

```
In [1]: import pandas as pd
import numpy as np
#
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
#
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
#
import csv
#
import xgboost as xgb
from sklearn.ensemble import RandomForestClassifier
#
import scipy.stats as stats
#
from sklearn.impute import KNNImputer
#
from sklearn import metrics
#
from sklearn.metrics import classification_report
#
import warnings
warnings.filterwarnings('ignore')
```

Read Data

```
In [2]: data=pd.read_csv("tested.csv",sep=",",encoding="utf-8")
data.head()
```

Out[2]:

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

Pclass: Passenger class (1 = 1st; 2 = 2nd; 3 = 3rd)

Survival: A Boolean indicating whether the passenger survived or not (0 = No; 1 = Yes); this is our target

Name: A Passenger name

Sex: passenger's gender(male/female)

Age: Age, as significant portion of values are missing

Sibsp: Number of siblings/spouses aboard

Parch: Number of parents/children aboard

Ticket: Ticket number.

Fare: Passenger fare (British Pound).

Cabin: Does the location of the cabin influence chances of survival?

Embarked: Port of embarkation (C = Cherbourg; Q = Queenstown; S = Southampton)

In [3]: data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 12 columns):
#   Column          Non-Null Count  Dtype
---  -
0   PassengerId     418 non-null    int64
1   Survived        418 non-null    int64
2   Pclass         418 non-null    int64
3   Name            418 non-null    object
4   Sex             418 non-null    object
5   Age            332 non-null    float64
6   SibSp          418 non-null    int64
7   Parch          418 non-null    int64
8   Ticket         418 non-null    object
9   Fare           417 non-null    float64
10  Cabin          91 non-null     object
11  Embarked       418 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 39.3+ KB
```

In [4]: data.describe()

Out[4]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	418.000000	418.000000	418.000000	332.000000	418.000000	418.000000	417.000000
mean	1100.500000	0.363636	2.265550	30.272590	0.447368	0.392344	35.627188
std	120.810458	0.481622	0.841838	14.181209	0.896760	0.981429	55.907576
min	892.000000	0.000000	1.000000	0.170000	0.000000	0.000000	0.000000
25%	996.250000	0.000000	1.000000	21.000000	0.000000	0.000000	7.895800
50%	1100.500000	0.000000	3.000000	27.000000	0.000000	0.000000	14.454200
75%	1204.750000	1.000000	3.000000	39.000000	1.000000	0.000000	31.500000
max	1309.000000	1.000000	3.000000	76.000000	8.000000	9.000000	512.329200

In [5]: data.describe(include="object").T

Out[5]:

	count	unique	top	freq
Name	418	418	Kelly, Mr. James	1
Sex	418	2	male	266
Ticket	418	363	PC 17608	5
Cabin	91	76	B57 B59 B63 B66	3
Embarked	418	3	S	270

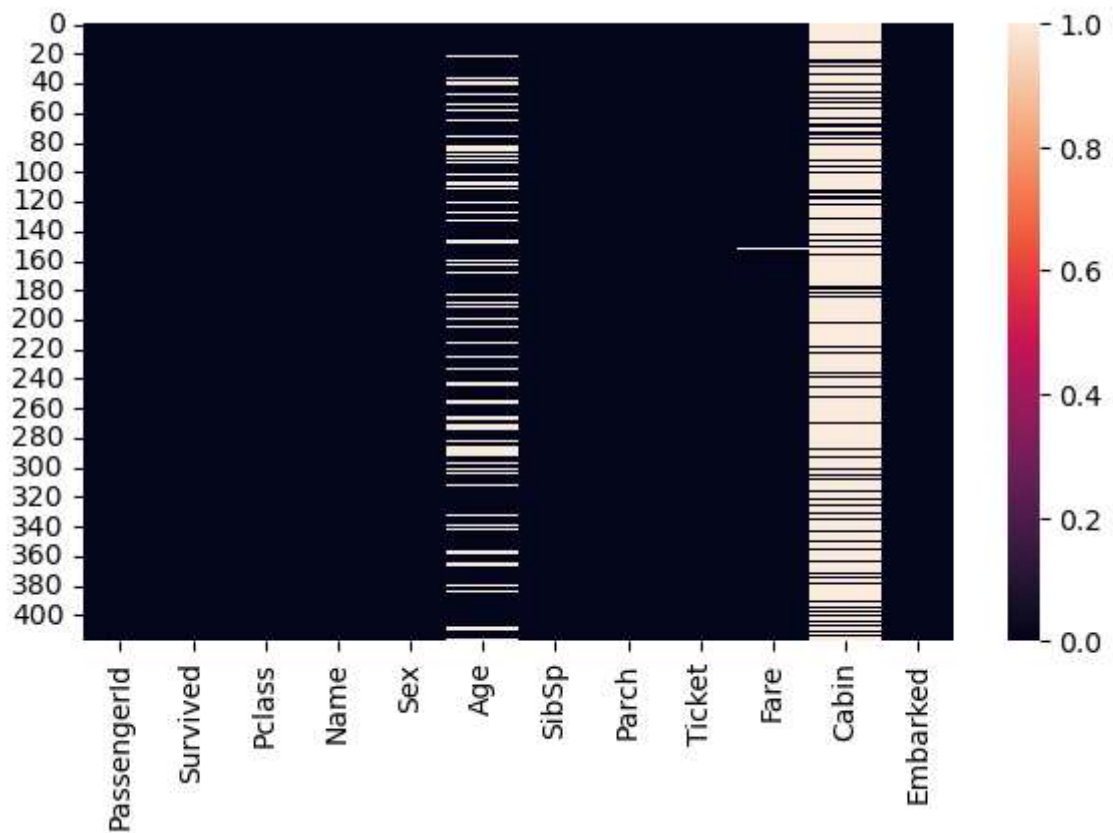
Preprocessing

```
In [6]: data.isnull().sum()
```

```
Out[6]: PassengerId      0
Survived      0
Pclass        0
Name          0
Sex           0
Age          86
SibSp         0
Parch         0
Ticket        0
Fare          1
Cabin       327
Embarked      0
dtype: int64
```

```
In [7]: plt.figure(figsize=(7,4))
sns.heatmap(data.isnull())
```

```
Out[7]: <AxesSubplot:>
```



```
In [8]: data[data["Age"]<=0].shape
```

```
Out[8]: (0, 12)
```

```
In [9]: data["PassengerId"].duplicated().sum()
```

```
Out[9]: 0
```

```
In [10]: numerical_data = []
         object_data = []

         for column in data.columns:
             if data.dtypes[column] != 'object':
                 numerical_data.append(column)
             else:
                 object_data.append(column)
```

```
In [11]: numerical_data
```

```
Out[11]: ['PassengerId', 'Survived', 'Pclass', 'Age', 'SibSp', 'Parch', 'Fare']
```

```
In [12]: imputer = KNNImputer(n_neighbors=5)
```

```
In [13]: data[numerical_data] = imputer.fit_transform(data[numerical_data])
```

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

```
Out[14]: PassengerId      0
         Survived        0
         Pclass          0
         Name            0
         Sex             0
         Age             0
         SibSp           0
         Parch           0
         Ticket          0
         Fare            0
         Cabin          327
         Embarked        0
         dtype: int64
```

Random Choice

```
In [15]: for column in data.columns:
         missing_indices = data[data[column].isnull()].index
         available_values = data[column].dropna()

         for index in missing_indices:
             random_choice = np.random.choice(available_values)
             data.at[index, column] = random_choice
```

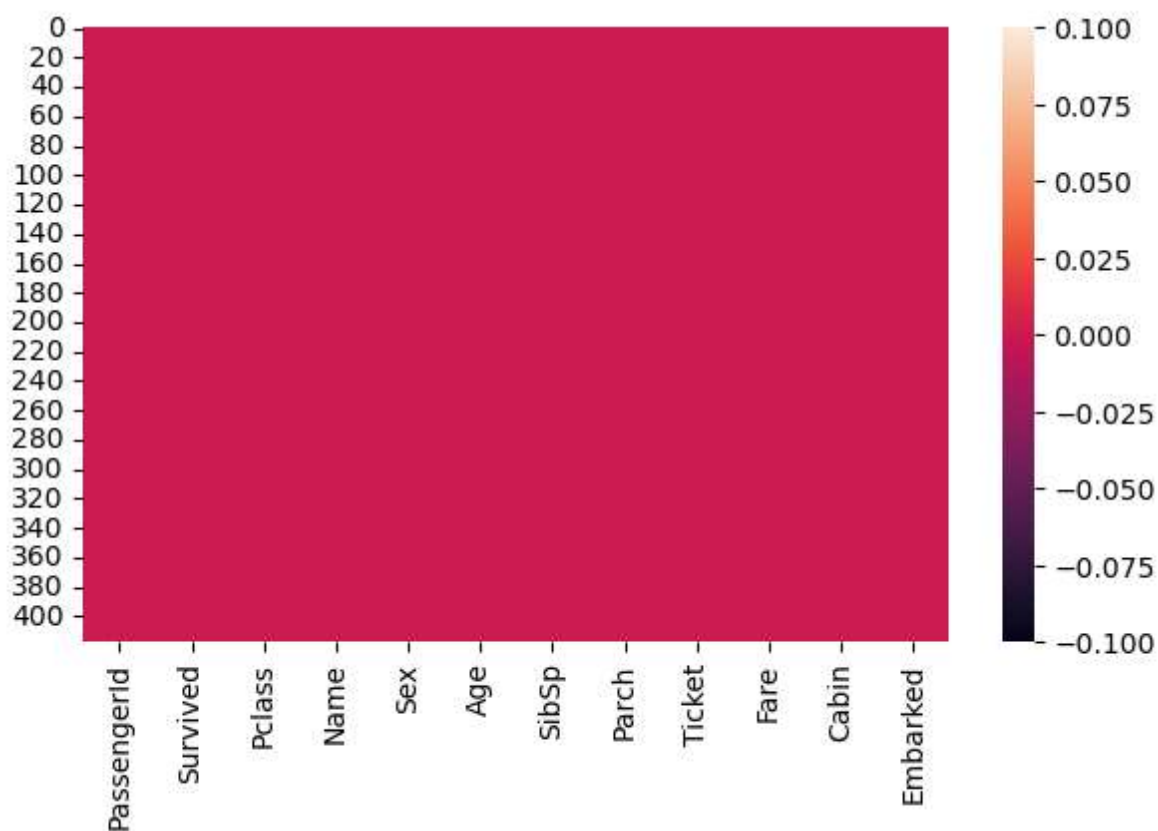
```
In [16]: data.isnull().sum()
```

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

```
In [17]: data['Fare']=data['Fare'].round(2)
```

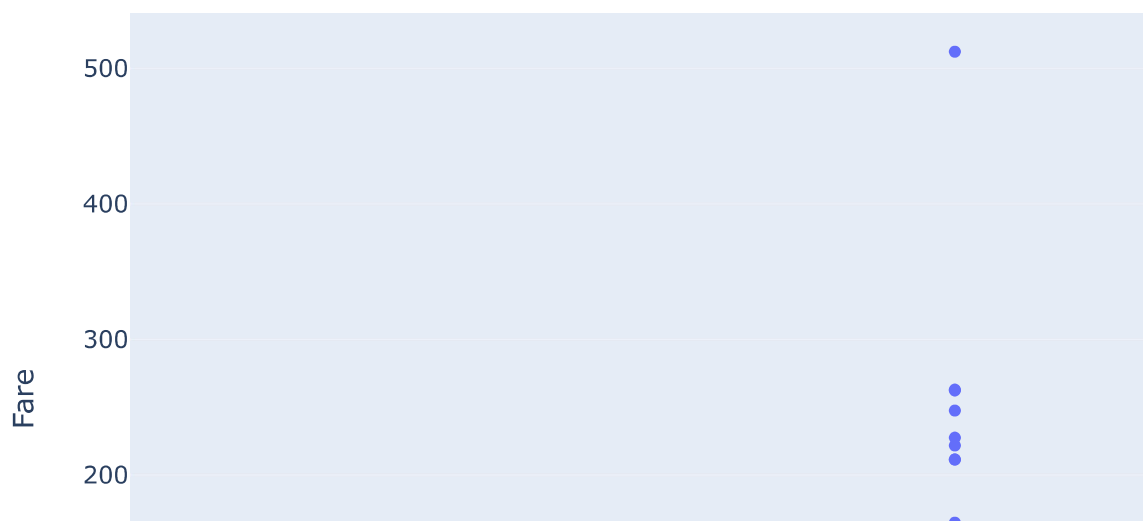
```
In [18]: plt.figure(figsize=(7,4))  
sns.heatmap(data.isnull())
```

```
Out[18]: <AxesSubplot:>
```



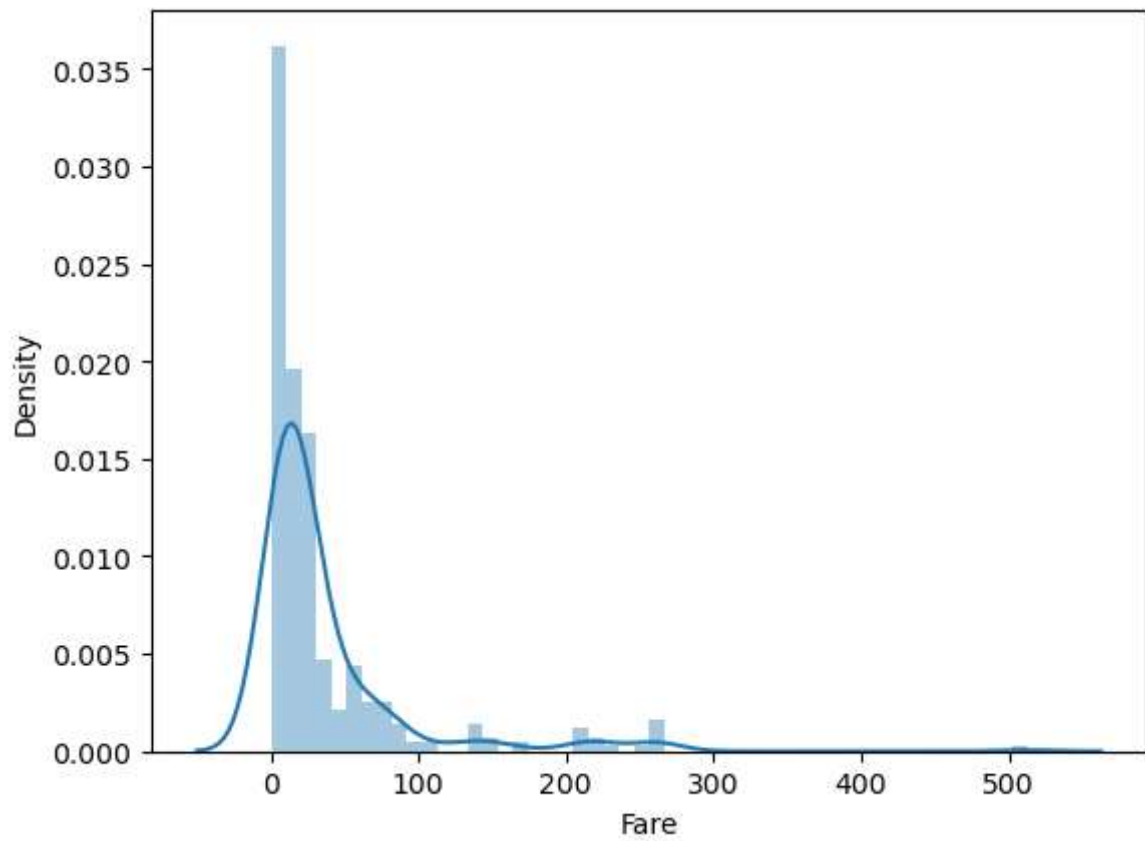
Check & Remove Outliers

```
In [19]: plt.figure(figsize=(7,5))  
px.box(data_frame=data, y="Fare")
```



<Figure size 700x500 with 0 Axes>

```
In [20]: sns.distplot(data["Fare"])  
plt.show()
```



```
In [21]: (data["Fare"]>=76).sum()
```

```
Out[21]: 45
```

```
In [22]: #find the limits  
upper_limit=data["Fare"].mean() + 3*data["Fare"].std()  
lower_limit=data["Fare"].mean() - 3*data["Fare"].std()  
print("upper limit: ",upper_limit)  
print("lower limit: ",lower_limit)
```

```
upper limit: 203.31658471212668  
lower limit: -131.891321554232
```

```
In [23]: #find the outliers  
outliers_df=data.loc[(data["Fare"]> upper_limit) |(data["Fare"] < lower_limit)]  
outliers_df.shape
```

```
Out[23]: (18, 12)
```



```
In [24]: #remove outliers from the data
new_df = data.loc[(data["Fare"] < upper_limit) & (data["Fare"] > lower_limit)]
print("before removing the outliers: ", len(data))
print("after removing the outliers: ", len(new_df))
print("the outliers: ", len(data) - len(new_df))
```

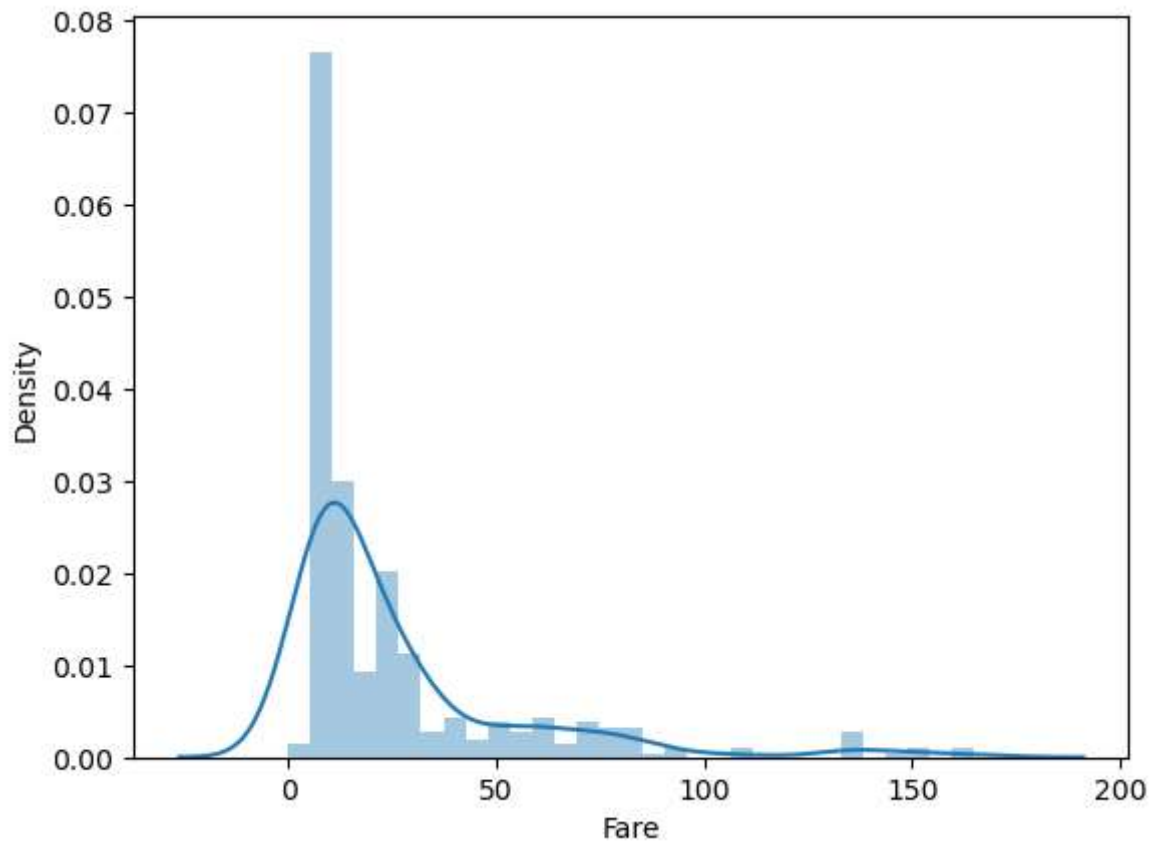
```
before removing the outliers: 418
after removing the outliers: 400
the outliers: 18
```

```
In [25]: plt.figure(figsize=(7,5))
px.box(data_frame=new_df, y="Fare")
```



<Figure size 700x500 with 0 Axes>

```
In [26]: sns.distplot(new_df["Fare"])  
plt.show()
```



```
In [27]: file_path = "new_df.csv"  
  
with open(file_path, mode="w", newline="") as file:  
    writer = csv.writer(file)  
    writer.writerows(new_df)  
  
print("Data saved to", file_path)
```

Data saved to new_df.csv

EDA

```
In [28]: from pandas_profiling import ProfileReport

#EDA using pandas-profiling
profile = ProfileReport(pd.read_csv('new_df.csv'), explorative=True)

#Saving results to a HTML file
profile
```

Summarize dataset: 0%| | 0/5 [00:00<?, ?it/s]

Generate report structure: 0%| | 0/1 [00:00<?, ?it/s]

Render HTML: 0%| | 0/1 [00:00<?, ?it/s]

Overview

Dataset statistics

Number of variables	11
Number of observations	11
Missing cells	64
Missing cells (%)	52.9%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	4.6 KiB
Average record size in memory	426.4 B

Variable types

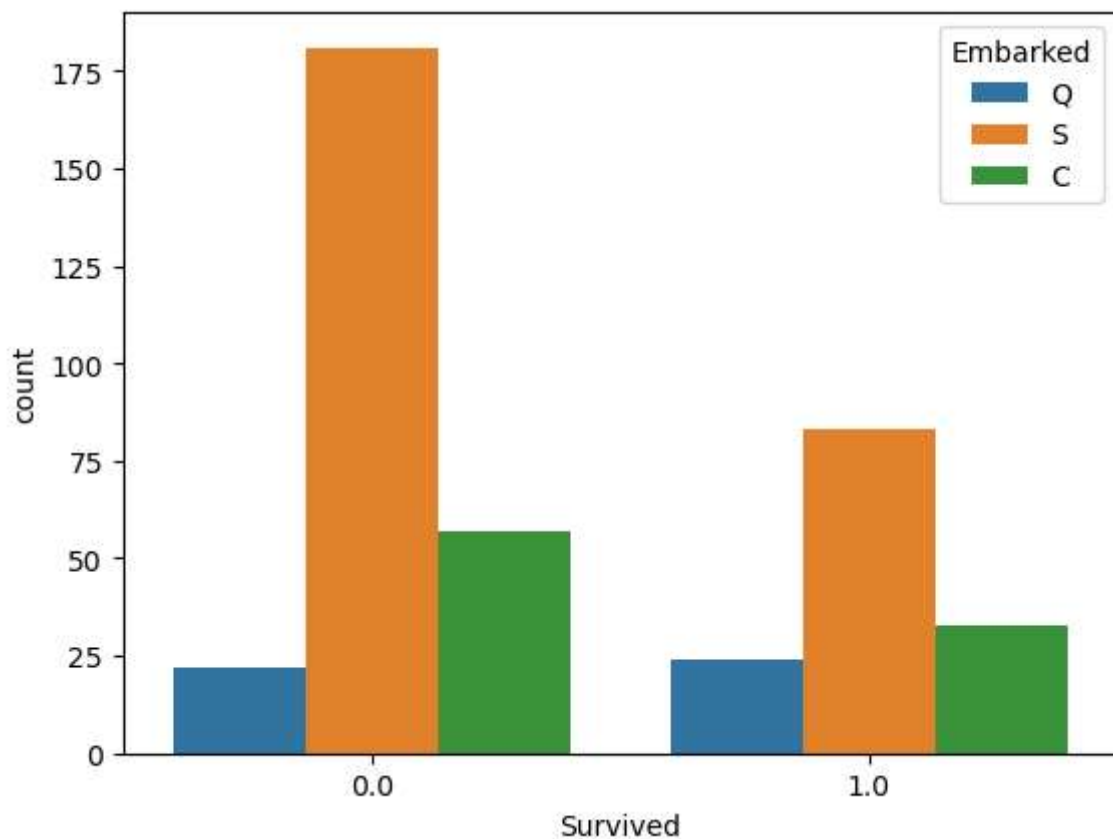
Categorical	8
Unsupported	3

Alerts

g has constant value "e"	Constant
e.1 has constant value "d"	Constant
P is highly overall correlated with e and 1 other fields (e, n)	High correlation
a is highly overall correlated with a and 1 other fields (a	High correlation

Out[28]:

```
In [29]: sns.countplot( x='Survived', data=new_df, hue="Embarked");
```



```
In [30]: plt.figure(figsize=(10,4))
sns.heatmap(new_df.corr(),annot=True)
plt.show
```

```
Out[30]: <function matplotlib.pyplot.show(close=None, block=None)>
```



Preparation

```
In [31]: new_df["Embarked"].value_counts()
```

```
Out[31]: S      264  
         C      90  
         Q      46  
         Name: Embarked, dtype: int64
```

```
In [32]: new_df["Embarked"]=new_df["Embarked"].replace("S",0)  
         new_df["Embarked"]=new_df["Embarked"].replace("C",1)  
         new_df["Embarked"]=new_df["Embarked"].replace("Q",2)
```

```
In [33]: new_df["Sex"].value_counts()
```

```
Out[33]: male      260  
         female    140  
         Name: Sex, dtype: int64
```

```
In [34]: new_df["Sex"]=new_df["Sex"].replace("male",0)  
         new_df["Sex"]=new_df["Sex"].replace("female",1)
```

In [35]: new_df

Out[35]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	C
0	892.0	0.0	3.0	Kelly, Mr. James	0	34.5	0.0	0.0	330911	7.83	
1	893.0	1.0	3.0	Wilkes, Mrs. James (Ellen Needs)	1	47.0	1.0	0.0	363272	7.00	
2	894.0	0.0	2.0	Myles, Mr. Thomas Francis	0	62.0	0.0	0.0	240276	9.69	
3	895.0	0.0	3.0	Wirz, Mr. Albert	0	27.0	0.0	0.0	315154	8.66	
4	896.0	1.0	3.0	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	1	22.0	1.0	1.0	3101298	12.29	F
...	
413	1305.0	0.0	3.0	Spector, Mr. Woolf	0	22.5	0.0	0.0	A.5. 3236	8.05	
414	1306.0	1.0	1.0	Oliva y Ocana, Dona. Fermina	1	39.0	0.0	0.0	PC 17758	108.90	
415	1307.0	0.0	3.0	Saether, Mr. Simon Sivertsen	0	38.5	0.0	0.0	SOTON/O.Q. 3101262	7.25	
416	1308.0	0.0	3.0	Ware, Mr. Frederick	0	22.5	0.0	0.0	359309	8.05	
417	1309.0	0.0	3.0	Peter, Master. Michael J	0	26.5	1.0	1.0	2668	22.36	

400 rows × 12 columns



```

In [36]: new_df["Embarked"]=new_df["Embarked"].astype("int64")
new_df["Sex"]=new_df["Sex"].astype("int64")
new_df["PassengerId"]=new_df["PassengerId"].astype("int64")
new_df["Pclass"]=new_df["Pclass"].astype("int64")
new_df["Age"]=new_df["Age"].astype("int64")
new_df["SibSp"]=new_df["SibSp"].astype("int64")
new_df["Parch"]=new_df["Parch"].astype("int64")

```

Feature Selection

```
In [37]: # Create a contingency table for each categorical column
for col in new_df.columns:
    contingency_table = pd.crosstab(new_df[col], new_df['Survived'])
    # Apply the chi-square test
    chi2, p, dof, expected = stats.chi2_contingency(contingency_table)
    print(f"Chi-square test results for {col}:")
    print(f"Chi-square statistic: {chi2}")
    print(f"P-value: {p}")
    print(f"Degrees of freedom: {dof}")
    print(f"Expected frequencies table:\n{expected}\n")
```



```
In [39]: X = new_df.drop(['Survived', 'Name', 'Cabin', 'Ticket'],axis=1)
y = new_df['Survived']
```

Scaling

```
In [40]: sc = StandardScaler()
X = sc.fit_transform(X)
```

Modling

1-Random Forest

```
In [41]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
In [42]: RF = RandomForestClassifier(n_estimators=100, random_state=42)
RF.fit(X_train, y_train)
```

```
Out[42]: RandomForestClassifier(random_state=42)
```

```
In [43]: print(RF.score(X_train,y_train))
print(RF.score(X_test,y_test))
```

```
1.0
1.0
```

```
In [44]: y_pred=RF.predict(X_test)
y_pred
```

```
Out[44]: array([0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1,
                1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1,
                1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
                1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0], dtype=int8)
```

```
In [45]: df=pd.DataFrame({"y_predict":y_pred,"y_test":y_test})
df
```

Out[45]:

	y_predict	y_test
223	0	0
294	0	0
34	0	0
224	1	1
101	0	0
...
260	0	0
241	1	1
386	0	0
188	1	1
303	0	0

80 rows × 2 columns

```
In [46]: report = classification_report(y_test, y_pred)
print(report)
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	46
1	1.00	1.00	1.00	34
accuracy			1.00	80
macro avg	1.00	1.00	1.00	80
weighted avg	1.00	1.00	1.00	80

2-XGBoost

```
In [47]: xgboost = xgb.XGBClassifier(objective='multi:softmax', num_class=3, random_state=42)

xgboost.fit(X_train, y_train)

y_pred = xgboost.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
```

Accuracy: 1.00

