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

Load the Titanic dataset

```
df = pd.read_csv('/content/drive/MyDrive/DataSets/Titanic-Dataset.csv')
print(df.head())
print(df.info())
print(df.describe())
```

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
<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
None
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
```

Check for missing values

```
print(df.isnull().sum())
```

```
PassengerId      0
Survived         0
Pclass           0
```

```
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

Fixing the Missing Values: Age with "Median", cabin with "unknown", Embarked with "S" which is most common.

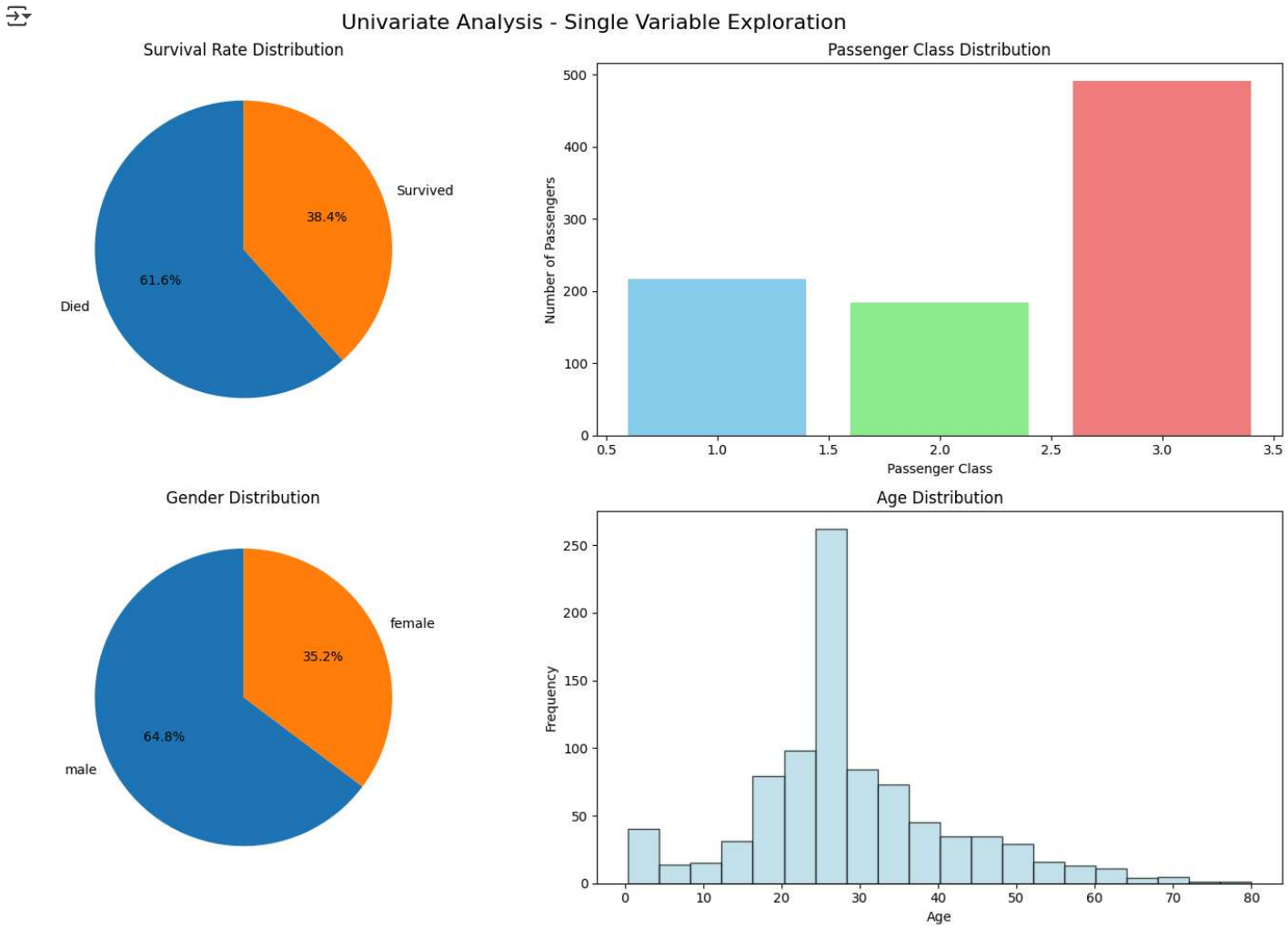
```
if df['Age'].isnull().sum() > 0:
  df['Age'].fillna(df['Age'].median(), inplace = True)

if df['Cabin'].isnull().sum() > 0:
  df['Cabin'].fillna('Unknown',inplace = True)

if df['Embarked'].isnull().sum() > 0:
  df['Embarked'].fillna('S', inplace = True)

print(df.isnull().sum())
```

```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Cabin          0
Embarked       0
AgeGroup       0
FamilySize     0
dtype: int64
```

EDA(Exploratory Data Analysis)

```
# figure with multiple subplots for better organization
fig, axes = plt.subplots(2, 2, figsize=(15, 10))
fig.suptitle('Univariate Analysis - Single Variable Exploration', fontsize=16)

# 1. Survival Rate
survival_counts = df['Survived'].value_counts()
axes[0, 0].pie(survival_counts.values, labels=['Died', 'Survived'], autopct='%1.1f%%', startangle=90)
axes[0, 0].set_title('Survival Rate Distribution')

# 2. Passenger Class Distribution
pclass_counts = df['Pclass'].value_counts().sort_index()
axes[0, 1].bar(pclass_counts.index, pclass_counts.values, color=['skyblue', 'lightgreen', 'lightcoral'])
axes[0, 1].set_title('Passenger Class Distribution')
axes[0, 1].set_xlabel('Passenger Class')
axes[0, 1].set_ylabel('Number of Passengers')

# 3. Gender Distribution
gender_counts = df['Sex'].value_counts()
axes[1, 0].pie(gender_counts.values, labels=gender_counts.index, autopct='%1.1f%%', startangle=90)
axes[1, 0].set_title('Gender Distribution')

# 4. Age Distribution
axes[1, 1].hist(df['Age'], bins=20, color='lightblue', edgecolor='black', alpha=0.7)
axes[1, 1].set_title('Age Distribution')
axes[1, 1].set_xlabel('Age')
axes[1, 1].set_ylabel('Frequency')

plt.tight_layout()
plt.show()

# some basic statistics
print("\nKey Statistics:")
print(f"Total Passengers: {len(df)}")
```

```
print(f"Survival Rate: {df['Survived'].mean():.2%}")
print(f"Average Age: {df['Age'].mean():.1f} years")
print(f"Age Range: {df['Age'].min():.0f} - {df['Age'].max():.0f} years")
```

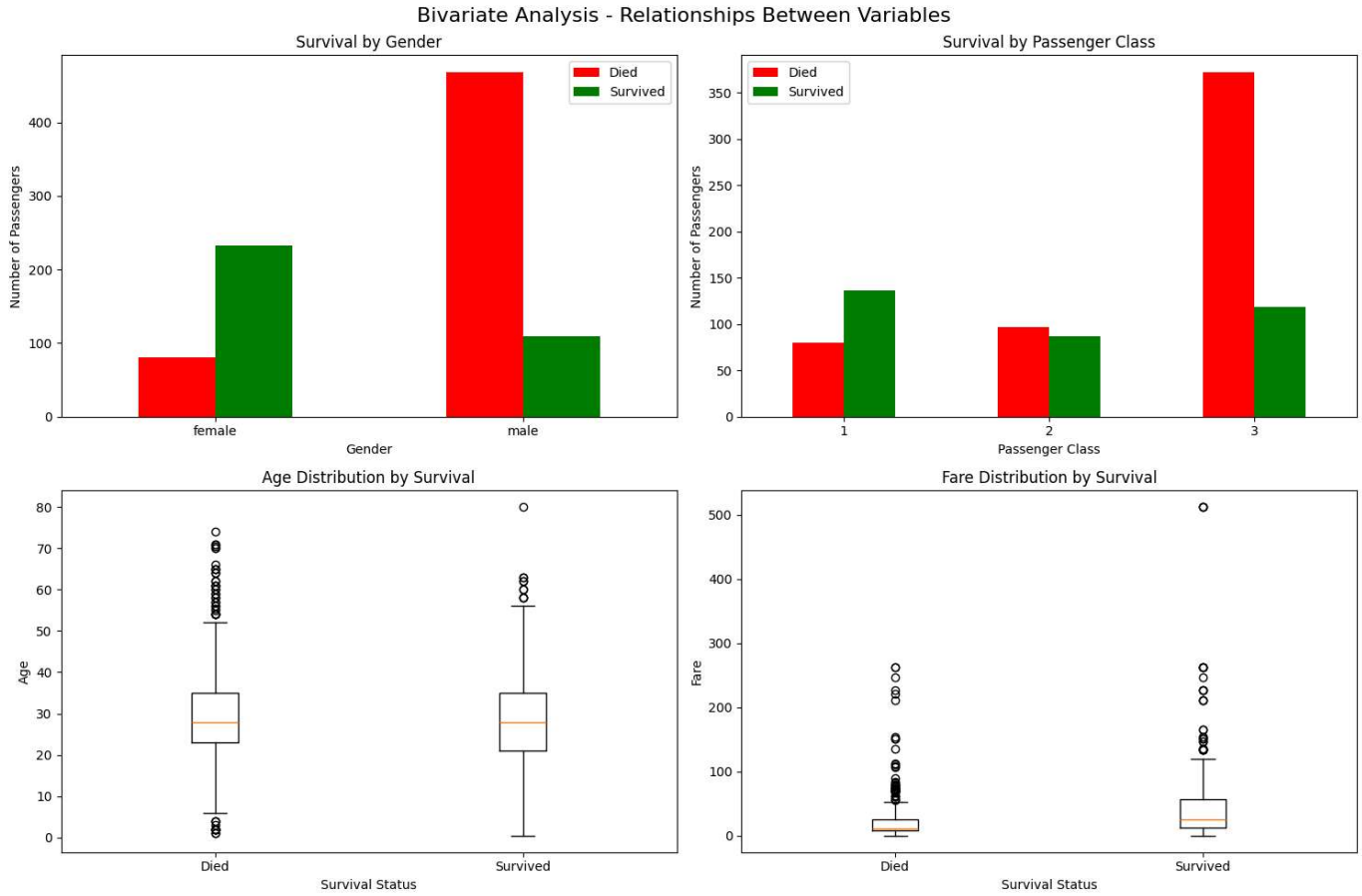



```
Key Statistics:
Total Passengers: 891
Survival Rate: 38.38%
Average Age: 29.4 years
Age Range: 0 - 80 years
```

```
print("\n" + "="*50)
print("BIVARIATE ANALYSIS")
print("="*50)


# Create figure for bivariate analysis
fig, axes = plt.subplots(2, 2, figsize=(15, 10))
fig.suptitle('Bivariate Analysis - Relationships Between Variables', fontsize=16)

# 1. Survival by Gender
survival_by_gender = pd.crosstab(df['Sex'], df['Survived'])
survival_by_gender.plot(kind='bar', ax=axes[0, 0], color=['red', 'green'])
axes[0, 0].set_title('Survival by Gender')
```

```
axes[0, 0].set_xlabel('Gender')
axes[0, 0].set_ylabel('Number of Passengers')
axes[0, 0].legend(['Died', 'Survived'])
axes[0, 0].tick_params(axis='x', rotation=0)

# 2. Survival by Passenger Class
survival_by_class = pd.crosstab(df['Pclass'], df['Survived'])
survival_by_class.plot(kind='bar', ax=axes[0, 1], color=['red', 'green'])
axes[0, 1].set_title('Survival by Passenger Class')
axes[0, 1].set_xlabel('Passenger Class')
axes[0, 1].set_ylabel('Number of Passengers')
axes[0, 1].legend(['Died', 'Survived'])
axes[0, 1].tick_params(axis='x', rotation=0)

# 3. Age vs Survival (Box plot)
survival_labels = ['Died', 'Survived']
age_by_survival = [df[df['Survived'] == 0]['Age'], df[df['Survived'] == 1]['Age']]
axes[1, 0].boxplot(age_by_survival, labels=survival_labels)
axes[1, 0].set_title('Age Distribution by Survival')
axes[1, 0].set_xlabel('Survival Status')
axes[1, 0].set_ylabel('Age')

# 4. Fare vs Survival (Box plot)
fare_by_survival = [df[df['Survived'] == 0]['Fare'], df[df['Survived'] == 1]['Fare']]
axes[1, 1].boxplot(fare_by_survival, labels=survival_labels)
axes[1, 1].set_title('Fare Distribution by Survival')
axes[1, 1].set_xlabel('Survival Status')
axes[1, 1].set_ylabel('Fare')

plt.tight_layout()
plt.show()

# survival rates by different categories
print("\nSurvival Rates by Category:")
print(f"Overall Survival Rate: {df['Survived'].mean():.2%}")
print("\nBy Gender:")
print(df.groupby('Sex')['Survived'].mean().apply(lambda x: f"{x:.2%}"))
print("\nBy Passenger Class:")
print(df.groupby('Pclass')['Survived'].mean().apply(lambda x: f"{x:.2%}"))
```

```
==================================================
BIVARIATE ANALYSIS
==================================================
<ipython-input-46-7c2f65e9d662>:31: MatplotlibDeprecationWarning: The 'labels' parameter of boxplot() has been renamed 'tick_labels'
  axes[1, 0].boxplot(age_by_survival, labels=survival_labels)
<ipython-input-46-7c2f65e9d662>:38: MatplotlibDeprecationWarning: The 'labels' parameter of boxplot() has been renamed 'tick_labels'
  axes[1, 1].boxplot(fare_by_survival, labels=survival_labels)
```




```
Survival Rates by Category:
Overall Survival Rate: 38.38%

By Gender:
Sex
female    74.20%
male      18.89%
Name: Survived, dtype: object

By Passenger Class:
Pclass
1    62.96%
2    47.28%
3    24.24%
Name: Survived, dtype: object
```

```
# Correlation Analysis
print("\n" + "="*50)
print("CORRELATION ANALYSIS")
```

```
print("="*50)

# Selected only numeric columns for correlation
numeric_columns = df.select_dtypes(include=[np.number]).columns
correlation_matrix = df[numeric_columns].corr()

# correlation heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0,
            square=True, fmt='.2f')
plt.title('Correlation Matrix of Numeric Variables')
plt.tight_layout()
plt.show()

# strong correlations
print("\nStrong Correlations with Survival:")
survival_corr = correlation_matrix['Survived'].abs().sort_values(ascending=False)
for var, corr in survival_corr.items():
    if var != 'Survived' and corr > 0.1:  # Show correlations above 0.1
        print(f"{var}: {correlation_matrix['Survived'][var]:.3f}")
```

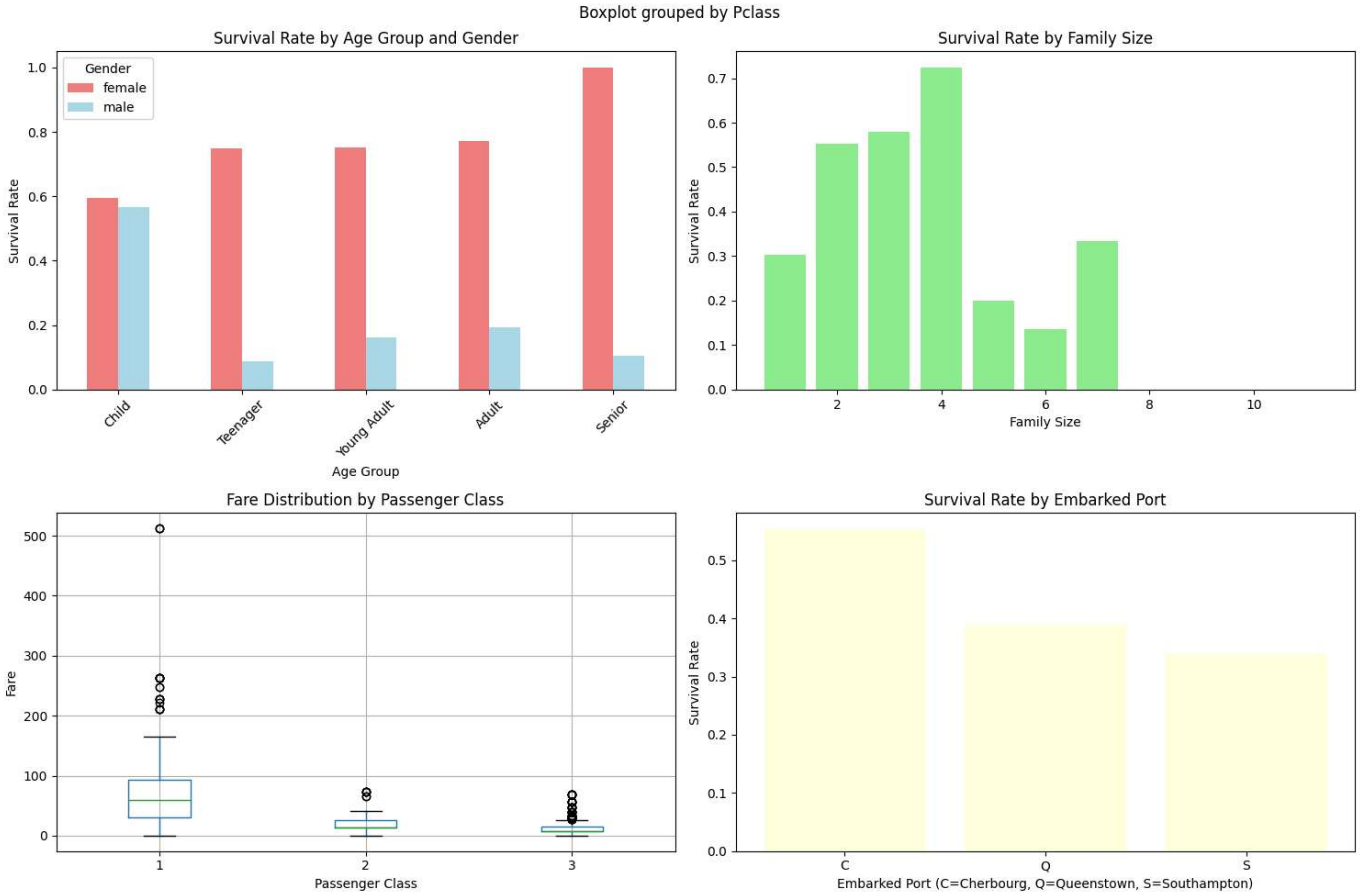
```
==================================================
CORRELATION ANALYSIS
==================================================
```


```
Strong Correlations with Survival:
Pclass: -0.338
Fare: 0.257
```

```
# Advanced Visualizations
print("\n" + "="*50)
print("ADVANCED VISUALIZATIONS")
print("="*50)
```

```
# comprehensive visualization
fig, axes = plt.subplots(2, 2, figsize=(15, 10))
fig.suptitle('Advanced Analysis - Multiple Variable Relationships', fontsize=16)

# 1. Survival by Age groups and Gender
df['AgeGroup'] = pd.cut(df['Age'], bins=[0, 12, 18, 35, 60, 100],
                        labels=['Child', 'Teenager', 'Young Adult', 'Adult', 'Senior'])
age_gender_survival = df.groupby(['AgeGroup', 'Sex'])['Survived'].mean().unstack()
age_gender_survival.plot(kind='bar', ax=axes[0, 0], color=['lightcoral', 'lightblue'])
axes[0, 0].set_title('Survival Rate by Age Group and Gender')
axes[0, 0].set_xlabel('Age Group')
axes[0, 0].set_ylabel('Survival Rate')
axes[0, 0].legend(title='Gender')
axes[0, 0].tick_params(axis='x', rotation=45)

# 2. Family Size vs Survival
df['FamilySize'] = df['SibSp'] + df['Parch'] + 1
family_survival = df.groupby('FamilySize')['Survived'].mean()
axes[0, 1].bar(family_survival.index, family_survival.values, color='lightgreen')
axes[0, 1].set_title('Survival Rate by Family Size')
axes[0, 1].set_xlabel('Family Size')
axes[0, 1].set_ylabel('Survival Rate')

# 3. Fare distribution by Class
df.boxplot(column='Fare', by='Pclass', ax=axes[1, 0])
axes[1, 0].set_title('Fare Distribution by Passenger Class')
axes[1, 0].set_xlabel('Passenger Class')
axes[1, 0].set_ylabel('Fare')

# 4. Embarked Port vs Survival
if 'Embarked' in df.columns:
    embarked_survival = df.groupby('Embarked')['Survived'].mean()
    axes[1, 1].bar(embarked_survival.index, embarked_survival.values, color='lightyellow')
    axes[1, 1].set_title('Survival Rate by Embarked Port')
    axes[1, 1].set_xlabel('Embarked Port (C=Cherbourg, Q=Queenstown, S=Southampton)')
    axes[1, 1].set_ylabel('Survival Rate')

plt.tight_layout()
plt.show()
```

```
==================================================
ADVANCED VISUALIZATIONS
==================================================
<ipython-input-48-ed87d0fc00b1>:13: FutureWarning: The default of observed=False is deprecated and will be changed to True in a futur
  age_gender_survival = df.groupby(['AgeGroup', 'Sex'])['Survived'].mean().unstack()
```




```
# Key Findings and Insights
print("\n" + "="*50)
print("KEY FINDINGS AND INSIGHTS")
print("="*50)

print("\n1. SURVIVAL INSIGHTS:")
print(f"   • Overall survival rate: {df['Survived'].mean():.1%}")
print(f"   • Women had higher survival rate: {df[df['Sex']=='female']['Survived'].mean():.1%}")
print(f"   • Men had lower survival rate: {df[df['Sex']=='male']['Survived'].mean():.1%}")

print("\n2. CLASS INSIGHTS:")
for pclass in sorted(df['Pclass'].unique()):
    rate = df[df['Pclass']==pclass]['Survived'].mean()
    print(f"   • Class {pclass} survival rate: {rate:.1%}")

print("\n3. AGE INSIGHTS:")
child_survival = df[df['Age'] < 18]['Survived'].mean()
adult_survival = df[df['Age'] >= 18]['Survived'].mean()
print(f"   • Children (<18) survival rate: {child_survival:.1%}")
print(f"   • Adults (18+) survival rate: {adult_survival:.1%}")
```

```
print("\n4. FAMILY INSIGHTS:")
alone_survival = df[df['FamilySize'] == 1]['Survived'].mean()
with_family_survival = df[df['FamilySize'] > 1]['Survived'].mean()
print(f"   • Passengers alone survival rate: {alone_survival:.1%}")
print(f"   • Passengers with family survival rate: {with_family_survival:.1%}")

print("\n5. ECONOMIC INSIGHTS:")
avg_fare_survived = df[df['Survived'] == 1]['Fare'].mean()
avg_fare_died = df[df['Survived'] == 0]['Fare'].mean()
print(f"   • Average fare of survivors: ${avg_fare_survived:.2f}")
print(f"   • Average fare of non-survivors: ${avg_fare_died:.2f}")

# Summary Report
print("\n" + "="*50)
print("SUMMARY REPORT")
print("="*50)

print("""
TITANIC DATASET ANALYSIS SUMMARY

Dataset Overview:
- Total passengers analyzed: """ + str(len(df)) + """
- Features analyzed: """ + str(len(df.columns)) + """ variables
- Missing data handled: Age and Embarked columns

Key Patterns Discovered:
1. Gender was the strongest predictor of survival (Women > Men)
2. Passenger class significantly affected survival chances (1st > 2nd > 3rd)
3. Age played a role with children having better survival rates
4. Family size had optimal survival rates for small families (2-4 members)
5. Higher fare passengers had better survival chances

Strongest Correlations with Survival:
- Gender (Female advantage)
- Passenger Class (Higher class advantage)
- Fare (Higher fare advantage)

Data Quality:
- Clean dataset after handling missing values
- No major outliers that would skew analysis
- Representative sample of Titanic passengers

Recommendations for Further Analysis:
1. Investigate cabin location impact on survival
2. Analyze specific embarkation port effects
3. Study family composition in more detail
4. Examine crew vs passenger survival rates
""")

print("\n" + "="*50)
print("ANALYSIS COMPLETE!")
print("="*50)
```