

EXPLORATORY DATA ANALYSIS – TITANIC

COMPREHENSIVE STATISTICAL & VISUAL EXPLORATION

Data Sources:

train.csv (n=891), test.csv (n=418), gender_submission.csv

Objective:

- Extract insights via descriptive statistics and visualization.
- Identify relationships and trends related to survival.

Tools:

Python (Pandas, Matplotlib, Seaborn)

Data Overview

.info() excerpt:

<class 'pandas.core.frame.DataFrame'> RangeIndex: 891 entries, 0 to 890

Data columns (total 12 columns):

#	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

Numeric .describe() (top rows):

	count	mean	std	min	25%	50%	75%	max
PassengerId	891.0	446.00	257.35	1.00	223.50	446.00	668.5	891.00
Survived	891.0	0.38	0.49	0.00	0.00	0.00	1.0	1.00
Pclass	891.0	2.31	0.84	1.00	2.00	3.00	3.0	3.00
Age	714.0	29.70	14.53	0.42	20.12	28.00	38.0	80.00
SibSp	891.0	0.52	1.10	0.00	0.00	0.00	1.0	8.00
Parch	891.0	0.38	0.81	0.00	0.00	0.00	0.0	6.00
Fare	891.0	32.20	49.69	0.00	7.91	14.45	31.0	512.33

Observations:

- Training set: 891 rows, 13 columns.
- Missingness in Age and Cabin; minor in Embarked.
- Fare is highly right-skewed; scales vary across numeric features.
- 'Survived' is class-imbalanced (more non-survivors).

Missing Values

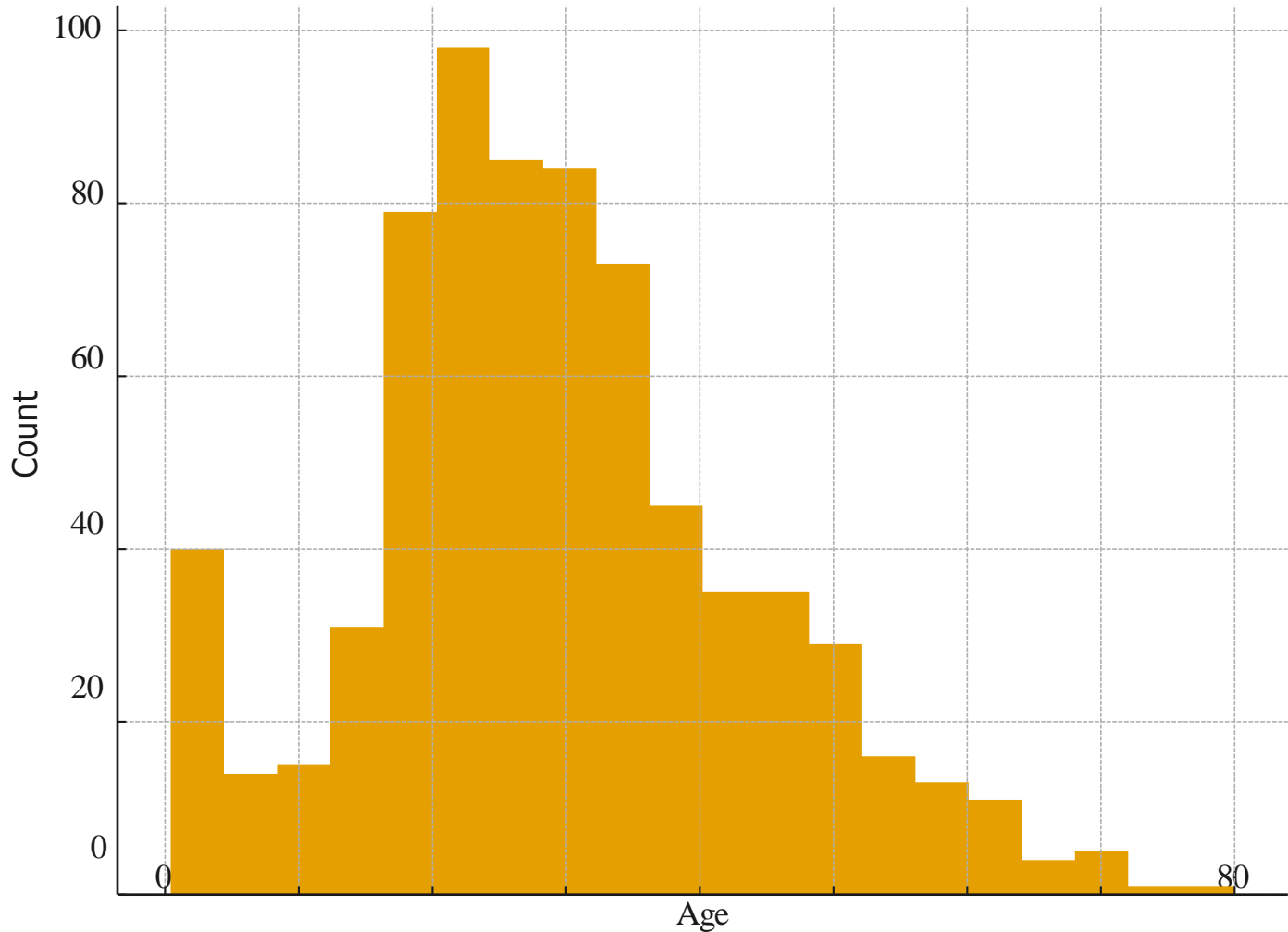
Missing values (top 15):

	missing	percent
Cabin	687	77.10
Age	177	19.87
Embarked	2	0.22
PassengerId	0	0.00
Survived	0	0.00
Pclass	0	0.00
Name	0	0.00
Sex	0	0.00
SibSp	0	0.00
Parch	0	0.00
Ticket	0	0.00
Fare	0	0.00

Observations:

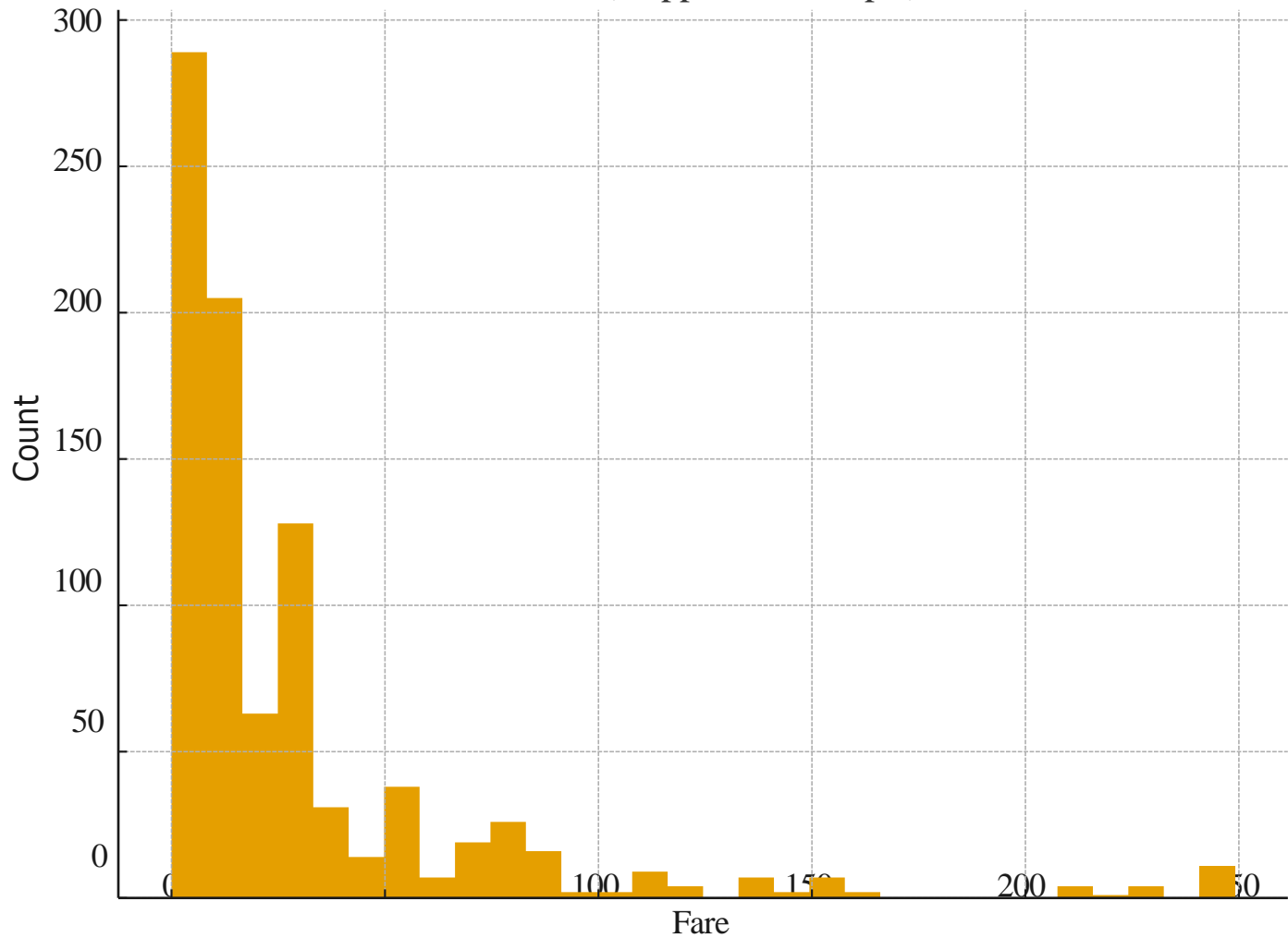
- 'Cabin' is mostly missing - use a-'has_cabin' flag or drop.
- 'Age' missingness needs imputation (e.g., by Title+Pclass medians).
- 'Embarked' missing can be filled with mode.

Age Distribution



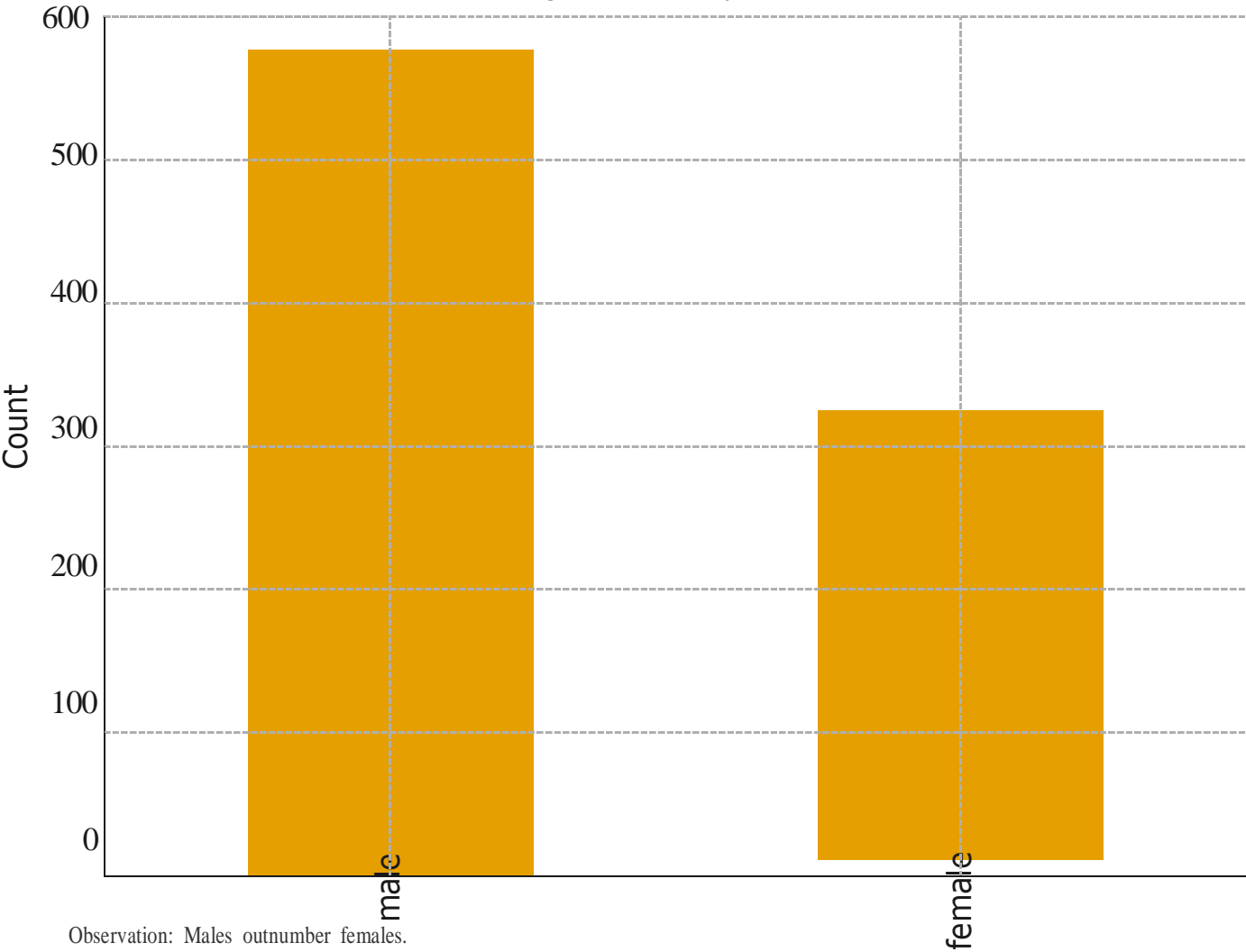
Observation: Age concentrates around young adults (20 40).

Fare Distribution (Clipped at 99th pct)

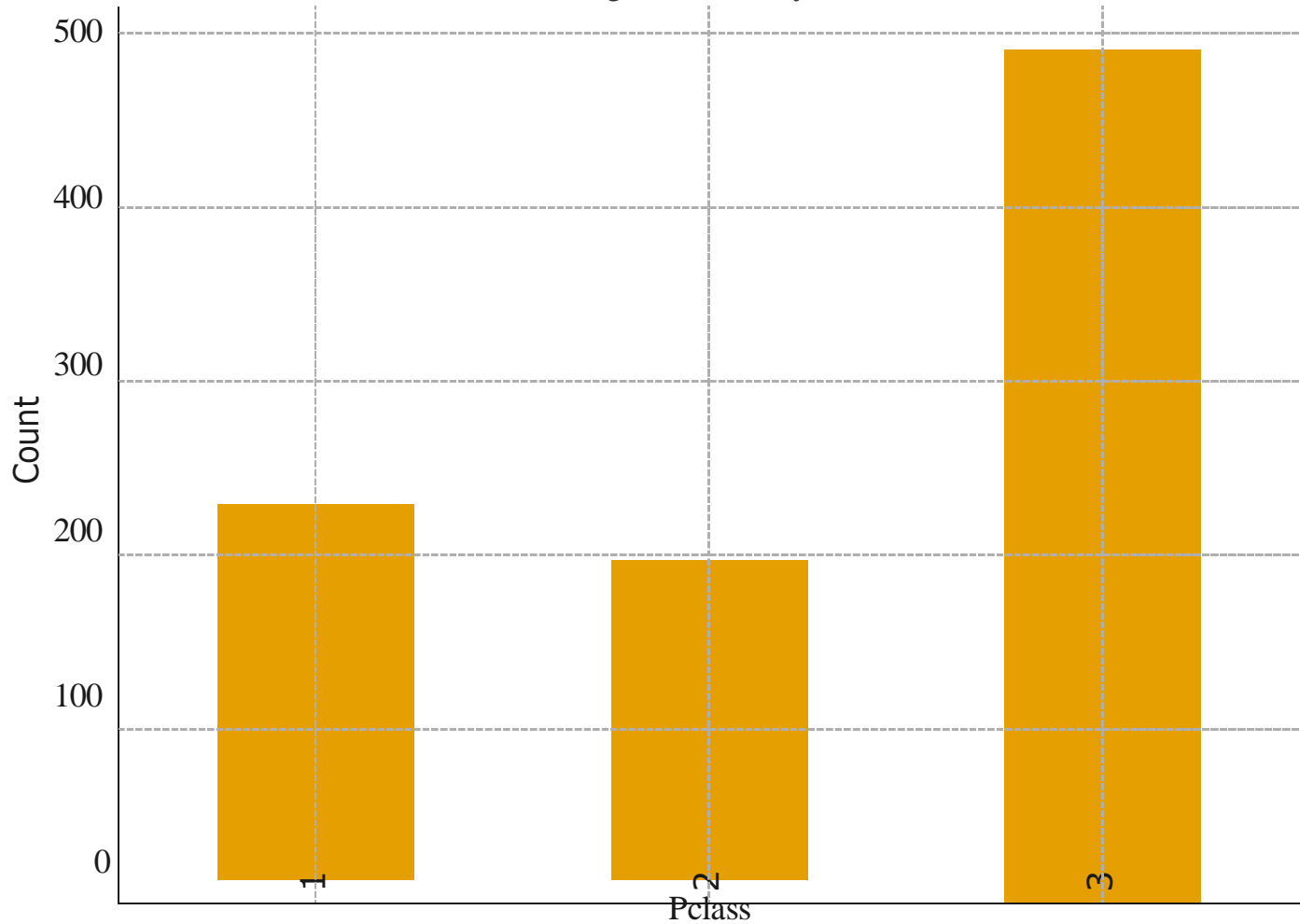


Observation: Strong right skew; consider log transform.

Passenger Count by Sex

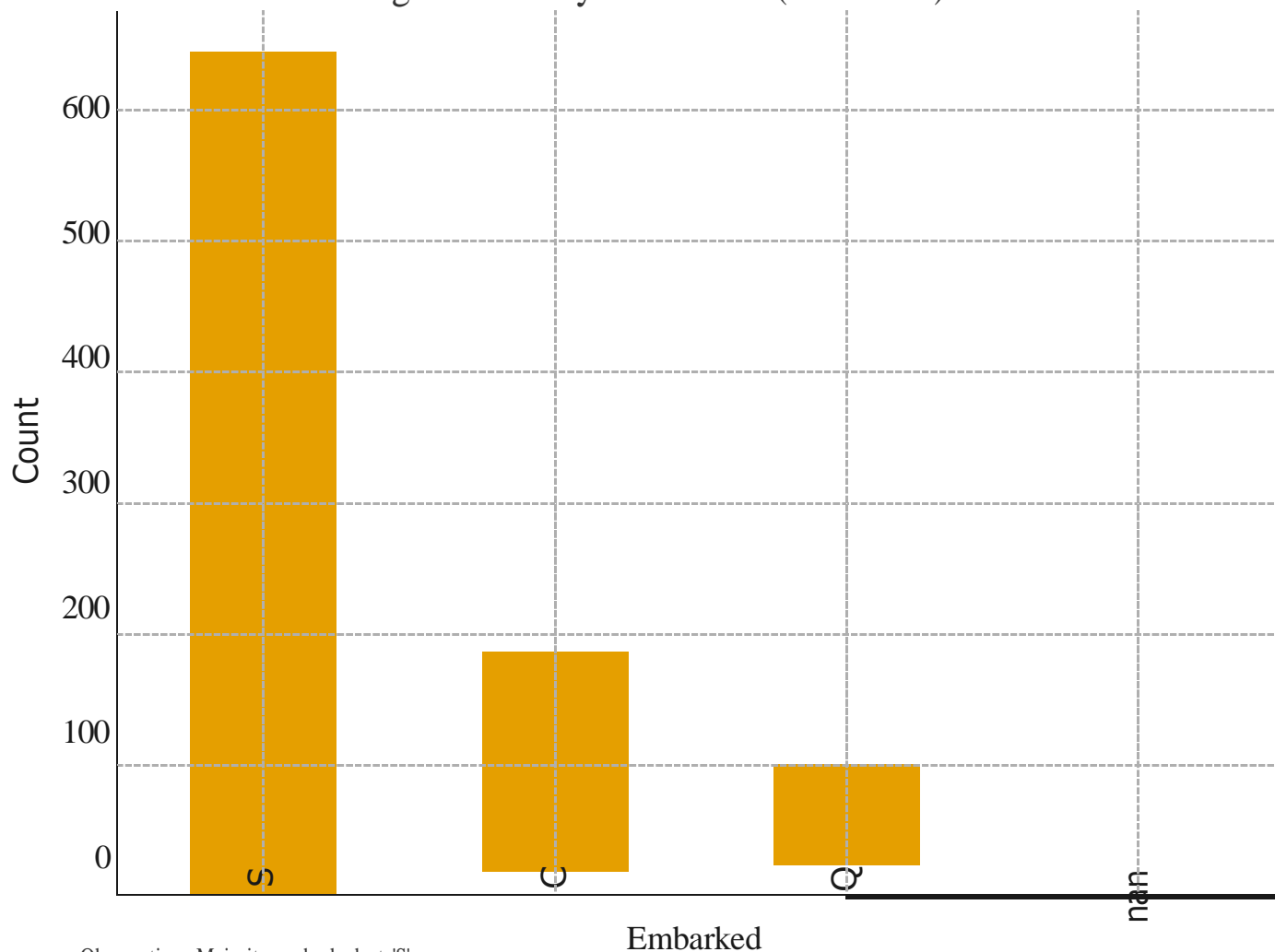


Passenger Count by Pclass

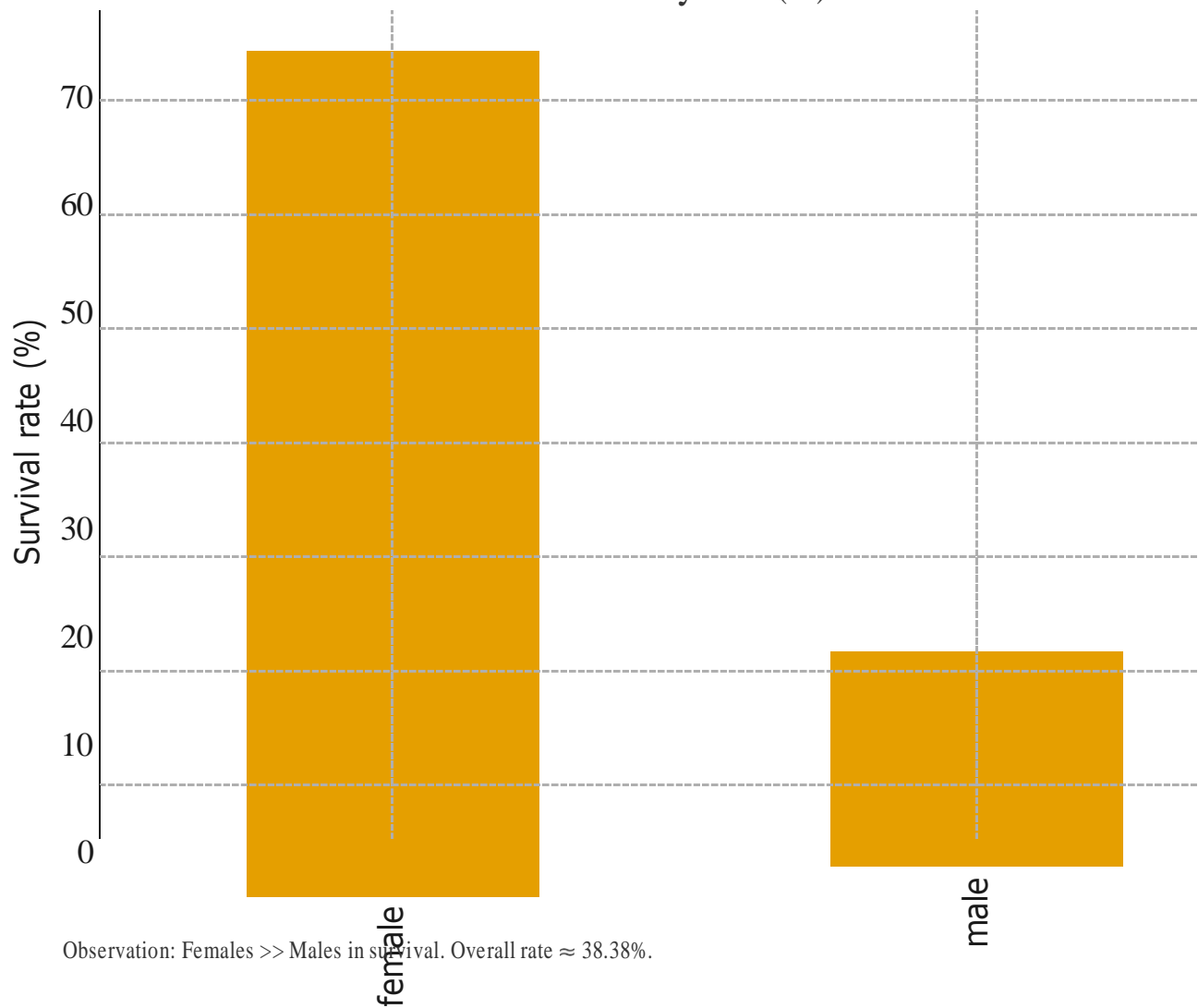


Observation: 3rd class is the largest cohort.

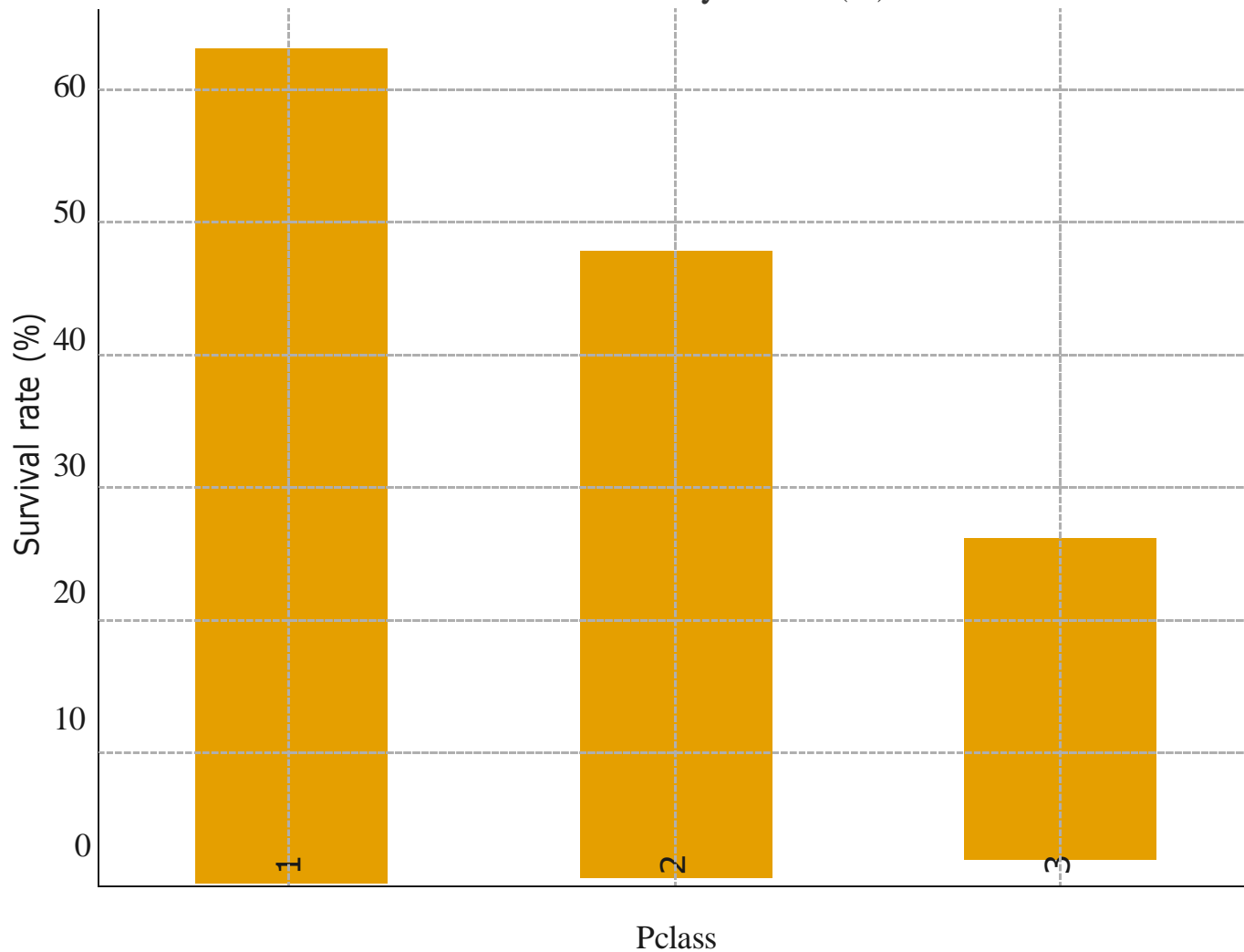
Passenger Count by Embarked (incl. NaN)



Survival Rate by Sex (%)

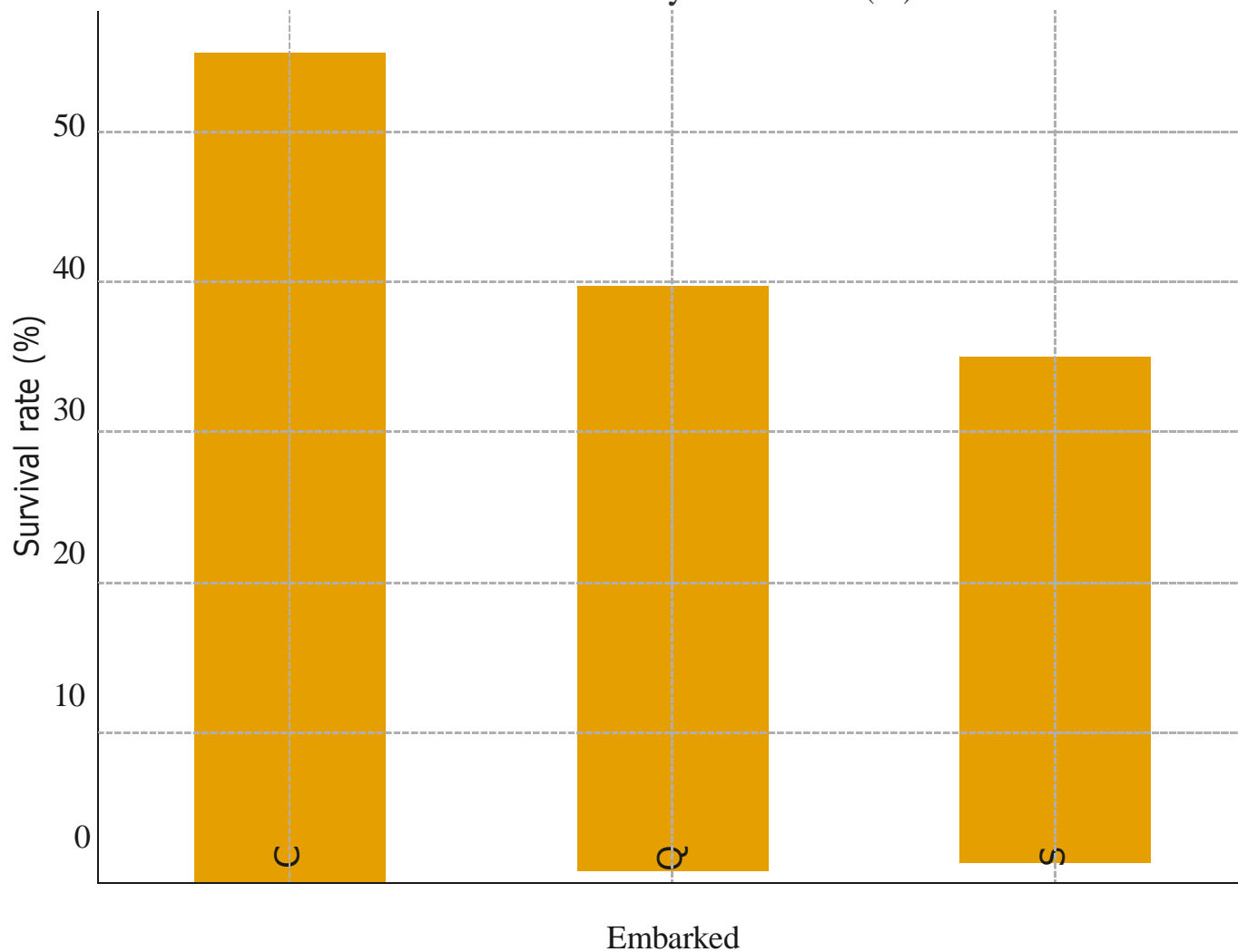


Survival Rate by Pclass (%)



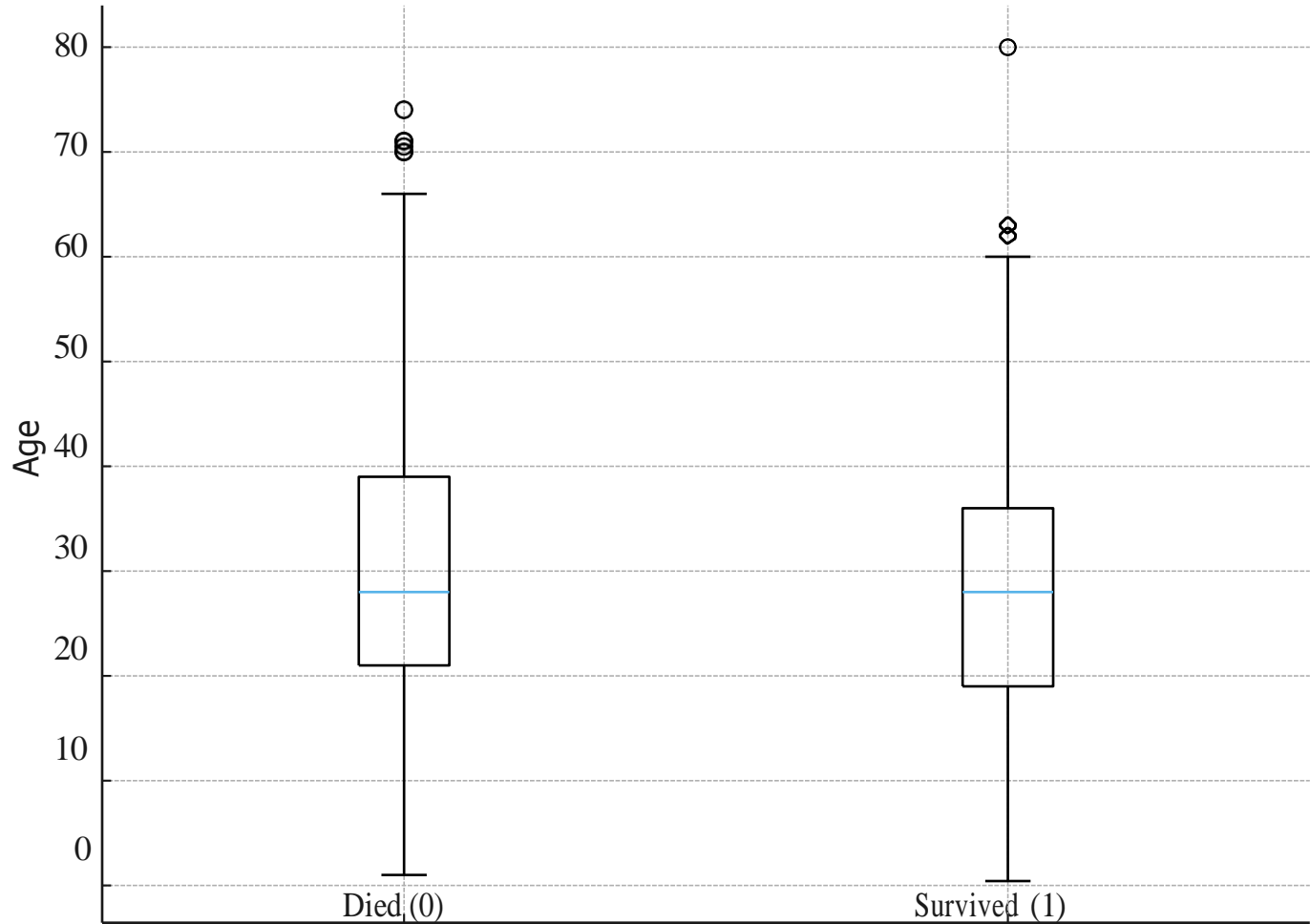
Observation: 1st class survival highest; class is a strong driver.

Survival Rate by Embarked (%)



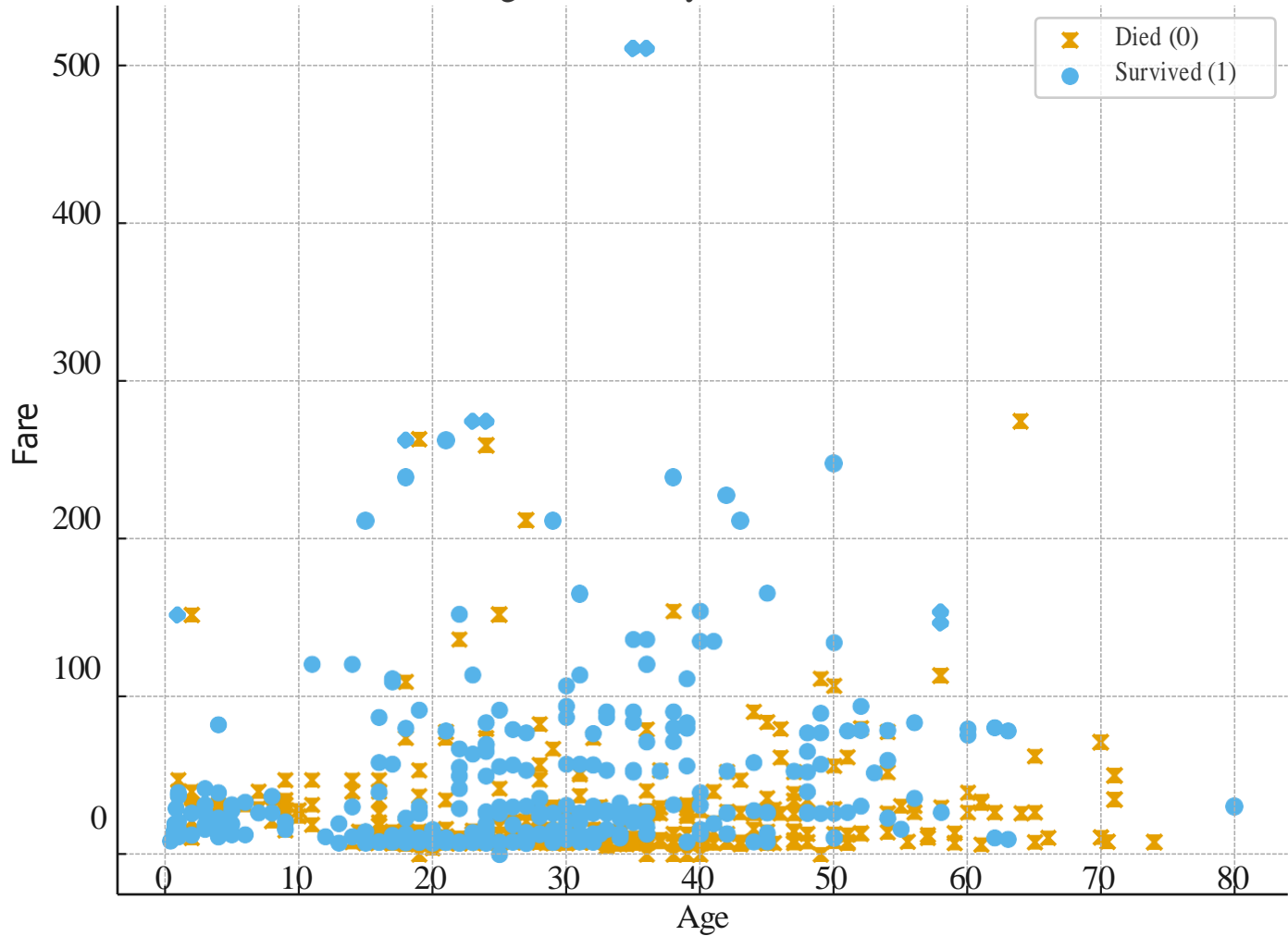
Observation: 'C' often exceeds 'S'/'Q' in survival.

Age by Survival Outcome



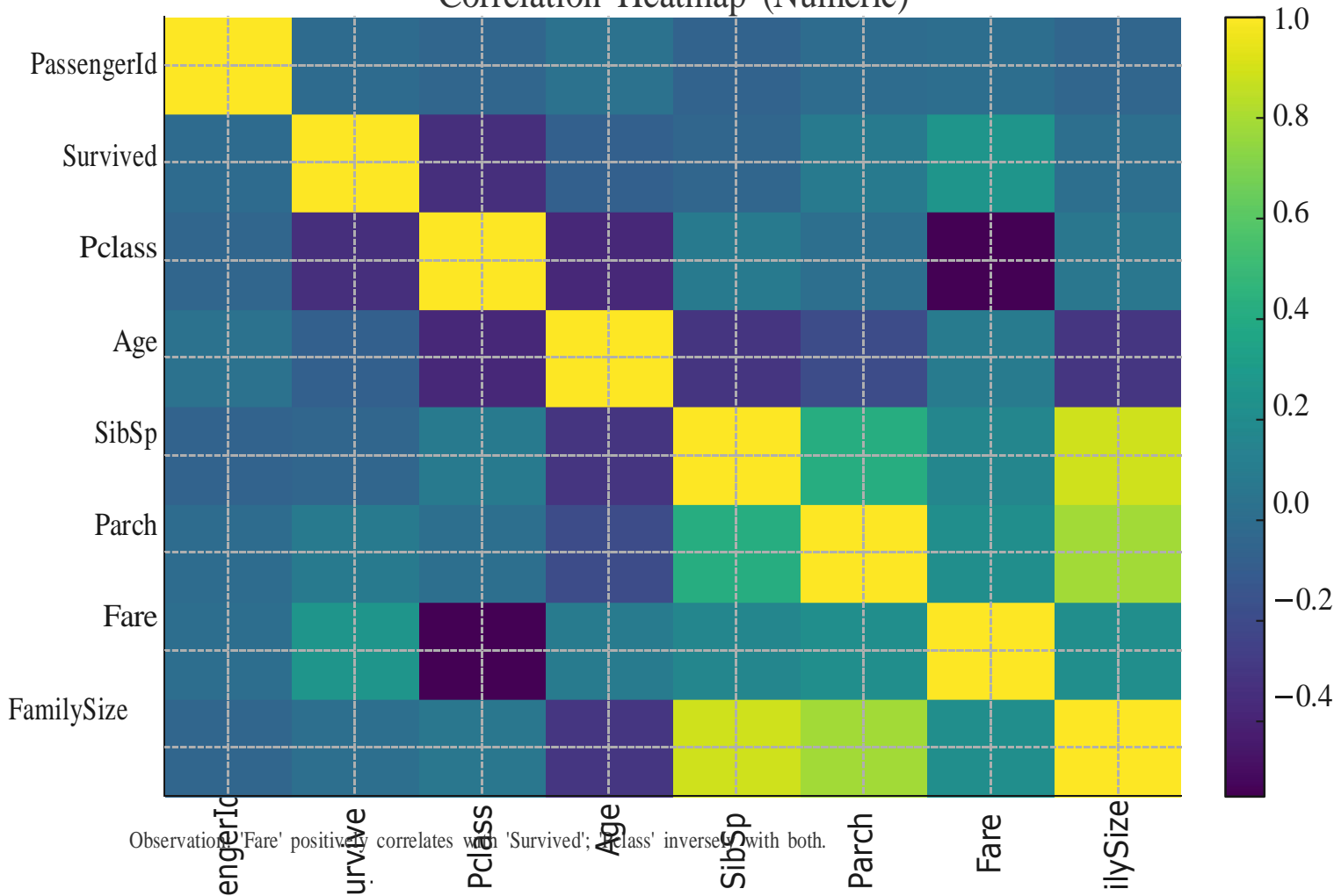
Observation: Survivors skew slightly younger; children benefited from evacuation priority.

Age vs Fare by Survival



Observation: Survivors concentrate at higher fares (proxying Pclass).

Correlation Heatmap (Numeric)



Observation: 'Fare' positively correlates with 'Survived'; 'Pclass' inversely with both. 'SibSp' and 'Parch' positively correlate with 'FamilySize'.

Summary & Next Steps

Key Findings:

- Overall survival rate: 38.38%.
- Sex and Class are the strongest differentiators.
- Higher fares (proxying socioeconomics/class) associate with higher survival.
- Age effects are nuanced; children tend to survive more.
- Missingness: Cabin (heavy), Age (moderate), Embarked (minor).

Recommendations:

- Impute Age (Title+Pclass medians); add has_cabin flag.
- Feature engineering: FamilySize, IsAlone, Title from Name; consider Fare log transform.
- Baselines: Logistic Regression, Decision Tree, Random Forest; stratified CV.