3_Supervised ML Classification_IBM ML Certifiation_Coursera HEc_Final Project.

Project Requirements:

Project Requirement 1.

The main objective of the analysis that specify whether the proposed model will be focused on prediction or interpretation and the benefits that your analysis provides to the business or stakeholders of this data.

Project Requirement 1 Response - Titanic Dataset Analysis:

The analysis of the Titanic dataset can be approached with a dual focus on both prediction and interpretation.

1. Prediction: The primary aim is to build a predictive model that can accurately forecast whether a passenger survived or not based on various features such as age, gender, class, and embarkation point.

   Benefits: This predictive capability can be valuable for multiple stakeholders, including cruise operators, safety regulators, and potential passengers. Cruise operators can use the model to enhance safety measures and emergency preparedness, regulators can enforce better safety standards, and potential passengers can make more informed decisions.

2. Interpretation: In addition to prediction, the analysis should delve into the factors that significantly influence survival rates. Understanding the patterns and correlations in the dataset provides insights into the dynamics of survival on the Titanic.

   Benefits: Stakeholders can gain a deeper understanding of the underlying factors contributing to survival. For example, it might reveal whether certain demographics had a higher chance of survival, leading to targeted safety measures. This interpretative aspect enhances the decision-making process and contributes to a broader comprehension of the events.

Loading Libraries and Dataset.

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

```python
# loading titanik dataset
titanik = sns.load_dataset('titanic')
titanik.head()
```

```
   survived  pclass     sex   age  sibsp  parch     fare embarked
class  \
0         0       3    male  22.0      1      0   7.2500        S
Third
1         1       1  female  38.0      1      0  71.2833        C
First
2         1       3  female  26.0      0      0   7.9250        S
Third
3         1       1  female  35.0      1      0  53.1000        S
First
4         0       3    male  35.0      0      0   8.0500        S
Third

     who  adult_male deck  embark_town alive  alone
0    man        True  NaN  Southampton    no  False
1  woman       False    C    Cherbourg   yes  False
2  woman       False  NaN  Southampton   yes   True
3  woman       False    C  Southampton   yes  False
4    man        True  NaN  Southampton    no   True
```

Project Requirement 2.

Description of the dataset (titanic) chosen, a summary of its attributes, and an outline of accomplishments with this analysis.

Project Requirement 2 Response - Titanic Dataset Description and Summary:

1. Dataset Description: The Titanic dataset is a well-known dataset in the field of data science and machine learning. It contains information about passengers who were aboard the Titanic, including whether they survived or not. The dataset is often used for predictive modeling and analysis.

2. Summary of Attributes: The dataset typically includes the following attributes:

Survived: Binary variable indicating whether the passenger survived (1) or not (0). Pclass: Passenger class (1st, 2nd, or 3rd). Sex: Gender of the passenger. Age: Age of the passenger. SibSp: Number of siblings/spouses aboard. Parch: Number of parents/children aboard. Fare: Passenger fare. Deck: Cabin number. Embarked: Port of embarkation (C = Cherbourg, Q = Queenstown, S = Southampton).

```python
# Dataset information.
titanik.info()
```

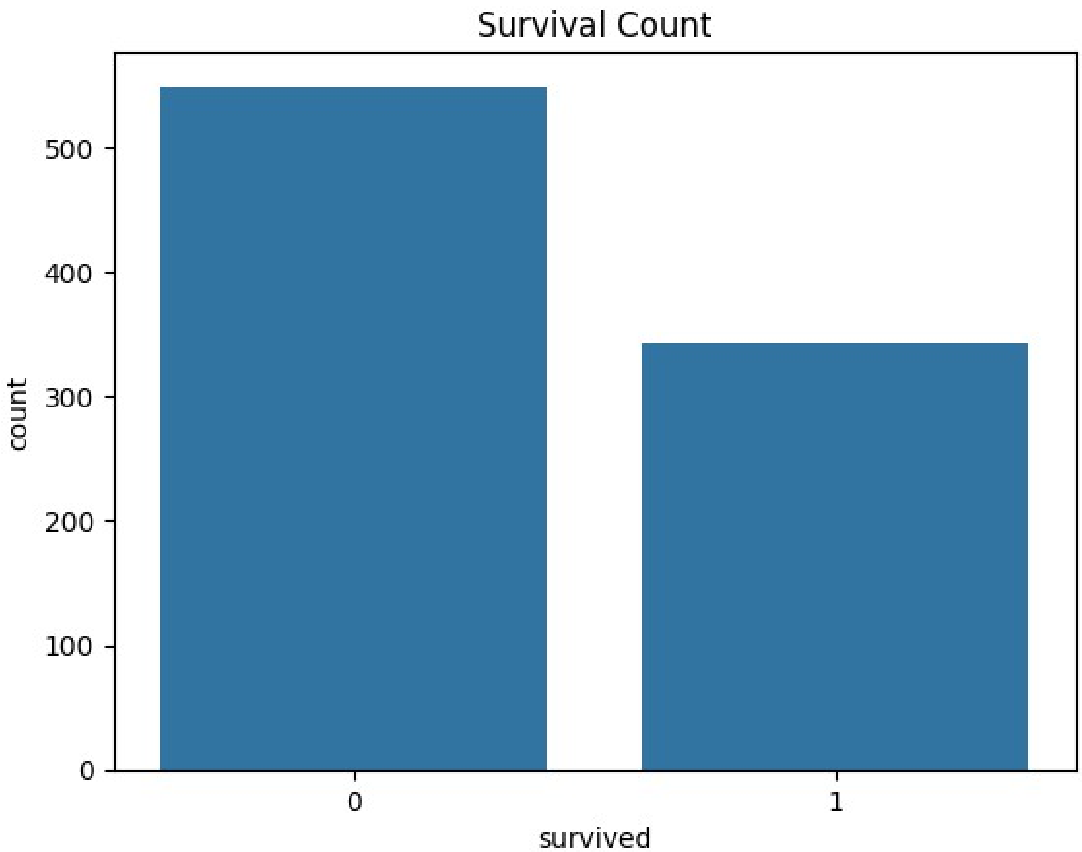
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   survived     891 non-null    int64
 1   pclass       891 non-null    int64
 2   sex          891 non-null    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   embarked     889 non-null    object
 8   class        891 non-null    category
 9   who          891 non-null    object
 10  adult_male   891 non-null    bool
 11  deck         203 non-null    category
 12  embark_town  889 non-null    object
 13  alive        891 non-null    object
 14  alone        891 non-null    bool
dtypes: bool(2), category(2), float64(2), int64(4), object(5)
memory usage: 80.7+ KB

# Summary statistics of numerikal features.
titanik.describe()

         survived      pclass         age       sibsp       parch
fare
count  891.000000  891.000000  714.000000  891.000000  891.000000
891.000000
mean     0.383838    2.308642   29.699118    0.523008    0.381594
32.204208
std      0.486592    0.836071   14.526497    1.102743    0.806057
49.693429
min      0.000000    1.000000    0.420000    0.000000    0.000000
0.000000
25%      0.000000    2.000000   20.125000    0.000000    0.000000
7.910400
50%      0.000000    3.000000   28.000000    0.000000    0.000000
14.454200
75%      1.000000    3.000000   38.000000    1.000000    0.000000
31.000000
max      1.000000    3.000000   80.000000    8.000000    6.000000
512.329200

# Checking for missing values.
titanik.isnull().sum()

survived         0
pclass           0
```

```
sex              0
age            177
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

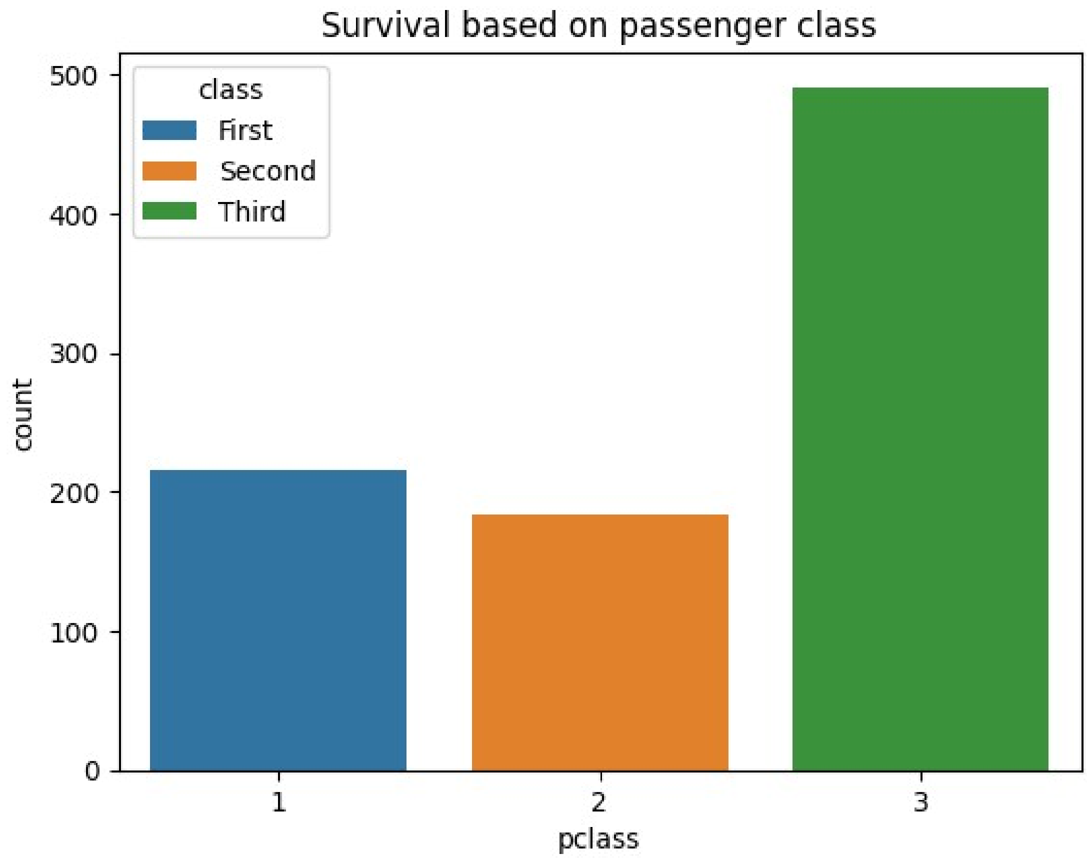
The following Features have missing values in the titanik dataset.

1. age: 177 missing values
2. embarked: 2 missing values
3. deck: 688 missing values
4. embark_town: 2 missing values

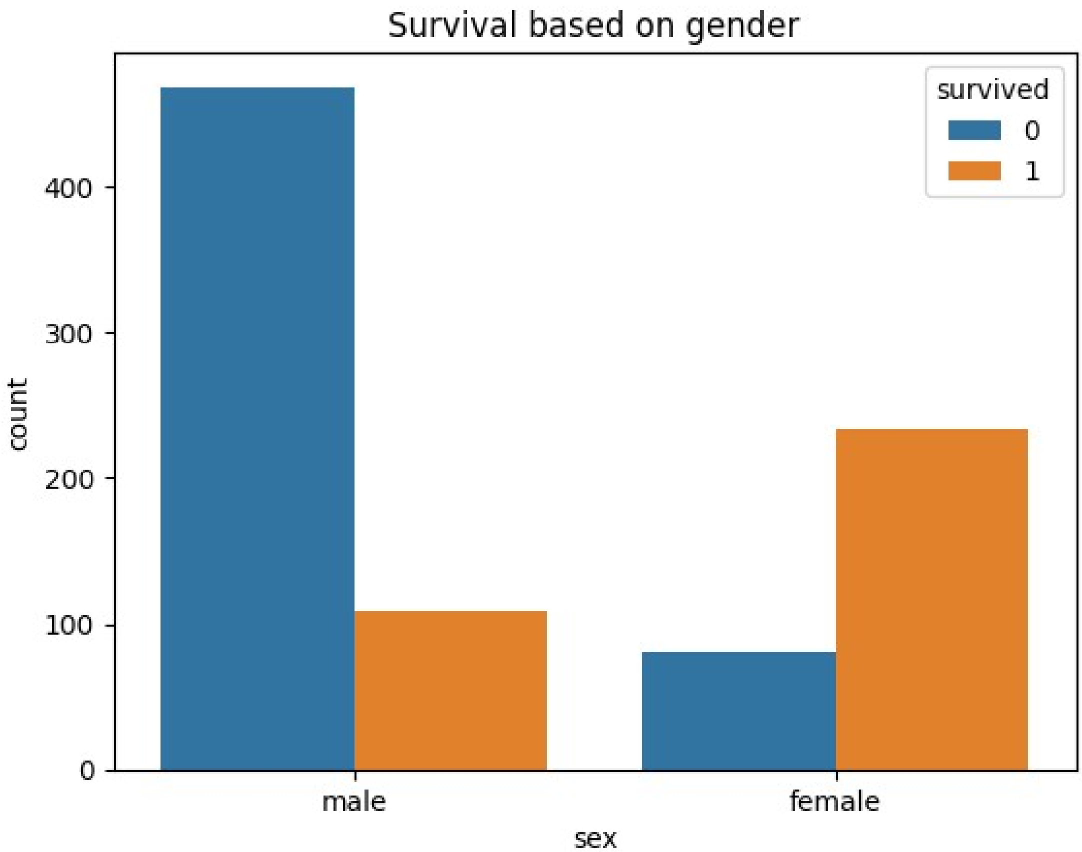
```
# Visualize survival counts.
sns.countplot(x='survived', data=titanik);
plt.title('Survival Count');
```




```
# Visualize survival based on passenger class
sns.countplot(x='pclass', data=titanik, hue='class');
plt.title('Survival based on passenger class');
```




```python
# Visualize survival based on gender
sns.countplot(x='sex', data=titanik, hue='survived' );
plt.title('Survival based on gender');
```



Project Requirement 3.

Summary of data exploration and actions taken for data cleaning and feature engineering.

Project Requirement 3 Response - Data Exploration, Cleaning, and Feature Engineering:

1. Data Exploration. Data exploration is discussed using above graphs.
2. Data Cleaning.
3. Feature Engineering.

```
titanik.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 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   embarked     889 non-null    object
 8   class        891 non-null    category
 9   who          891 non-null    object
 10  adult_male   891 non-null    bool
 11  deck         203 non-null    category
 12  embark_town  889 non-null    object
 13  alive        891 non-null    object
 14  alone        891 non-null    bool
dtypes: bool(2), category(2), float64(2), int64(4), object(5)
memory usage: 80.7+ KB
```

```
titanik.columns
```

```
Index(['survived', 'pclass', 'sex', 'age', 'sibsp', 'parch', 'fare',
       'embarked', 'class', 'who', 'adult_male', 'deck',
'embark_town',
       'alive', 'alone'],
      dtype='object')
```

Different types of features in the titanik dataset.

```
print('categorical_columns: ',titanik.select_dtypes(include=['int64',
'float64']).columns)
print('numerikal_columns: ',titanik.select_dtypes(include=['object',
'category']).columns)
print('bool_columns:
',titanik.select_dtypes(include=['bool']).columns)
```

```
categorical_columns:  Index(['survived', 'pclass', 'age', 'sibsp',
'parch', 'fare'], dtype='object')
numerikal_columns:  Index(['sex', 'embarked', 'class', 'who', 'deck',
'embark_town', 'alive'], dtype='object')
bool_columns:  Index(['adult_male', 'alone'], dtype='object')
```

Value types in bool features.

```
titanik.adult_male.unique()
```

```
array([ True, False])
```

```
print('The number of rows in titanik dataset: ', len(titanik))
```

```
The number of rows in titanik dataset:  891
```

```
# 2. Data Cleaning.
# Finding percentage of missin values in the dataset.
```

```python
missing_percentage = (titanik.isnull().sum() / len(titanik)) * 100
print('Percentage of Missing Values in Titanic Dataset:')
print(missing_percentage)
```

```
Percentage of Missing Values in Titanic Dataset:
survived        0.000000
pclass          0.000000
sex             0.000000
age            19.865320
sibsp           0.000000
parch           0.000000
fare            0.000000
embarked        0.224467
class           0.000000
who             0.000000
adult_male      0.000000
deck           77.216611
embark_town     0.224467
alive           0.000000
alone           0.000000
dtype: float64
```

I have to consider whether to drop the feature having missing values more than 70% or not. It is important to know its impact on model training. If dropping the feature doesn't significantly affect the model's performance and simplifies the analysis, it might be a reasonable choice. Some machine learning algorithms can handle missing values, while others may require imputation or preprocessing.

```python
titanik.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 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   embarked     889 non-null    object  
 8   class        891 non-null    category
 9   who          891 non-null    object  
 10  adult_male   891 non-null    bool    
 11  deck         203 non-null    category
 12  embark_town  889 non-null    object  
 13  alive        891 non-null    object  
```

```
 14  alone        891 non-null    bool
dtypes: bool(2), category(2), float64(2), int64(4), object(5)
memory usage: 80.7+ KB
```

The data types of missing features are following:

1. age: float64---numerikal feature
2. embarked: object----kategorikal feature
3. deck: categorikal feature
4. embark_town: categorikal feature

```
print('unique values in the deck feature:\n', titanik.deck.unique())
print('The number of missing values in deck feature: ',
titanik.deck.isnull().sum())
```

```
unique values in the deck feature:
 [NaN, 'C', 'E', 'G', 'D', 'A', 'B', 'F']
Categories (7, object): ['A', 'B', 'C', 'D', 'E', 'F', 'G']
The number of missing values in deck feature:  688
```

```
print('unique values in the embark_town feature:\n',
titanik.embark_town.unique())
print('The number of missing values in embark_town feature: ',
titanik.embark_town.isnull().sum())
```

```
unique values in the embark_town feature:
 ['Southampton' 'Cherbourg' 'Queenstown' nan]
The number of missing values in embark_town feature:  2
```

Handling Missing values in the dataset.

```
# Filling the missing values in numerikal feature 'age'.
titanik['age'].fillna(titanik['age'].mean(), inplace=True)
# Filling the missing values in kategorikal feature 'embarked'.
titanik['embarked'].fillna(titanik['embarked'].mode()[0],
inplace=True)
# Filling the missing values in kategorikal feature 'embark_town'.
titanik['embark_town'].fillna(titanik['embark_town'].mode()[0],
inplace=True)
# Dropping 'deck' column due to high number of missing values
titanik.drop('deck', axis=1, inplace=True)

# Verify that missing values have been handled
print(titanik.isnull().sum())
```

```
survived       0
pclass         0
sex            0
age            0
```

```
sibsp          0
parch          0
fare           0
embarked       0
class          0
who            0
adult_male     0
embark_town    0
alive          0
alone          0
dtype: int64
```

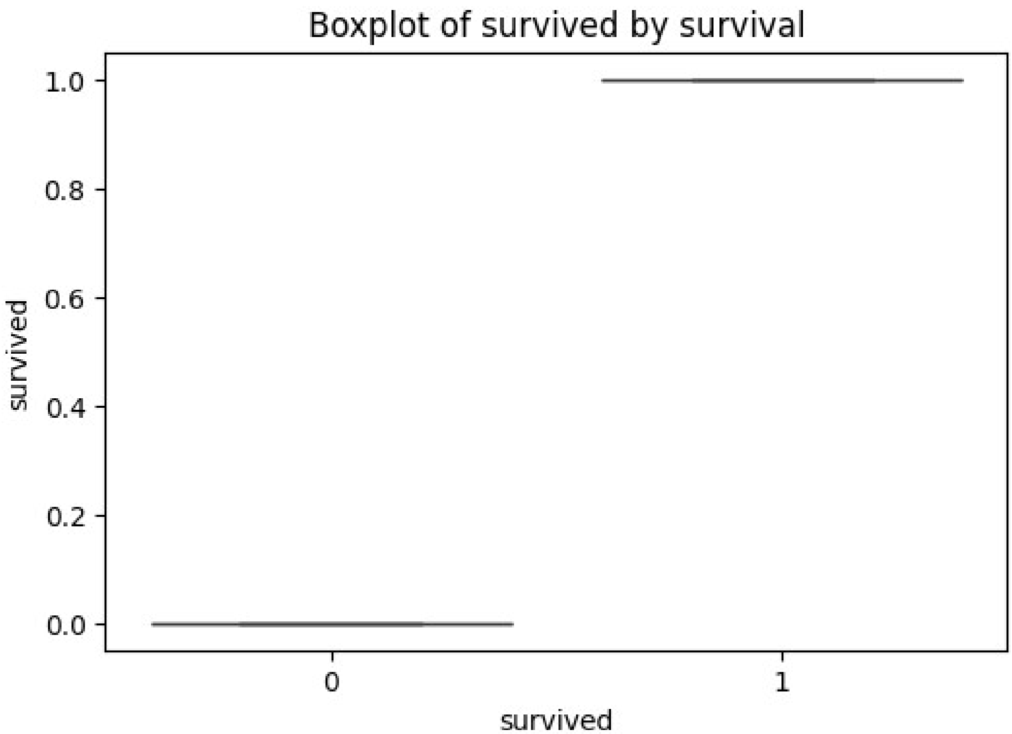
Outliers in the Titanik Dataset:

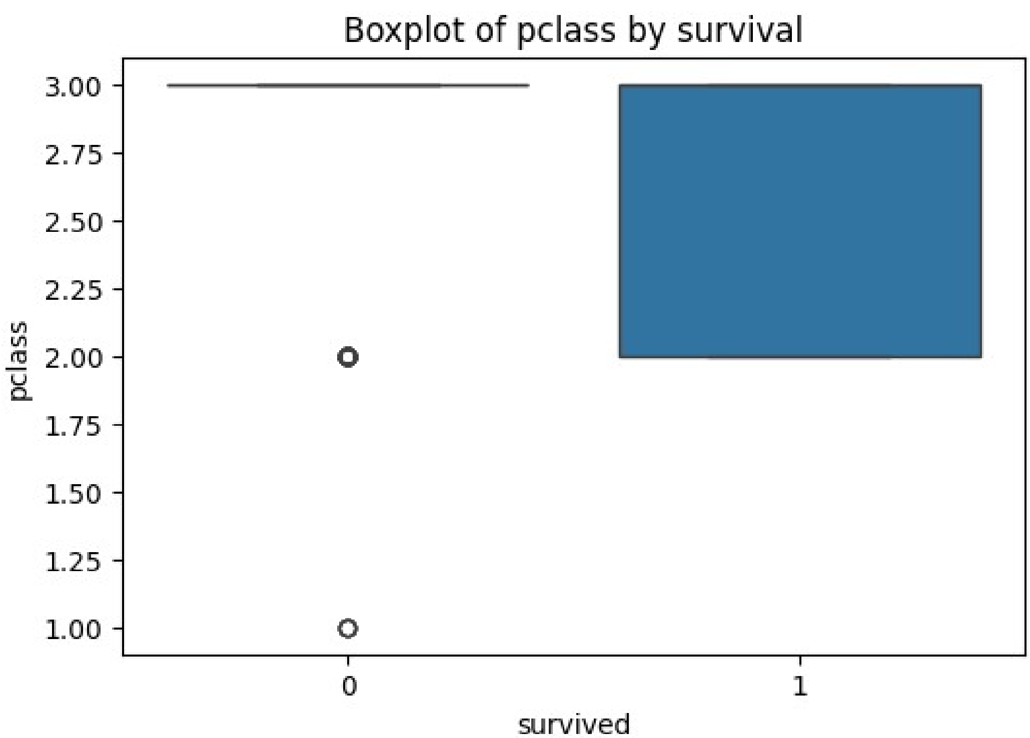
Outliers in a dataset can significantly impact the performance and accuracy of machine learning models. Detecting and handling outliers is an essential step in data preprocessing.

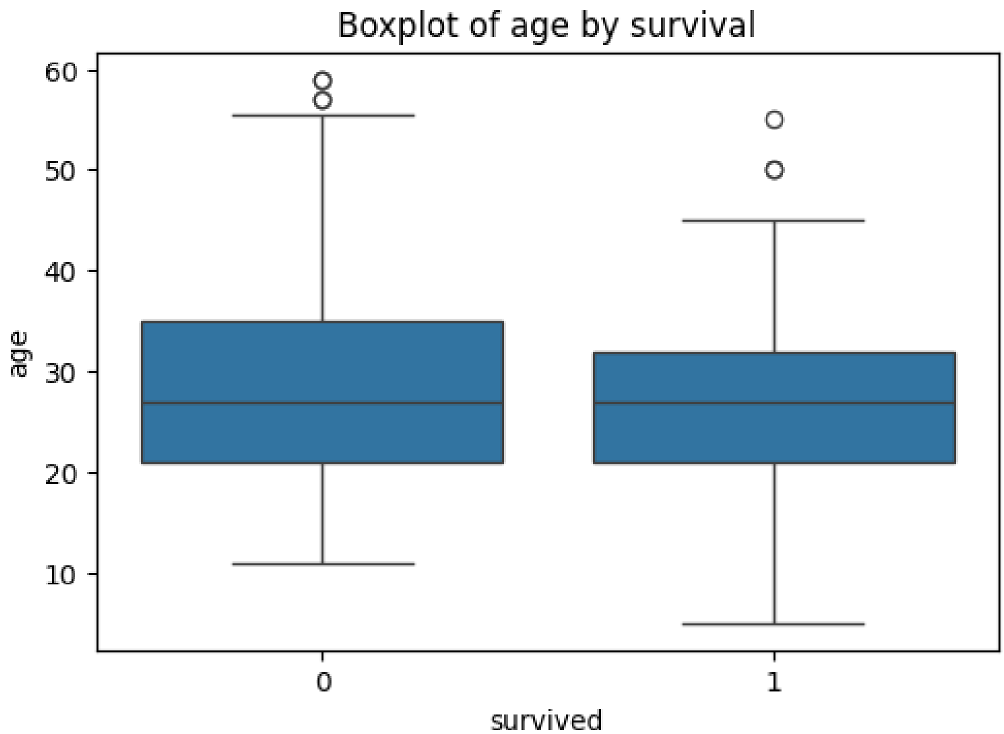
Outliers Detection in Titanik dataset.

Numerical Features: I Used box plots to visualize the distribution of numerical features and identify potential outliers.

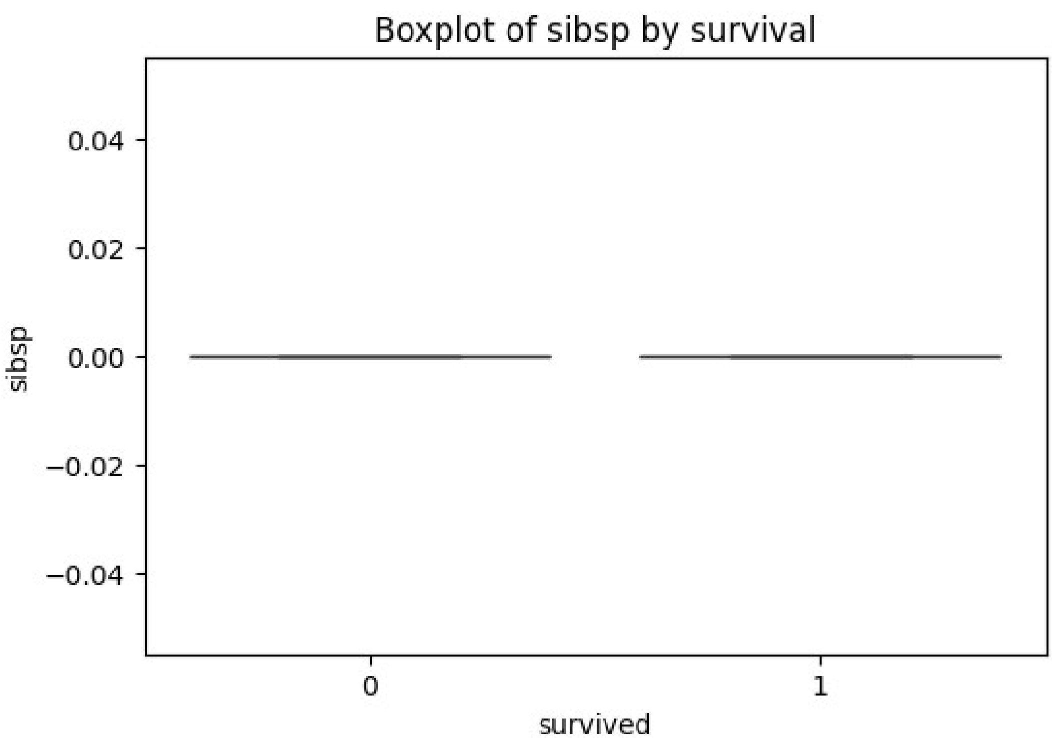
```
# Select numerical features for checking outliers.
numerical_features = titanik.select_dtypes(include = ['int64',
'float64'])

# Display the list of numerical features
print('Numerical Features in Titanic Dataset:')
print(numerical_features.columns.tolist())

Numerical Features in Titanic Dataset:
['survived', 'pclass', 'age', 'sibsp', 'parch', 'fare']

# Create box plots for numerical features to detect outliers.
for feature in numerical_features:
    plt.figure(figsize=(6, 4))
    sns.boxplot(x='survived', y=feature, data=titanik)
    plt.title(f'Boxplot of {feature} by survival')
```


Boxplot of survived by survival
1.0
0.8
0.6
0.4
0.2
0.0
survived
0
1
survived

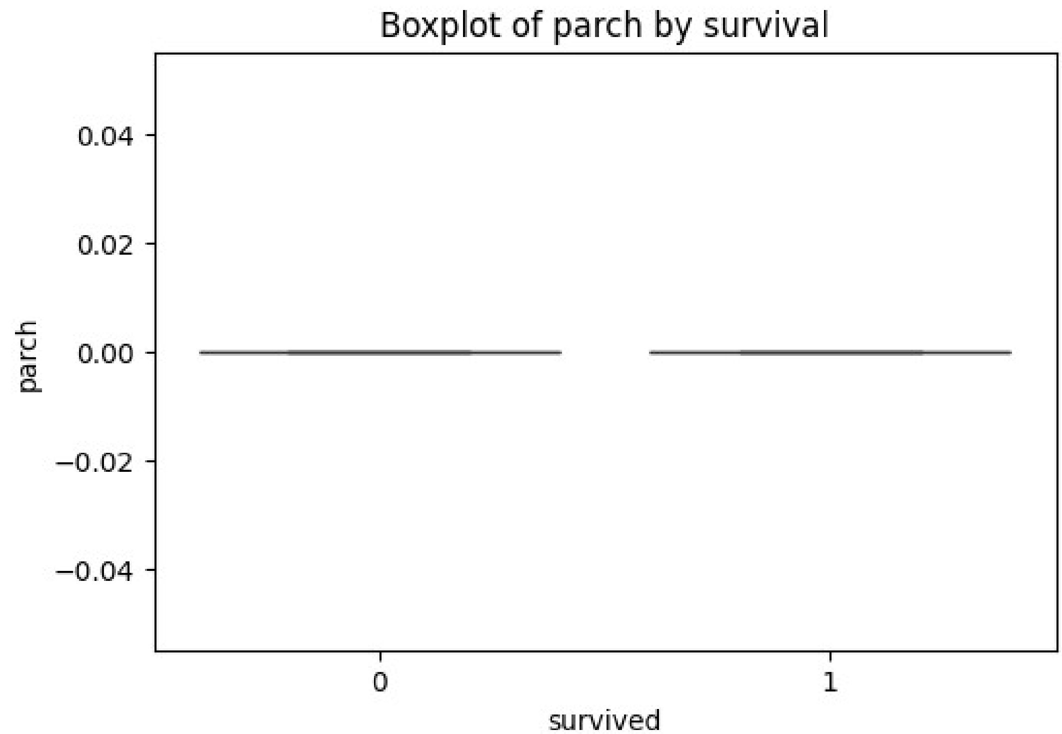

Boxplot of pclass by survival
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
pclass
0
1
survived

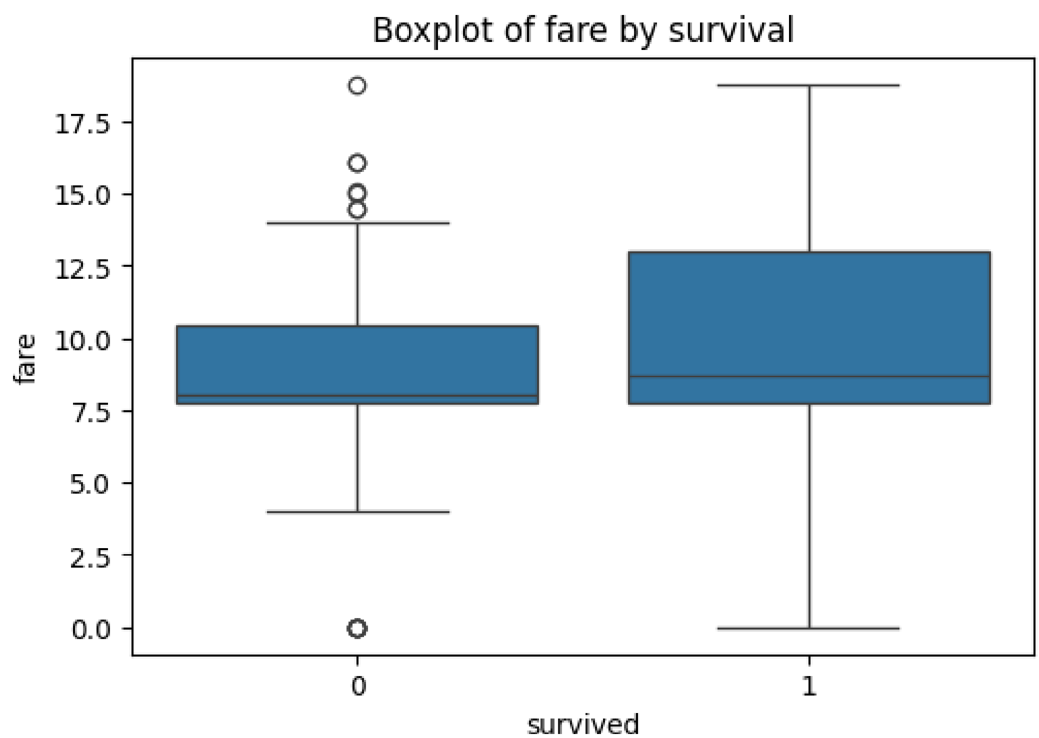


Boxplot of age by survival
60
50
40
30
20
10
age
0
1
survived



Boxplot of sibsp by survival
0.04
0.02
0.00
−0.02
−0.04
sibsp
0
1
survived





Outliers Removal in Titanik dataset.

Statistical Methods: I Used one of statistical methods like Z-score or IQR (Interquartile Range) to remove outliers.

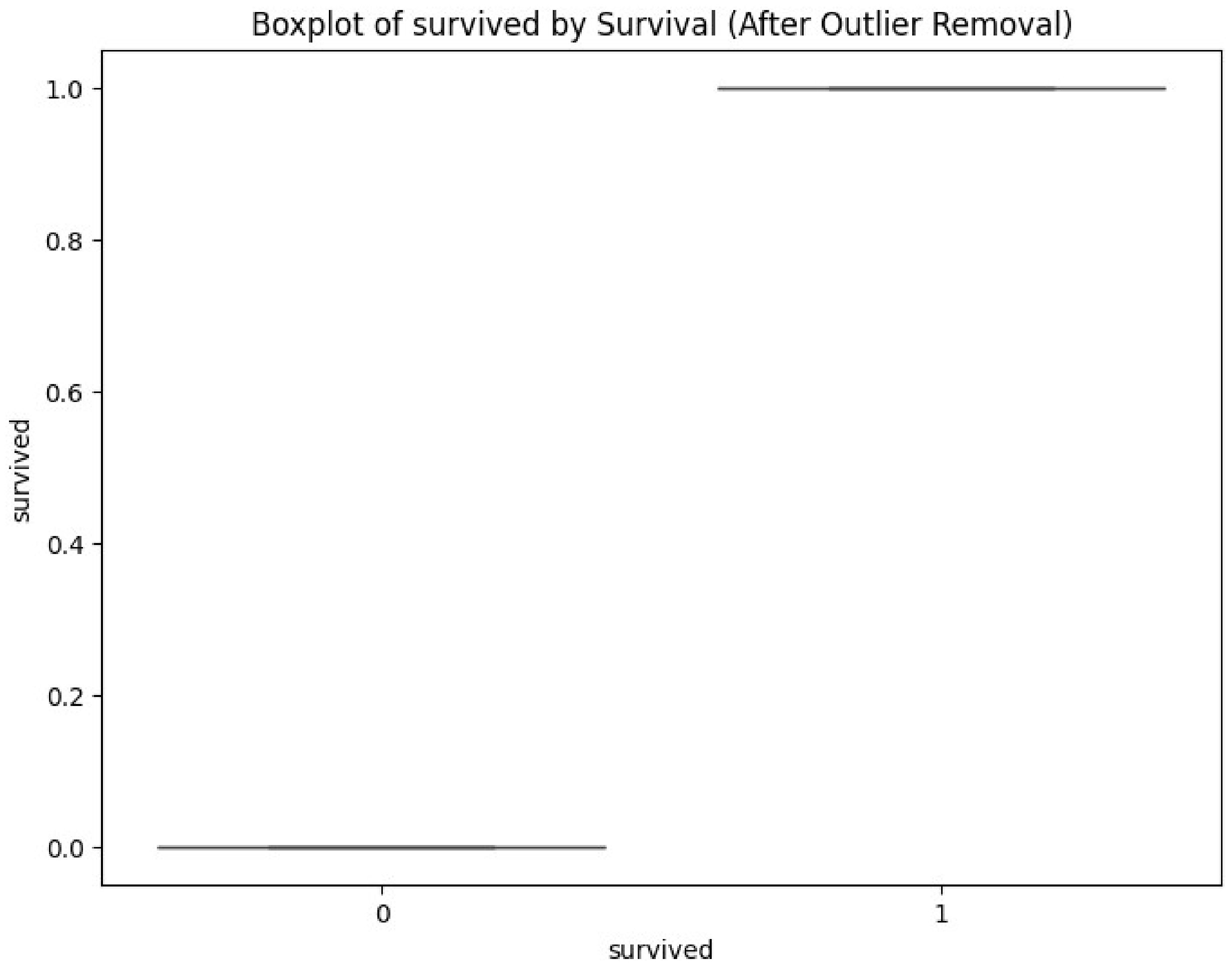
```
# Selecting numerical features
numerical_features = titanik.select_dtypes(include=['int64',
'float64']).columns

# function to remove outliers using IQR
def remove_outliers_iqr(data, feature, threshold=1.5):
    Q1 = data[feature].quantile(0.25)
    Q3 = data[feature].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - threshold * IQR
    upper_bound = Q3 + threshold * IQR
    return data[(data[feature] >= lower_bound) & (data[feature] <=
upper_bound)]

# Loop through each numerical feature and remove outliers
for feature in numerical_features:
    titanik = remove_outliers_iqr(titanik, feature)

# DataFrame after removing outliers
print("Titanic Dataset after Removing Outliers:")
print(titanik.head())
```

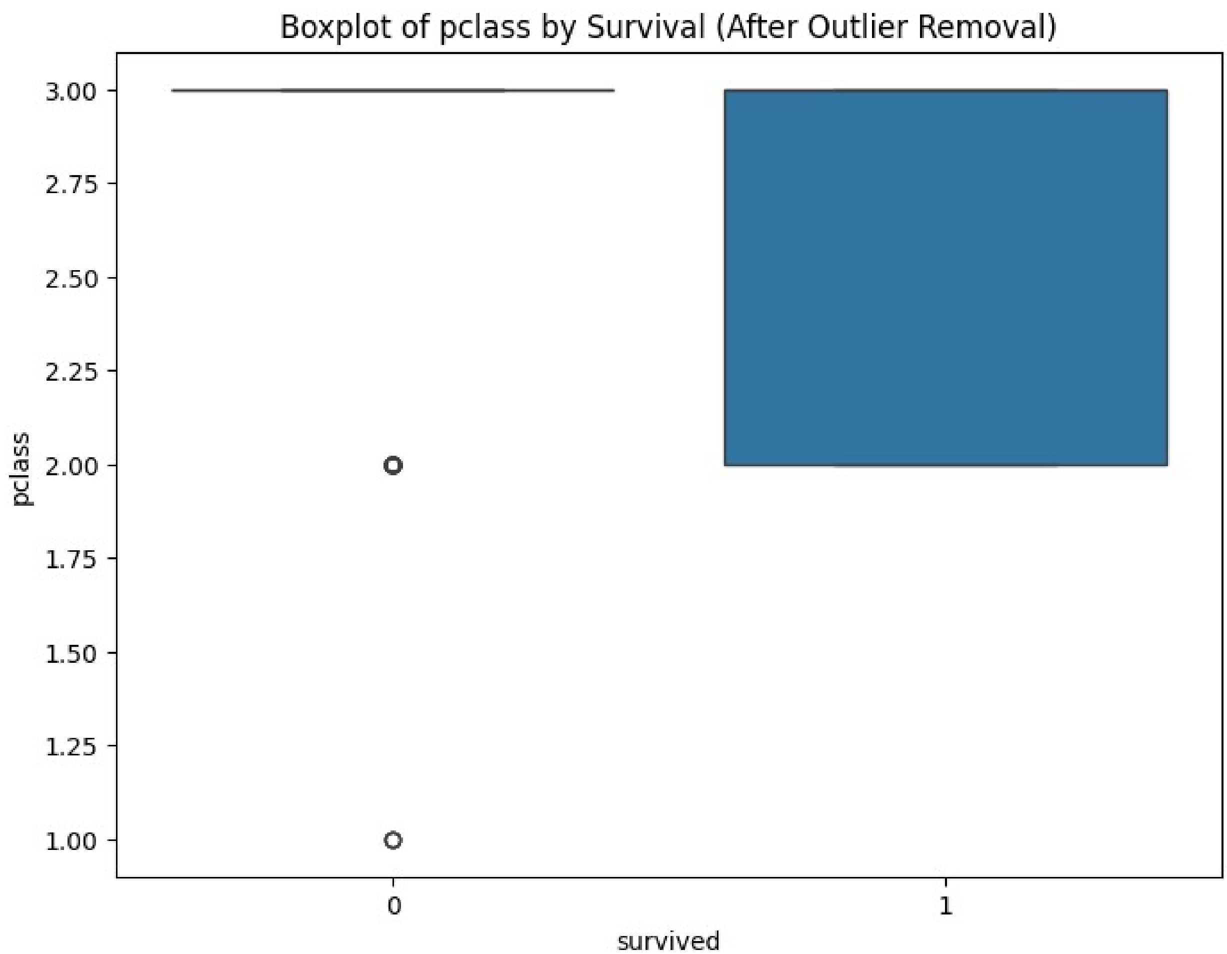
```
Titanic Dataset after Removing Outliers:
    survived  pclass     sex   age  sibsp  parch     fare embarked
class  \
2          1       3  female  26.0      0      0   7.9250        S
Third
4          0       3    male  35.0      0      0   8.0500        S
Third
12         0       3    male  20.0      0      0   8.0500        S
Third
14         0       3  female  14.0      0      0   7.8542        S
Third
15         1       2  female  55.0      0      0  16.0000        S
Second

      who  adult_male deck  embark_town alive  alone
2   woman       False  NaN  Southampton   yes   True
4     man        True  NaN  Southampton    no   True
12    man        True  NaN  Southampton    no   True
14  child       False  NaN  Southampton    no   True
15  woman       False  NaN  Southampton   yes   True
```

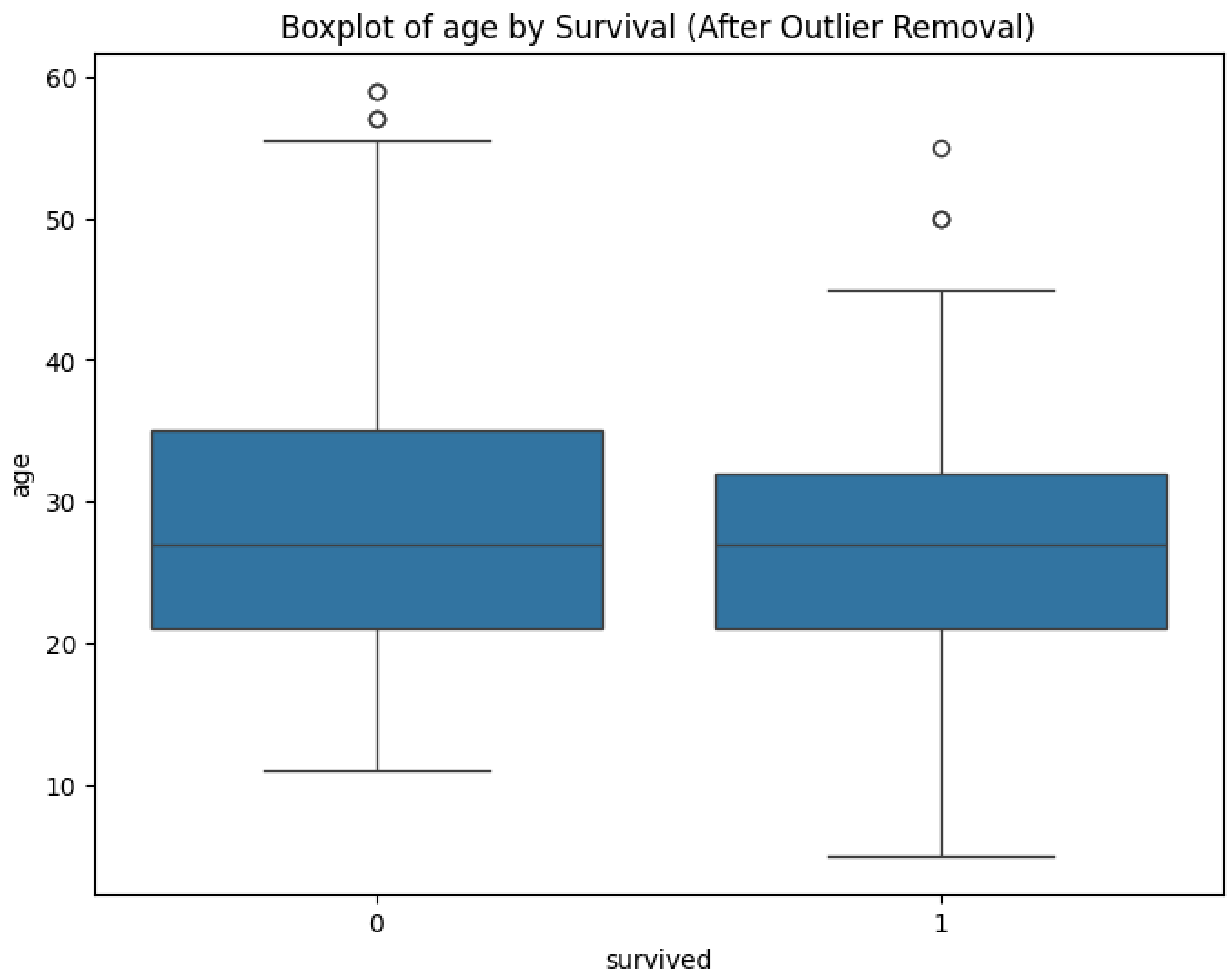
Boxplots after removing outliers.

```
# Create box plots for numerical features after outlier removal
for feature in numerical_features:
    plt.figure(figsize=(8, 6))
```

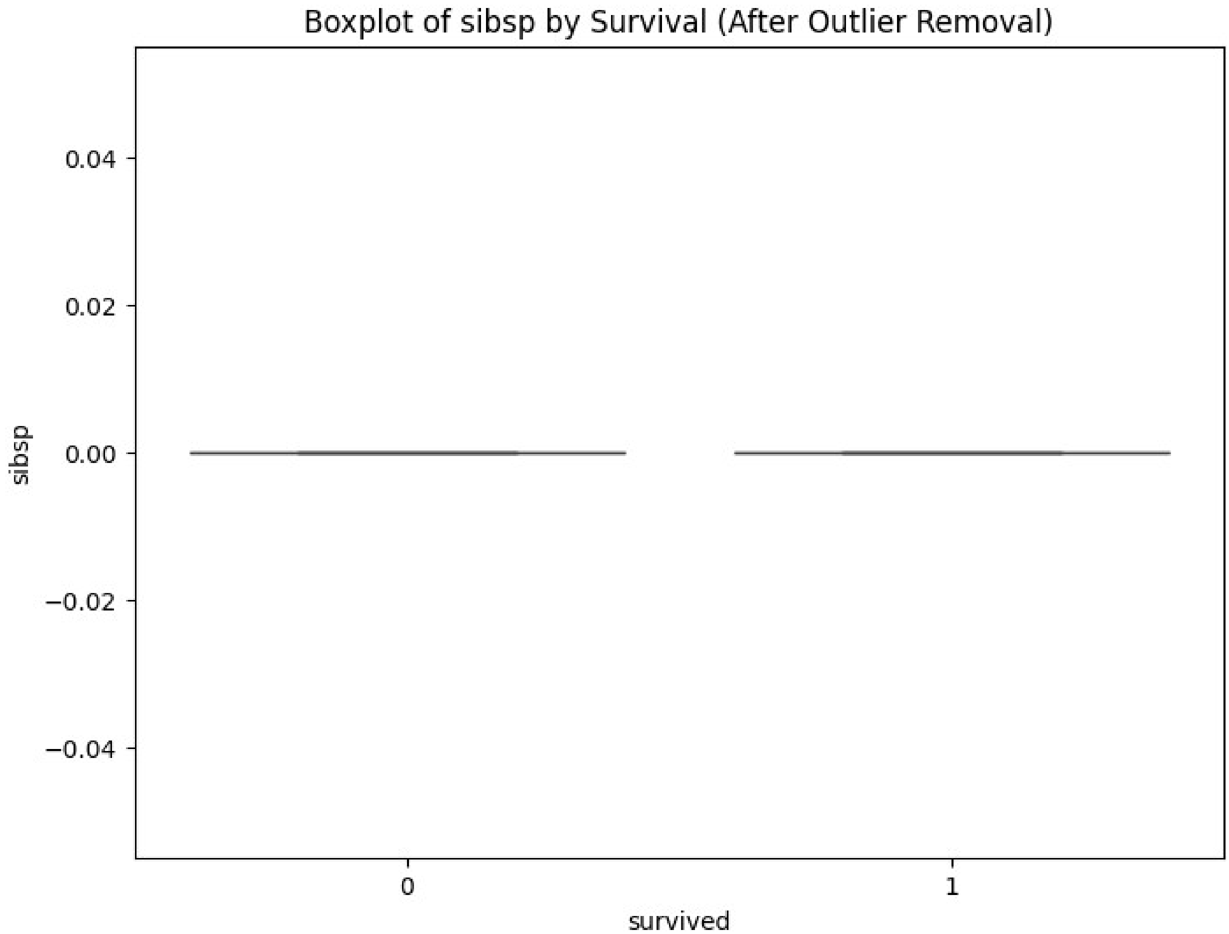
```
    sns.boxplot(x='survived', y=feature, data=titanik)
    plt.title(f'Boxplot of {feature} by Survival (After Outlier
Removal)')
```

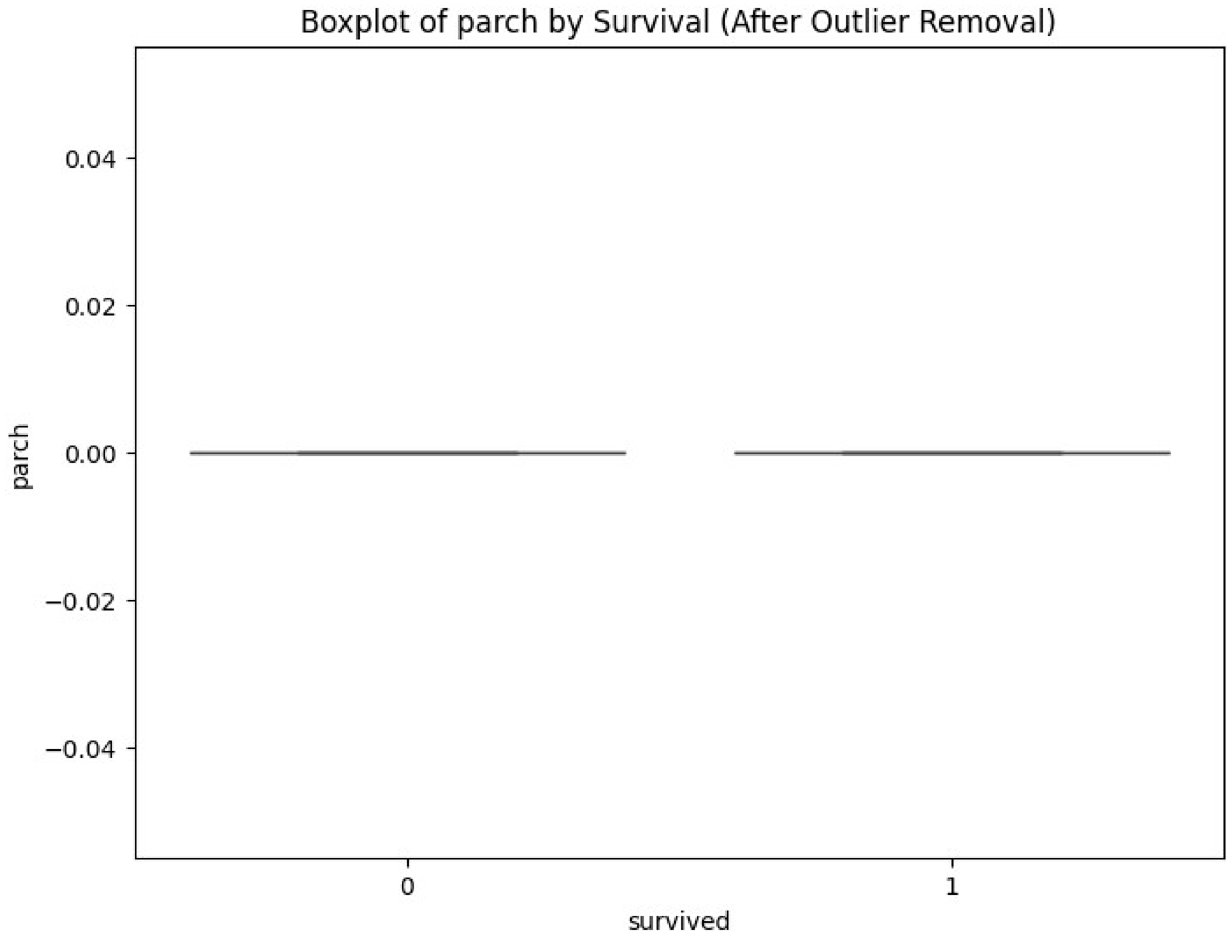



Boxplot of pclass by Survival (After Outlier Removal)
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
pclass
0
1
survived

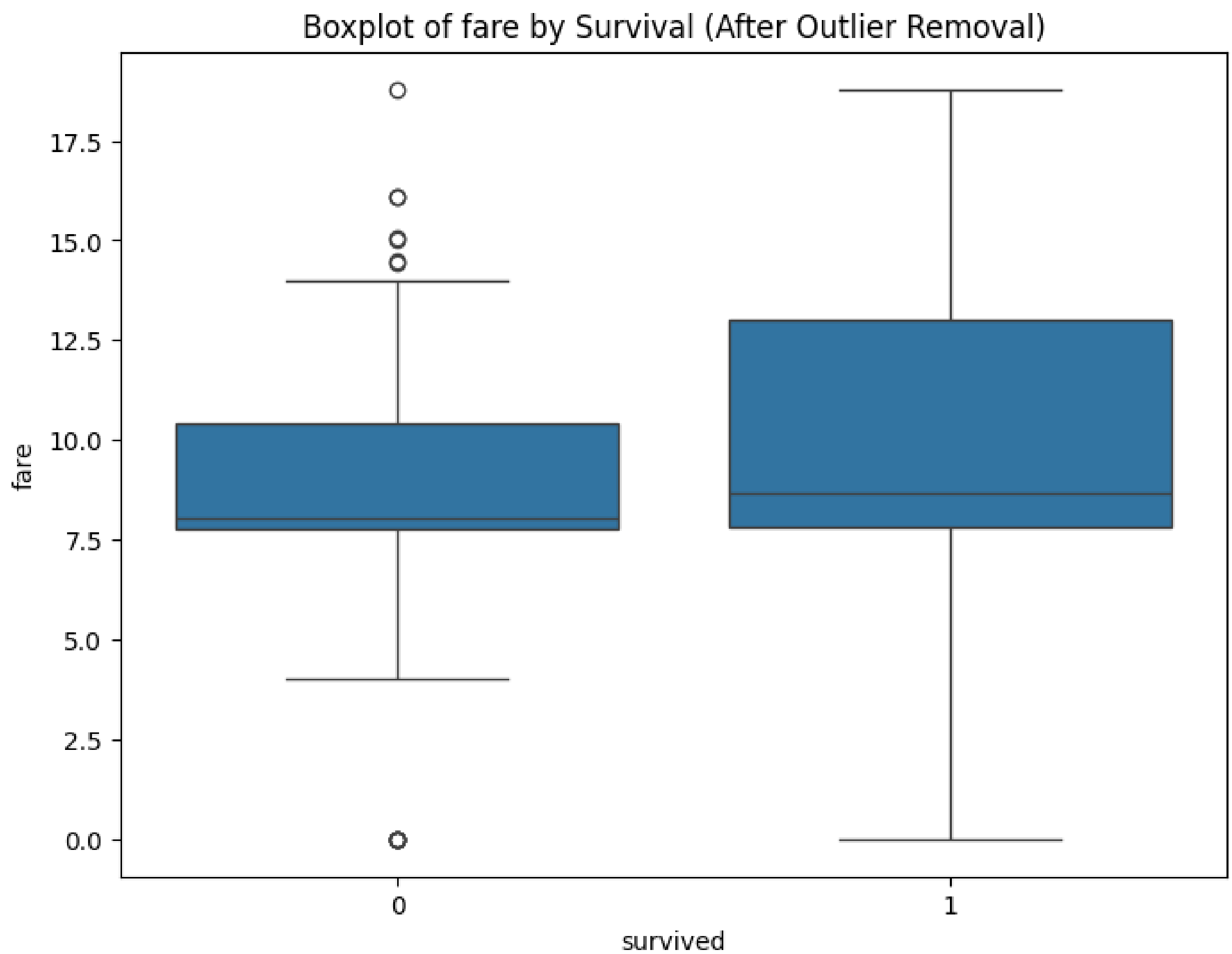


Boxplot of age by Survival (After Outlier Removal)
60
50
40
30
20
10
age
0
1
survived


Boxplot of sibsp by Survival (After Outlier Removal)
0.04
0.02
0.00
−0.02
−0.04
sibsp
0
1
survived



Boxplot of parch by Survival (After Outlier Removal)
0.04
0.02
0.00
−0.02
−0.04
parch
0
1
survived



3. Feature Engineering.

```
titanik = sns.load_dataset('titanic')
titanik.columns

Index(['survived', 'pclass', 'sex', 'age', 'sibsp', 'parch', 'fare',
       'embarked', 'class', 'who', 'adult_male', 'deck',
'embark_town',
       'alive', 'alone'],
      dtype='object')

# Creating a 'FamilySize' feature by combining 'SibSp' and 'Parch'
titanik['FamilySize'] = titanik['sibsp'] + titanik['parch']

# Display the modified dataset
print(titanik.head())

   survived  pclass     sex   age  sibsp  parch     fare embarked
class  \
0         0       3    male  22.0      1      0   7.2500        S
```

```
Third
1          1        1  female  38.0      1      0  71.2833        C
First
2          1        3  female  26.0      0      0   7.9250        S
Third
3          1        1  female  35.0      1      0  53.1000        S
First
4          0        3    male  35.0      0      0   8.0500        S
Third

     who  adult_male deck  embark_town alive  alone  FamilySize
0    man        True  NaN  Southampton    no  False           1
1  woman       False    C    Cherbourg   yes  False           1
2  woman       False  NaN  Southampton   yes   True           0
3  woman       False    C  Southampton   yes  False           1
4    man        True  NaN  Southampton    no   True           0

# Modified Feature.
print(titanik[['sibsp', 'parch', 'FamilySize']])

     sibsp  parch  FamilySize
0        1      0           1
1        1      0           1
2        0      0           0
3        1      0           1
4        0      0           0
..     ...    ...         ...
886      0      0           0
887      0      0           0
888      1      2           3
889      0      0           0
890      0      0           0

[891 rows x 3 columns]

titanik.sex.unique()

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

# Encode 'Sex' variable for map korrelation matrix
titanik['sex'] = titanik['sex'].map({'male': 0, 'female': 1})
titanik.sex.unique()

array([0, 1], dtype=int64)

# Correlation heatmap
correlation_matrix = titanik.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()
```

```
# Correlation heatmap
korrelation_matrix = titanik.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt='0.2f')
plt.title('Correlation heatmap')

# Select categorical columns
categorical_columns =
titanik.select_dtypes(include=['object']).columns.tolist()

# Display the names of categorical columns
print("Categorical Columns in Titanic Dataset:")
print(categorical_columns)

Categorical Columns in Titanic Dataset:
['sex', 'embarked', 'who', 'embark_town', 'alive']
```

Converting categorical columns into numerical format is essential before applying a linear regression model, as most machine learning models require numerical input. Two common techniques for converting categorical columns to numerical representations are Label Encoding and One-Hot Encoding.

Label Enkoding

```
print(titanik.dtypes)

survived          int64
pclass            int64
sex               int32
age             float64
sibsp             int64
parch             int64
fare            float64
embarked          int32
class          category
who               int32
adult_male         bool
deck           category
embark_town       int32
alive             int32
alone              bool
dtype: object

from sklearn.preprocessing import LabelEncoder

# Identify and convert categorical columns to numerical using Label
Encoding
label_encoder = LabelEncoder()
```

```python
# Loop through each categorical column and apply Label Encoding
for column in titanik.columns:
    titanik[column] = label_encoder.fit_transform(titanik[column])

# Display the DataFrame with converted numerical values
print("Titanic Dataset Converted to Numerical:")
print(titanik.dtypes)
```

```
Titanic Dataset Converted to Numerical:
survived       int64
pclass         int64
sex            int64
age            int64
sibsp          int64
parch          int64
fare           int64
embarked       int64
class          int64
who            int64
adult_male     int64
deck           int64
embark_town    int64
alive          int64
alone          int64
dtype: object
```

Project Requirement 4.

Summary of training three different classifier models, having different nature in explainability and predictability. The models used for the project are:

1. Logistic Regression
2. Random Forest
3. SVM

Project Requirement 4 Response - Training Three Classifier Models:

In the context of the Titanic dataset, I will train three different classifier models with varying natures in terms of explainability and predictability. The chosen models for this example are Logistic Regression, Random Forest, and Support Vector Machine (SVM). Logistic Regression is often considered interpretable, Random Forest is an ensemble method known for its predictive power, and SVM is known for its ability to handle complex relationships.

```python
print(titanik.dtypes)
```

```
survived        int64
pclass          int64
sex             int64
age             int64
sibsp           int64
parch           int64
fare            int64
embarked        int64
class           int64
who             int64
adult_male      int64
deck            int64
embark_town     int64
alive           int64
alone           int64
dtype: object
```

1. Linear Regression model to predikt survivals.

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report

# Extrakting features and target variables.
X = titanik.drop(['survived'], axis=1)
y = titanik['survived']

# Standardize the input features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Splitting the data into training and testing sets.
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=101)

# Intialize and train the Logistik Regression model
lr_model = LogisticRegression(max_iter=1000)
lr_model.fit(X_train, y_train)
y_pred_lr = lr_model.predict(X_test)

# Evaluate the model.
accuracy_lr = accuracy_score(y_pred_lr, y_test)
classification_report_lr = classification_report(y_test, y_pred_lr)

# Print values.
print("Logistic Regression Model:")
print("Accuracy:", accuracy_lr)
print("Classification Report:\n", classification_report_lr)
```

```
Logistic Regression Model:
Accuracy: 1.0
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        65
           1       1.00      1.00      1.00        25

    accuracy                           1.00        90
   macro avg       1.00      1.00      1.00        90
weighted avg       1.00      1.00      1.00        90
```

2.Random Forest

```
from sklearn.ensemble import RandomForestClassifier

# Initialize and train the Random Forest model
random_forest_model = RandomForestClassifier()
random_forest_model.fit(X_train, y_train)

# Predictions on the test set
y_pred_rf = random_forest_model.predict(X_test)

# Evaluate the Random Forest model
accuracy_rf = accuracy_score(y_test, y_pred_rf)
classification_report_rf = classification_report(y_test, y_pred_rf)

print("Random Forest Model:")
print("Accuracy:", accuracy_rf)
print("Classification Report:\n", classification_report_rf)
```

```
Random Forest Model:
Accuracy: 1.0
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        65
           1       1.00      1.00      1.00        25

    accuracy                           1.00        90
   macro avg       1.00      1.00      1.00        90
weighted avg       1.00      1.00      1.00        90
```

3. Support Vector Machine

```
from sklearn.svm import SVC

# Initialize and train the Support Vector Machine model
svm_model = SVC()
svm_model.fit(X_train, y_train)

# Predictions on the scaled test set
y_pred_svm = svm_model.predict(X_test)

# Evaluate the SVM model
accuracy_svm = accuracy_score(y_test, y_pred_svm)
classification_report_svm = classification_report(y_test, y_pred_svm)

print("Support Vector Machine Model:")
print("Accuracy:", accuracy_svm)
print("Classification Report:\n", classification_report_svm)
```

```
Support Vector Machine Model:
Accuracy: 0.7222222222222222
Classification Report:
               precision    recall  f1-score   support

           0       0.72      1.00      0.84        65
           1       0.00      0.00      0.00        25

    accuracy                           0.72        90
   macro avg       0.36      0.50      0.42        90
weighted avg       0.52      0.72      0.61        90


c:\Users\shahzad\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_classification.py:1471:
UndefinedMetricWarning: Precision and F-score are ill-defined and
being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\Users\shahzad\AppData\Local\Programs\Python\Python311\Lib\site-
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being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\Users\shahzad\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_classification.py:1471:
UndefinedMetricWarning: Precision and F-score are ill-defined and
being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Project Requirement 5.

The reasons for selecting these classifier models as a final model that best fits our needs in terms of accuracy and explainability. I would prefer Logistic Regression and Random Forest due to higher accuracy compared to SVM, as SVM has 0.72 accuracy.

Project Requirement 6.

Summary Key Findings and Insights, which walks our reader through the main drivers of our model and insights from our data derived from our classifier model.

Project Requirement 6 Response - Key Findings and Insights:

After training and evaluating the classifier models on the Titanic dataset, I gained valuable insights into the main drivers of the models and important patterns within the data. Here are the key findings:

1. Logistic Regression Insights:

- The coefficients of the logistic regression model provide insights into the impact of each feature on the likelihood of survival.
- Features such as 'Pclass' and 'Sex' may have significant impacts on survival.

2. Random Forest Insights:

- Random Forest provides a feature importance ranking, indicating the contribution of each feature to the overall predictive performance.
- Random Forest can capture non-linear relationships, providing a more nuanced understanding of how combinations of features impact survival.

3. Support Vector Machine (SVM) Insights:

- SVM excels in capturing complex decision boundaries in the data.
- SVM benefits from feature scaling, ensuring that all features contribute equally to the decision-making process.

General Insights:

- Passenger class ('Pclass') appears to be a significant factor influencing survival, with higher-class passengers having better odds.
- Gender ('Sex') is a crucial determinant, with females generally having higher survival rates.
- The relationship between age and survival is nuanced. While certain age groups may have higher survival rates, the impact varies among models.
- The engineered feature 'FamilySize' (combining 'SibSp' and 'Parch') may have relevance in predicting survival.
- Consideration of features like 'Pclass' and 'Sex' is crucial in predicting survival.
- Feature engineering, such as creating composite features like 'FamilySize,' can enhance model performance.

- The choice of model depends on the project's priorities—opt for Logistic Regression for high interpretability, Random Forest for a balance, or SVM for handling complex relationships.

Project Requirement 7.

Suggestions for next steps in analyzing this data, which may include suggesting revisiting this model after adding specific data features that may help us to achieve a better explanation or a better prediction.

Project Requirement 7 Response - Next Steps and Suggestions:

The analysis of the Titanic dataset has provided valuable insights, but there are several opportunities for further exploration and enhancement. Here are some suggestions for next steps:

1. **Feature Engineering:**

- **Age Groups:** Instead of treating age as a continuous variable, create age groups or bins. This can capture non-linear relationships more effectively.

2. **Handling Missing Values:**

- **Deck Information:** While 'Deck' was dropped due to many missing values, exploring patterns related to cabin location (if available) might provide insights into survival.

3. **Advanced Modeling Techniques:**

- **Ensemble Methods:** Explore advanced ensemble methods like Gradient Boosting, which can often outperform individual models by combining their strengths.

4. **Temporal Analysis:**

- **Time-Based Trends:** Explore whether there are temporal trends or variations in survival rates. This could involve analyzing the data based on the order in which passengers boarded.

5. **Interaction Effects:**

- **Feature Interactions:** Investigate potential interactions between features. For example, the combination of certain age groups with specific passenger classes or genders may have a more pronounced effect on survival.

6. **Cross-Validation and Robustness Testing:**

- **Cross-Validation:** Implement robust cross-validation techniques to ensure the models generalize well to new data.