```
\overline{\Rightarrow}
```

```
Choose Files train.csv
```

Data columns (total 12 columns):

• train.csv(text/csv) - 61194 bytes, last modified: 6/30/2025 - 100% done Saving train.csv to train (1).csv <class 'pandas.core.frame.DataFrame'> RangeIndex: 891 entries, 0 to 890

#	Column	Non-Null Count	Dtype
0	PassengerId	891 non-null	int64
1	Survived	891 non-null	int64
2	Pclass	891 non-null	int64
3	Name	891 non-null	object
4	Sex	891 non-null	object
5	Age	714 non-null	float64
6	SibSp	891 non-null	int64
7	Parch	891 non-null	int64
8	Ticket	891 non-null	object
9	Fare	891 non-null	float64
10	Cabin	204 non-null	object
11	Embarked	889 non-null	object

dtypes: float64(2), int64(5), object(5)

memory usage: 83.7+ KB

Sex male

577

female 314

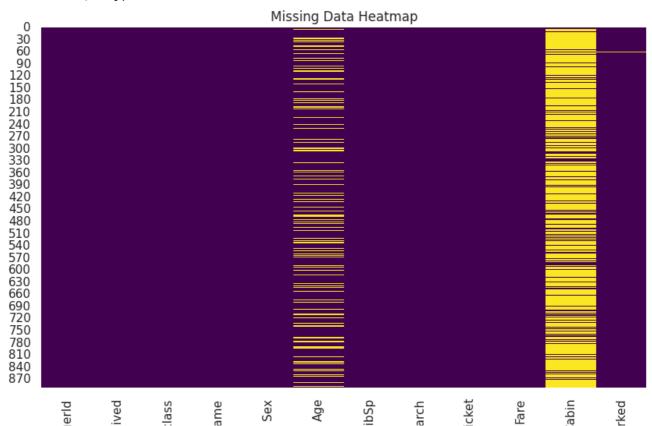
Name: count, dtype: int64

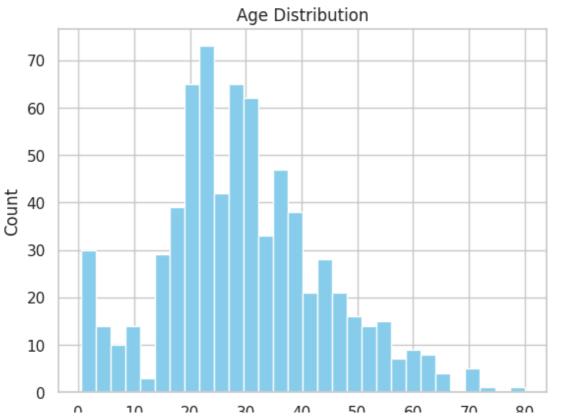
Pclass 3 491 1 216 2 184

Name: count, dtype: int64

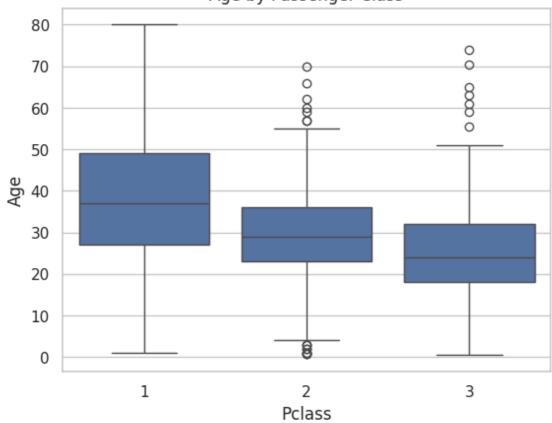
Embarked S 644 C 168 Q 77

Name: count, dtype: int64

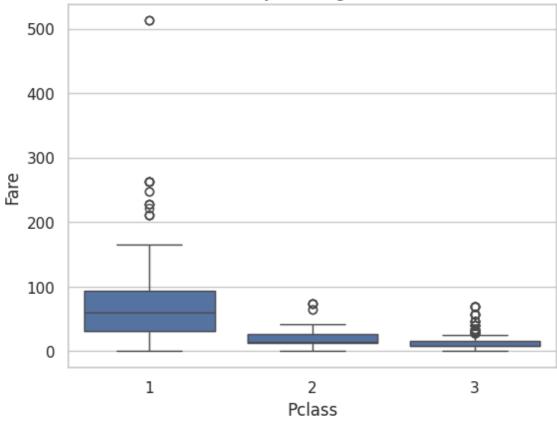




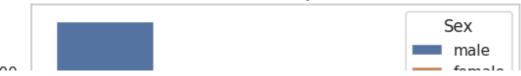


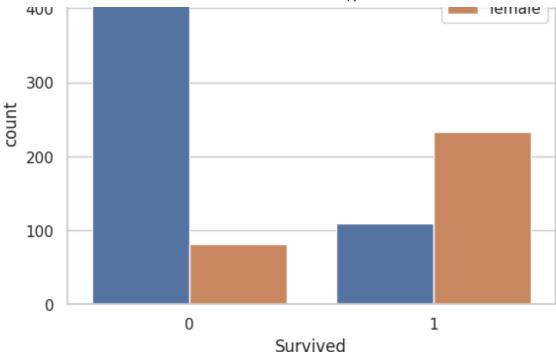


Fare by Passenger Class



Survival Count by Gender





Summary of Findings

- Data Quality Issues: Significant missing data in Age, Cabin, and some in Embarked need cleaning.
- **Survival Correlates**: Gender and Passenger Class have strong relationships with survival outcomes. Females and 1st class passengers survived more.
- **Age Trends**: Younger passengers were mostly in 3rd class. Age has right-skewed distribution, impacting modeling.
- Fare Patterns: Fare shows strong skew and varies significantly by class, indicating socioeconomic differences
- **Next Steps**: Impute or drop missing values, encode categorical variables, and use these insights for building predictive models.