Titanic Survival Prediction

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Project Description:

In this project focused on data analytics, our goal is to develop a predictive model to ascertain the survival outcome of passengers on the Titanic. The dataset under examination encompasses diverse details about each passenger, such as age, gender, ticket class, fare, cabin specifics, and the ultimate status of survival.

Project Contents

Collecting Data: Our initial step involves obtaining information from a dataset that includes details about various individuals, specifically whether a Titanic passenger survived. I have obtained this dataset from Kaggle.

Visualising Data: We will closely inspect the data to enhance our understanding using the power of visualisation. This includes identifying and addressing any missing values while gaining insights from the available information.

Preprocessing Data: Recognizing that data can be disorganized, our next phase focuses on data wrangling, feature engineering and structuring the data in a format comprehensible to a computer.

Constructing a Model⚙: Utilizing a computer program (model), we aim to enable it to learn from the data. The objective is for the model to recognize patterns indicative of whether a Titanic passenger survived.

Testing the Model: To validate the effectiveness of our model, we will assess its performance using a distinct dataset that it hasn't encountered previously. This evaluation will gauge the accuracy of our model in making predictions.assengers.

In [5]:
```
# Importing a few basic data analysis libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# importing warnings
import warnings

warnings.filterwarnings("ignore")
```

In [6]:
```
# Reading the data
titanic = pd.read_csv(r'C:\Users\pc\CodSoft\Data Science Projects\Task1-Titanic Survival Prediction\tested.csv'
```

In [7]:
```
titanic.head(10)
```

Out[7]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S
5	897	0	3	Svensson, Mr. Johan Cervin	male	14.0	0	0	7538	9.2250	NaN	S
6	898	1	3	Connolly, Miss. Kate	female	30.0	0	0	330972	7.6292	NaN	Q
7	899	0	2	Caldwell, Mr. Albert Francis	male	26.0	1	1	248738	29.0000	NaN	S
8	900	1	3	Abrahim, Mrs. Joseph (Sophie Halaut Easu)	female	18.0	0	0	2657	7.2292	NaN	C
9	901	0	3	Davies, Mr. John Samuel	male	21.0	2	0	A/4 48871	24.1500	NaN	S

Understanding the data

In [8]:

```
print("The size of the dataset is : ", titanic.size)
print("Total number of rows in the dataset is : ", titanic.shape[0])
print("Total number of columns in the dataset is : ", titanic.shape[1])
```

```
The size of the dataset is :  5016
Total number of rows in the dataset is :  418
Total number of columns in the dataset is :  12
```

In [9]:

```
titanic.describe()
```

Out[9]:

	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 [10]:

```
titanic.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 [11]:

```
titanic.duplicated().sum()
```

Out[11]:

```
0
```

In [12]:

```
titanic['Sex'].value_counts()
```

Out[12]:

```
male      266
female    152
Name: Sex, dtype: int64
```

In [13]:
```
titanic['Survived'].value_counts()
```

Out[13]:
```
0    266
1    152
Name: Survived, dtype: int64
```

In [14]:
```
titanic['Pclass'].value_counts()
```

Out[14]:
```
3    218
1    107
2     93
Name: Pclass, dtype: int64
```

In [15]:
```
titanic['Embarked'].value_counts()
```

Out[15]:
```
S    270
C    102
Q     46
Name: Embarked, dtype: int64
```

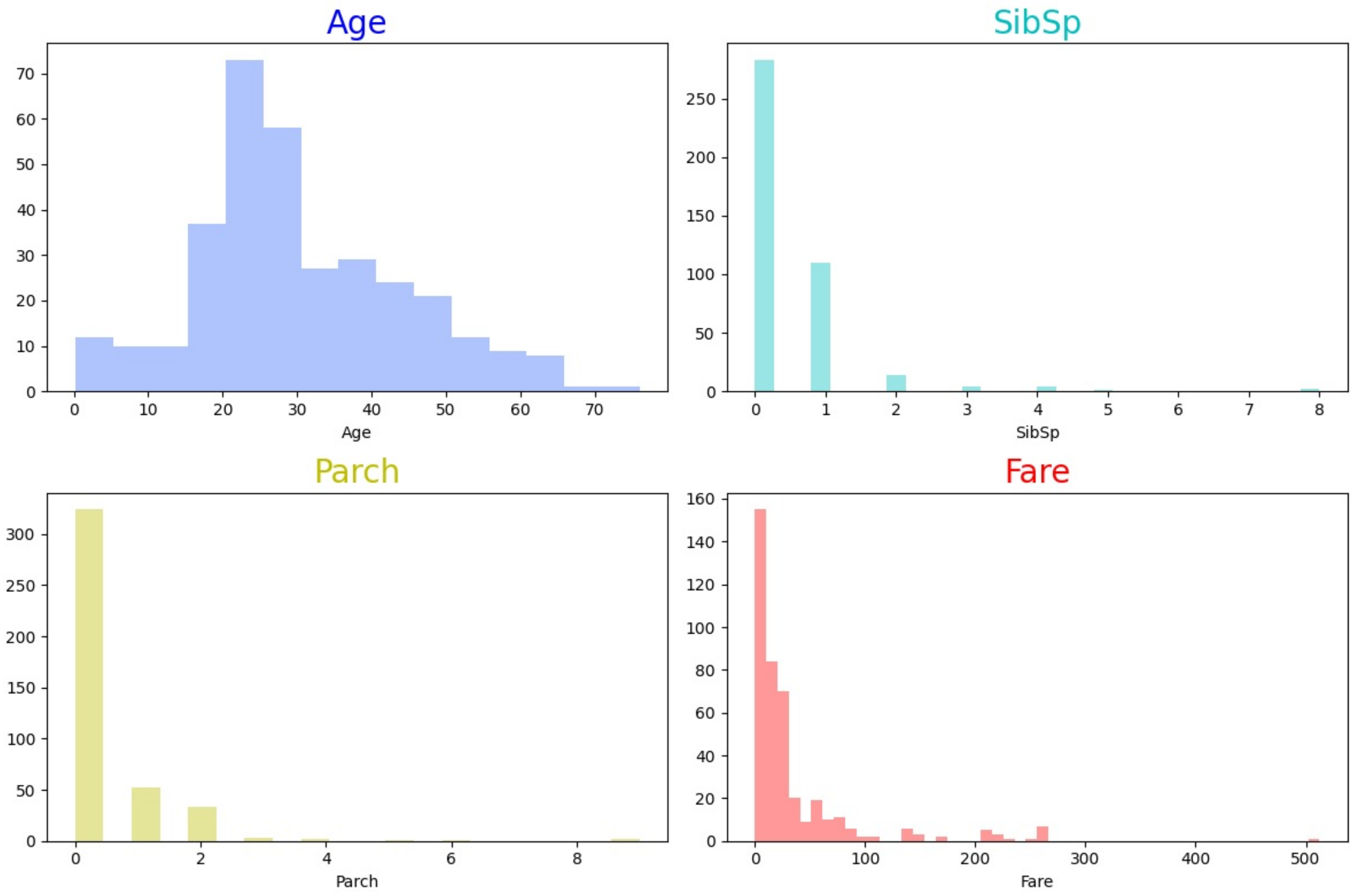
In a nutshell, in our dataset

- We have **418** rows and **12** columns.
- Numeric Features: *PassengerId, Survived, Pclass, Age, SibSp, Parch, Fare.*
- Categorical Features: *Name, Sex, Ticket, Cabin, Embarked.*
- 0 : *Not Survived*, 1 : *Survived*
- Q : *Queenstown*, S : *Southampton*, C : *Cherbourgh*

Visualising the data

We will try to understand things like distribution of different data features, relation between various features and their impact on Survival etc. using various charts.

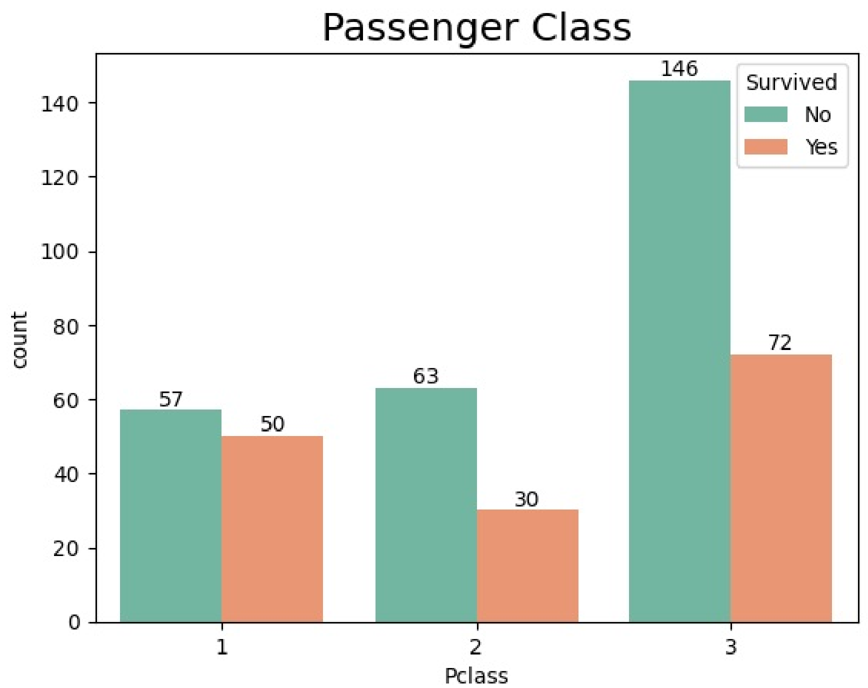
In [16]:
```
sns.set_palette('rainbow')
plt.figure(figsize=(12,8))

plt.subplot(2,2,1)
sns.distplot(titanic['Age'], kde=False)
plt.title('Age', color='b', fontsize=20)

plt.subplot(2,2,2)
sns.distplot(titanic['SibSp'], kde=False, color='c')
plt.title('SibSp', color='c', fontsize=20)

plt.subplot(2,2,3)
sns.distplot(titanic['Parch'], kde=False, color='y')
plt.title('Parch', color='y', fontsize=20)

plt.subplot(2,2,4)
sns.distplot(titanic['Fare'], kde=False, color='r')
plt.title('Fare', color='r', fontsize=20)

plt.tight_layout()
plt.show()
```



We can observe the following things:

1. Most people were between the age of 20-30 while, a fair number of people were in the age group of 30-50.
2. Most number of people had no siblings. However, around 100 people had one sibling.
3. People with no spouses were the most amongst the passengers and only a few of them had a spouse.
4. The fare price of most of the tickets that were bought was between 0 to 50 pounds.

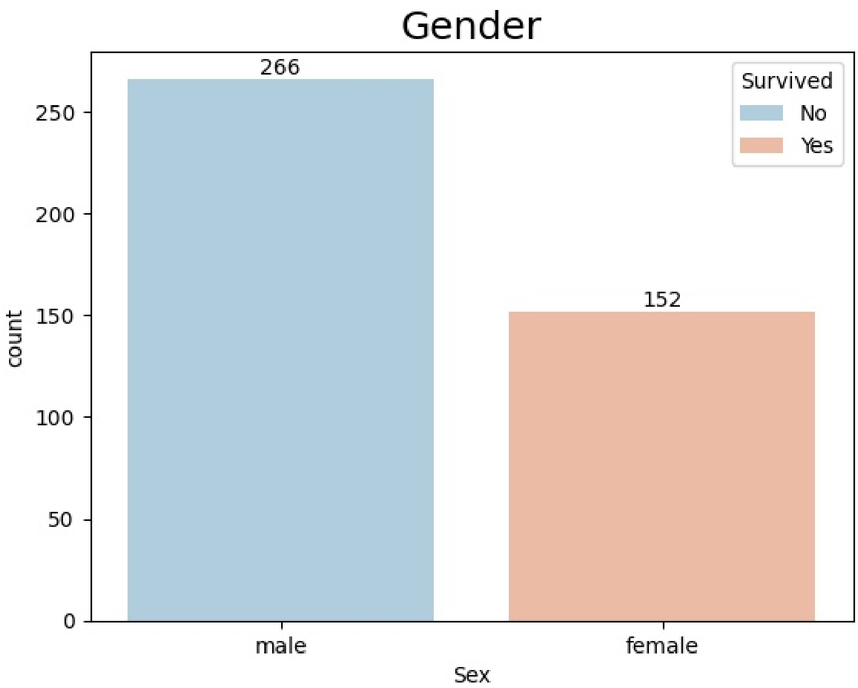
In [17]:
```
count_plot_pclass = sns.countplot(x='Pclass', hue='Survived', data=titanic, palette='Set2')

for container in count_plot_pclass.containers:
    count_plot_pclass.bar_label(container)

plt.title('Passenger Class', fontsize=18)
plt.legend(title='Survived', loc='upper right', labels= ['No','Yes'])
plt.show()
```



Out of all the people belonging to the passenger class 2 and passenger class 3, only half of them survived . Whereas, only a few casualties (7 people) were noted from people belonging to the passenger class 1.

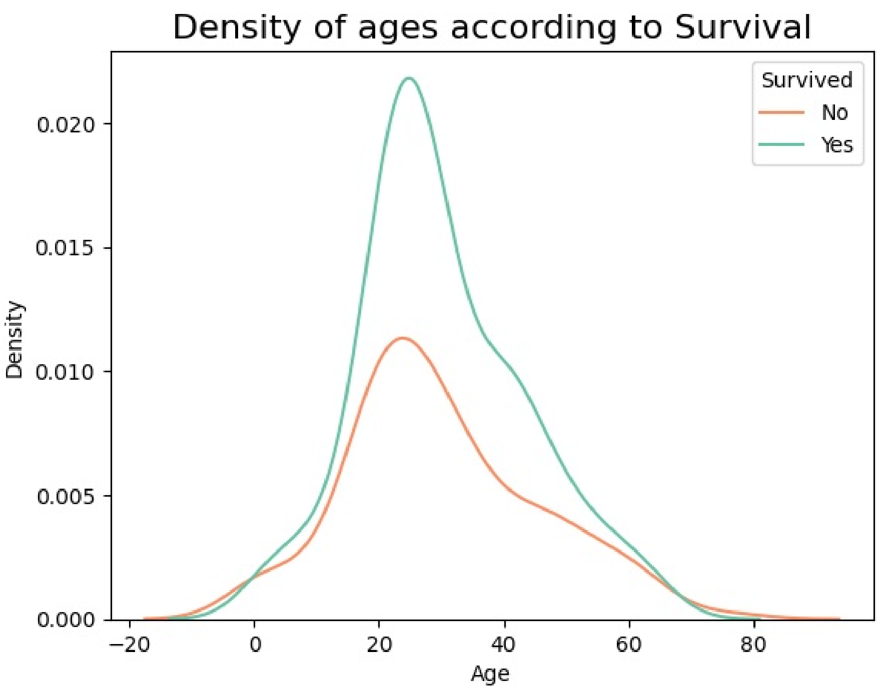
This suggests that the passenger class 1 people were given the priority over the others.

In [18]:
```
count_plot_gender = sns.countplot(x='Sex', hue='Survived', data=titanic, palette='RdBu_r')

for container in count_plot_gender.containers:
    count_plot_gender.bar_label(container)

plt.title('Gender', fontsize=18)
plt.legend(title='Survived', loc='upper right', labels= ['No','Yes'])
plt.show()
```



The above bar graph depicts that **none of the males survived** meanwhile, **all the females did**.

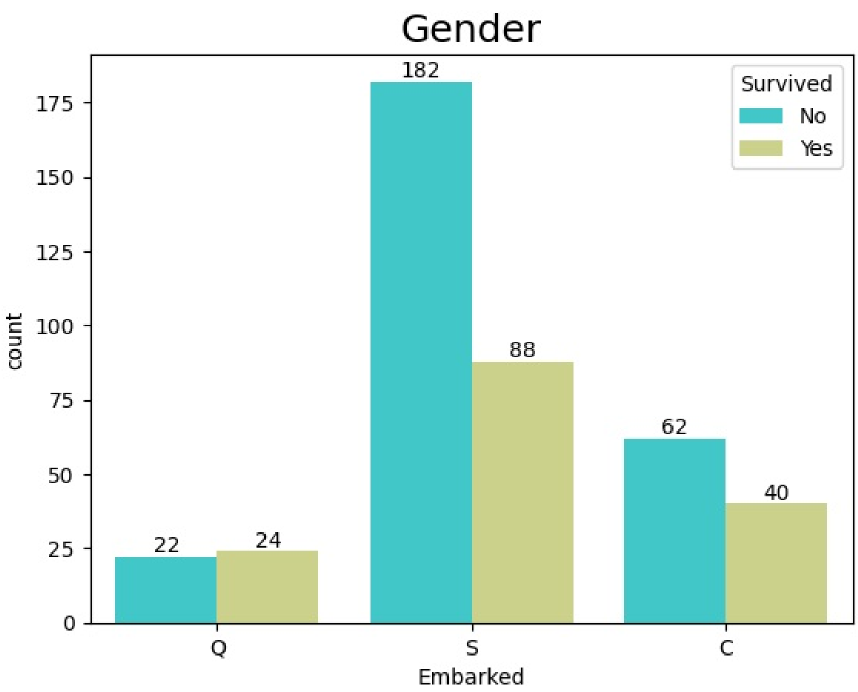
In [19]:
```
sns.kdeplot(data=titanic, x='Age', hue='Survived', palette='Set2')
plt.title("Density of ages according to Survival", fontsize=16)
plt.legend(title='Survived', loc='upper right', labels= ['No','Yes'])
plt.grid(False)
plt.show()
```



The survivers and the non-survivers both were mostly between the age of 20 to 40.

In [20]:
```
count_plot_embarked = sns.countplot(x='Embarked', hue='Survived', data=titanic, palette='rainbow')

for container in count_plot_embarked.containers:
    count_plot_embarked.bar_label(container)

plt.title('Gender', fontsize=18)
```

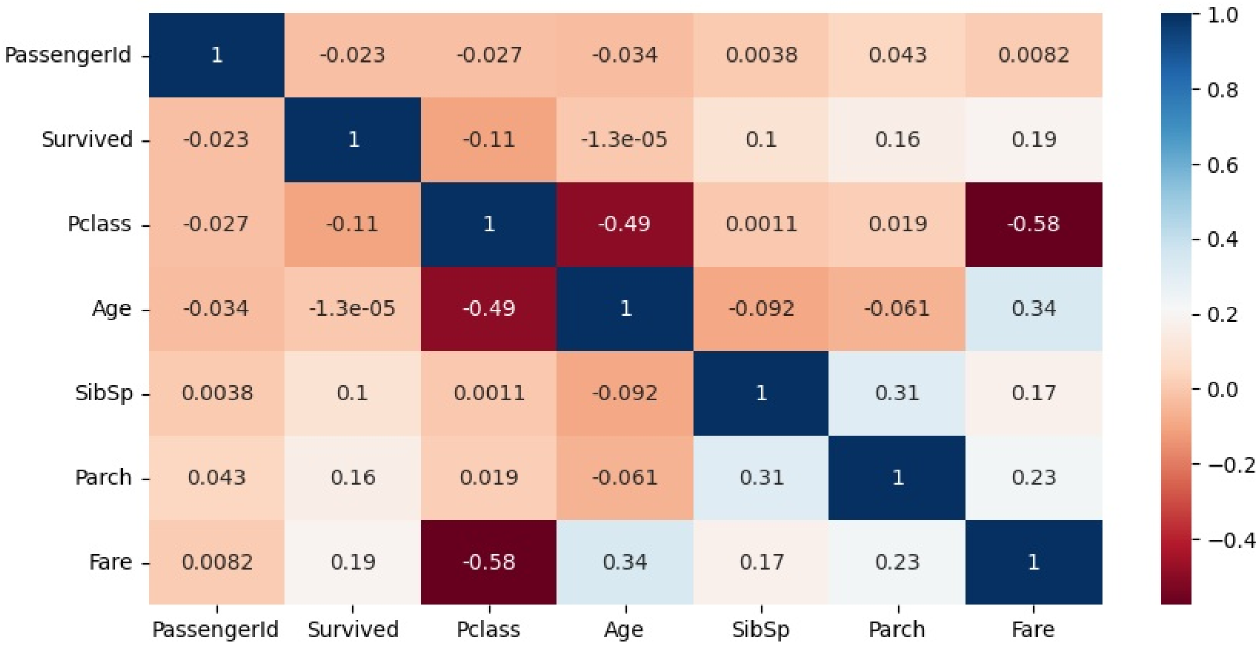
```
plt.legend(title='Survived', loc='upper right', labels= ['No','Yes'])
plt.show()
```



1. **Queenstown** : Approximately all the passengers survived.
2. **Southampton** : More than half of the passengers were deceased(could not survive).
3. **Cherbourgh** : Most number or moderate or a fair number of people survived.

The reason behind the maximum number of survivers from Queenstown can perhaps be that they were mostly from the first class as first class passengers were given the priority over others.

In [21]:
```
corr = titanic.corr()

plt.figure(figsize=(10,5))
sns.heatmap(corr, cmap='RdBu', annot=True)
plt.show()
```

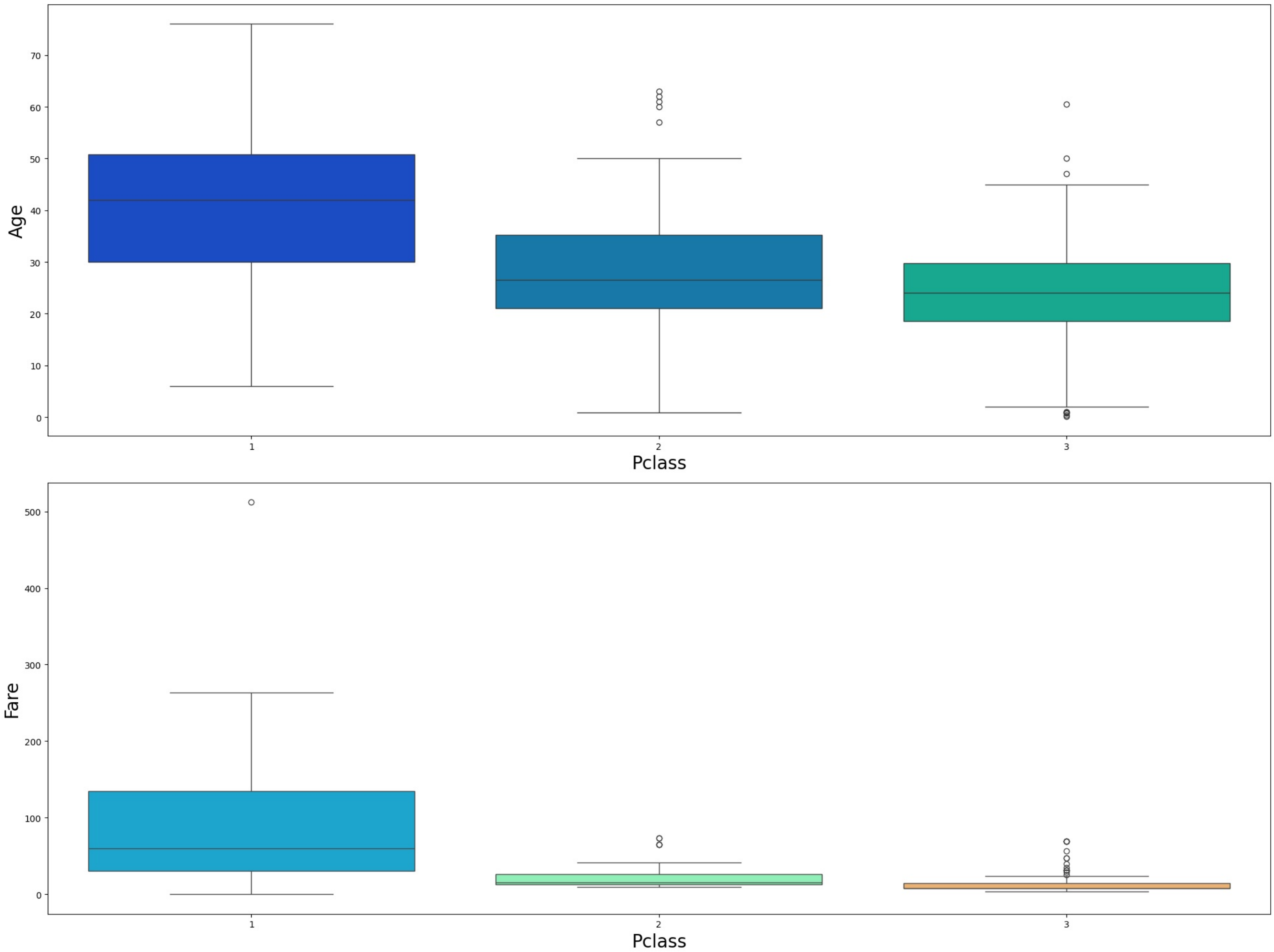


This heatmap suggests that, there is a **moderately negative** correlation between both **Passenger class and Age** and also between **Passenger class and Fare**.

Further, let's create a boxplot to have a better understanding of the correlation between Passenger class & Age and Passenger class & Fare.

In [22]:
```
plt.figure(figsize=(20,15))

plt.subplot(2, 1, 1)
sns.boxplot(x='Pclass', y='Age', data=titanic, palette='winter')
```

```
plt.xlabel("Pclass", fontsize=20)
plt.ylabel("Age", fontsize=20)

plt.subplot(2, 1, 2)
sns.boxplot(x='Pclass', y='Fare', data=titanic, palette='rainbow')
plt.xlabel("Pclass", fontsize=20)
plt.ylabel("Fare", fontsize=20)

plt.tight_layout()
plt.show()
```



1. Pclass and Age: We notice a few outliers in Passenger class 2 and in Passenger class 3.

2. Pclass and Fare: We notice only one outlier in Passenger class 1 which is extreme, two outliers in Passenger class 2 and many outliers in Passenger class 3.

Different ways to visualise missing values

Here, we will use different graphs and charts to visualise our data and identify the missing values

DataFrame form

In [23]:
```
missing_data = titanic.isnull().sum().reset_index()
missing_data.columns = ['Column', 'Missing Value']
```

In [24]:
```
missing_data
```

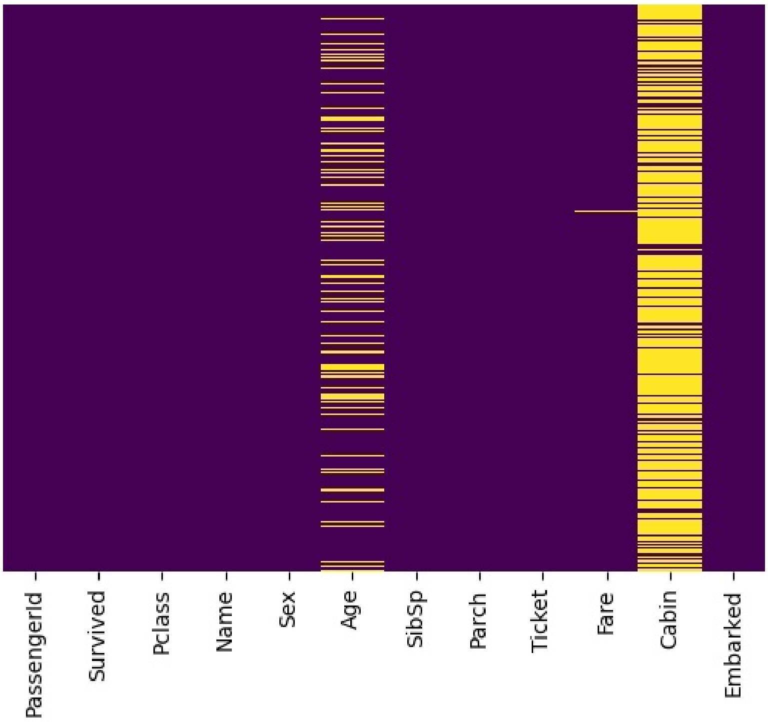
Out[24]:

	Column	Missing Value
0	PassengerId	0
1	Survived	0
2	Pclass	0
3	Name	0
4	Sex	0
5	Age	86
6	SibSp	0
7	Parch	0
8	Ticket	0
9	Fare	1
10	Cabin	327
11	Embarked	0

Heatmap

In [25]:

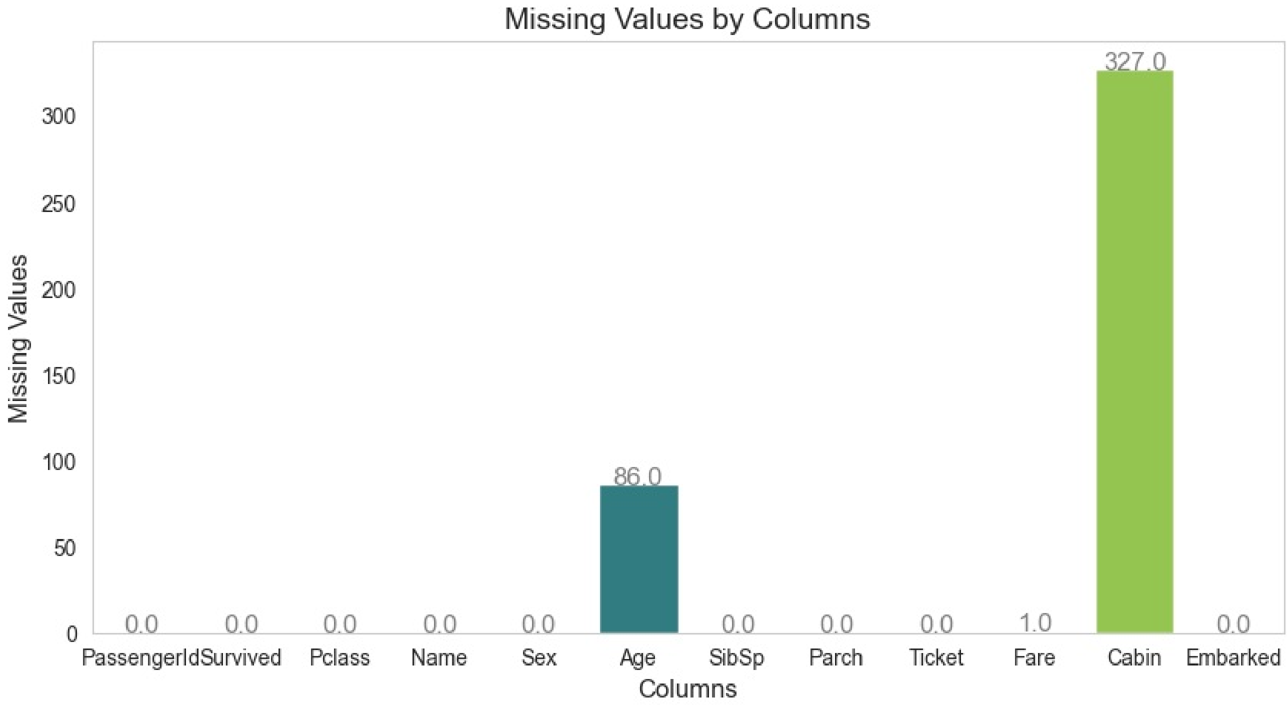
```
sns.heatmap(titanic.isnull(), yticklabels=False, cbar=False, cmap='viridis')
plt.show()
```



Barchart

In [26]:

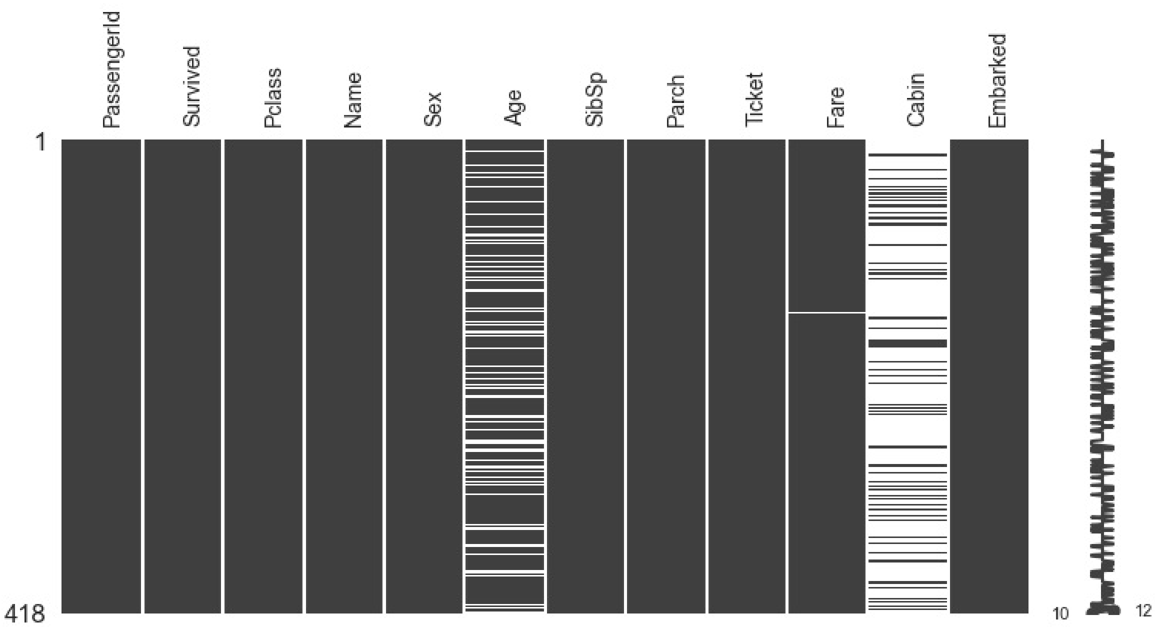
```
sns.set_style('whitegrid')

plt.figure(figsize=(10,5))
ax = sns.barplot(x = 'Column', y = 'Missing Value', data = missing_data, palette = 'viridis')

for p in ax.patches:
    ax.annotate(f"{p.get_height()}", (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=12, color='grey')

plt.title('Missing Values by Columns', fontsize=14)
plt.xlabel('Columns', fontsize=12)
plt.ylabel('Missing Values', fontsize=12)
plt.grid(False)
plt.show()
```



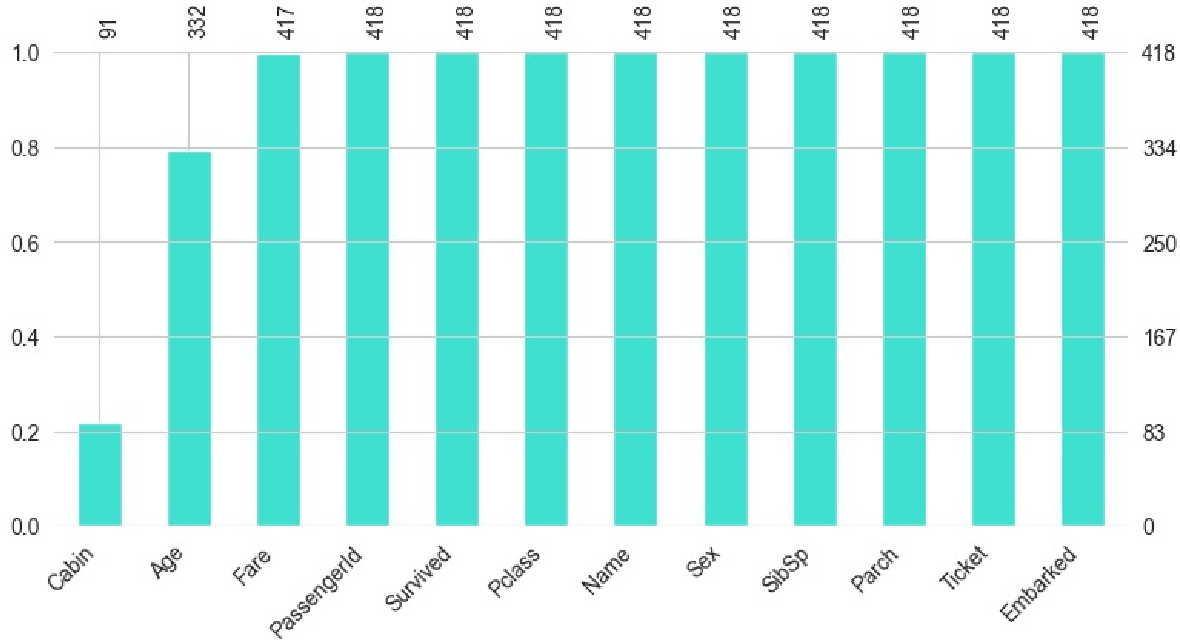
Missingno Plots

Missingno library offers a very nice way to visualize the distribution of NaN values. Missingno is a Python library and is compatible with Pandas.

In [27]:
```
import missingno as msno
msno.matrix(titanic, figsize=(9,4), fontsize=10)
plt.xticks(rotation=90)
plt.show()
```



In [28]:
```
msno.bar(titanic, sort='ascending' ,color='turquoise',figsize=(9,4), fontsize=10)
plt.xticks(rotation=90)
plt.show()
```



There are missing values present in the features namely **'Cabin', 'Age'** and **'Fare'**.

Data Wrangling

Now, we will try to impute the missing values in our dataset.

In [29]:
```
avg_age = titanic.groupby(['Sex', 'Pclass'])['Age'].mean()
```

In [30]:
```
avg_age.to_frame()
```

Out[30]:

Sex	Pclass	Age
female	1	41.333333
	2	24.376552
	3	23.073400
male	1	40.520000
	2	30.940678
	3	24.525104

The below function is created to impute the null values present in the 'Age' column.

Here, we are imputing the null values using two features i.e. based on genderwise distribution among all the three passsenger classes.

In [31]:
```
def impute_age(cols):
    Age = cols[0]
    Pclass = cols[1]
    Sex = cols[2]

    if pd.isnull(Age):

        if Sex == "female":
            if Pclass == 1:
                return 41.0
            elif Pclass == 2:
                return 24.0
            else:
                return 23.0

        else:
            if Pclass == 1:
                return 40.0

            elif Pclass == 2:
                return 31.0

            else:
                return 25.0
```

```
    else:
        return Age
```

In [32]:
```
titanic['Age'] = titanic[['Age', 'Pclass', 'Sex']].apply(impute_age, axis=1)
```

We see around 79% of data is missing in the Cabin column so we decide to simply drop it.

In [33]:
```
titanic['Fare'] = titanic['Fare'].fillna(titanic['Fare'].mean())
```

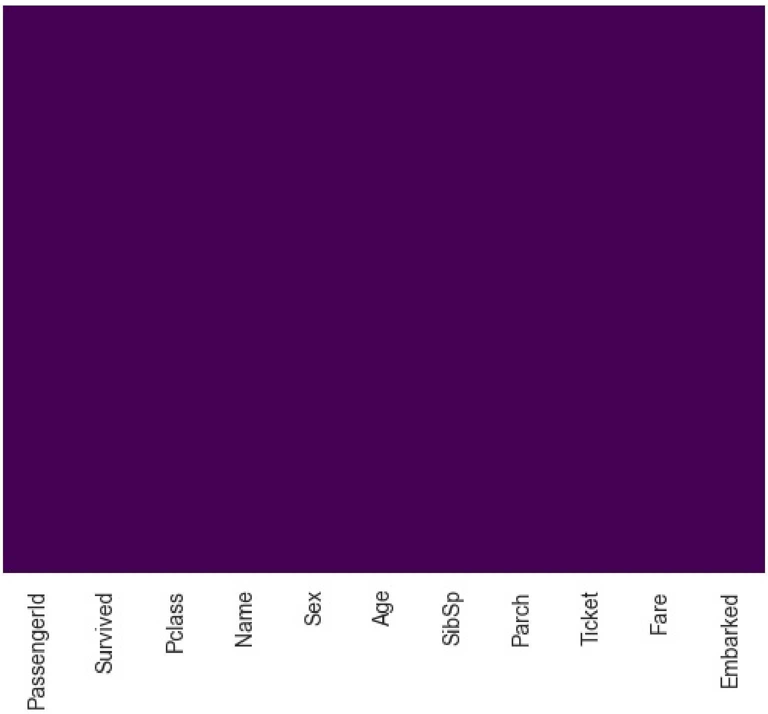
In [34]:
```
titanic.drop('Cabin', axis=1, inplace=True)
```

In [35]:
```
titanic.head(10)
```

Out[35]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	Q
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	S
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	Q
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	S
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	S
5	897	0	3	Svensson, Mr. Johan Cervin	male	14.0	0	0	7538	9.2250	S
6	898	1	3	Connolly, Miss. Kate	female	30.0	0	0	330972	7.6292	Q
7	899	0	2	Caldwell, Mr. Albert Francis	male	26.0	1	1	248738	29.0000	S
8	900	1	3	Abrahim, Mrs. Joseph (Sophie Halaut Easu)	female	18.0	0	0	2657	7.2292	C
9	901	0	3	Davies, Mr. John Samuel	male	21.0	2	0	A/4 48871	24.1500	S

In [36]:
```
sns.heatmap(titanic.isnull(), yticklabels = False, cbar=False, cmap='viridis')
plt.show()
```



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

Out[37]:
```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
dtype: int64
```

We can now observe that there are no more missing values present in our dataset.

Converting Categorical Features

We need to convert the categorical features into dummy variables using pandas otherwise our machine learning algorithm won't be able to take directly those features as inputs.

In [38]:
```
titanic.head()
```

Out[38]:

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

In [39]:
```
# Creating Dummy Variables
sex = pd.get_dummies(titanic['Sex'], drop_first=True)
embarked = pd.get_dummies(titanic['Embarked'], drop_first=True)
```

In [40]:
```
# Dropping the unneccessary features
titanic.drop(columns=['PassengerId', 'Name', 'Ticket', 'Sex', 'Embarked'], axis=1, inplace=True)
```

In [41]:
```
titanic.head()
```

Out[41]:

	Survived	Pclass	Age	SibSp	Parch	Fare
0	0	3	34.5	0	0	7.8292
1	1	3	47.0	1	0	7.0000
2	0	2	62.0	0	0	9.6875
3	0	3	27.0	0	0	8.6625
4	1	3	22.0	1	1	12.2875

In [42]:
```
# Adding Dummy Variables
titanic_df = pd.concat([titanic, sex, embarked], axis=1)
```

In [43]:
```
titanic_df.head()
```

Out[43]:

	Survived	Pclass	Age	SibSp	Parch	Fare	male	Q	S
0	0	3	34.5	0	0	7.8292	1	1	0
1	1	3	47.0	1	0	7.0000	0	0	1
2	0	2	62.0	0	0	9.6875	1	1	0
3	0	3	27.0	0	0	8.6625	1	0	1
4	1	3	22.0	1	1	12.2875	0	0	1

Splitting Train and Test dataset.

In [44]:
```
X = titanic_df.iloc[:, :-1] # Independent features
y = titanic_df.iloc[:, -1]  # Dependent features
```

In [45]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 42)
```

Model Implementation

Logistic Regression

We know that in general, for binary classification, Logistic Regression works better than most other machine learning algorithms.

In [46]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

lr = LogisticRegression()
```

```
lr.fit(X_train, y_train)
y_pred_lr = lr.predict(X_test)

print("Training set score: {:.2f}".format(lr.score(X_train, y_train)), '\n')
print("Test set score: {:.2f}".format(lr.score(X_test, y_test)), '\n')
print("Accuracy Score: {:.2f}".format(accuracy_score(y_test, y_pred_lr)),'\n')
print("Confusion Matrix: \n", confusion_matrix(y_test, y_pred_lr),'\n')
print("Classification Report: \n", classification_report(y_test, y_pred_lr))

accuracy = accuracy_score(y_test,y_pred_lr) * 100
print("\nLogistic Regression Accuracy:  " +str(round(accuracy,2)) + '%')
```

```
Training set score: 0.77

Test set score: 0.79

Accuracy Score: 0.79

Confusion Matrix:
 [[18 23]
 [ 3 82]]

Classification Report:
               precision    recall  f1-score   support

           0       0.86      0.44      0.58        41
           1       0.78      0.96      0.86        85

    accuracy                           0.79       126
   macro avg       0.82      0.70      0.72       126
weighted avg       0.81      0.79      0.77       126


Logistic Regression Accuracy:  79.37%
```

Breakdown of the Classification Report

- **Precision**: Precision is the ratio of correctly predicted positive observations to the total predicted positives. It's also called Positive Predictive Value. It is a measure of a classifier's exactness. Low precision indicates a high number of false positives.
  - For class 0, the precision is 0.86, which means that 86% of the total instances predicted as class 0 are actually class 0.
  - For class 1, the precision is 0.78, which means that 78% of the total instances predicted as class 1 are actually class 1.
- **Recall (Sensitivity)**: Recall is the ratio of correctly predicted positive observations to all observations in actual class. It's also called Sensitivity, Hit Rate, or True Positive Rate. It is a measure of a classifier's completeness. Low recall indicates a high number of false negatives.
  - For class 0, the recall is 0.44, which means that the classifier correctly identified 44% of the total actual class 0 instances.
  - For class 1, the recall is 0.96, which means that the classifier correctly identified 96% of the total actual class 1 instances.
- **F1-Score**: F1 Score is the weighted average of Precision and Recall. It tries to find the balance between precision and recall. It is a better measure than accuracy especially for uneven class distribution.
  - For class 0, the F1-score is 0.58, which means that considering both precision and recall, the performance of the classifier for class 0 is 58%.
  - For class 1, the F1-score is 0.86, which means that considering both precision and recall, the performance of the classifier for class 1 is 86%.
- **Support**: Support is the number of actual occurrences of the class in the dataset.
  - For class 0, there are 41 instances.
  - For class 1, there are 85 instances.
- **Accuracy**: Accuracy is the ratio of correctly predicted observations to the total observations. It is the most intuitive performance measure. Here, the accuracy is 0.79, which means the model is correct 79% of the time.

- **Macro Avg**: Macro-average will compute the metric independently for each class and then take the average treating all classes equally, whereas micro-average will aggregate the contributions of all classes to compute the average metric. In a multi-class classification setup, macro-average is preferable if you suspect there might be class imbalance.

- **Weighted Avg**: This is the average of metrics but when calculated, it takes into account the number of instances in each class. It gives more weight to the metrics of the clasave any other questions.

Conclusion

Based on the classification report, here are some conclusions we can draw:

1. **Model Performance**: The model has an overall accuracy of 0.79, which means it correctly predicts the class 79% of the time. This is a decent score, but there might be room for improvement.

2. **Class 0 Performance**: For class 0, the precision is high (0.86), but the recall is quite low (0.44). This means that while the model is good at predicting class 0 when it is indeed class 0 (high precision), it's not so good at identifying class 0 instances in general (low recall). The F1-score for class 0 is 0.58, indicating that the model's performance for class 0 is less than optimal.

3. **Class 1 Performance**: For class 1, both the precision (0.78) and recall (0.96) are relatively high, leading to a high F1-score (0.86). This suggests that the model performs well for class 1.

4. **Class Imbalance**: The support values show that there are twice as many instances of class 1 (85) as there are of class 0 (41). This class imbalance might be affecting the model's performance, particularly for class 0.

5. **Macro Avg vs Weighted Avg**: The macro average F1-score is 0.72, while the weighted average F1-score is 0.77. The difference between these two scores suggests that the model's performance is better on the class with more instances (class 1).

In conclusion, the model performs well overall and particularly well with class 1 but struggles with class 0. This might be due to the Data Imbalance. We should consider handling such imbalance of data in order to improve the model's accuracy for class 0.

We can further do the Model Deployment using softwares like AWS Sagemaker, Azure or Web framework like Flask etc.

Model Improvement Tips

Now, there are a few things that can be done to improve the model accuracy such as,

1. **Use a larger dataset**: The more data you have, the better your model will be able to learn from it and generalize to unseen data.

2. **Try different algorithms**: By trying different algorithms, you can identify which ones work best for your data.

3. **Tune hyperparameters**: Hyperparameters are the parameters that are not learned from the data. They are set prior to the commencement of the learning process. Tuning them can lead to better model performance.

4. **Treat outlier values**: Proper handling of outlier values can improve the model's performance.

5. **Feature engineering**: This involves creating new features from existing ones which might help improve the model's performance.

6. **Feature selection**: It is the process of choosing which features to include in a machine learning model.

7. **Use multiple algorithms or ensemble methods**: Combining the predictions of multiple models can often yield better results.

8. **Cross-validation**: It is a technique where the data is split into several parts, and the model is trained on some parts and tested on others. This helps in understanding how well the model is likely to perform on unseen data.

Remember, there's no one-size-fits-all strategy for improving machine learning models. It all comes down to the business problem, the available data, and the type of algorithm.

Now, I have used only Logistic Regression since the survivers are genderwise segregated so the classification problem is not that complex but we can implement more classification algorithms like Naive Baye's, Decision Tree, Random Forest etc. for the sake of learning and try to understand which algorithm does a better job at classification.

Thank you 😃