#DATA PREPROCESSING

#1.IMPORT LIBRARIES

```
# guna devineni
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

#2.IMPORT DATASET

```
df=pd.read_csv("Titanic-Dataset.csv")

df.head()

   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

df.tail()

     PassengerId  Survived  Pclass
Name  \
886          887         0       2                     Montvila, Rev.
Juozas
887          888         1       1              Graham, Miss. Margaret
```

```
Edith
888          889         0       3  Johnston, Miss. Catherine Helen
"Carrie"
889          890         1       1                     Behr, Mr. Karl
Howell
890          891         0       3                       Dooley, Mr.
Patrick

        Sex   Age  SibSp  Parch      Ticket   Fare Cabin Embarked
886    male  27.0      0      0      211536  13.00   NaN        S
887  female  19.0      0      0      112053  30.00   B42        S
888  female   NaN      1      2  W./C. 6607  23.45   NaN        S
889    male  26.0      0      0      111369  30.00  C148        C
890    male  32.0      0      0      370376   7.75   NaN        Q
```

```
df.shape
```

```
(891, 12)
```

```
df.describe()
```

```
       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
```

```
df.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
```

```
df.corr()
```

```
<ipython-input-8-2f6f6606aa2c>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it
will default to False. Select only valid columns or specify the value
of numeric_only to silence this warning.
  df.corr()
```

```
             PassengerId  Survived    Pclass       Age     SibSp
Parch  \
PassengerId     1.000000 -0.005007 -0.035144  0.036847 -0.057527 -
0.001652   
Survived       -0.005007  1.000000 -0.338481 -0.077221 -0.035322  
0.081629   
Pclass         -0.035144 -0.338481  1.000000 -0.369226  0.083081  
0.018443   
Age             0.036847 -0.077221 -0.369226  1.000000 -0.308247 -
0.189119   
SibSp          -0.057527 -0.035322  0.083081 -0.308247  1.000000  
0.414838   
Parch          -0.001652  0.081629  0.018443 -0.189119  0.414838  
1.000000   
Fare            0.012658  0.257307 -0.549500  0.096067  0.159651  
0.216225   

                 Fare  
PassengerId  0.012658  
Survived     0.257307  
Pclass      -0.549500  
Age          0.096067  
SibSp        0.159651  
Parch        0.216225  
Fare         1.000000  
```

#3.HANDLING NULL VALUES

```
df.isnull().any()
```

```
PassengerId    False
Survived       False
Pclass         False
Name           False
Sex            False
Age             True
SibSp          False
Parch          False
Ticket         False
Fare           False
Cabin           True
Embarked        True
dtype: bool
```

```
df.isnull().sum()
```

```
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
```

```
df.Embarked.unique()
```

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

```
df.Embarked.value_counts()
```

```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

```
df.Cabin.nunique()
```

```
147
```

```
# IMPUTATION
```

```
df["Age"].fillna(df["Age"].mean(),inplace=True)
```

```
df["Age"].isnull().sum()
```

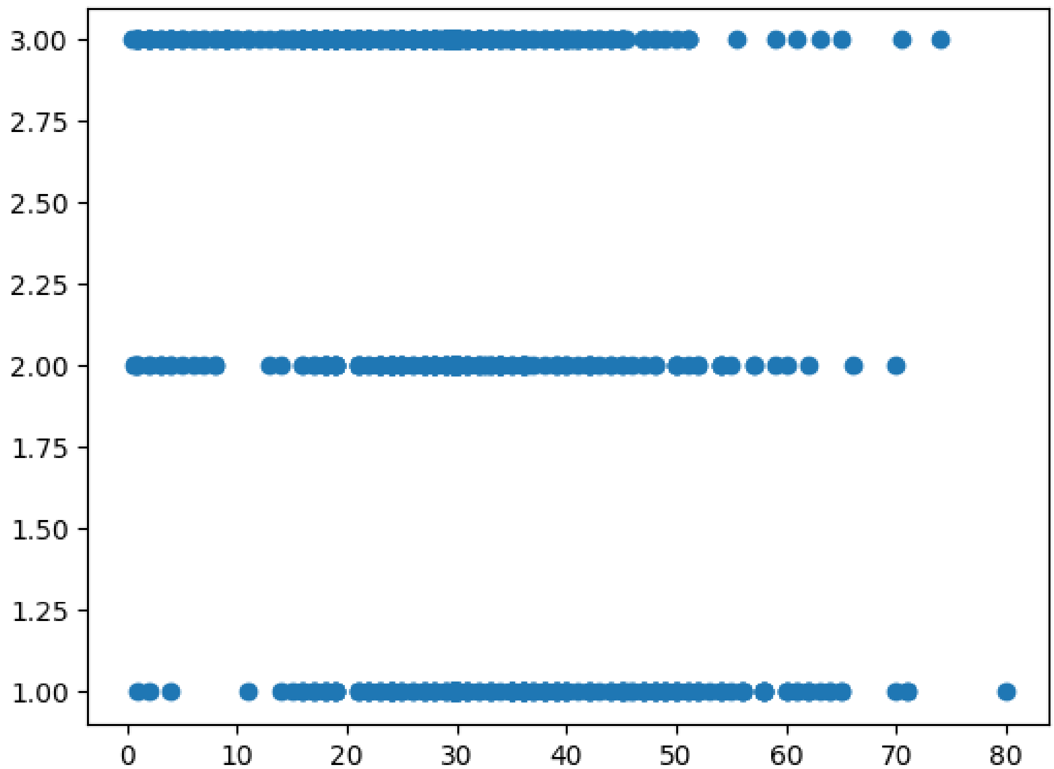
```
0
```

```
# IMPUTATION

df["Embarked"].fillna(df["Embarked"].mode()[0],inplace=True)

df["Embarked"].isnull().sum()

0

# REMOVAL

df.drop("Cabin", axis=1, inplace=True)

df.shape

(891, 11)

df.isnull().sum()

PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
dtype: int64
```

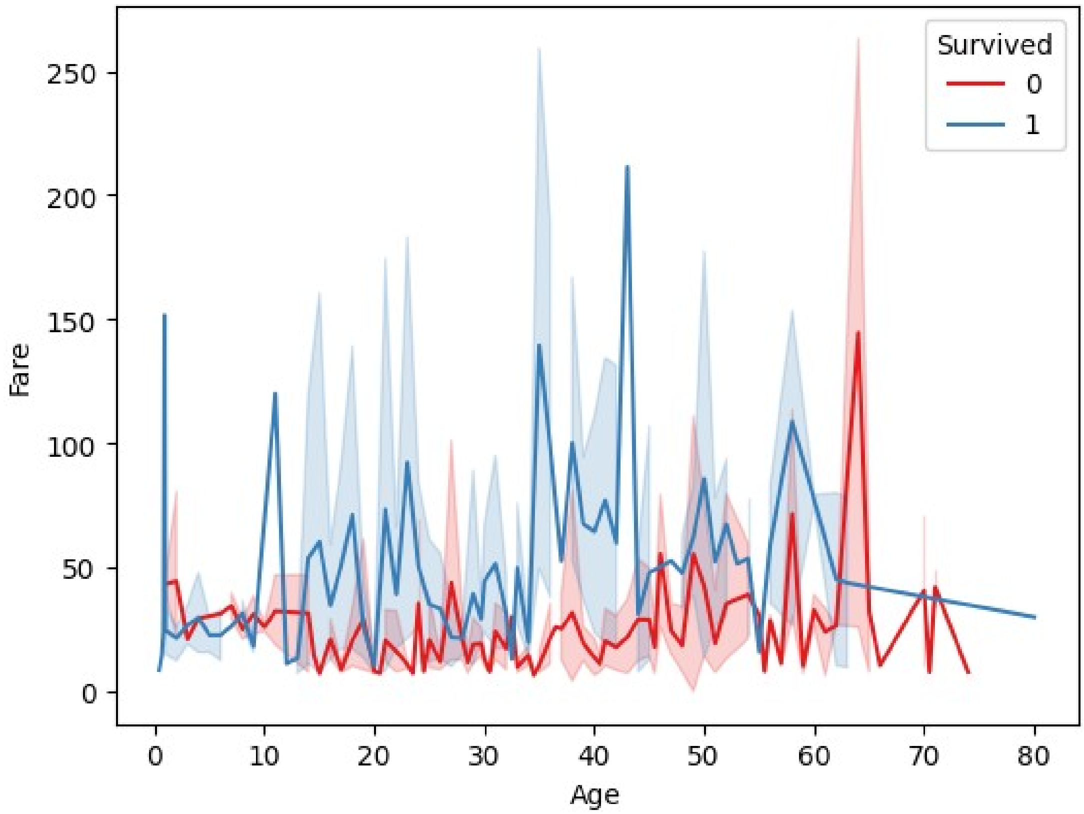
4.DATA VISUALISATION

```
df.corr().Fare.sort_values(ascending=False)

<ipython-input-24-f51f352aac84>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it
will default to False. Select only valid columns or specify the value
of numeric_only to silence this warning.
  df.corr().Fare.sort_values(ascending=False)

Fare           1.000000
Survived       0.257307
Parch          0.216225
SibSp          0.159651
Age            0.091566
PassengerId    0.012658
Pclass        -0.549500
Name: Fare, dtype: float64

plt.scatter(df["Age"],df["Pclass"])
```

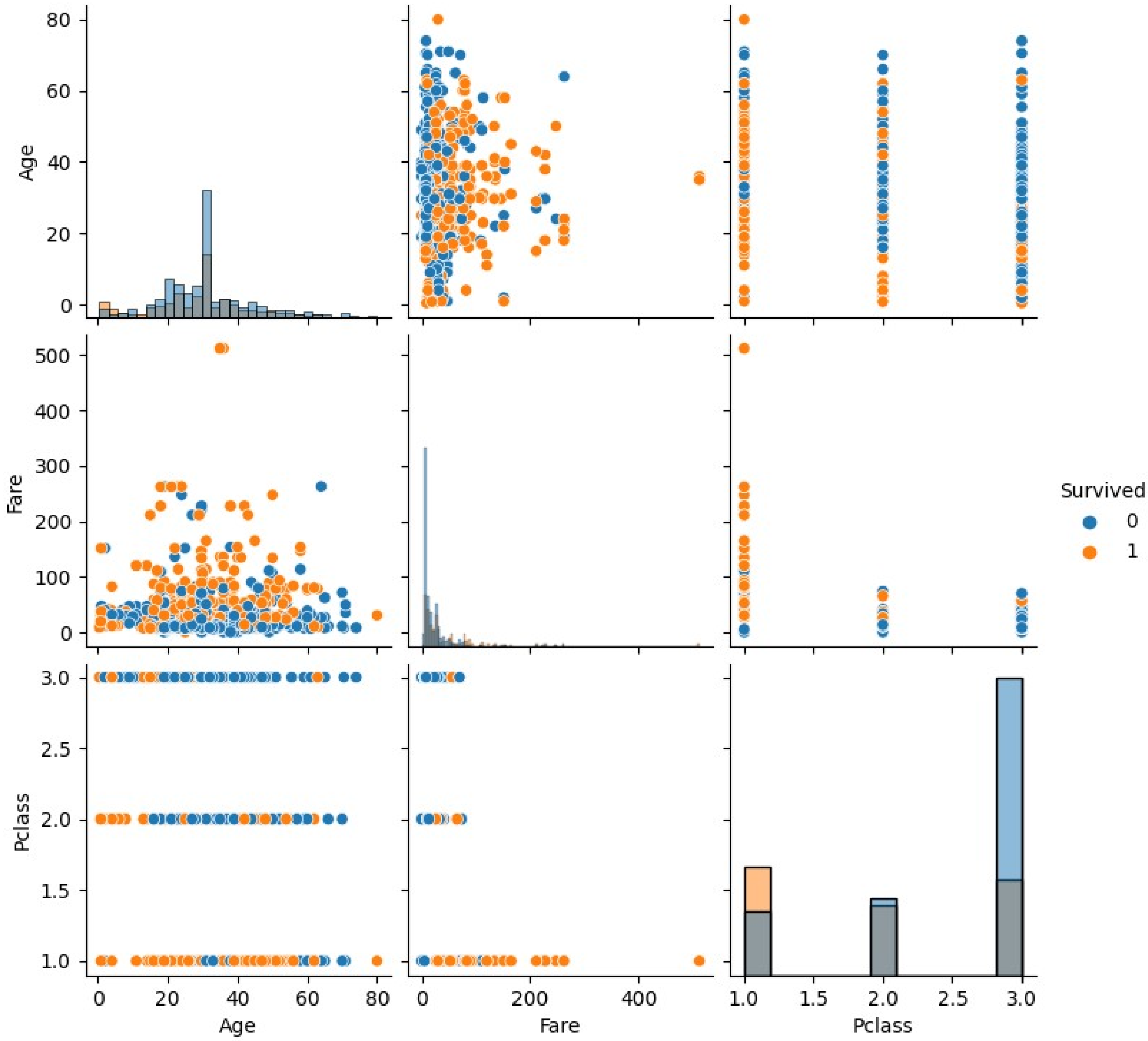
```
<matplotlib.collections.PathCollection at 0x7874bb998a00>
```



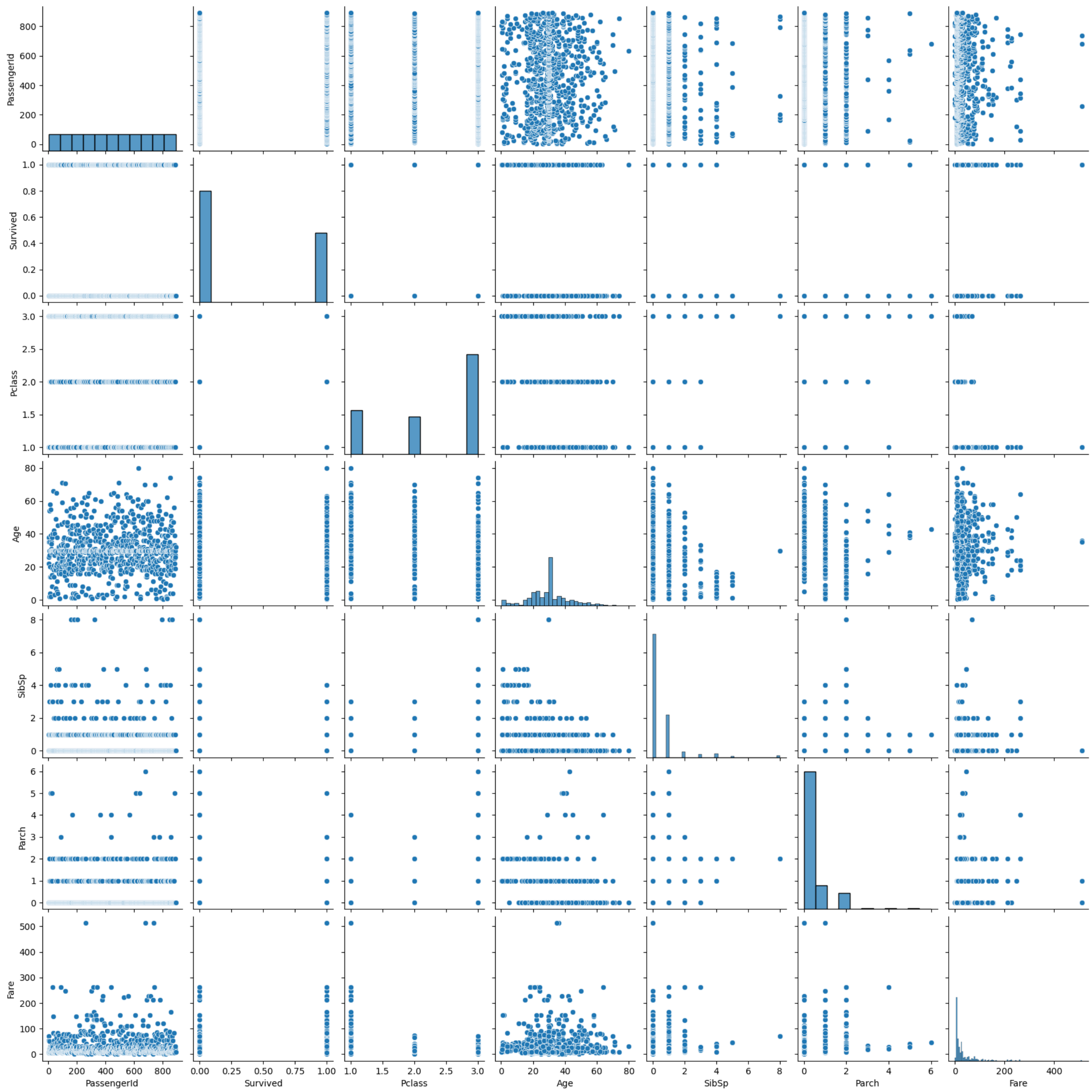

```
#INFERENCE:
#Age vs. Pclass (Inverse): Older passengers tended to be in lower
classes, while younger passengers were more often found in higher
classes, suggesting an inversely direct relationship between age and
class.

sns.lineplot(x='Age', y='Fare', data=df, hue='Survived',
palette='Set1')
plt.xlabel("Age")
plt.ylabel("Fare")
plt.show()
```




```
#INFERENCE:
#The line plot shows that there is no clear boundary separating
survivors from non-survivors based solely on age and fare.

#  INFERENCE:
#  This code creates a bar plot showing the survival rate of
passengers categorized by age, using a color palette 'Set1', with
confidence intervals disabled. However, the plot's labels suggest a
mismatch between the variables used (Age and Passenger Class) and
their descriptions (Survival Rate and Passenger Class).


columns_to_plot = ['Age', 'Fare', 'Survived', 'Pclass']
sns.pairplot(df[columns_to_plot], hue='Survived', diag_kind='hist')
plt.show()
```

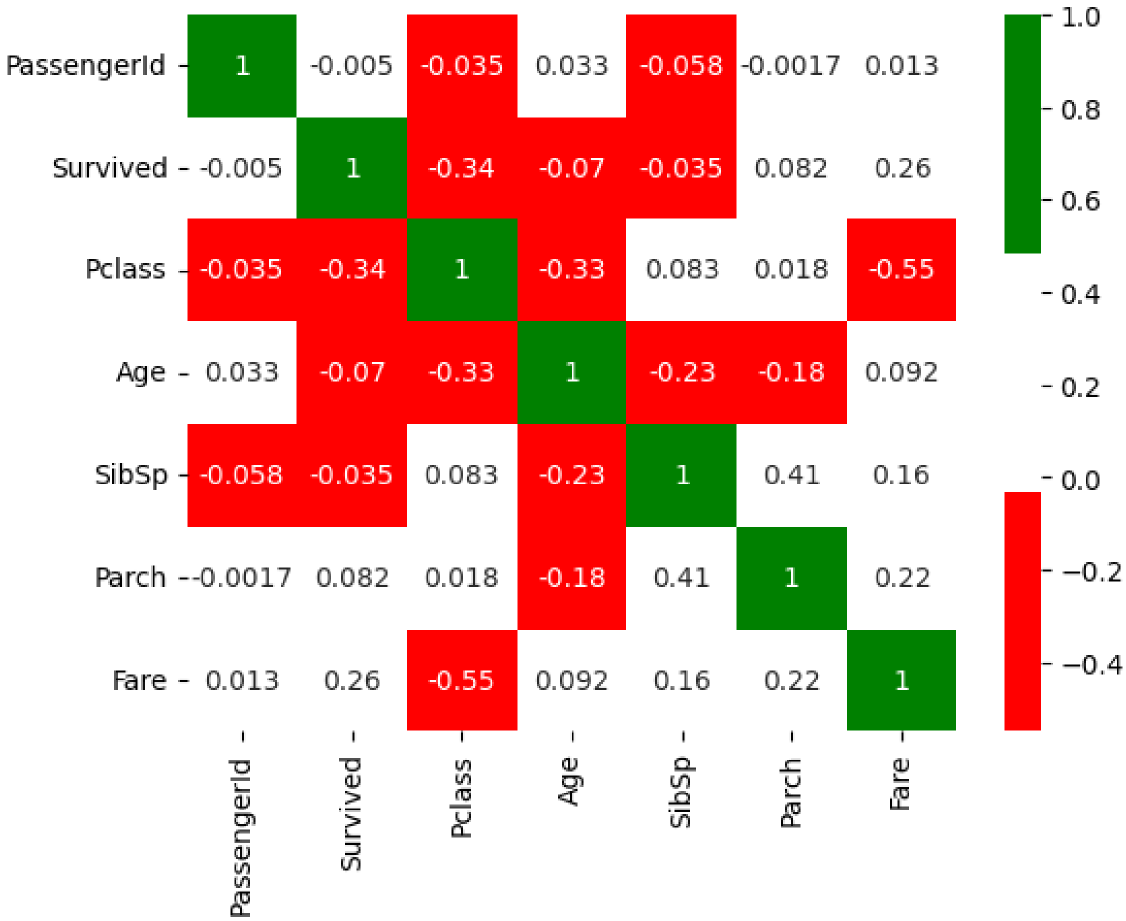



```
sns.pairplot(df)
<seaborn.axisgrid.PairGrid at 0x7874b976b430>
```




```
custom_colors = ['#ff0000', '#ffffff', '#008000']
sns.heatmap(df.corr(), annot=True, cmap=custom_colors)
```

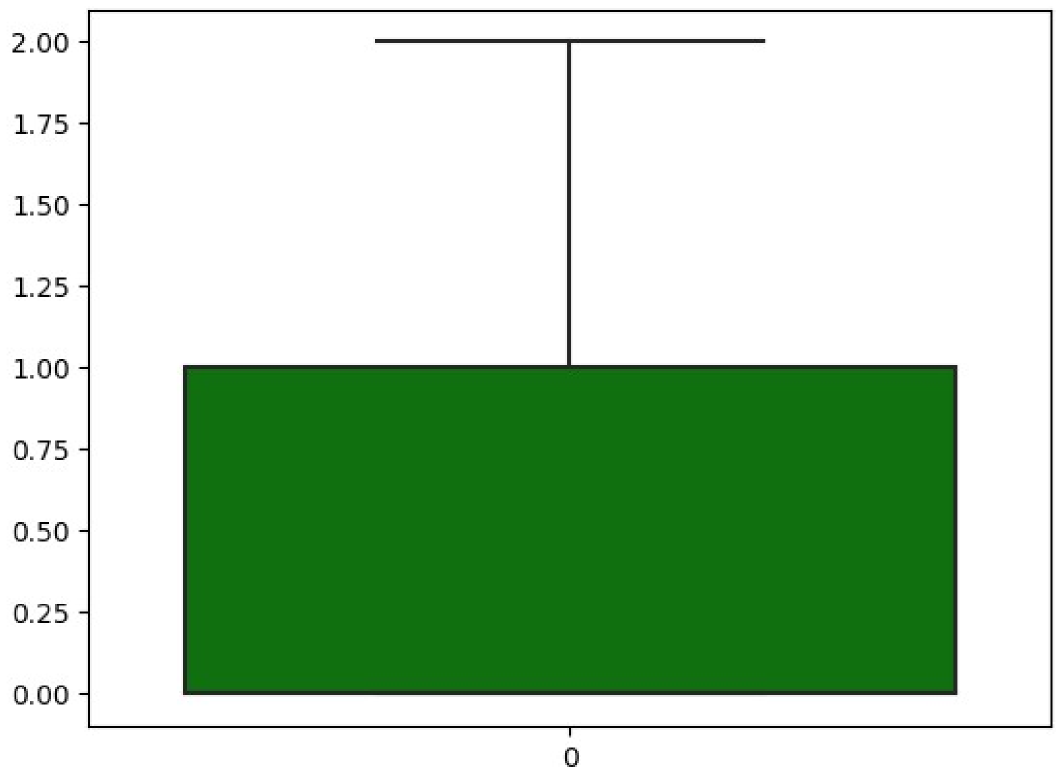
```
<ipython-input-33-b11be6d25f21>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(df.corr(), annot=True, cmap=custom_colors)

<Axes: >
```



5.OUTLIER DETECTION

```
#SibSp
sns.boxplot(df["SibSp"],color="Green")
```

```
<Axes: >
```



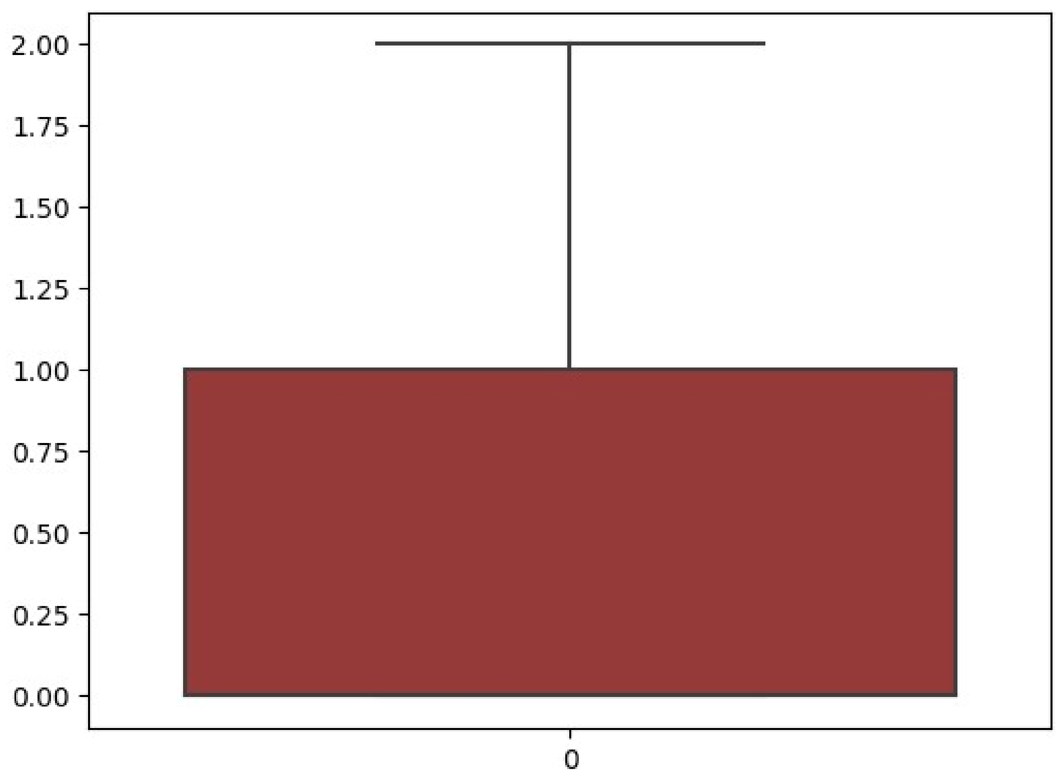

```
q1=df.SibSp.quantile(0.25)
q3=df.SibSp.quantile(0.75)
print(q1)
print(q3)

0.0
1.0

IQR=q3-q1
IQR

1.0

upper_limit=q3+1.5*IQR
upper_limit

2.5

df.median() #50% quantile

<ipython-input-38-db7476078f8f>:1: FutureWarning: The default value of
numeric_only in DataFrame.median is deprecated. In a future version,
it will default to False. In addition, specifying 'numeric_only=None'
is deprecated. Select only valid columns or specify the value of
numeric_only to silence this warning.
  df.median() #50% quantile
```

```
PassengerId    446.000000
Survived         0.000000
Pclass           3.000000
Age             29.699118
SibSp            0.000000
Parch            0.000000
Fare            14.454200
dtype: float64
```

```
df=df[df.SibSp<upper_limit]
```

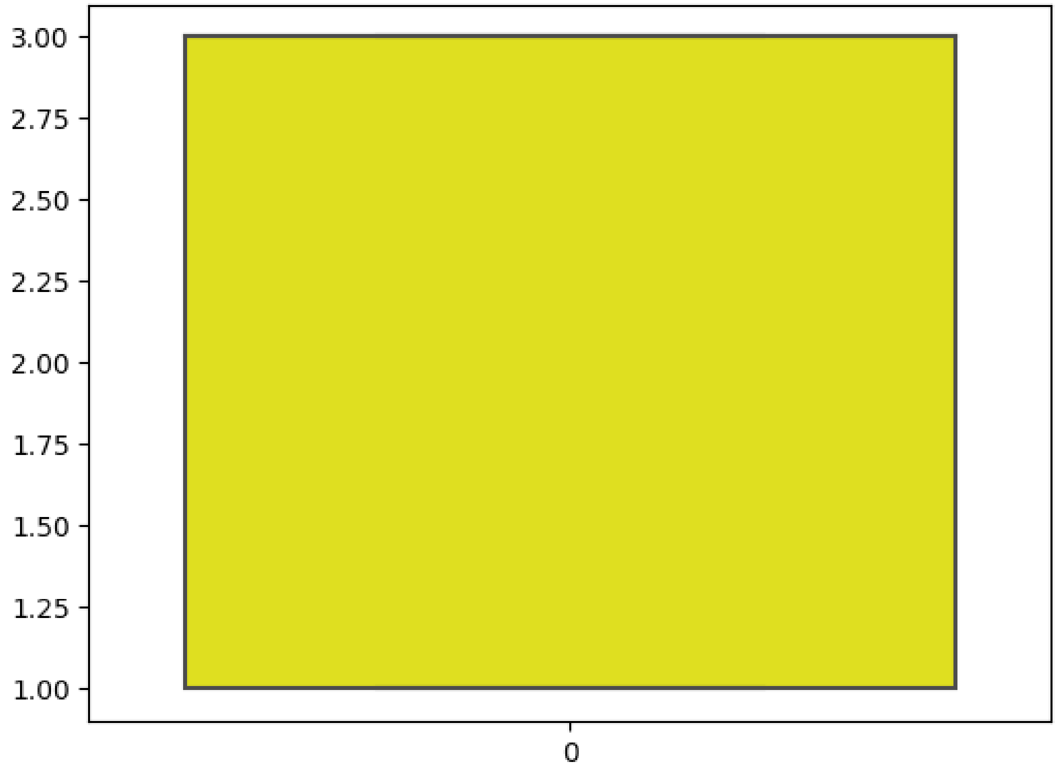
```
sns.boxplot(df["SibSp"],color="Brown")
```

```
<Axes: >
```



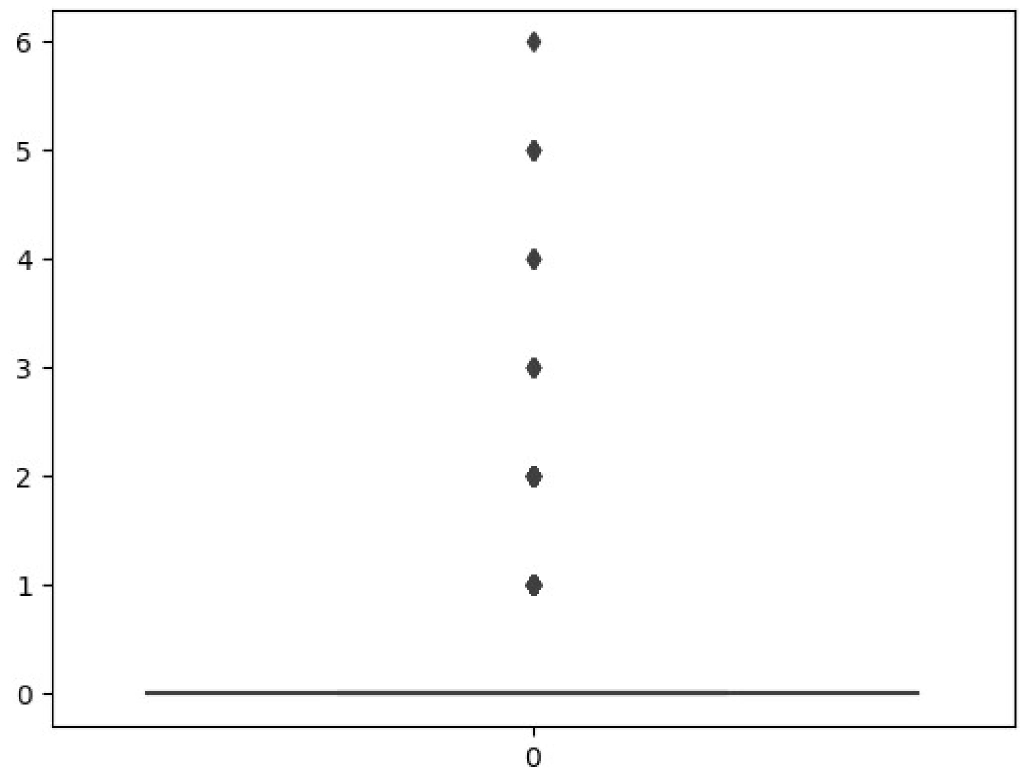

```
#Pclass
sns.boxplot(df.Pclass,color="yellow")
```

```
<Axes: >
```

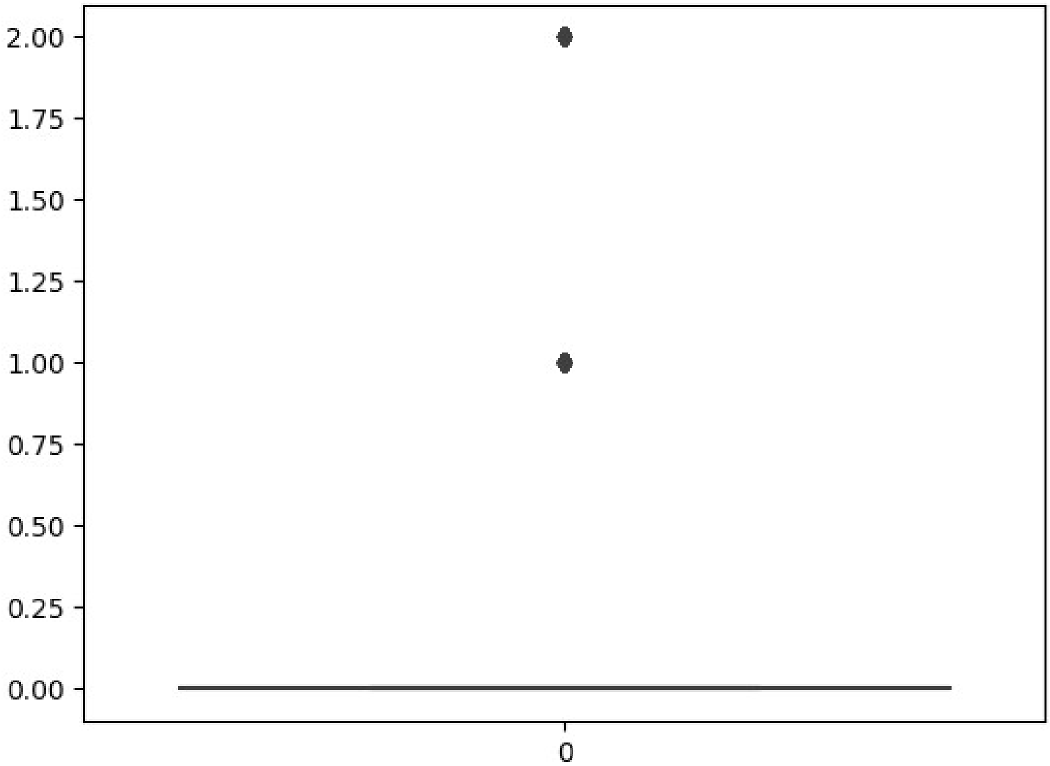



```
#Parch
sns.boxplot(df.Parch)
```

```
<Axes: >
```

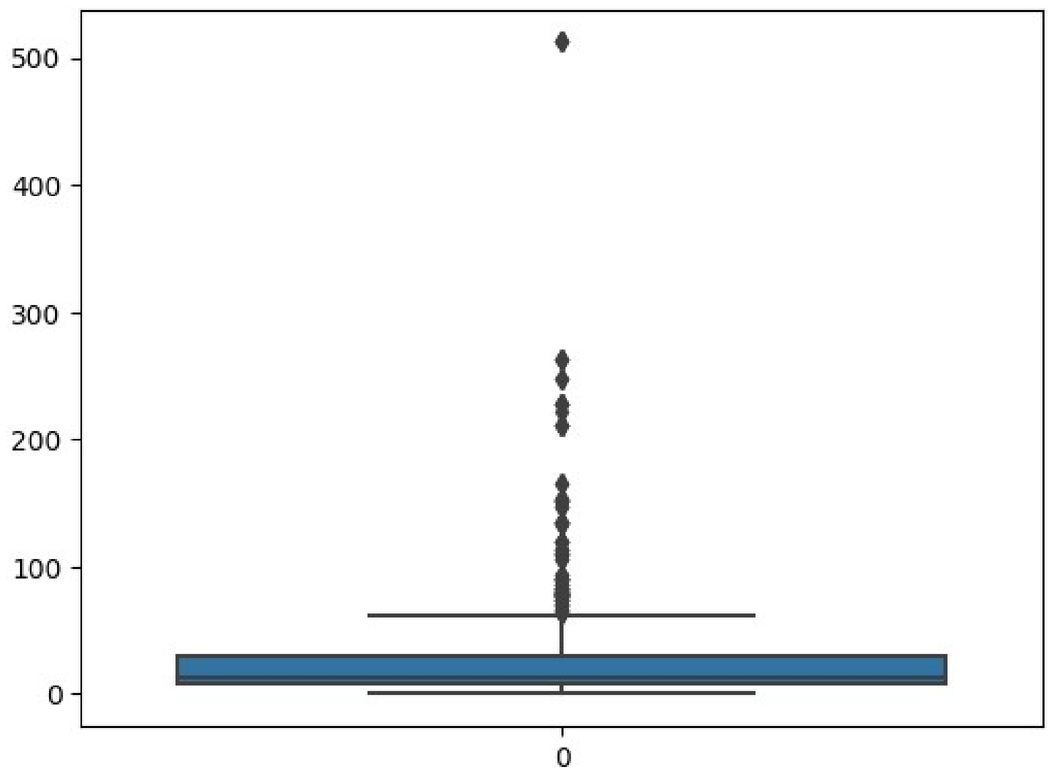



```
from scipy import stats

Parch_zscore=stats.zscore(df.Parch)
Parch_zscore

0      -0.414384
1      -0.414384
2      -0.414384
3      -0.414384
4      -0.414384
          ...
886    -0.414384
887    -0.414384
888     2.198711
889    -0.414384
890    -0.414384
Name: Parch, Length: 845, dtype: float64

df_z=df[np.abs(Parch_zscore)<=3]
sns.boxplot(df_z.Parch)

<Axes: >
```



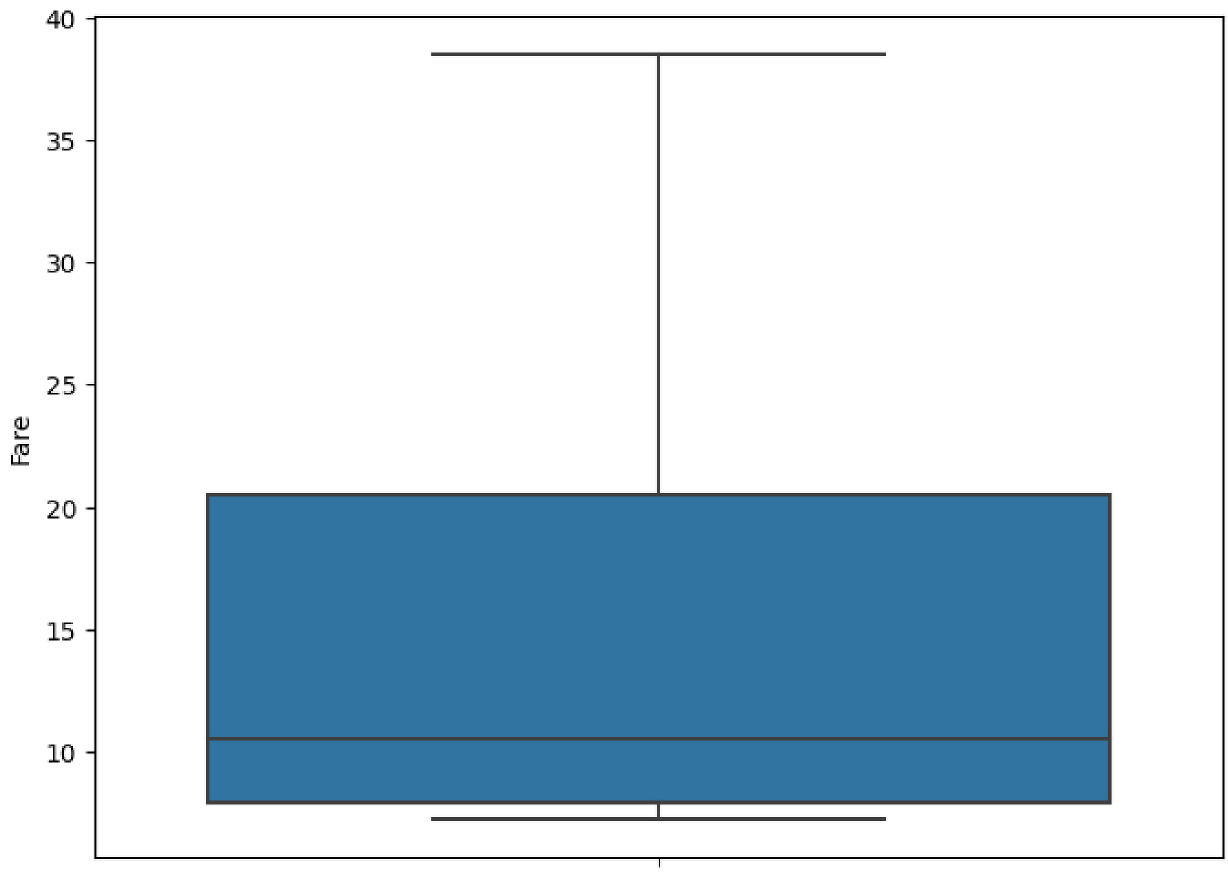

```
#Fare
sns.boxplot(df.Fare)
```

```
<Axes: >
```




```
#Fare
lower_percentile = 5
upper_percentile = 80

# Calculate the lower and upper bounds based on percentiles
lower_bound = df['Fare'].quantile(lower_percentile / 100)
upper_bound = df['Fare'].quantile(upper_percentile / 100)

df_no_outliers = df[(df['Fare'] >= lower_bound) & (df['Fare'] <=
upper_bound)]

# Create a boxplot to visualize the 'Age' column without outliers
plt.figure(figsize=(8, 6))
sns.boxplot(data=df_no_outliers, y='Fare')
```

```
<Axes: ylabel='Fare'>
```




```
#Age
lower_percentile = 5
upper_percentile = 85

# Calculate the lower and upper bounds based on percentiles
lower_bound = df['Age'].quantile(lower_percentile / 100)
upper_bound = df['Age'].quantile(upper_percentile / 100)

df_no_outliers = df[(df['Age'] >= lower_bound) & (df['Age'] <=
upper_bound)]

# Create a boxplot to visualize the 'Age' column without outliers
plt.figure(figsize=(8, 6))
sns.boxplot(data=df_no_outliers, y='Age',color="green")
plt.title('Boxplot of Age without Outliers')
plt.show()
```

6.SPLITTING OF DEPENDENT AND INDEPENDENT DATA Survived---dependent

---

```
columns_d=["Survived","PassengerId","Name","Sex","Ticket"]
x=df.drop(columns=columns_d)
x.head()
```

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

```
type(x)
```

```
pandas.core.frame.DataFrame
```

```
y=df["Survived"]
y
```

```
0      0
1      1
2      1
3      1
4      0
      ..
886    0
887    1
888    0
889    1
890    0
Name: Survived, Length: 845, dtype: int64
```

```
type(y)
```

```
pandas.core.series.Series
```

7.ENCODING

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()

# encoding
x.Embarked.value_counts()
```

```
S    604
C    168
Q     73
Name: Embarked, dtype: int64
```

```
x["Embarked"]=le.fit_transform(x["Embarked"])

mapping=dict(zip(le.classes_,range(len(le.classes_))))
mapping
```

```
{'C': 0, 'Q': 1, 'S': 2}
```

8.SCALING FEATURES

```
from sklearn.preprocessing import MinMaxScaler
ms=MinMaxScaler()

x_Scaled=pd.DataFrame(ms.fit_transform(x),columns=x.columns)
x_Scaled.head()
```

	Pclass	Age	SibSp	Parch	Fare	Embarked
0	1.0	0.271174	0.5	0.0	0.014151	1.0
1	0.0	0.472229	0.5	0.0	0.139136	0.0
2	1.0	0.321438	0.0	0.0	0.015469	1.0
3	0.0	0.434531	0.5	0.0	0.103644	1.0
4	1.0	0.434531	0.0	0.0	0.015713	1.0

9.SPLIT TRAINING AND TESTING DATA

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x_Scaled,y,test_size=0.
2,random_state=0)

print(x_train.shape,x_test.shape,y_train.shape,y_test.shape)

(676, 6) (169, 6) (676,) (169,)
```