Titanic - Exploratory Data Analysis

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
import plotly.express as px
```

Objective

- To explore the Titanic dataset and understand patterns in passenger data.
- To analyze how factors like age, gender, class, and fare affected passenger survival.
- To visualize relationships between features and survival using Python libraries like Pandas, Matplotlib, Seaborn, and Plotly.
- To gain insights that show how demographics and socio-economic status influenced survival chances.

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

df = titanic

df.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

df.shape
```

```
(891, 15)
```

```
df.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
```

```
df.dtypes
```

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

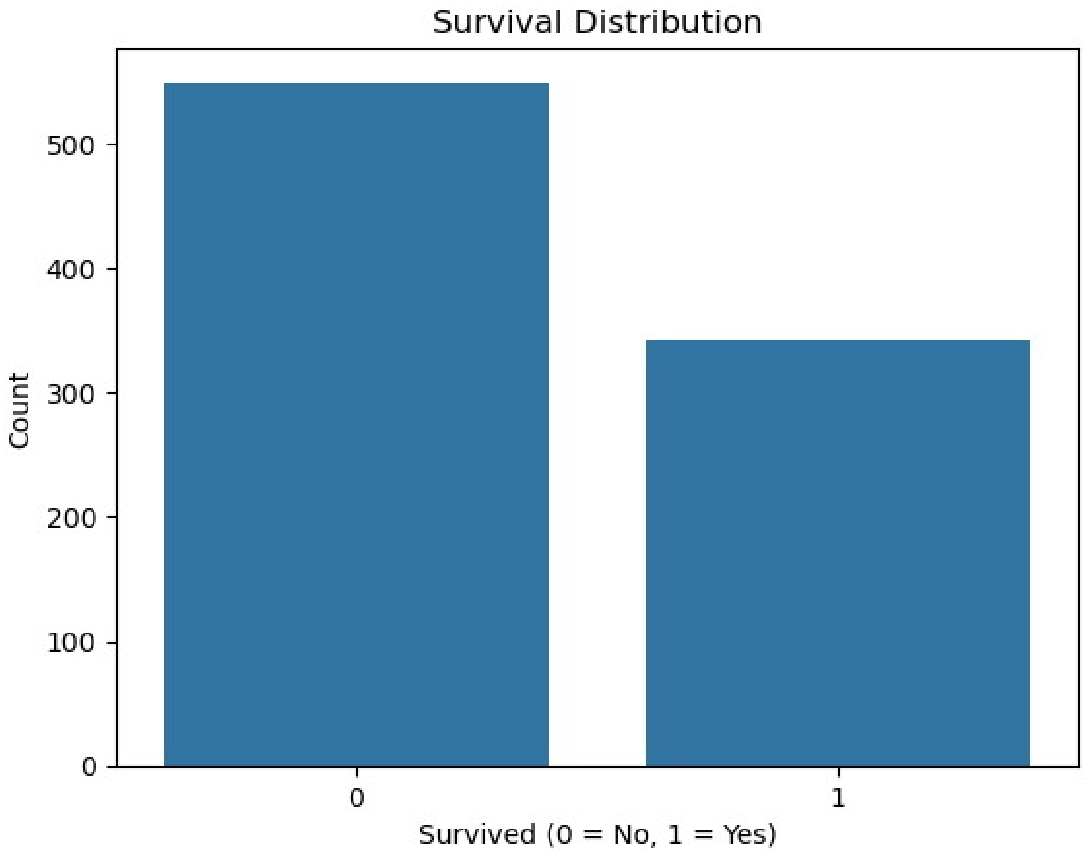
df.isnull().sum()

```
missing_percent = (df.isnull().sum() / len(df)) * 100
missing_percent
```

```
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
```

Survival Distrubution

```
sns.countplot(data=df, x='survived')
plt.title('Survival Distribution')
plt.xlabel('Survived (0 = No, 1 = Yes)')
plt.ylabel('Count')
plt.show()
```



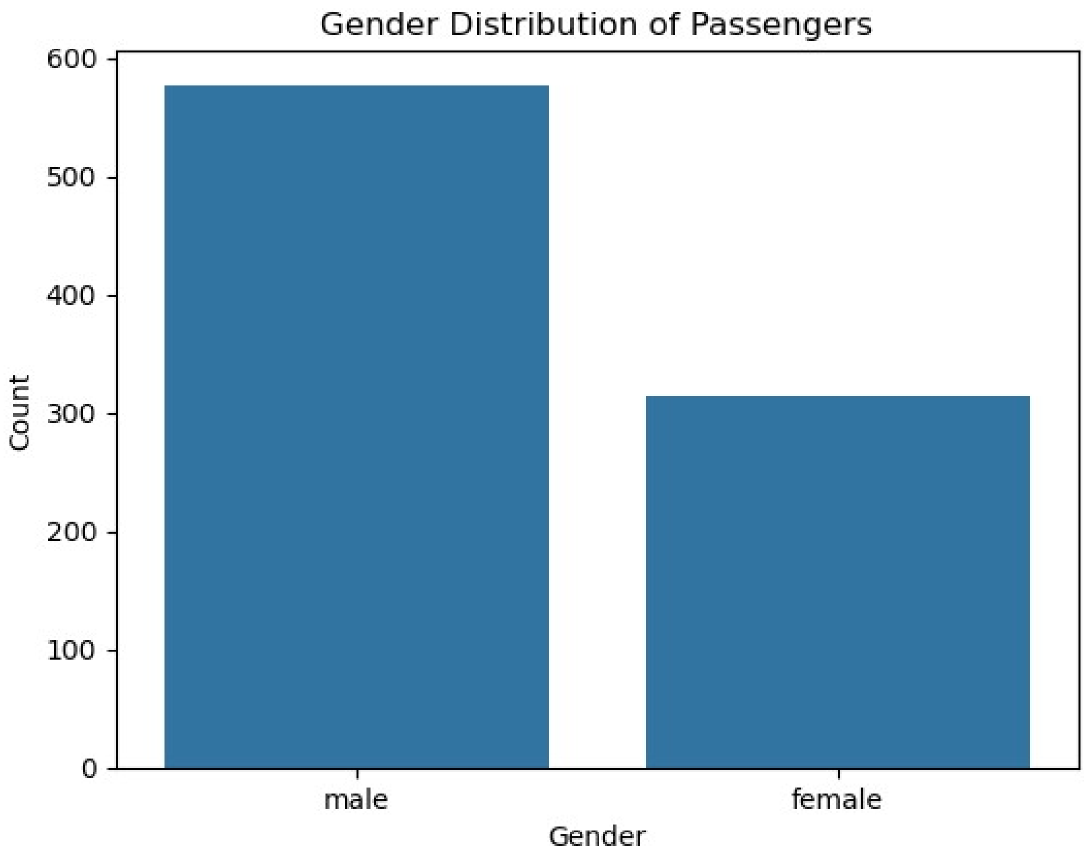
Insights

- The countplot shows the number of passengers who **did not survive (0)** versus those who **survived (1)**.
- It helps quickly compare survival distribution and see which group is larger.

```
survival_rate = df['survived'].mean() * 100
survival_rate

np.float64(38.38383838383838)
```

Gender Distribution

```
sns.countplot(data=df, x='sex')
plt.title('Gender Distribution of Passengers')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()

df['sex'].value_counts()
```



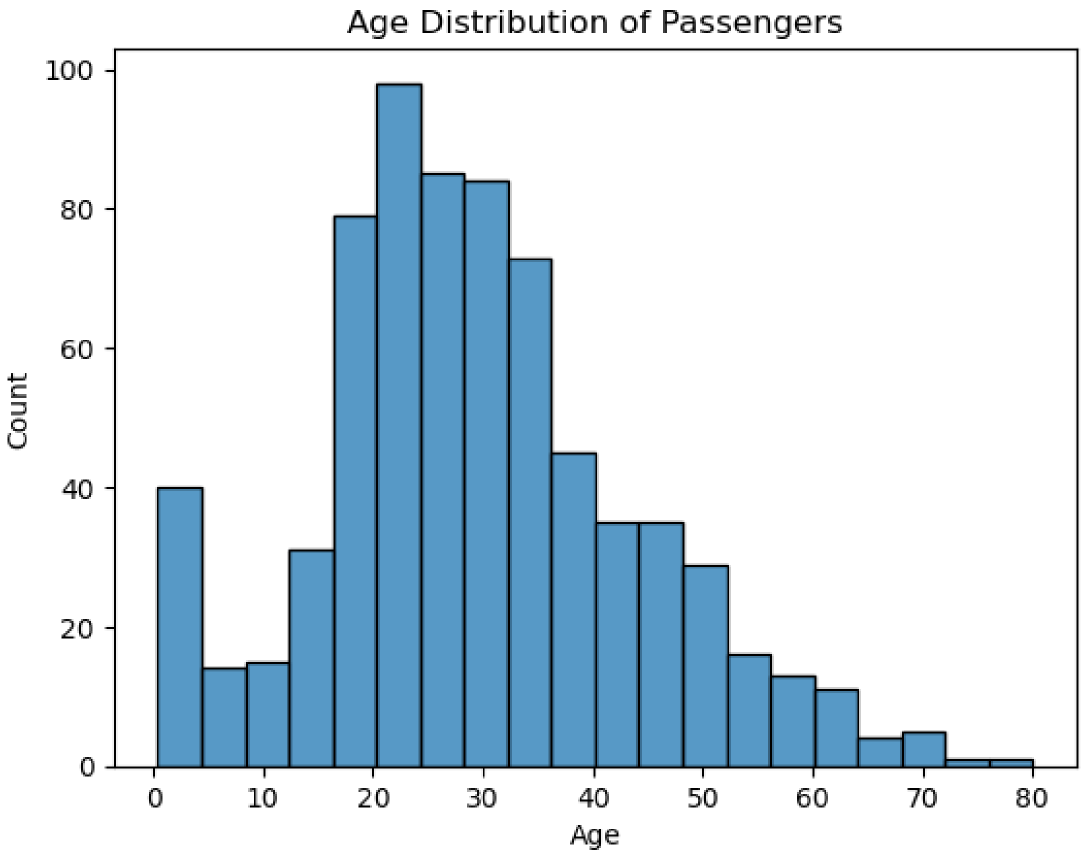

```
sex
male      577
female    314
Name: count, dtype: int64
```

Insights

- The plot and value counts show the distribution of passengers by gender.
- It is clear which gender has a higher number of passengers in the dataset.

Age Distribution

```
sns.histplot(data=df,x='age',bins=20, kde=False)
plt.title('Age Distribution of Passengers')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()

df['age'].value_counts()
```



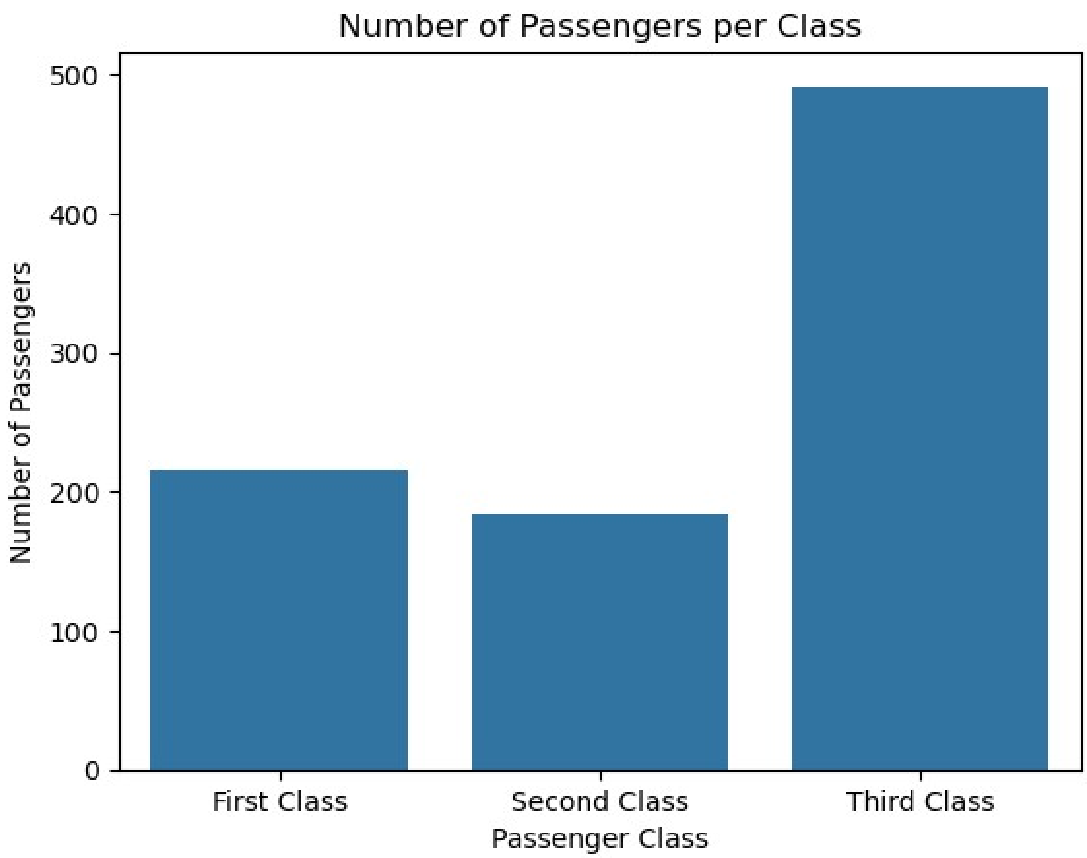

```
age
24.00    30
22.00    27
18.00    26
28.00    25
30.00    25
         ..
24.50     1
0.67      1
0.42      1
34.50     1
74.00     1
Name: count, Length: 88, dtype: int64
```

Insights

- The histogram shows how passengers are distributed across different age groups.
- Most passengers fall into a few common age ranges, while very young and very old ages are less frequent.

Passenger Class Distribution

```
sns.countplot(data=df, x='pclass')
plt.xticks([0, 1, 2], ['First Class', 'Second Class', 'Third Class'])
plt.xlabel('Passenger Class')
plt.ylabel('Number of Passengers')
plt.title('Number of Passengers per Class')
plt.show()
```



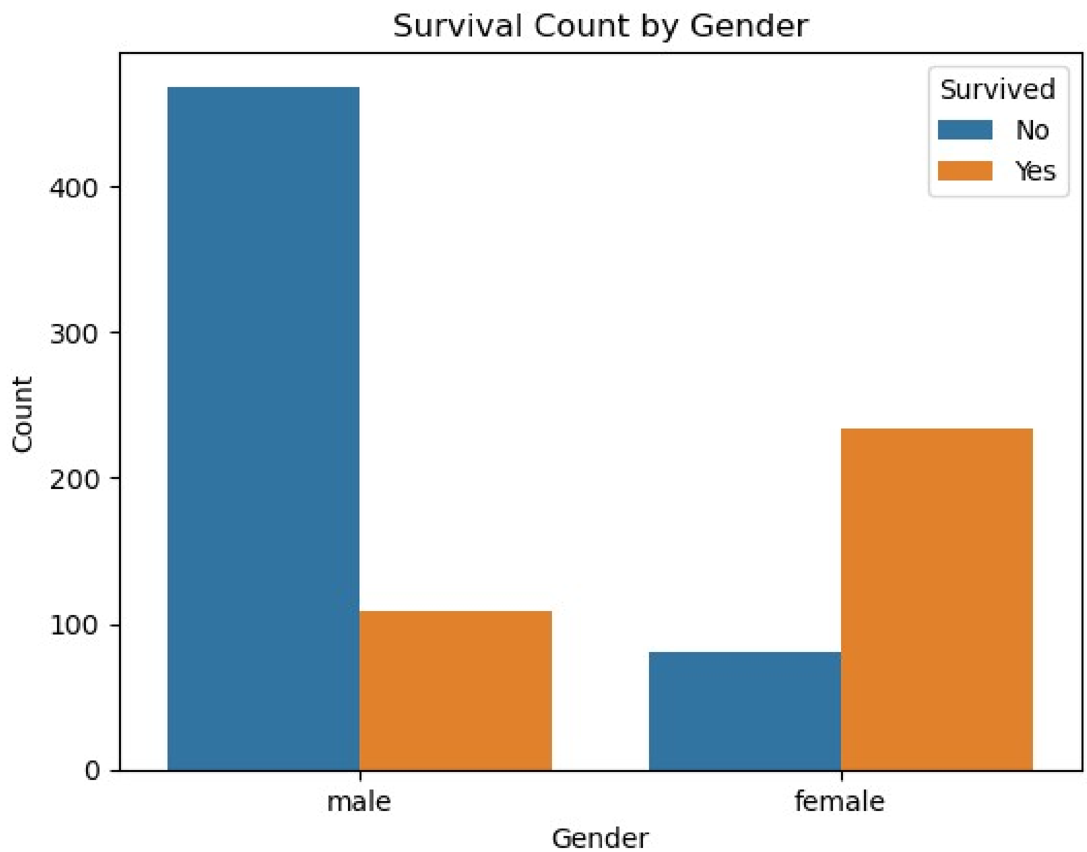
Insights

- The countplot shows the distribution of passengers across First, Second, and Third classes.
- Most passengers belong to the Third Class, followed by Second and First Class.

Survival vs Gender

```
sns.countplot(data=df, x='sex', hue='survived')
plt.title('Survival Count by Gender')
plt.xlabel('Gender')
```

```
plt.ylabel('Count')
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.show()
```



Insights

- The plot shows survival counts for males and females separately.
- Females have a higher survival rate compared to males.

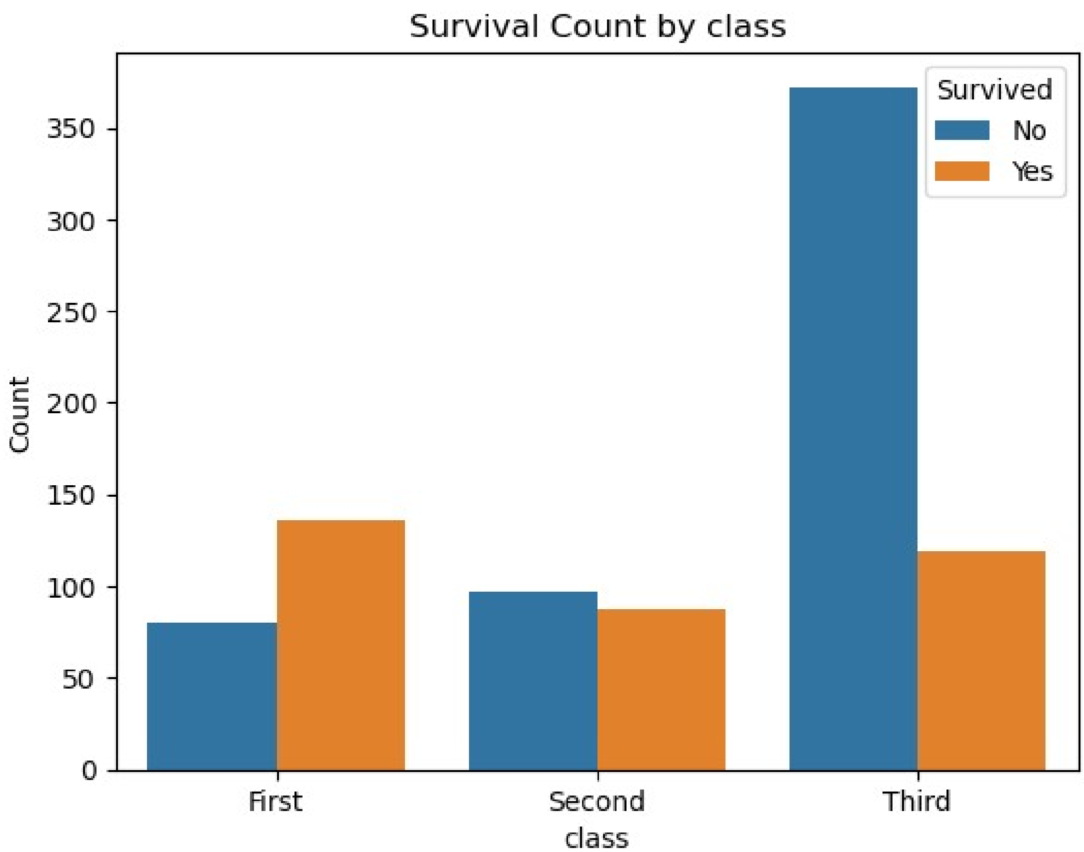
```
survival_by_gender = df.groupby('sex')['survived'].mean()
survival_by_gender

sex
female    0.742038
male      0.188908
Name: survived, dtype: float64
```

Insights

- Females had a higher survival probability than males on the Titanic.

Survival vs Passenger Class

```
sns.countplot(data=df, x='class', hue='survived')
plt.title('Survival Count by class')
plt.xlabel('class')
plt.ylabel('Count')
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.show()
```



Insights

- The plot shows survival distribution across different passenger classes.
- Passengers in First Class have a higher survival rate compared to Second and Third Class.

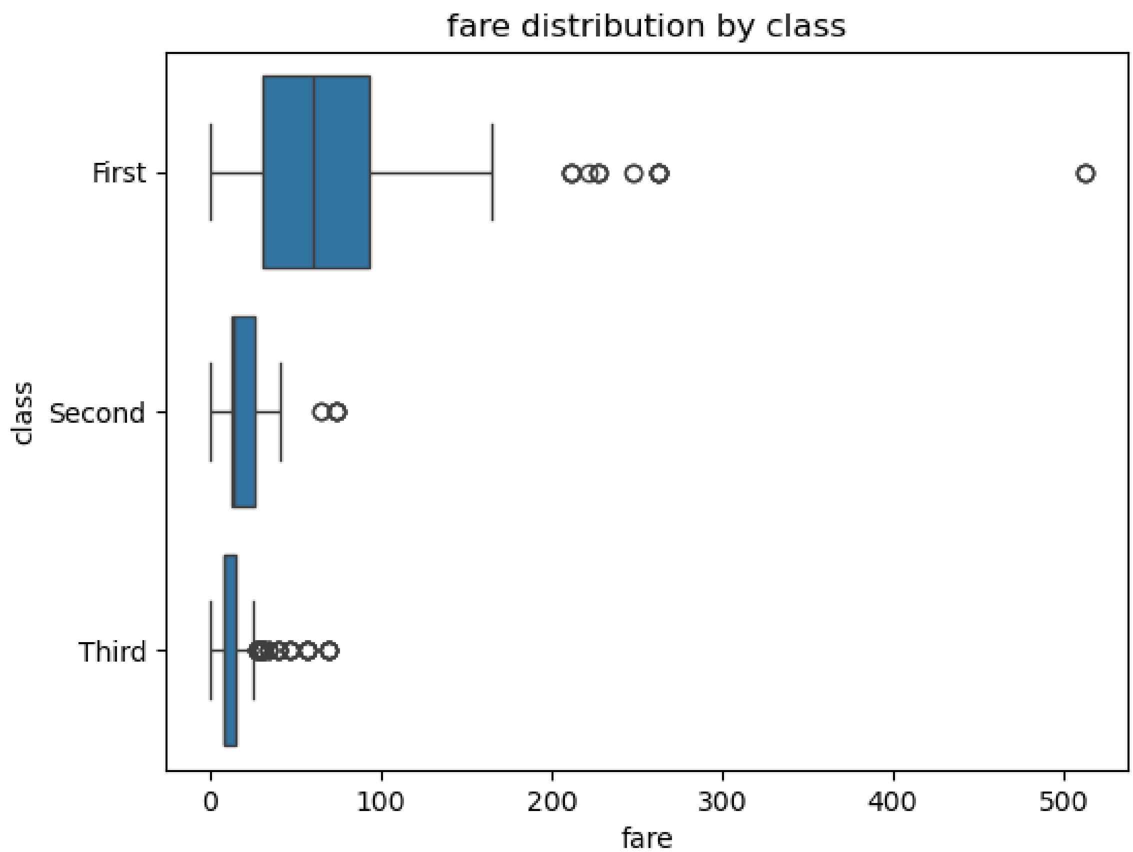
```
df.groupby('class')['survived'].mean() * 100

class
First     62.962963
Second    47.282609
Third     24.236253
Name: survived, dtype: float64
```

Insights

- First Class passengers had the best survival chances.
- Survival rate of First Class was the highest compared to Second and Third Class.

Fare Analysis

```
sns.boxplot(data=df, y='class',x='fare')
plt.title('fare distribution by class')
plt.ylabel('class')
plt.xlabel('fare')
plt.show()
```



Insights

- The boxplot shows that **First Class passengers paid higher fares** compared to Second and Third Class.
- Fare values vary widely in First Class, while Third Class fares are generally lower and more consistent.

Comparison

- 1st Class → Highest fare range
- 3rd Class → Lowest fare range

GroupBy Analysis – Gender

```
df.groupby('sex')['survived'].mean() * 100

sex
female    74.203822
male      18.890815
Name: survived, dtype: float64
```

Insights

- Females had much higher survival rate than males

GroupBy Analysis – Class

```
df.groupby('class')['survived'].mean() * 100

class
First     62.962963
Second    47.282609
Third     24.236253
Name: survived, dtype: float64
```

Insights

- Survival rate decreases from 1st → 3rd class.

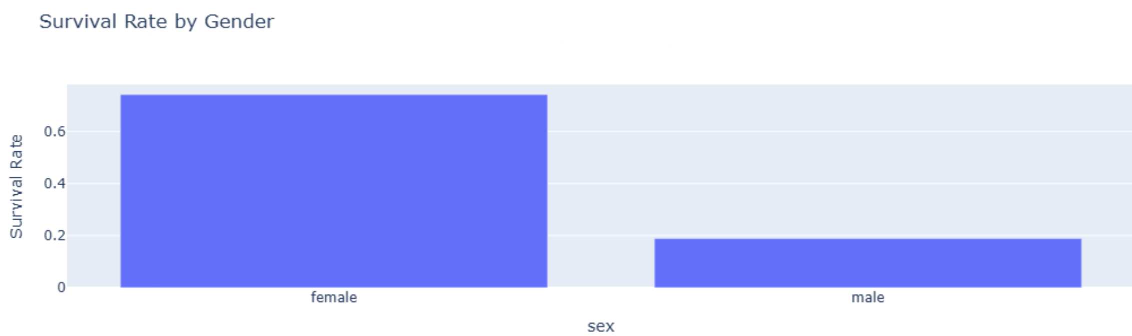
GroupBy Analysis – Age

```
df.groupby('survived')['age'].mean()

survived
0    30.626179
1    28.343690
Name: age, dtype: float64
```

Insights

- Survivors were slightly younger than non-survivors on average.

```
survival_gender = df.groupby('sex')['survived'].mean().reset_index()

fig = px.bar(
    survival_gender,
    x='sex',
    y='survived',
    title='Survival Rate by Gender',
    labels={'survived':'Survival Rate'}
)
fig.show()
```



Insights

- The bar chart shows the **average survival rate** for each gender.
- Females have a higher survival rate compared to males.

Conclusion

Gender was the most influential factor – females had significantly higher survival chances.

Passenger class strongly affected survival – 1st class passengers survived more.

Fare and class are correlated, indicating socio-economic impact on survival.