



Titanic Dataset - Exploratory Data Analysis (EDA)

1. Dataset Loading & Overview

```
In [1]: # Importing major libraries
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
```

```
In [2]: # Load dataset
df = sns.load_dataset("titanic")
```

```
In [3]: # First 5 records
df.head()
```

```
Out[3]:   survived  pclass    sex   age  sibsp  parch     fare  embarked class who
          0         0      3 male  22.0      1      0    7.2500      S Third  man
          1         1      1 female  38.0      1      0   71.2833      C First woman
          2         1      3 female  26.0      0      0    7.9250      S Third woman
          3         1      1 female  35.0      1      0   53.1000      S First woman
          4         0      3 male  35.0      0      0    8.0500      S Third  man
```

```
In [4]: # Dataset shape
df.shape
```

```
Out[4]: (891, 15)
```

Observation:

The dataset contains information about passengers such as age, gender, class, fare, and survival status.

2. Data Structure Understanding

```
In [5]: # Column names and data types
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
```

Numerical Variables

- age
- fare
- sibsp
- parch

Categorical Variables

- sex
- class
- embarked
- who
- deck
- embark_town
- alive

3. Missing Value Analysis

```
In [8]: # Missing values count
df.isnull().sum()
```

```
Out[8]: 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
```

```
In [9]: # Missing value percentage
(df.isnull().mean() * 100).sort_values(ascending=False)
```

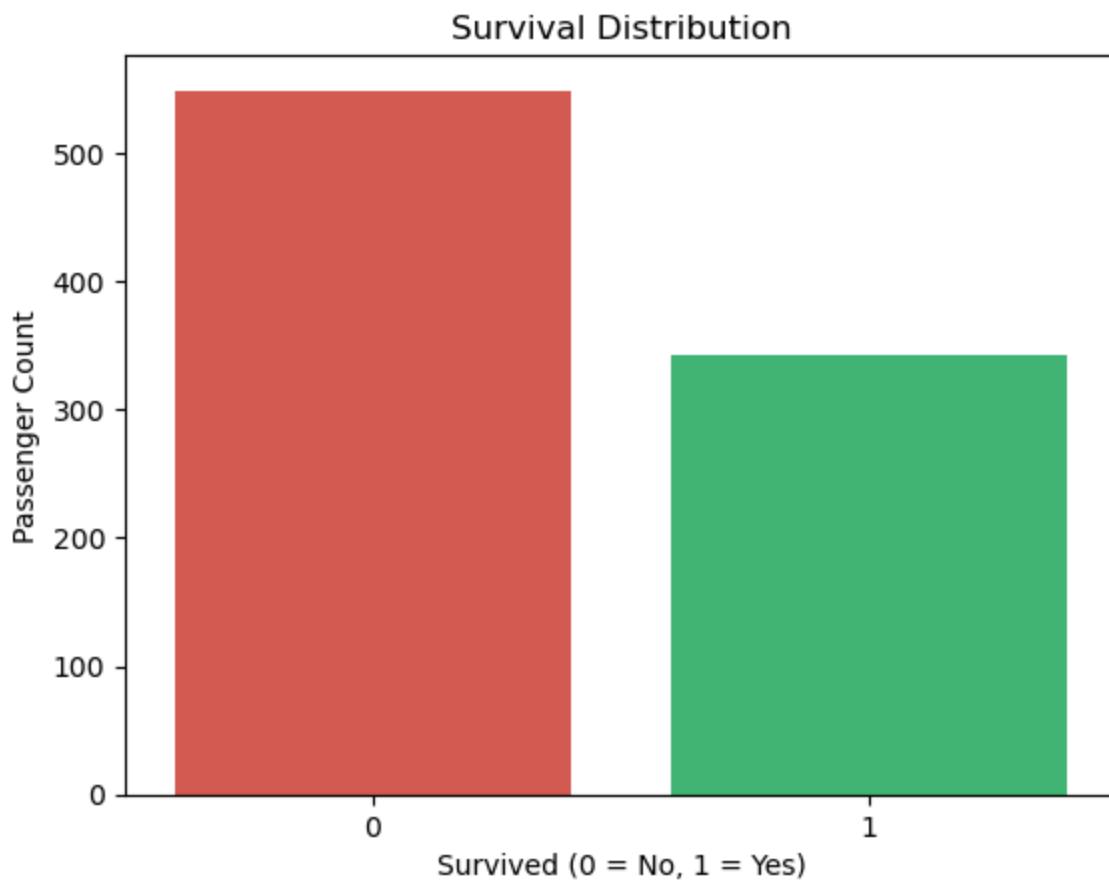
```
Out[9]: deck      77.216611
         age       19.865320
         embarked  0.224467
         embark_town 0.224467
         sex        0.000000
         pclass     0.000000
         survived   0.000000
         fare        0.000000
         parch      0.000000
         sibsp      0.000000
         class       0.000000
         adult_male  0.000000
         who        0.000000
         alive       0.000000
         alone      0.000000
         dtype: float64
```

Observation:

- deck has the highest percentage of missing values
- age also has a significant number of missing values

4. Survival Distribution

```
In [16]: colors=["#E74C3C", "#2ECC71"]
sns.countplot(x="survived",hue="survived", data=df,palette=colors,legend=False)
plt.xlabel("Survived (0 = No, 1 = Yes)")
plt.ylabel("Passenger Count")
plt.title("Survival Distribution")
plt.show()
```

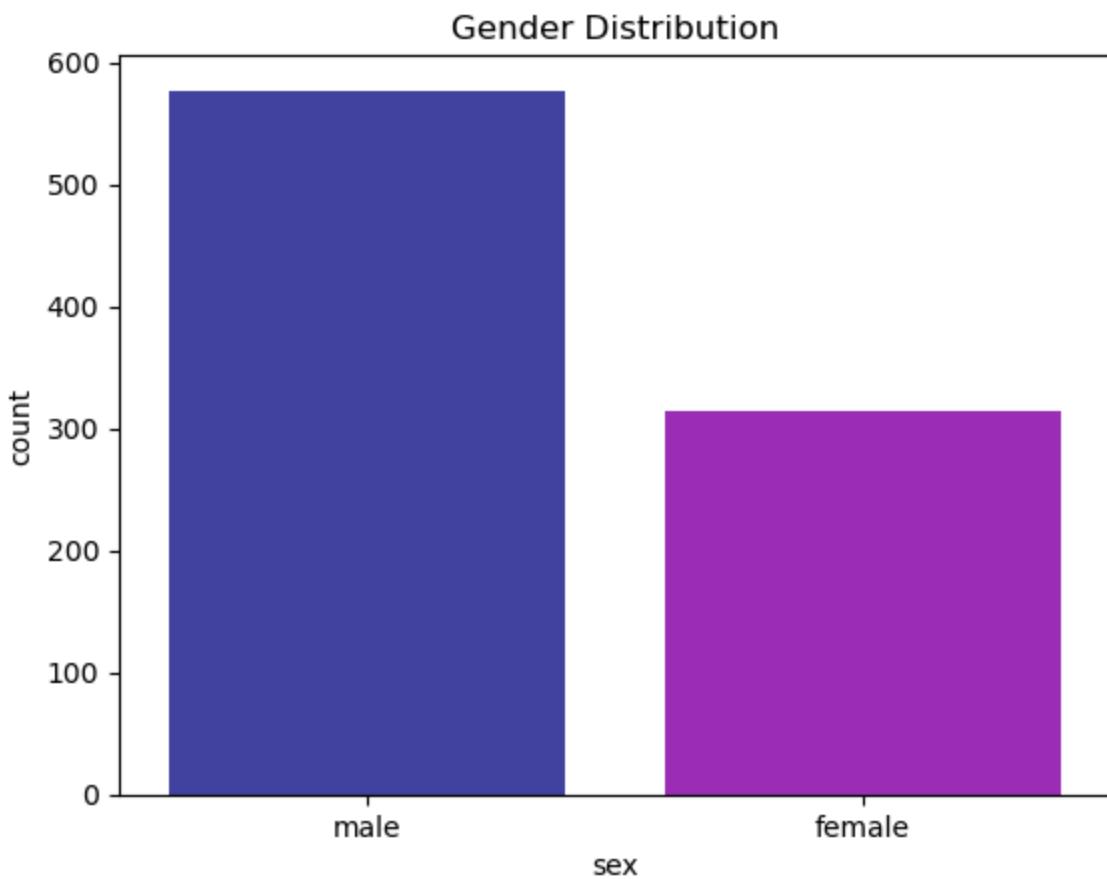


Comment:

More passengers did not survive compared to those who survived.

5. Gender Distribution

```
In [31]: colors=[ "#3333B0", "#A91BCC"]
sns.countplot(x="sex",hue="sex",data=df,palette=colors,legend=False)
plt.title("Gender Distribution")
plt.show()
```

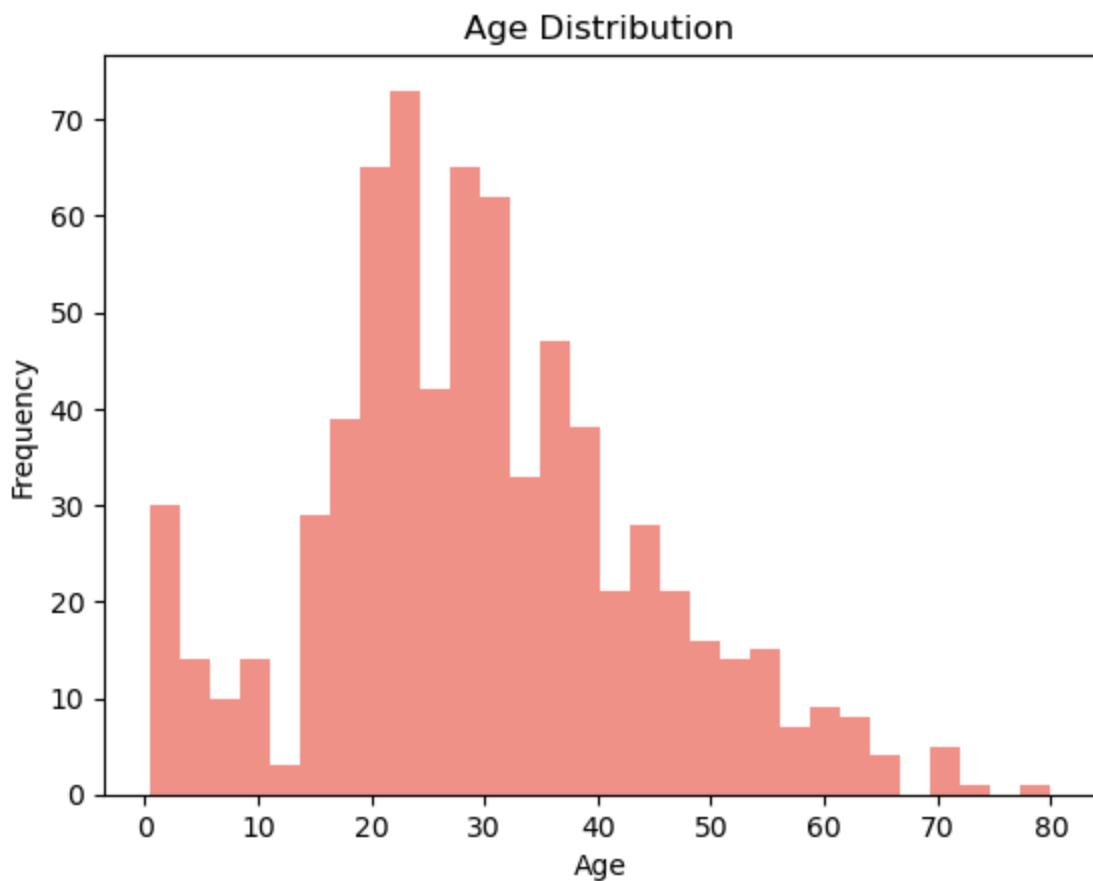


Observation:

Male passengers were dominant onboard.

6. Age Distribution

```
In [32]: colors = ["#F1948A"]
plt.hist(df["age"].dropna(), color=colors, bins=30)
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.title("Age Distribution")
plt.show()
```

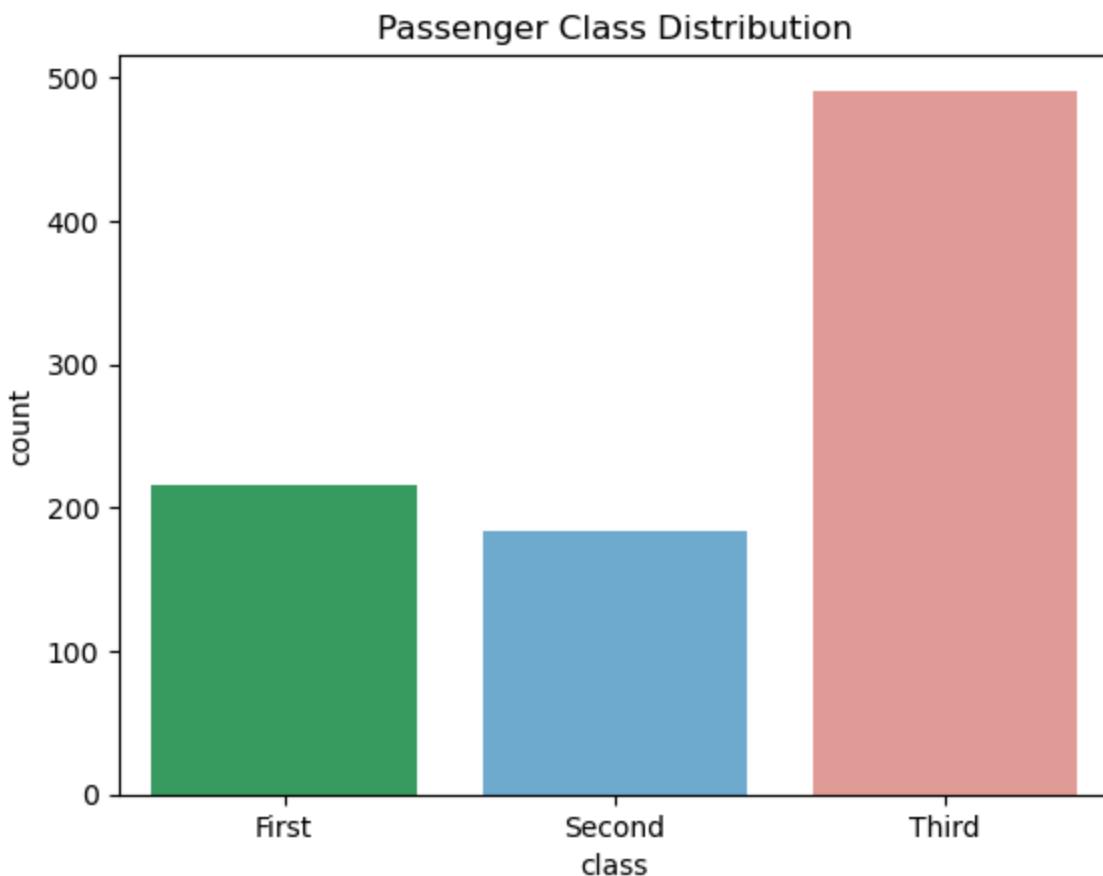


Observation:

Most passengers were between 20-40 years, which is the most frequent age group.

7. Passenger Class Distribution

```
In [37]: colors=["#27AE60", "#5DADE2", "#F1948A"]
sns.countplot(x="class", data=df, palette=colors, hue="class", legend=False)
plt.title("Passenger Class Distribution")
plt.show()
```

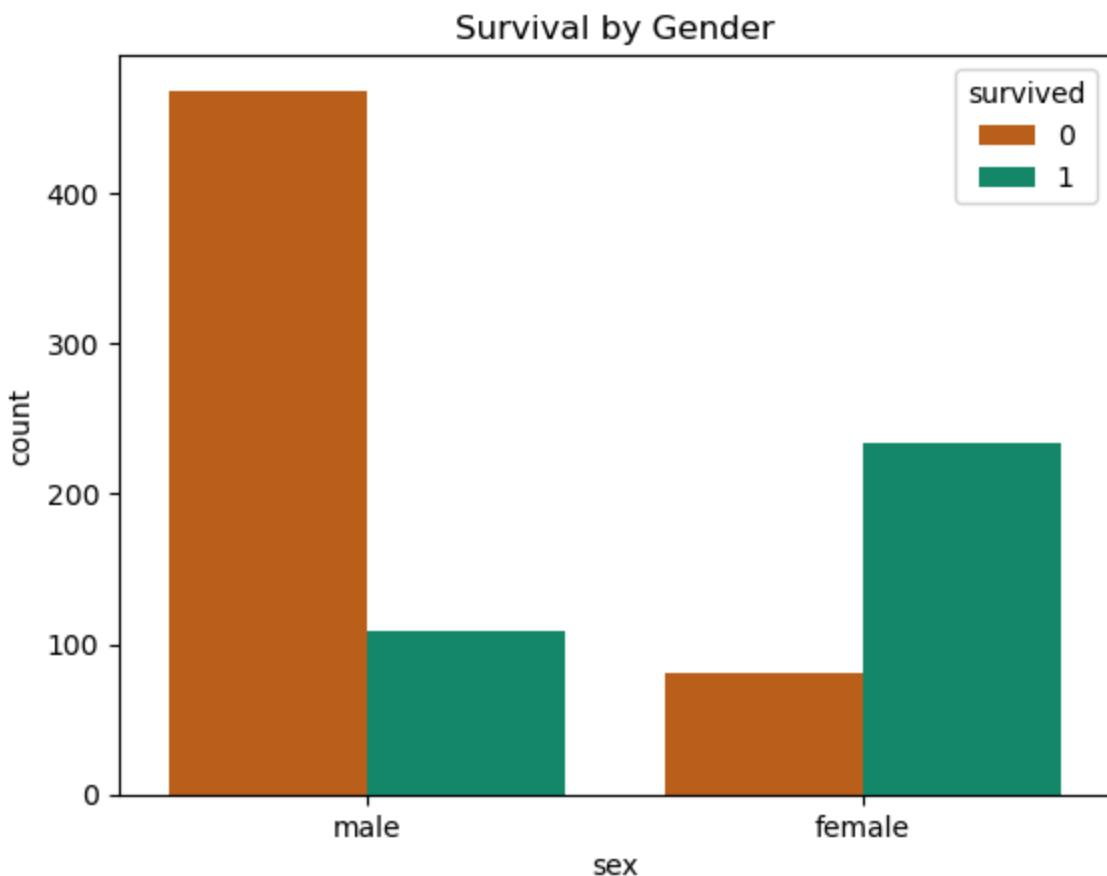


Observation:

Third class had the maximum number of passengers.

8. Survival vs Gender

```
In [41]: colors=["#D55E00", "#009E73"]
sns.countplot(x="sex", hue="survived", data=df, palette=colors)
plt.title("Survival by Gender")
plt.show()
```

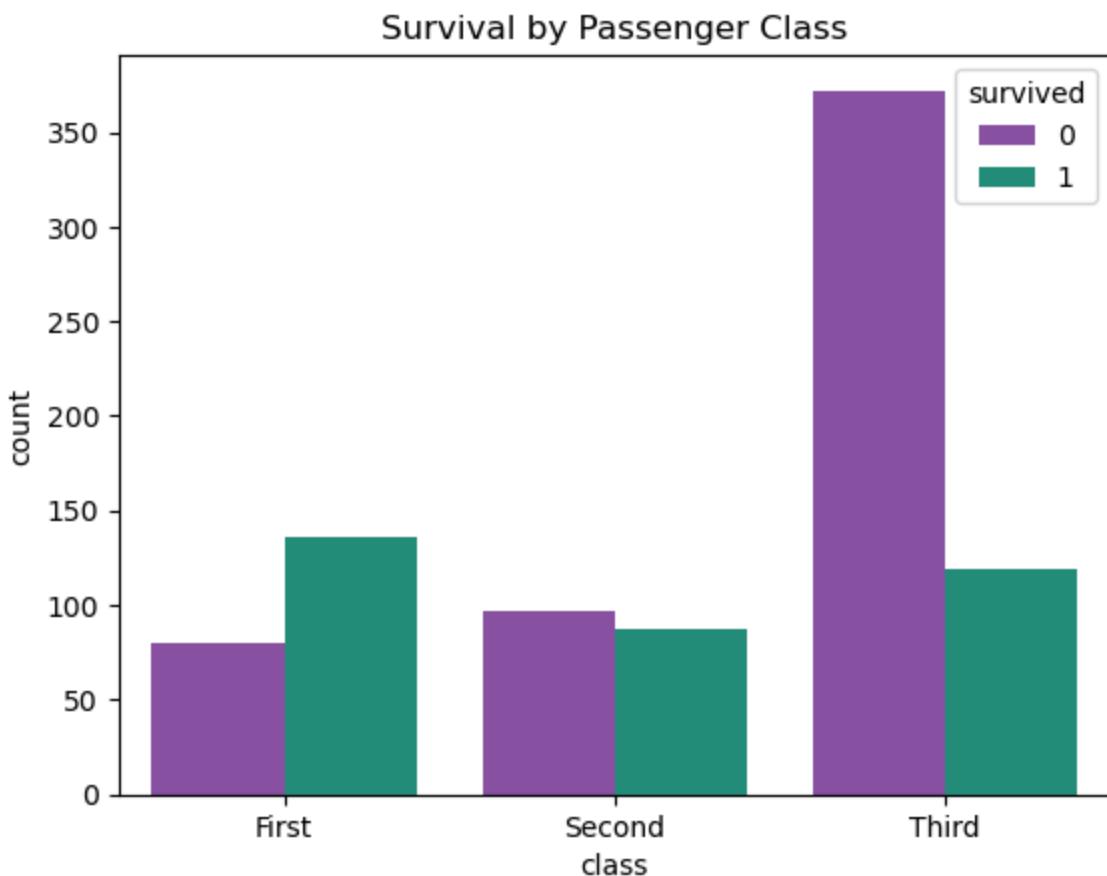


Observation:

Female passengers had a much higher survival rate than males.

9. Survival vs Passenger Class

```
In [44]: colors=["#8E44AD", "#16A085"]
sns.countplot(x="class", hue="survived", data=df, palette=colors)
plt.title("Survival by Passenger Class")
plt.show()
```



Observation:

First-class passengers had the best survival chances.

10. GroupBy Analysis – Gender

```
In [45]: df.groupby("sex")["survived"].mean()
```

```
Out[45]: sex
female    0.742038
male      0.188908
Name: survived, dtype: float64
```

Observation:

Females had a much higher survival rate compared to males

11. Interactive Visualization (Plotly)

```
In [53]: survival_gender = df.groupby("sex")["survived"].mean().reset_index()
fig = px.bar(data_frame=survival_gender,
              x="sex",
              y="survived",
```

```
title="Survival Rate by Gender",
labels={"survived": "Survival Rate"},
color="sex",
color_discrete_map={"male": "#5DADE2", "female": "#F1948A"})
fig.show()
```

12. Business Insights

- Gender was a major factor in survival — females had significantly higher survival rates.
- Passenger class strongly influenced survival, with first-class passengers having the best chances.
- Fare and class are correlated, indicating socio-economic status played an important role.

Most Influential Factor:

- Passenger class and gender were the most influential factors affecting survival.

In []: