+
```



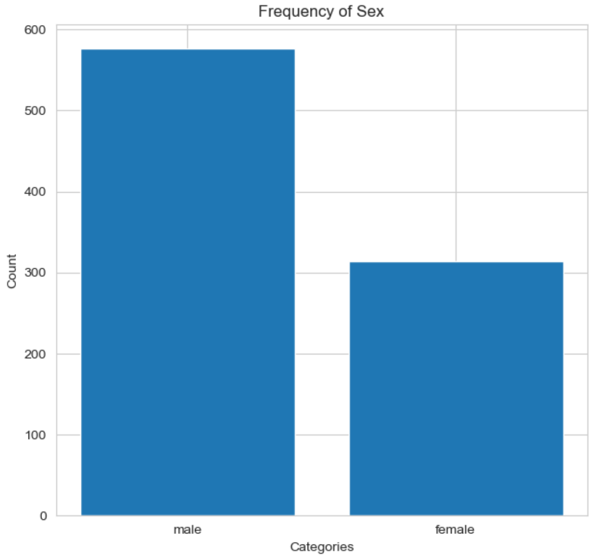


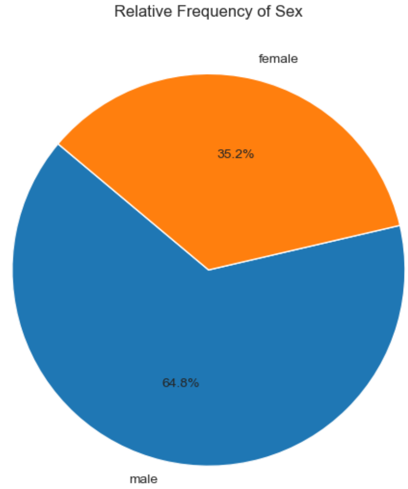
Sex frequency table

	Class	Frequency
0	male	577
1	female	314

Sex Relative frequency table

	Class	Frequency	Relative Frequency %
0	male	577	64.76
1	female	314	35.24



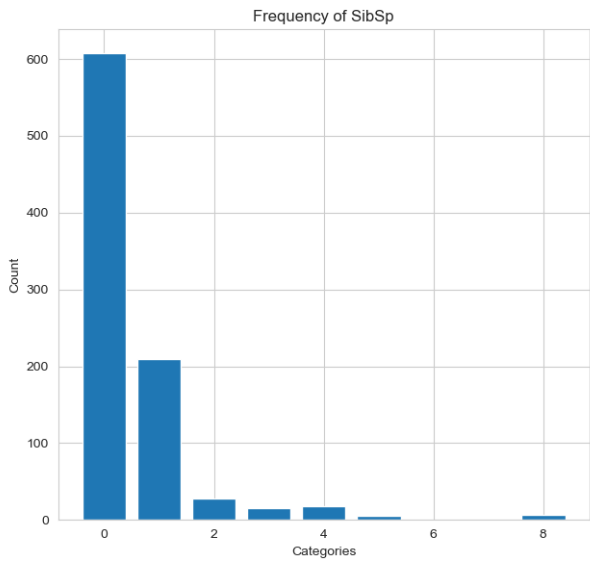


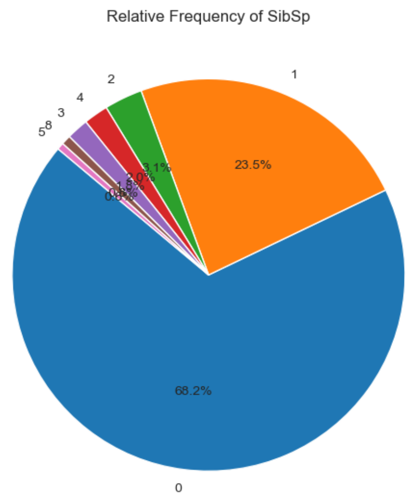
SibSp frequency table

	Class	Frequency
0	0	608
1	1	209
2	2	28
3	4	18
4	3	16
5	8	7
6	5	5

SibSp Relative frequency table

	Class	Frequency	Relative Frequency %
0	0.0	608.0	68.24
1	1.0	209.0	23.46
2	2.0	28.0	3.14
3	4.0	18.0	2.02
4	3.0	16.0	1.8
5	8.0	7.0	0.79
6	5.0	5.0	0.56



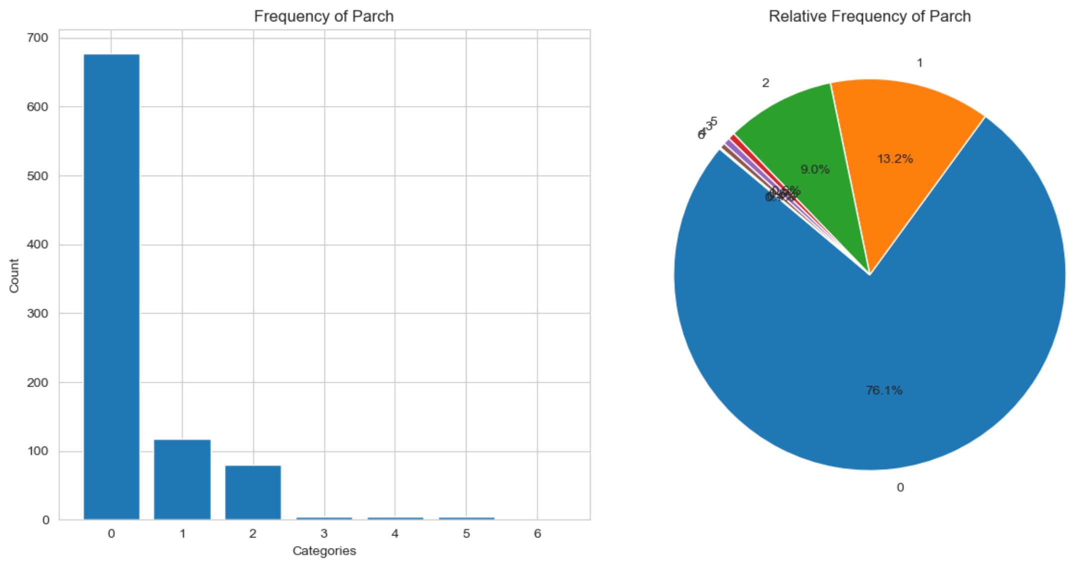


Parch frequency table

	Class	Frequency
0	0	678
1	1	118
2	2	80
3	5	5
4	3	5
5	4	4
6	6	1

Parch Relative frequency table

	Class	Frequency	Relative Frequency %
0	0.0	678.0	76.09
1	1.0	118.0	13.24
2	2.0	80.0	8.98
3	5.0	5.0	0.56
4	3.0	5.0	0.56
5	4.0	4.0	0.45
6	6.0	1.0	0.11



10 6. Handling Missing Values in Numerical Columns

[55]:
```python
titanic_df.isnull().sum()
```

[55]:
```
Survived      0
Pclass        0
Sex           0
Age         177
SibSp         0
Parch         0
Fare          0
dtype: int64
```

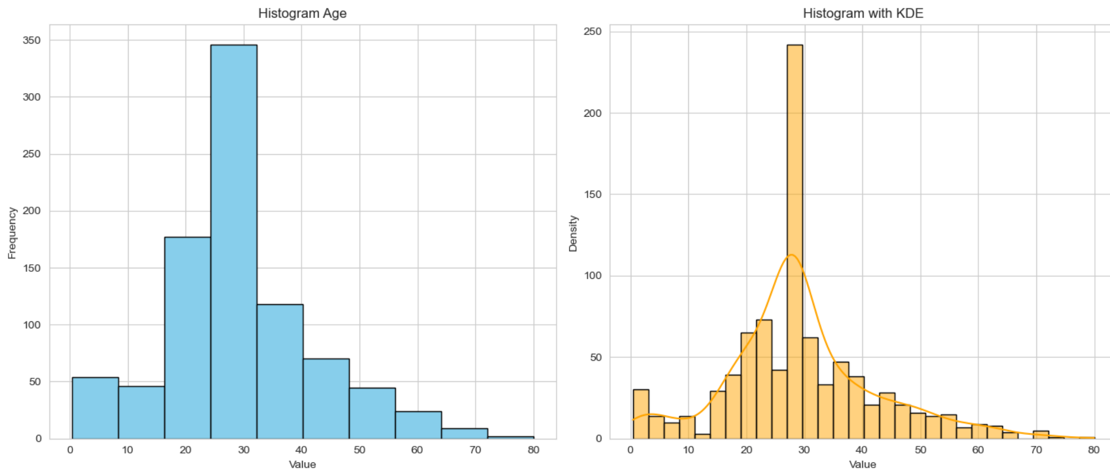
[56]:
```python
#filling with mean/median
titanic_df["Age"] = titanic_df["Age"].fillna(titanic_df["Age"].median())
titanic_df.head()
titanic_df.isnull().sum()
```

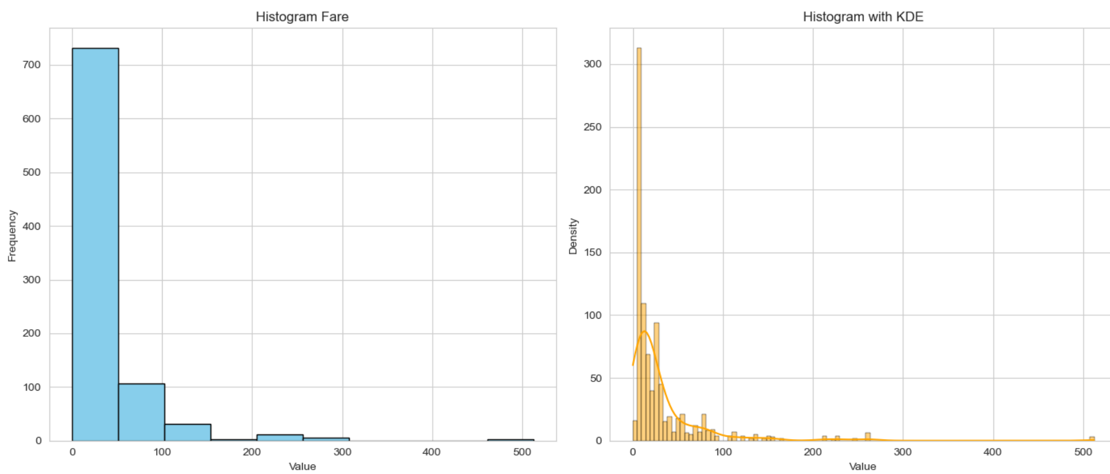
[56]:
```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
dtype: int64
```

11 7. Numerical - Variables - Analysis - Using -Pipeline

[57]:
```
class HistBoxChartTransformer(BaseEstimator, TransformerMixin):
    def __init__(self):
        pass

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        df=X.copy()
        num_cols = df.select_dtypes(exclude='object').columns
        for con_var in num_cols:

            # Create a figure and axes object
            fig, axes = plt.subplots(1, 2, figsize=(14, 6))

            # Plot histogram without KDE on the left
            axes[0].hist(df[con_var],  color='skyblue', edgecolor='black')
            axes[0].set_xlabel('Value')
            axes[0].set_ylabel('Frequency')
            axes[0].set_title(f'Histogram {con_var}')

            # Plot histogram with KDE on the right
            sns.histplot(data=df, x=con_var, kde=True, color='orange',␣
↪edgecolor='black', ax=axes[1])
            axes[1].set_xlabel('Value')
            axes[1].set_ylabel('Density')
            axes[1].set_title('Histogram with KDE')

            # Adjust layout
            plt.tight_layout()

            # Show the combined plot
            plt.show()
```

[58]:
```
pipeline_num_var = Pipeline([
    ('hist_box_chart', HistBoxChartTransformer())
])


# Fit and transform your data using the pipeline
processed_data = pipeline_num_var.fit_transform(titanic_df)
```





12 8. Numerical - Variables -Outliers Analysis

[59]:
```python
titanic_df.select_dtypes(exclude="object").columns
```

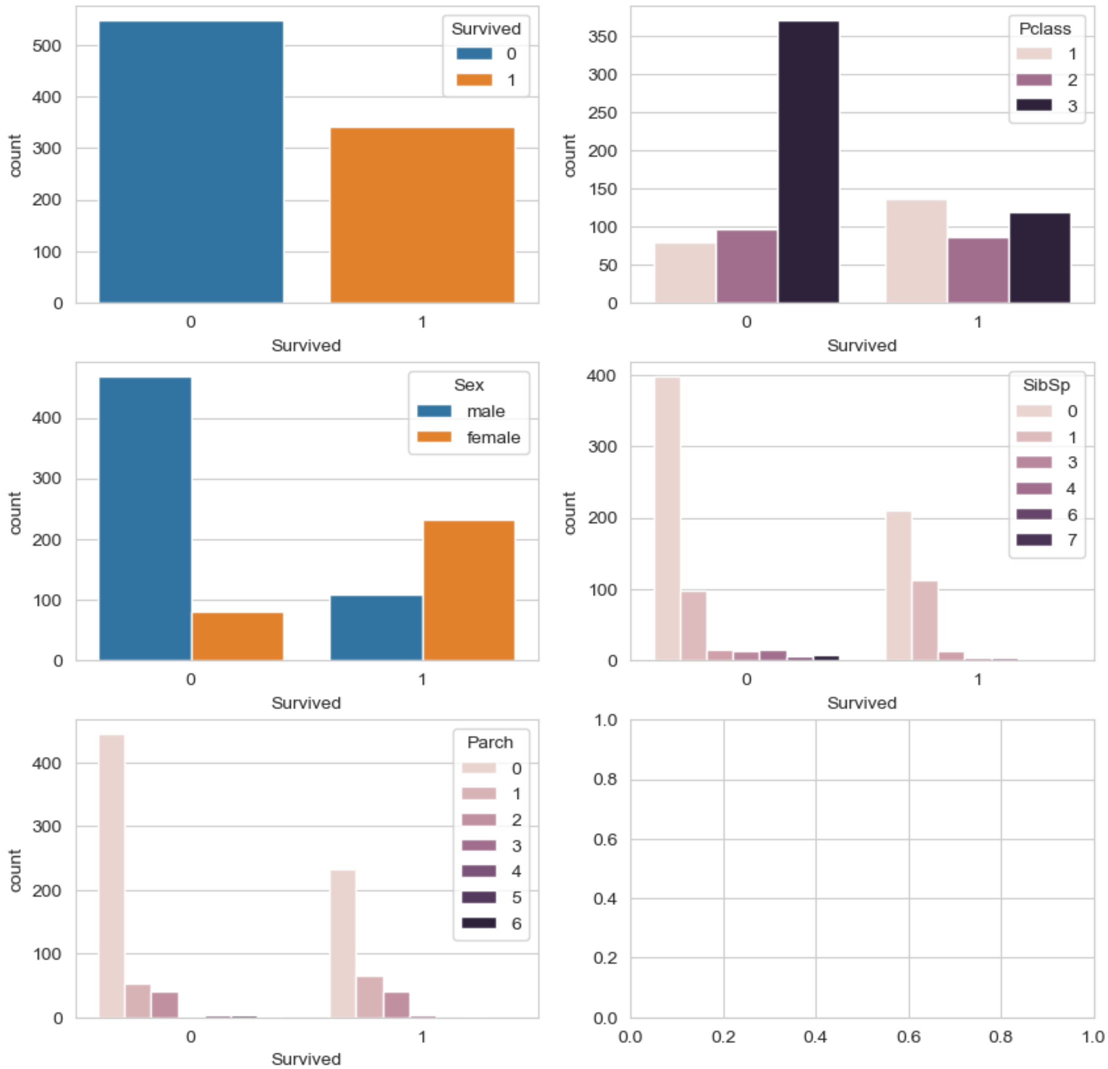
[59]: Index(['Age', 'Fare'], dtype='object')

13 9. Bi Variate Analyis

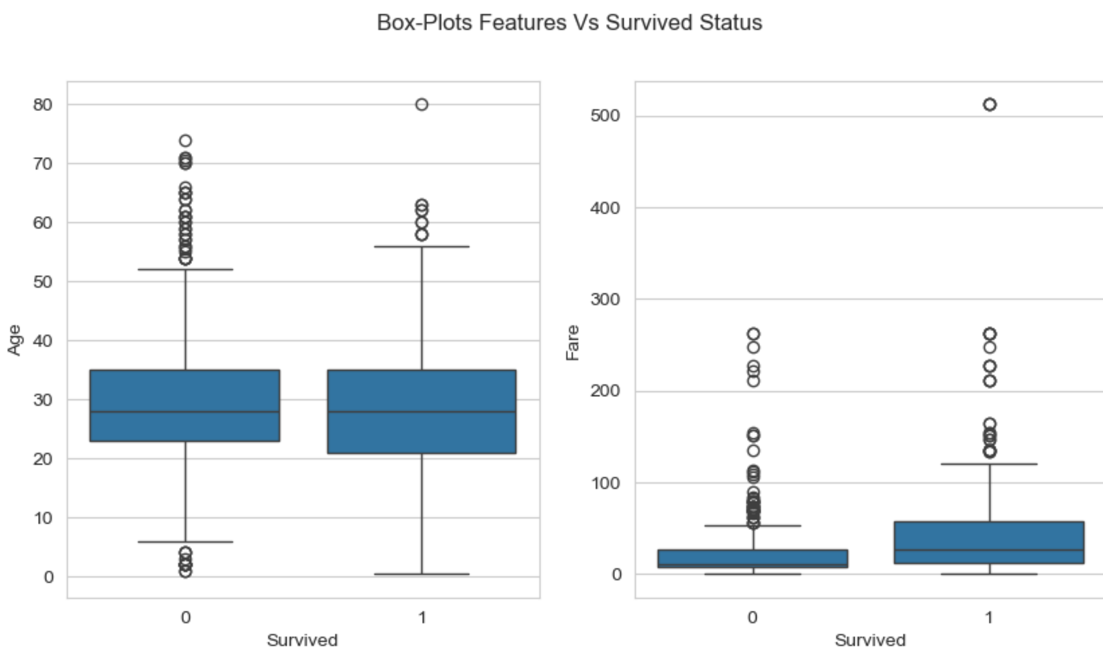
[60]:
```python
cat_vars = titanic_df.select_dtypes(include="object").columns
cat_vars
```

[60]: Index(['Survived', 'Pclass', 'Sex', 'SibSp', 'Parch'], dtype='object')

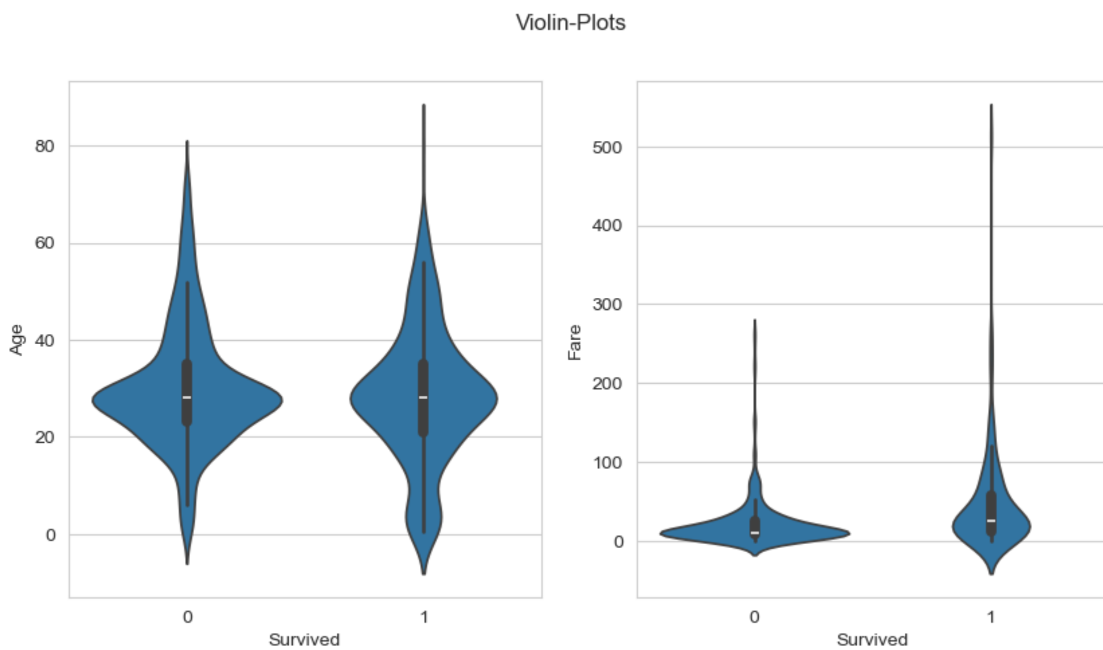
[61]:
```
## Cat Vs Cat
output_var="Survived"
fig,ax = plt.subplots(3,2,figsize=(10,10))
for axi,x in zip(ax.flat,cat_vars):
    sns.countplot(x=output_var,hue=x,ax=axi , data=titanic_df)
```



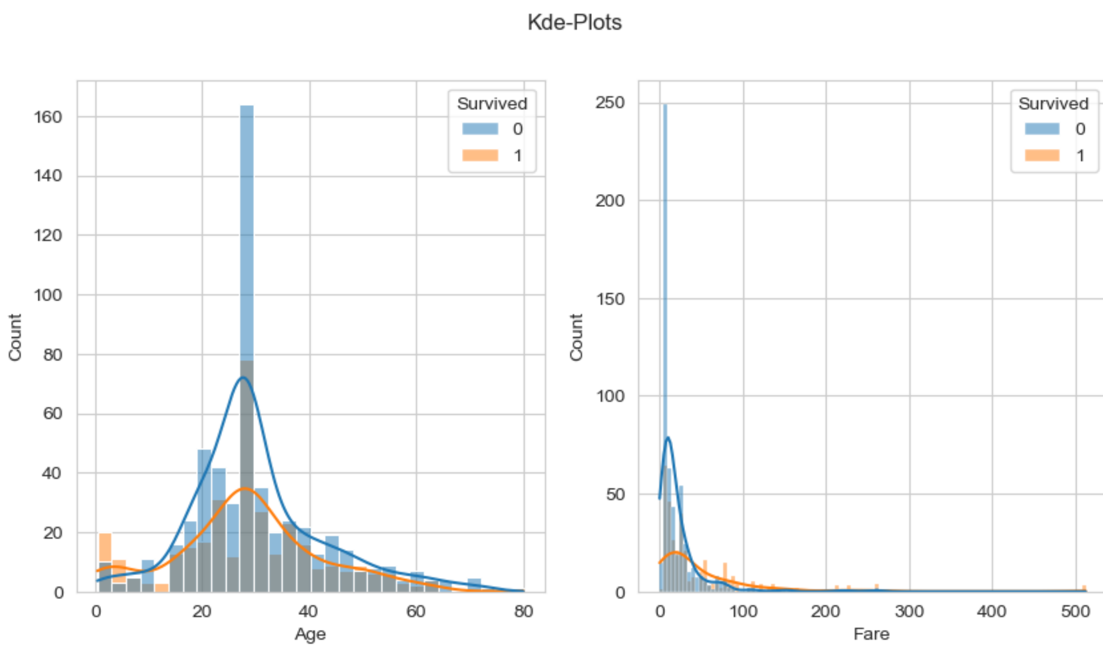
[62]:
```
num_vars = ['Age', 'Fare']
sns.set_style("whitegrid")
fig, axes = plt.subplots(1, 2, figsize=(10, 5))
fig.suptitle('Box-Plots Features Vs Survived Status')
sns.boxplot(ax=axes[0], x=output_var,y='Age', data=titanic_df)
sns.boxplot(ax=axes[1], x=output_var,y='Fare', data=titanic_df)
plt.show()
```



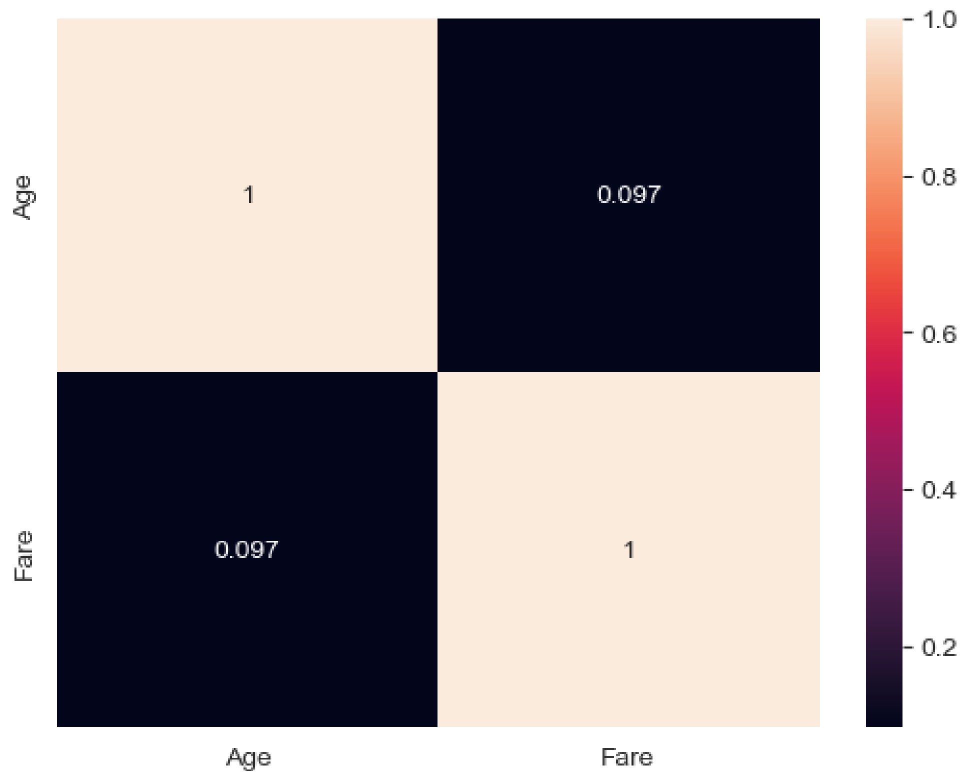
[63]:
```
num_vars = ['Age', 'Fare']
sns.set_style("whitegrid")
fig, axes = plt.subplots(1, 2, figsize=(10, 5))
fig.suptitle('Violin-Plots')
sns.violinplot(ax=axes[0], x=output_var,y='Age', data=titanic_df)
sns.violinplot(ax=axes[1], x=output_var,y='Fare', data=titanic_df)
plt.show()
```



[64]:
```
num_vars = ['Age', 'Fare']
sns.set_style("whitegrid")
fig, axes = plt.subplots(1, 2, figsize=(10, 5))
fig.suptitle('Kde-Plots')
sns.histplot(ax=axes[0], hue=output_var,x='Age', data=titanic_df,kde=True)
sns.histplot(ax=axes[1], hue=output_var,x='Fare', data=titanic_df,kde=True)
plt.show()
```



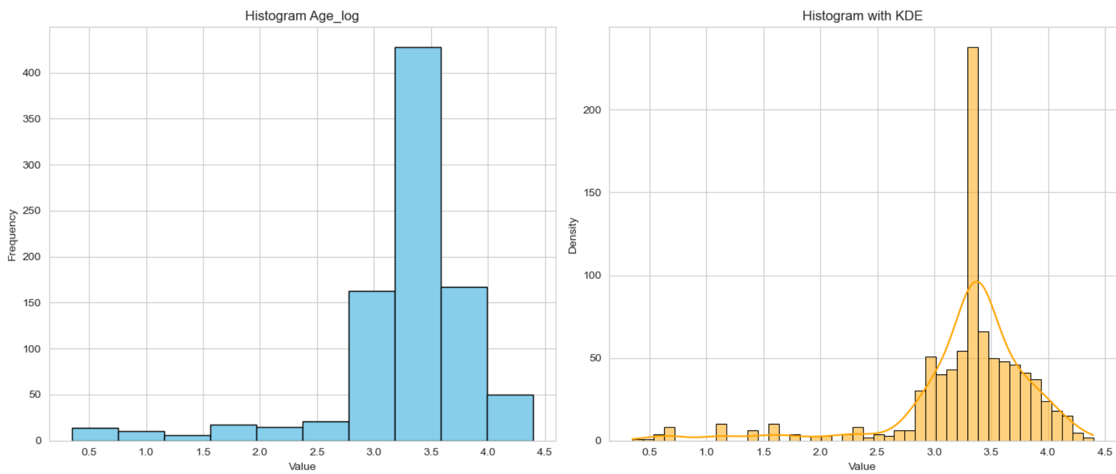
[65]:
```
corr_mat=titanic_df.corr(numeric_only=True)
sns.heatmap(corr_mat,annot=True)
plt.show()
```

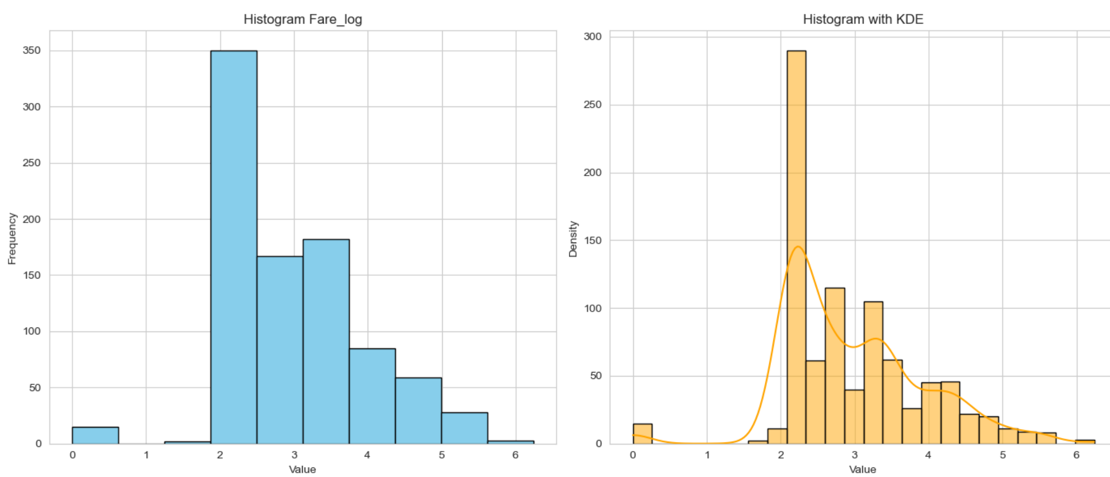


14 10. Data Transformation

[66]:
```
titanic_df["Age_log"]=np.log1p(titanic_df["Age"])
titanic_df["Fare_log"]=np.log1p(titanic_df["Fare"])
```

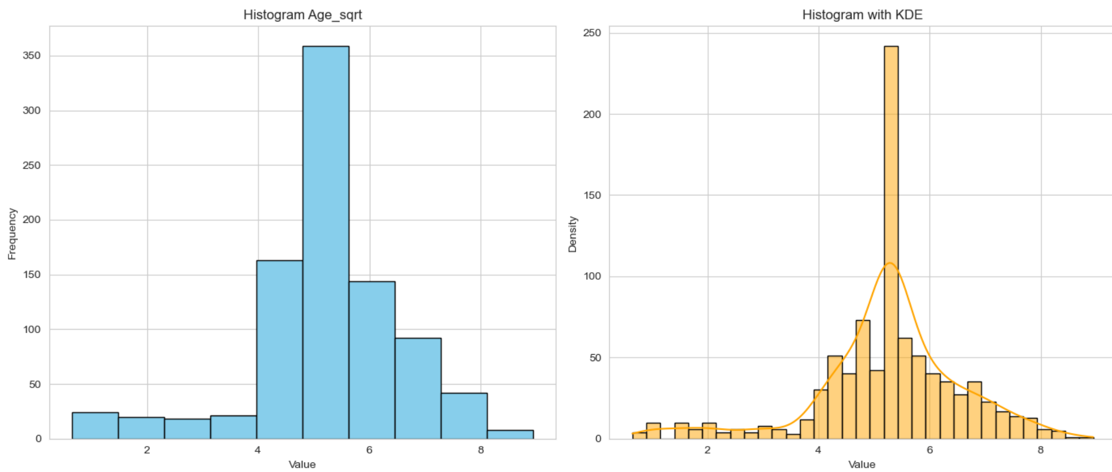
[67]:
```
titanic_num_df = titanic_df[['Age_log','Fare_log']].copy()
# Fit and transform your data using the pipeline
processed_data = pipeline_num_var.fit_transform(titanic_num_df)
```

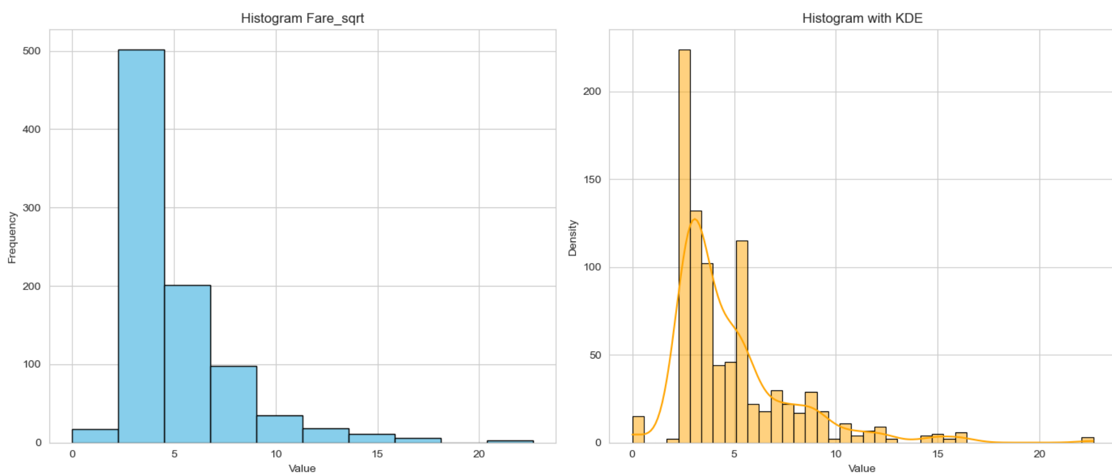




[68]:
```
titanic_df["Age_sqrt"]=np.sqrt(titanic_df["Age"])
titanic_df["Fare_sqrt"]=np.sqrt(titanic_df["Fare"])
```

[69]:
```python
titanic_num_df = titanic_df[['Age_sqrt','Fare_sqrt']].copy()
# Fit and transform your data using the pipeline
processed_data = pipeline_num_var.fit_transform(titanic_num_df)
```





15 11. Standization - Normalization

[70]:

```
scaler = StandardScaler()

# Fit and transform the scaler on the selected column
scaled_column = scaler.fit_transform(titanic_df[['Age_sqrt','Fare_sqrt']])

# Replace the original column with the scaled column
titanic_df[['Age_sqrt_stand','Fare_sqrt_stand']] = scaled_column
print(titanic_df)
```

```
     Survived  Pclass     Sex   Age  SibSp  Parch     Fare   Age_log  Fare_log  \
0           0       3    male  22.0      1      0   7.2500  3.135494  2.110213
1           1       1  female  38.0      1      0  71.2833  3.663562  4.280593
2           1       3  female  26.0      0      0   7.9250  3.295837  2.188856
3           1       1  female  35.0      1      0  53.1000  3.583519  3.990834
4           0       3    male  35.0      0      0   8.0500  3.583519  2.202765
..        …     …     …    …    …    …      …        …         …
886         0       2    male  27.0      0      0  13.0000  3.332205  2.639057
887         1       1  female  19.0      0      0  30.0000  2.995732  3.433987
888         0       3  female  28.0      1      2  23.4500  3.367296  3.196630
889         1       1    male  26.0      0      0  30.0000  3.295837  3.433987
890         0       3    male  32.0      0      0   7.7500  3.496508  2.169054

     Age_sqrt  Fare_sqrt  Age_sqrt_stand  Fare_sqrt_stand
0    4.690416   2.692582       -0.424180        -0.733117
1    6.164414   8.442944        0.686187         1.219822
2    5.099020   2.815138       -0.116378        -0.691495
3    5.916080   7.286975        0.499116         0.827232
4    5.916080   2.837252        0.499116        -0.683984
..        …          …             …              …
886  5.196152   3.605551       -0.043207        -0.423054
887  4.358899   5.477226       -0.673913         0.212604
888  5.291503   4.842520        0.028620        -0.002955
889  5.099020   5.477226       -0.116378         0.212604
890  5.656854   2.783882        0.303841        -0.702110

[891 rows x 13 columns]
```

16 12. Convert Cat - to - Numerical Columns

[71]:

```
titanic_df.columns
```

[71]:

```
Index(['Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare', 'Age_log',
       'Fare_log', 'Age_sqrt', 'Fare_sqrt', 'Age_sqrt_stand',
       'Fare_sqrt_stand'],
      dtype='object')
```

[72]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for var in ['Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch']:
    titanic_df[var]=le.fit_transform(titanic_df[var])
```

[73]:
```
titanic_df[output_var].value_counts()
```

[73]:
```
Survived
0    549
1    342
Name: count, dtype: int64
```

17 13. SMOTE for Balancing Data

[74]:
```
Y=titanic_df["Survived"]
X=titanic_df[[ 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch',  'Age_sqrt_stand',␣
 ↪'Fare_sqrt_stand']]
print(X.columns)
print(len(Y),len(X))
```

```
Index(['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Age_sqrt_stand',
       'Fare_sqrt_stand'],
      dtype='object')
891 891
```

[75]:
```
X, Y = SMOTE().fit_resample(X, Y)
print(X.columns)
print(len(Y),len(X))
```

```
Index(['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Age_sqrt_stand',
       'Fare_sqrt_stand'],
      dtype='object')
1098 1098
```

[76]:
```
Y.value_counts()
```

[76]:
```
Survived
0    549
1    549
Name: count, dtype: int64
```

18 ML Models

[77]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size=0.
 ↪2,random_state = 42)
```

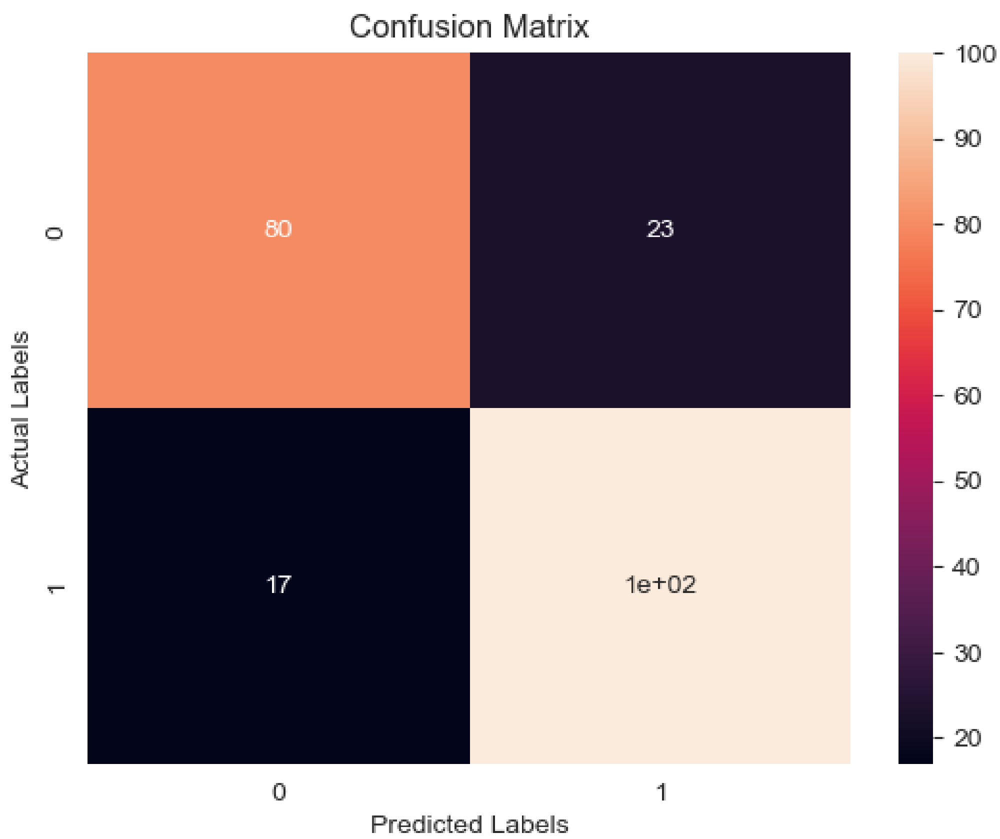
```
[78]: def draw_heatmap(conf_matrix):
    sns.heatmap(conf_matrix, annot=True)
    plt.xlabel('Predicted Labels')
    plt.ylabel('Actual Labels')
    plt.title('Confusion Matrix')
    plt.show()
```

18.1 Logistic Regression

```
[79]: lg_model = LogisticRegression(solver='saga', max_iter=500, random_state=42)
lg_model.fit(X_train, Y_train)

print("Model - Logistic Regression")
score = lg_model.score(X_train, Y_train)
print('accuracy train score overall :', score)
score = lg_model.score(X_test, Y_test)
print('accuracy test score overall :', score)

y_pred = lg_model.predict(X_test)
print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
Model - Logistic Regression
accuracy train score overall : 0.8120728929384966
accuracy test score overall : 0.8181818181818182
              precision    recall  f1-score   support

           0       0.82      0.78      0.80       103
           1       0.81      0.85      0.83       117

    accuracy                           0.82       220
   macro avg       0.82      0.82      0.82       220
weighted avg       0.82      0.82      0.82       220

[[ 80  23]
 [ 17 100]]
```

```
C:\Users\srishanm\AppData\Local\anaconda3\Lib\site-
packages\sklearn\linear_model\_sag.py:350: ConvergenceWarning: The max_iter was
reached which means the coef_ did not converge
  warnings.warn(
```

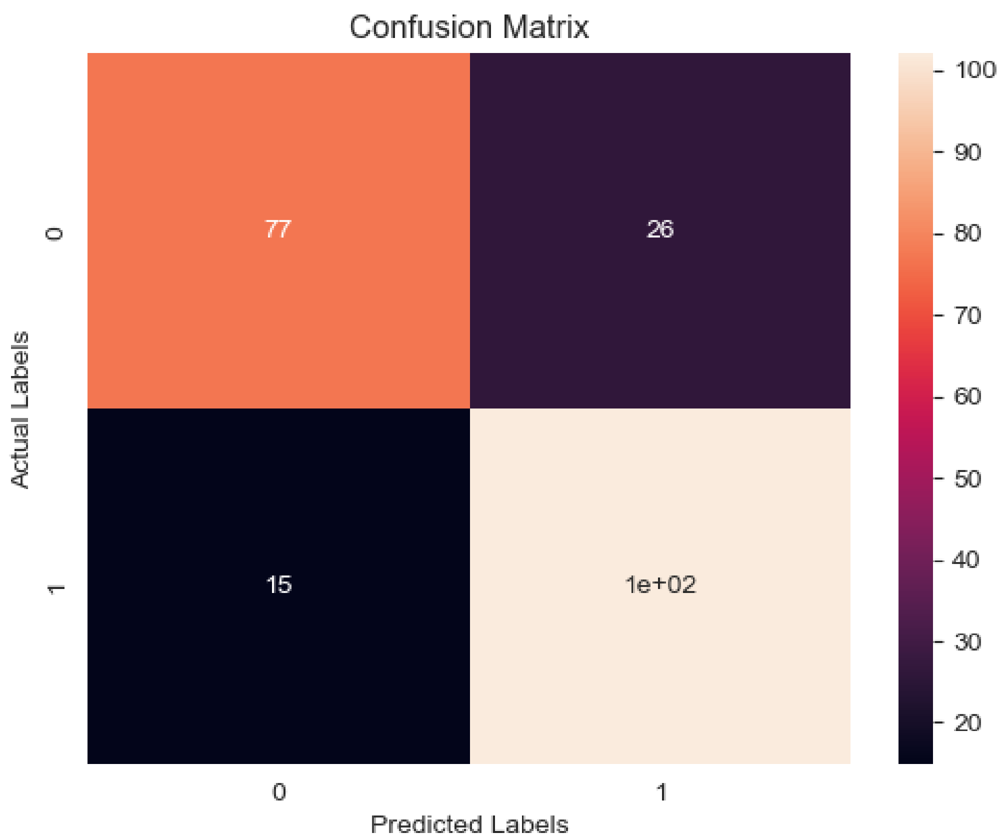


18.2 GaussianNB

[80]:
```
from sklearn.naive_bayes import GaussianNB, CategoricalNB
gnb_model = GaussianNB()
gnb_model.fit(X_train,Y_train)

print("Model-GaussianNB")
print("train score",gnb_model.score(X_train,Y_train))
print("test score",gnb_model.score(X_test,Y_test))

y_pred = gnb_model.predict(X_test)
print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
Model-GaussianNB
train score 0.7972665148063781
test score 0.8136363636363636
              precision    recall  f1-score   support
```

```
              0       0.84      0.75      0.79       103
              1       0.80      0.87      0.83       117

       accuracy                           0.81       220
      macro avg       0.82      0.81      0.81       220
   weighted avg       0.82      0.81      0.81       220

[[ 77  26]
 [ 15 102]]
```

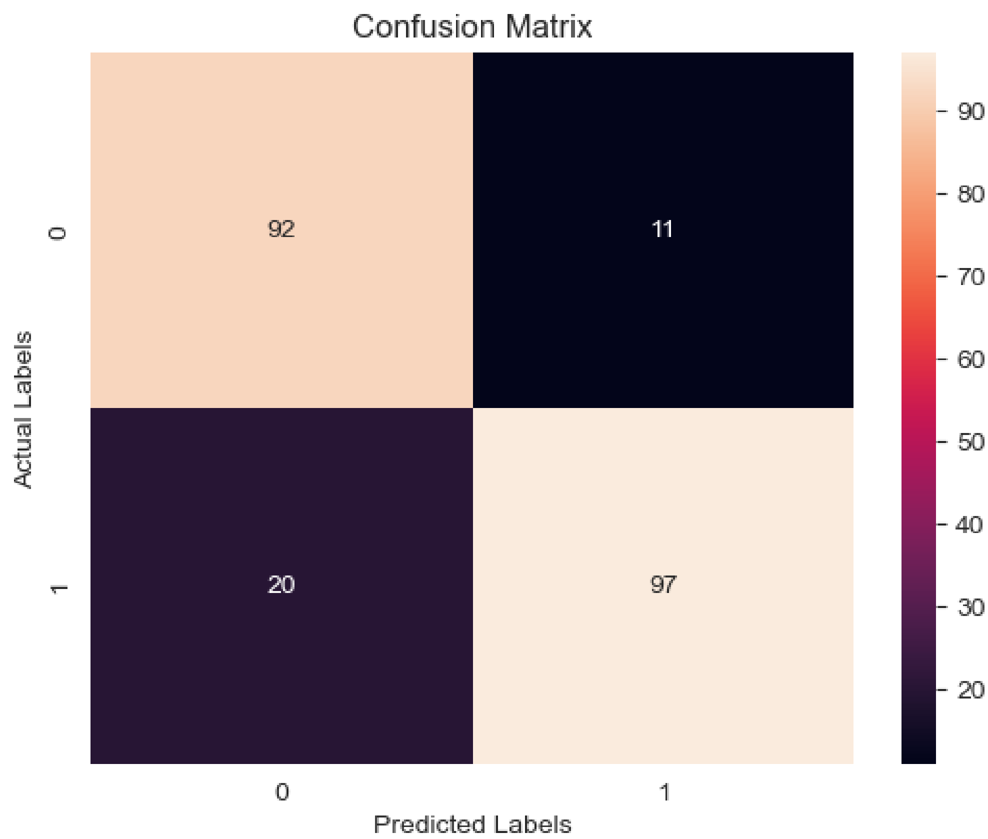


19 Suport Vector Machine - Classifier

[81]:
```python
from sklearn.svm import SVC
# Initialize the SVM classifier
svm_linear_classifier = SVC(kernel='linear', random_state=42)

# Train the SVM classifier
svm_linear_classifier.fit(X_train, Y_train)
print("model-Suport Vector Machine - kernel - linear -Classifier")
```

```python
y_pred = svm_linear_classifier.predict(X_train)
# Calculate the accuracy of the model
accuracy = accuracy_score(Y_train, y_pred)
print("Train Accuracy:", accuracy)

# Predict the classes for test set
y_pred = svm_linear_classifier.predict(X_test)
# Calculate the accuracy of the model
accuracy = accuracy_score(Y_test, y_pred)
print("Test Accuracy:", accuracy)

print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

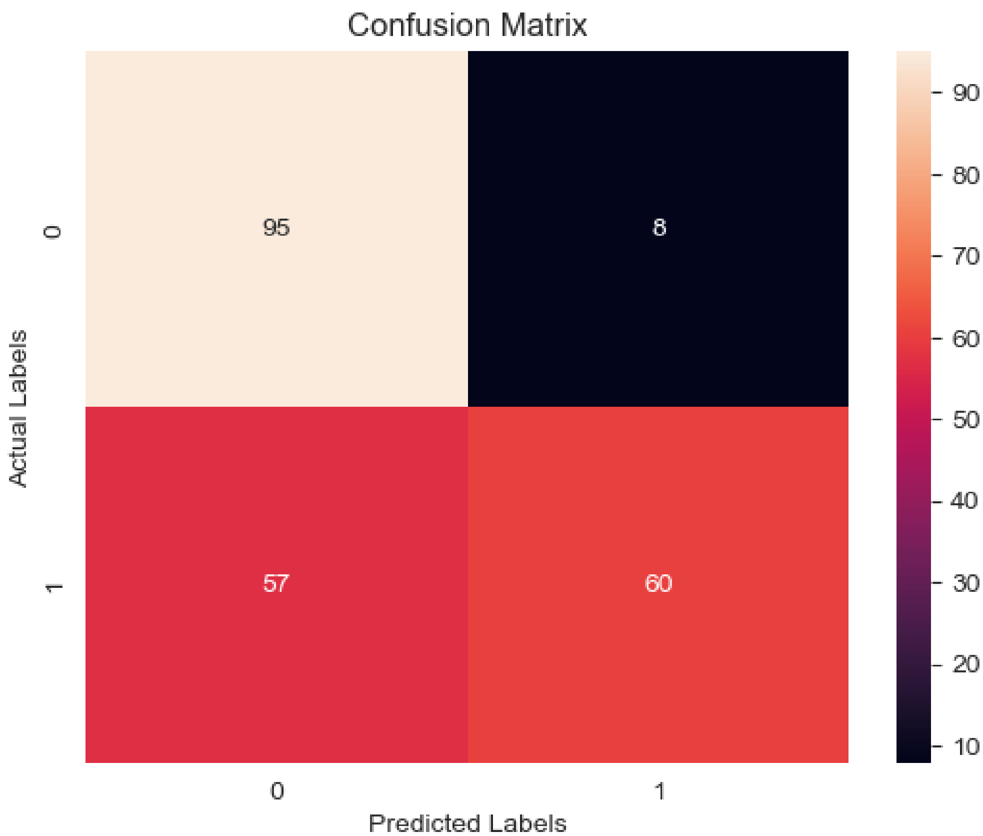
```
model-Suport Vector Machine - kernel - linear -Classifier
Train Accuracy: 0.8086560364464692
Test Accuracy: 0.8590909090909091
              precision    recall  f1-score   support

           0       0.82      0.89      0.86       103
           1       0.90      0.83      0.86       117

    accuracy                           0.86       220
   macro avg       0.86      0.86      0.86       220
weighted avg       0.86      0.86      0.86       220

[[92 11]
 [20 97]]
```



[82]:

```
svm_rbf_classifier = SVC(kernel='rbf', random_state=42)

# Train the SVM classifier
svm_rbf_classifier.fit(X_train, Y_train)
print("model-Suport Vector Machine - Kernel -rbf - Classifier")
y_pred = svm_rbf_classifier.predict(X_train)
# Calculate the accuracy of the model
accuracy = accuracy_score(Y_train, y_pred)
print("Train Accuracy:", accuracy)

# Predict the classes for test set
y_pred = svm_rbf_classifier.predict(X_test)
# Calculate the accuracy of the model
accuracy = accuracy_score(Y_test, y_pred)
print("Test Accuracy:", accuracy)

print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

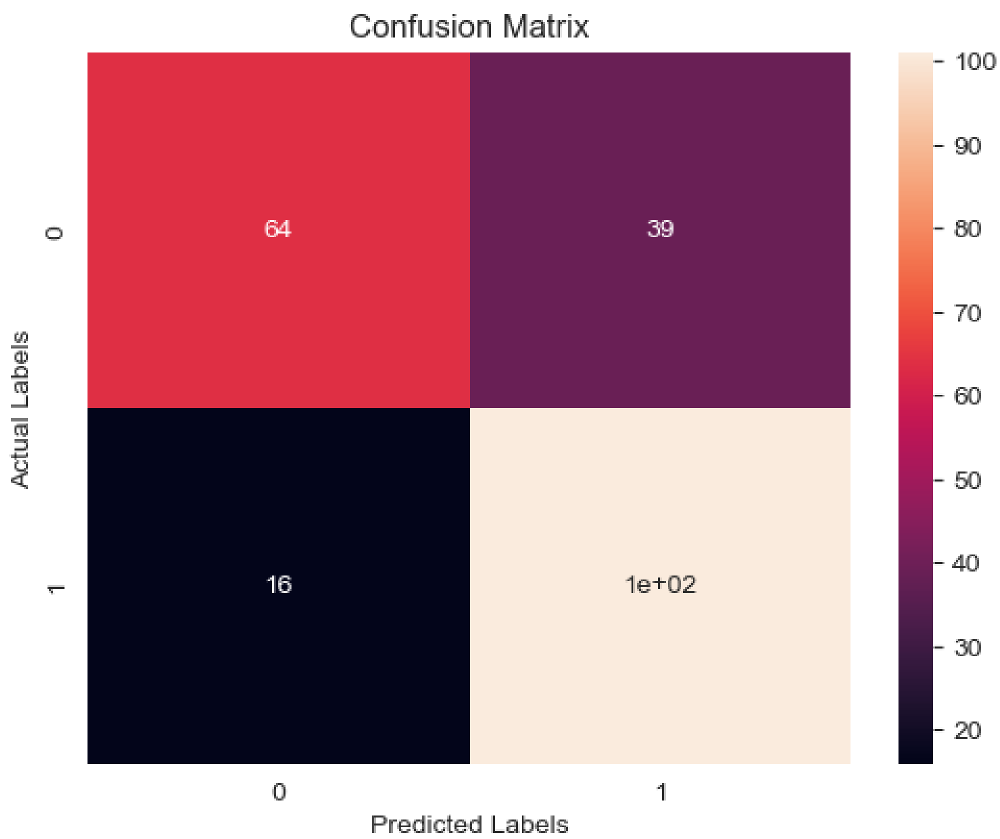
```
model-Suport Vector Machine - Kernel -rbf - Classifier
Train Accuracy: 0.6856492027334852
Test Accuracy: 0.7045454545454546
              precision    recall  f1-score   support

           0       0.62      0.92      0.75       103
           1       0.88      0.51      0.65       117

    accuracy                           0.70       220
   macro avg       0.75      0.72      0.70       220
weighted avg       0.76      0.70      0.69       220

[[95  8]
 [57 60]]
```



[83]:
```
svm_poly_classifier = SVC(kernel='poly', random_state=42)

# Train the SVM classifier
svm_poly_classifier.fit(X_train, Y_train)
print("model-Suport Vector Machine - Kernel -poly - Classifier")
```

```python
y_pred = svm_poly_classifier.predict(X_train)
# Calculate the accuracy of the model
accuracy = accuracy_score(Y_train, y_pred)
print("Train Accuracy:", accuracy)

# Predict the classes for test set
y_pred = svm_poly_classifier.predict(X_test)

# Calculate the accuracy of the model
accuracy = accuracy_score(Y_test, y_pred)
print("Test Accuracy:", accuracy)

print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
model-Suport Vector Machine - Kernel -poly - Classifier
Train Accuracy: 0.7095671981776766
Test Accuracy: 0.75
              precision    recall  f1-score   support

           0       0.80      0.62      0.70       103
           1       0.72      0.86      0.79       117

    accuracy                           0.75       220
   macro avg       0.76      0.74      0.74       220
weighted avg       0.76      0.75      0.75       220

[[ 64  39]
 [ 16 101]]
```

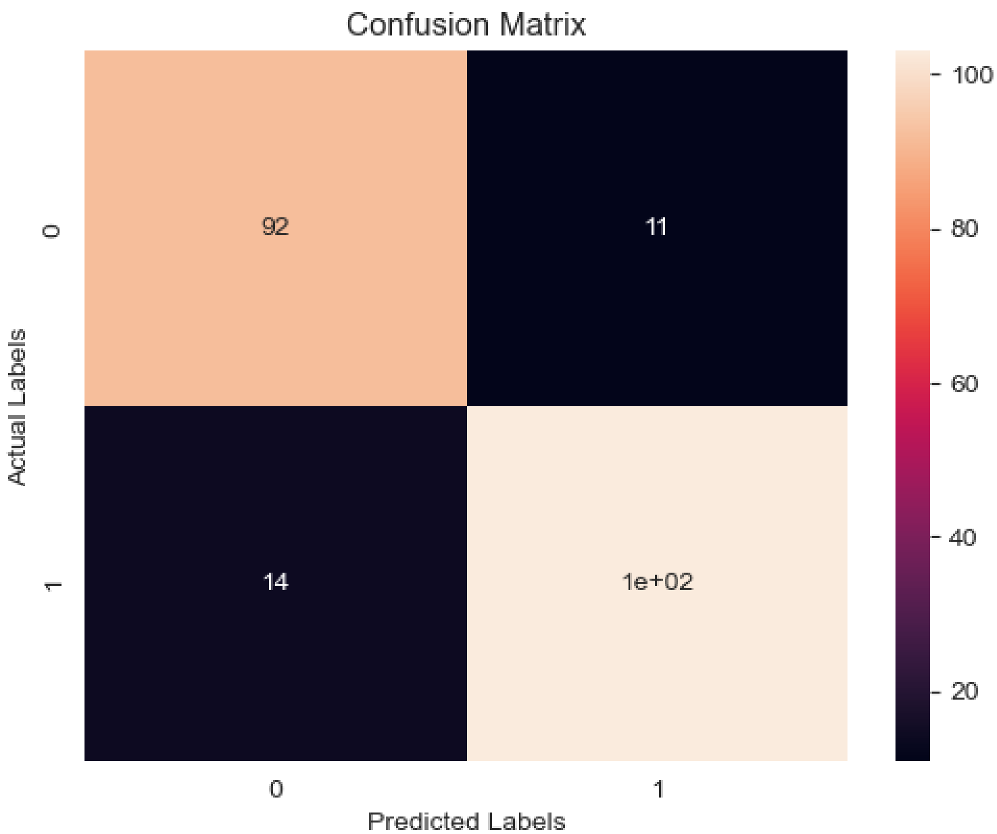


19.1 Decision Tree

[84]:
```
dt_clf = DecisionTreeClassifier(max_leaf_nodes=20,random_state=42)
dt_clf.fit(X_train, Y_train)
print("Model-Decion Tree")

accuracy=dt_clf.score(X_train, Y_train)
print(f"train score: {accuracy}")

accuracy=dt_clf.score(X_test, Y_test)
print(f"test score: {accuracy}")

y_pred=dt_clf.predict(X_test)
print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
Model-Decion Tree
train score: 0.857630979498861
test score: 0.8863636363636364
```

```
              precision    recall  f1-score   support

           0       0.87      0.89      0.88       103
           1       0.90      0.88      0.89       117

    accuracy                           0.89       220
   macro avg       0.89      0.89      0.89       220
weighted avg       0.89      0.89      0.89       220

[[ 92  11]
 [ 14 103]]
```

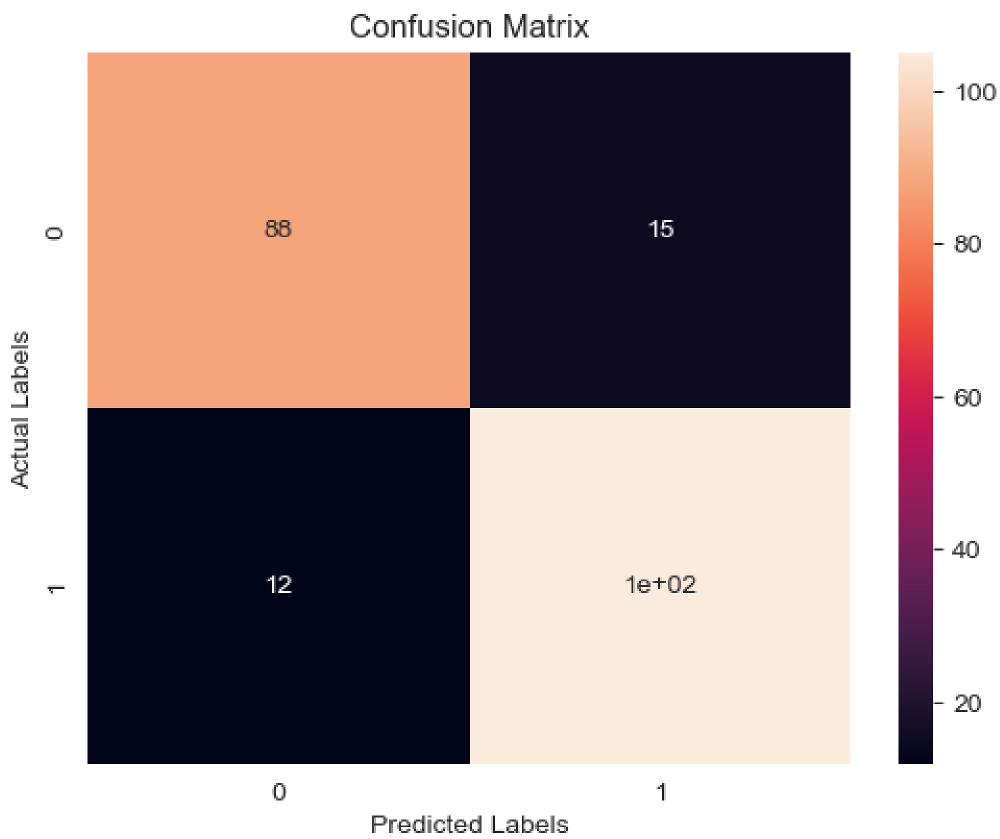


19.2 Radom Forest

[85]:
```
rf_clf= RandomForestClassifier(n_estimators = 1000, random_state = 42,␣
↪max_leaf_nodes=20)
rf_clf.fit(X_train, Y_train)
print("Model- Random Forest Tree")

accuracy=rf_clf.score(X_train, Y_train)
```

```python
print(f"train score: {accuracy}")

accuracy=rf_clf.score(X_test, Y_test)
print(f"test score: {accuracy}")

y_pred=rf_clf.predict(X_test)
print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
Model- Random Forest Tree
train score: 0.8712984054669703
test score: 0.8772727272727273
              precision    recall  f1-score   support

           0       0.88      0.85      0.87       103
           1       0.88      0.90      0.89       117

    accuracy                           0.88       220
   macro avg       0.88      0.88      0.88       220
weighted avg       0.88      0.88      0.88       220

[[ 88  15]
 [ 12 105]]
```

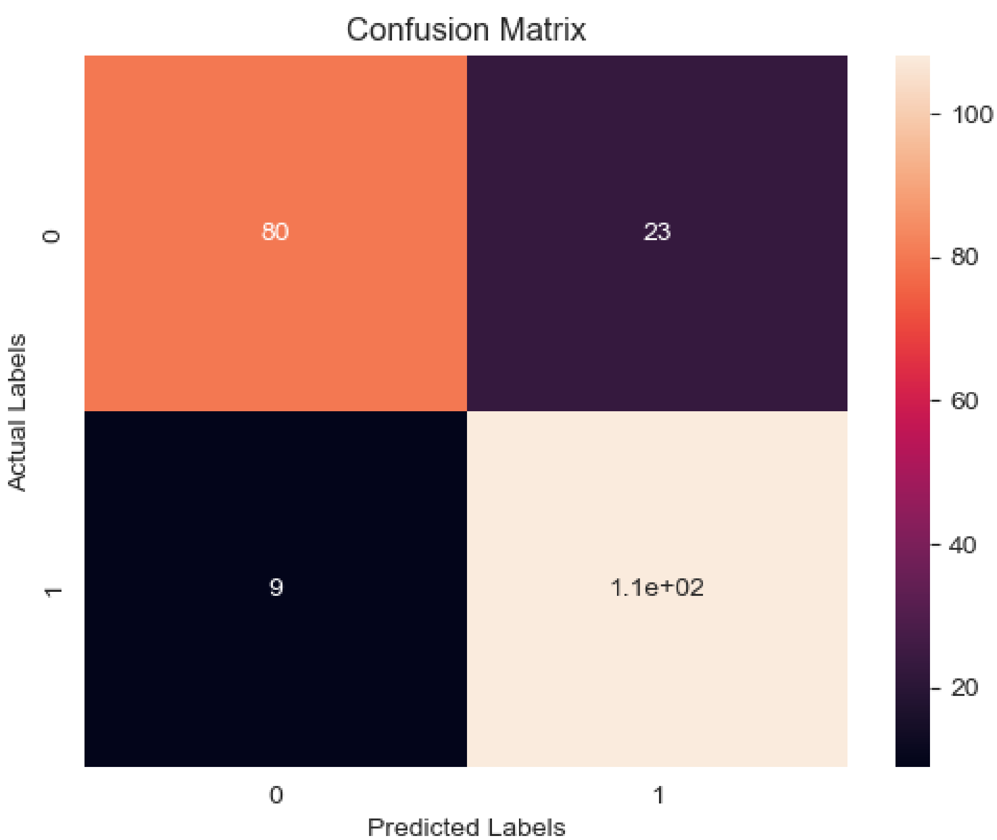


19.3 AdaBoost

[86]:
```
base_classifier = DecisionTreeClassifier(max_depth=1)
adaboost_clf = AdaBoostClassifier( n_estimators=50, random_state=42)

# Train the AdaBoost classifier
adaboost_clf.fit(X_train, Y_train)

print("Model-AdaBoost")
print("train score",adaboost_clf.score(X_train, Y_train))

# Predict on the test set
y_pred = adaboost_clf.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(Y_test, y_pred)
print(f"test score: {accuracy}")

print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
```

```
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

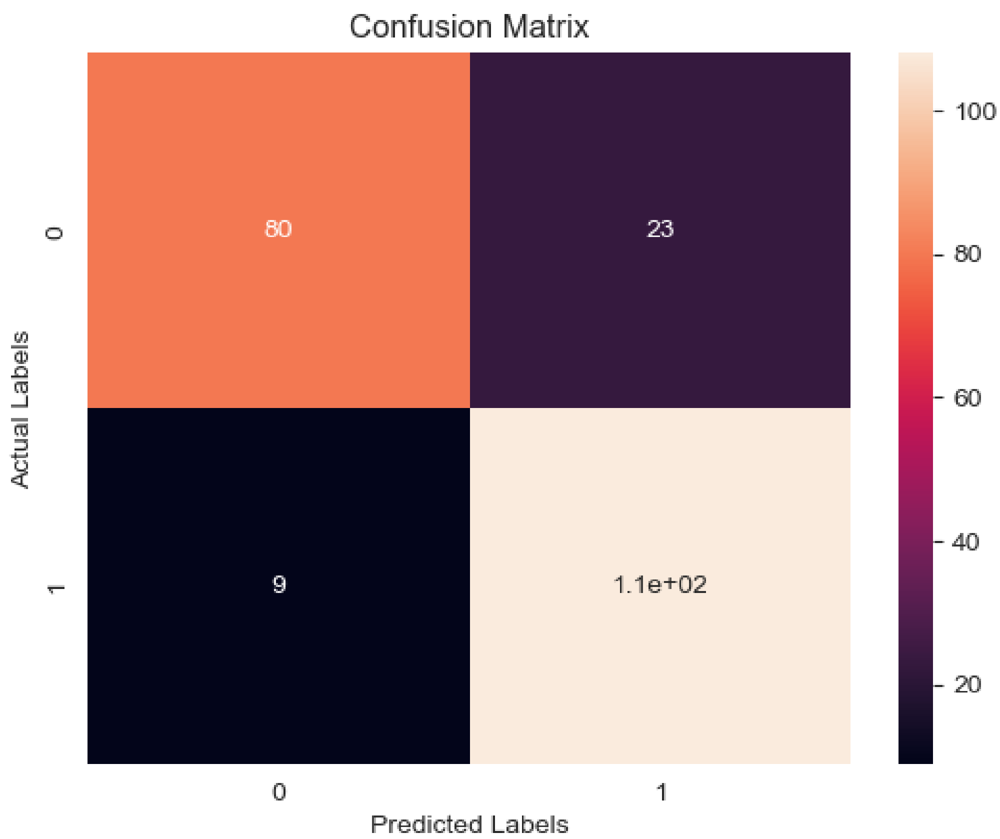
```
Model-AdaBoost
train score 0.8302961275626424
test score: 0.8545454545454545
              precision    recall  f1-score   support

           0       0.90      0.78      0.83       103
           1       0.82      0.92      0.87       117

    accuracy                           0.85       220
   macro avg       0.86      0.85      0.85       220
weighted avg       0.86      0.85      0.85       220

[[ 80  23]
 [  9 108]]
```



19.4 GradientBoostingClassifier

[87]:
```
gdb_clf = GradientBoostingClassifier(n_estimators=20, learning_rate=0.1,␣
 ↪max_depth=1, random_state=42)
gdb_clf.fit(X_train, Y_train)
print("model-Gradient Boosting Classifier")

accuracy = gdb_clf.score(X_train, Y_train)
print("Train Accuracy:", accuracy)

accuracy = gdb_clf.score(X_test, Y_test)
print("Test Accuracy:", accuracy)

print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
model-Gradient Boosting Classifier
Train Accuracy: 0.7813211845102506
Test Accuracy: 0.8272727272727273
              precision    recall  f1-score   support

           0       0.90      0.78      0.83       103
           1       0.82      0.92      0.87       117

    accuracy                           0.85       220
   macro avg       0.86      0.85      0.85       220
weighted avg       0.86      0.85      0.85       220

[[ 80  23]
 [  9 108]]
```



19.5 XGBClassifier

[88]:
```
from xgboost import XGBClassifier
xgmodel = XGBClassifier()
xgmodel.fit(X_train, Y_train)


print("model- XGB Classifier")
# Make predictions on the test set
y_pred = xgmodel.predict(X_train)
accuracy = accuracy_score(Y_train, y_pred)
print("Train Accuracy:", accuracy)
# Evaluate the model

# Make predictions on the test set
y_pred = xgmodel.predict(X_test)
accuracy = accuracy_score(Y_test, y_pred)
print("Test Accuracy:", accuracy)

print(classification_report(Y_test, y_pred))
```

```python
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
model- XGB Classifier
Train Accuracy: 0.9703872437357631
Test Accuracy: 0.8318181818181818
              precision    recall  f1-score   support

           0       0.79      0.86      0.83       103
           1       0.87      0.80      0.84       117

    accuracy                           0.83       220
   macro avg       0.83      0.83      0.83       220
weighted avg       0.83      0.83      0.83       220

[[89 14]
 [23 94]]
```