End-to-End Exploratory Data Analysis (EDA) on the Titanic Dataset

Project Objective: To perform a comprehensive, step-by-step exploratory data analysis to understand the key factors that influenced survival on the Titanic. This notebook will serve as a complete guide, covering data loading, cleaning, analysis, feature engineering, and visualization, with theoretical explanations at each stage.

Theoretical Concept: What is Exploratory Data Analysis (EDA)?

Exploratory Data Analysis is the crucial process of performing initial investigations on data to discover patterns, spot anomalies, test hypotheses, and check assumptions with the help of summary statistics and graphical representations. It is not about formal modeling or hypothesis testing; rather, it is about getting to know your data before you start building models.

Why is it important?

1. **Understand the Data:** It helps you understand the variables and their relationships.
2. **Data Cleaning:** It reveals missing values, outliers, and other inconsistencies that need to be handled.
3. **Feature Selection:** It helps identify which variables are the most important for your problem (feature engineering and selection).
4. **Assumption Checking:** It allows you to check assumptions that are required for certain machine learning models (e.g., normality, linearity).

Step 1: Setup - Importing Libraries

We'll start by importing the essential Python libraries for data manipulation (`pandas`, `numpy`) and visualization (`matplotlib`, `seaborn`).

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

# Set plot style for better aesthetics
sns.set(style='whitegrid')
```

Step 2: Data Loading and Initial Inspection

We'll load the dataset and take our first look at its structure, content, and overall health.

```
!git clone 'https://github.com/GeeksforgeeksDS/21-Days-21-Projects-Dataset'
```

```
fatal: destination path '21-Days-21-Projects-Dataset' already exists and is not an empty directory.
```

```
# Load the dataset from a URL
titanic_df = pd.read_csv('/content/21-Days-21-Projects-Dataset/Datasets/Titanic-Dataset.csv')

# Display the first 5 rows
print("First 5 rows of the dataset:")
titanic_df.head()
```

```
First 5 rows of the dataset:
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.45	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00	C148	C

```
titanic_df.tail()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.45	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00	C148	C

```
titanic_df.shape
```

```
(891, 12)
```

```
# Get a concise summary of the dataframe
print("\nDataset Information:")
titanic_df.info()
```

```
Dataset Information:
<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
```

Interpretation of `.info()`:

- The dataset contains 891 entries (passengers) and 12 columns.
- **Missing Values Identified:** `Age`, `Cabin`, and `Embarked` have missing values. `Cabin` is missing a significant amount of data (~77%), which will require special attention.

```
# Get descriptive statistics for numerical columns
print("\nDescriptive Statistics:")
titanic_df.describe()
```

Descriptive Statistics:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

Interpretation of `.describe()`:

- **Survived:** About 38.4% of passengers in this dataset survived.
- **Age:** The age ranges from ~5 months to 80 years, with an average age of about 30.
- **Fare:** The fare is highly skewed, with a mean of $32butamedianofonly$14.45. The maximum fare is over $512, indicating the presence of extreme outliers.

```
titanic_df['Cabin'].value_counts()
```

Cabin	count
G6	4
C23 C25 C27	4
B96 B98	4
F2	3
D	3
...	...
E17	1
A24	1
C50	1
B42	1
C148	1

147 rows × 1 columns

dtype: int64

Step 3: Data Cleaning

Before analysis, we must handle the missing values we identified.

Theoretical Concept: Missing Value Imputation

Imputation is the process of replacing missing data with substituted values. The strategy depends on the data type and its distribution:

- **Numerical Data:** For skewed distributions (like `Age` and `Fare`), using the **median** is more robust than the mean because it is not affected by outliers.
- **Categorical Data:** A common strategy is to fill with the **mode** (the most frequent value).
- **High Cardinality/Too Many Missing Values:** For columns like `Cabin`, where most data is missing, imputing might not be effective. We could either drop the column or engineer a new feature from it (e.g., `Has_Cabin`).

```
titanic_df.isna().sum()
```

	0
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

```
print("Missing values before cleaning:")
titanic_df.isna().sum()
```

Missing values before cleaning:

	0
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

```
median = titanic_df['Age'].median()
print(median)
```

```
28.0
```

```
# 1. Handle missing 'Age' values
# We use the median to fill missing ages because the age distribution can be skewed.
median_age = titanic_df['Age'].median()
titanic_df['Age'] = titanic_df['Age'].fillna(median_age)

# Verify that there are no more missing values in the columns we handled so far
print("Missing values after Age cleaning:")
print(titanic_df[['Age', 'Embarked', 'Cabin']].isna().sum())
```

```
Missing values after Age cleaning:
Age           0
Embarked      2
Cabin       687
dtype: int64
```

```
mode = titanic_df['Embarked'].mode()[0]
print(mode)
```

```
S
```

```
# 2. Handle missing 'Embarked' values
# Since there are only two missing values, we'll fill them with the most common port of embarka
mode_embarked = titanic_df['Embarked'].mode()[0]
titanic_df['Embarked'] = titanic_df['Embarked'].fillna(mode_embarked)

# Verify that there are no more missing values in the columns we handled so far
print("Missing values after Embarked cleaning:")
print(titanic_df[['Age', 'Embarked', 'Cabin']].isna().sum())
```

```
Missing values after Embarked cleaning:
Age           0
Embarked      0
Cabin       687
dtype: int64
```

```
# 3. Handle the 'Cabin' column
# With over 77% missing data, imputing is not a good idea. Instead, we'll create a new feature
titanic_df['Has_Cabin'] = titanic_df['Cabin'].notna().astype(int) # 1 if has cabin, 0 if not
titanic_df.drop('Cabin', axis=1, inplace=True) # Drop the original column
```

titanic_df['Cabin'].notna(): This checks each value in the 'Cabin' column to see if it is not a missing value (NaN). It returns a boolean Series (True for non-missing, False for missing).

```
titanic_df['Has_Cabin'].value_counts()
```

Has_Cabin	count
0	687
1	204

dtype: int64

```
titanic_df.head(5)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked	Has_Cabin
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S	0
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C	1
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S	0

```
# Verify that there are no more missing values in the columns we handled
print("Missing values after cleaning:")
titanic_df.isna().sum()
```

```
Missing values after cleaning:
```

	0
PassengerId	0
Survived	0
Pclass	0
Name	0
Sex	0
Age	0
SibSp	0
Parch	0
Ticket	0
Fare	0
Embarked	0
Has_Cabin	0

dtype: int64

Step 4: Univariate Analysis

We analyze each variable individually to understand its distribution.

Theoretical Concept: Univariate Analysis

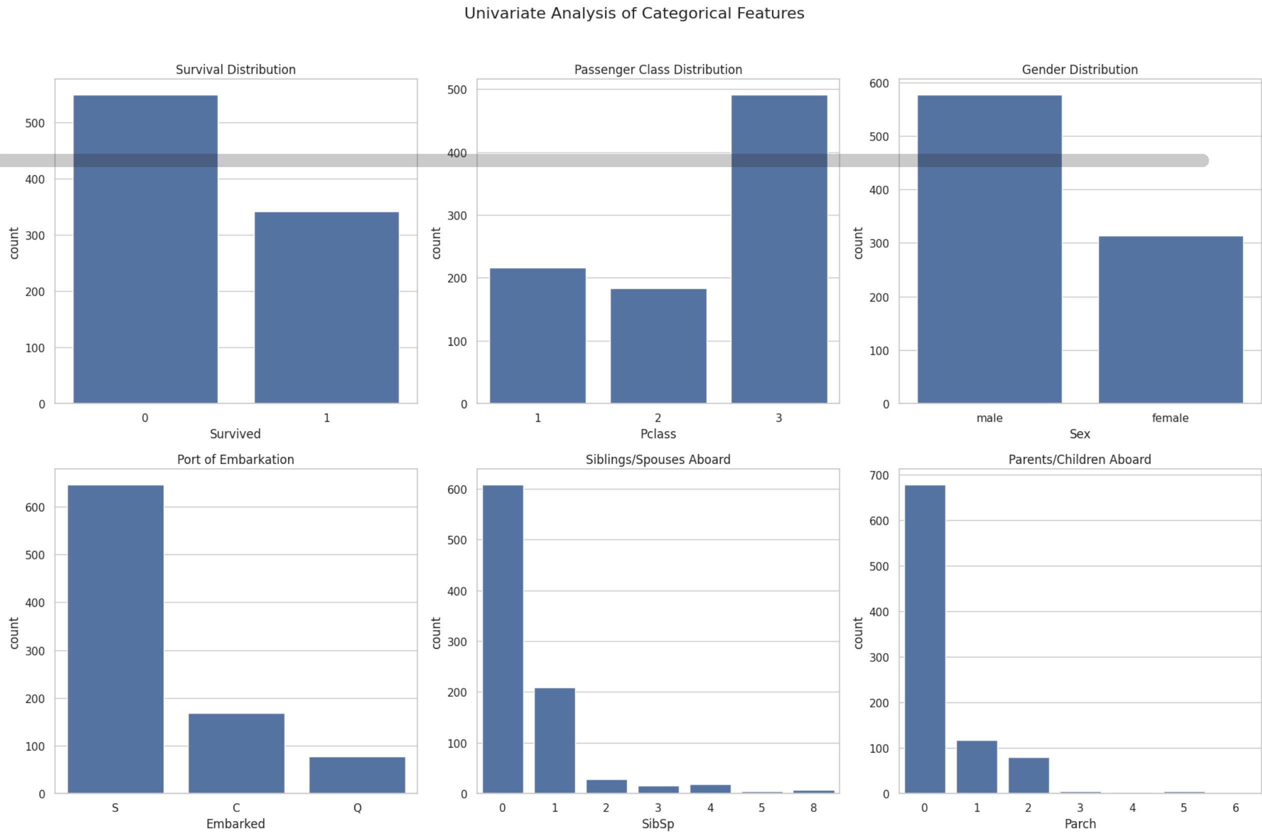
This is the simplest form of data analysis, where the data being analyzed contains only one variable. The main purpose is to describe the data and find patterns within it.

- **For Categorical Variables:** We use frequency tables, bar charts (`countplot`), or pie charts to see the count or proportion of each category.
- **For Numerical Variables:** We use histograms (`histplot`) or kernel density plots (`kdeplot`) to understand the distribution, and box plots (`boxplot`) to identify the central tendency, spread, and outliers.

```
print("Analyzing categorical features:")

# Set up the figure for plotting
fig, axes = plt.subplots(2, 3, figsize=(18, 12))
fig.suptitle('Univariate Analysis of Categorical Features', fontsize=16)
```

```
# Plotting each categorical feature
sns.countplot(ax=axes[0, 0], x='Survived', data=titanic_df).set_title('Survival Distribution')
sns.countplot(ax=axes[0, 1], x='Pclass', data=titanic_df).set_title('Passenger Class Distributi
sns.countplot(ax=axes[0, 2], x='Sex', data=titanic_df).set_title('Gender Distribution')
sns.countplot(ax=axes[1, 0], x='Embarked', data=titanic_df).set_title('Port of Embarkation')
sns.countplot(ax=axes[1, 1], x='SibSp', data=titanic_df).set_title('Siblings/Spouses Aboard')
sns.countplot(ax=axes[1, 2], x='Parch', data=titanic_df).set_title('Parents/Children Aboard')

plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
```

```
Analyzing categorical features:
```



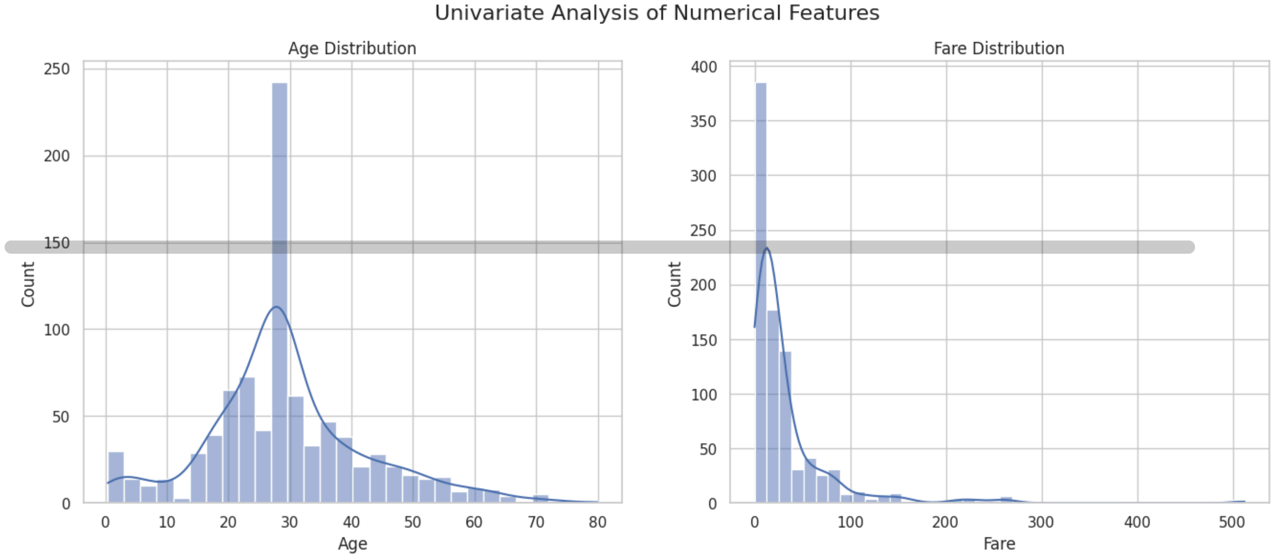
Key Insights (Categorical):

- **Survival:** Most passengers (over 500) did not survive.
- **Pclass:** The 3rd class was the most populated, followed by 1st and then 2nd.
- **Sex:** There were significantly more males than females.
- **Embarked:** The vast majority of passengers embarked from Southampton ('S').
- **SibSp & Parch:** Most passengers traveled alone.

```
print("\nAnalyzing numerical features:")

fig, axes = plt.subplots(1, 2, figsize=(16, 6))
fig.suptitle('Univariate Analysis of Numerical Features', fontsize=16)

# Plotting Age distribution
sns.histplot(ax=axes[0], data=titanic_df, x='Age', kde=True, bins=30).set_title('Age Distributi

# Plotting Fare distribution
sns.histplot(ax=axes[1], data=titanic_df, x='Fare', kde=True, bins=40).set_title('Fare Distribu
```

```
plt.show()
```

```
Analyzing numerical features:
```



Key Insights (Numerical):

- **Age:** The distribution peaks around the 20-30 age range. Remember we filled missing values with the median (28), which contributes to the height of that central bar.
- **Fare:** The distribution is heavily right-skewed, confirming that most tickets were cheap, with a few very expensive exceptions.

Step 5: Bivariate Analysis

Here, we explore the relationship between two variables. Our primary focus will be on how each feature relates to our target variable, `Survived`.

Theoretical Concept: Bivariate Analysis

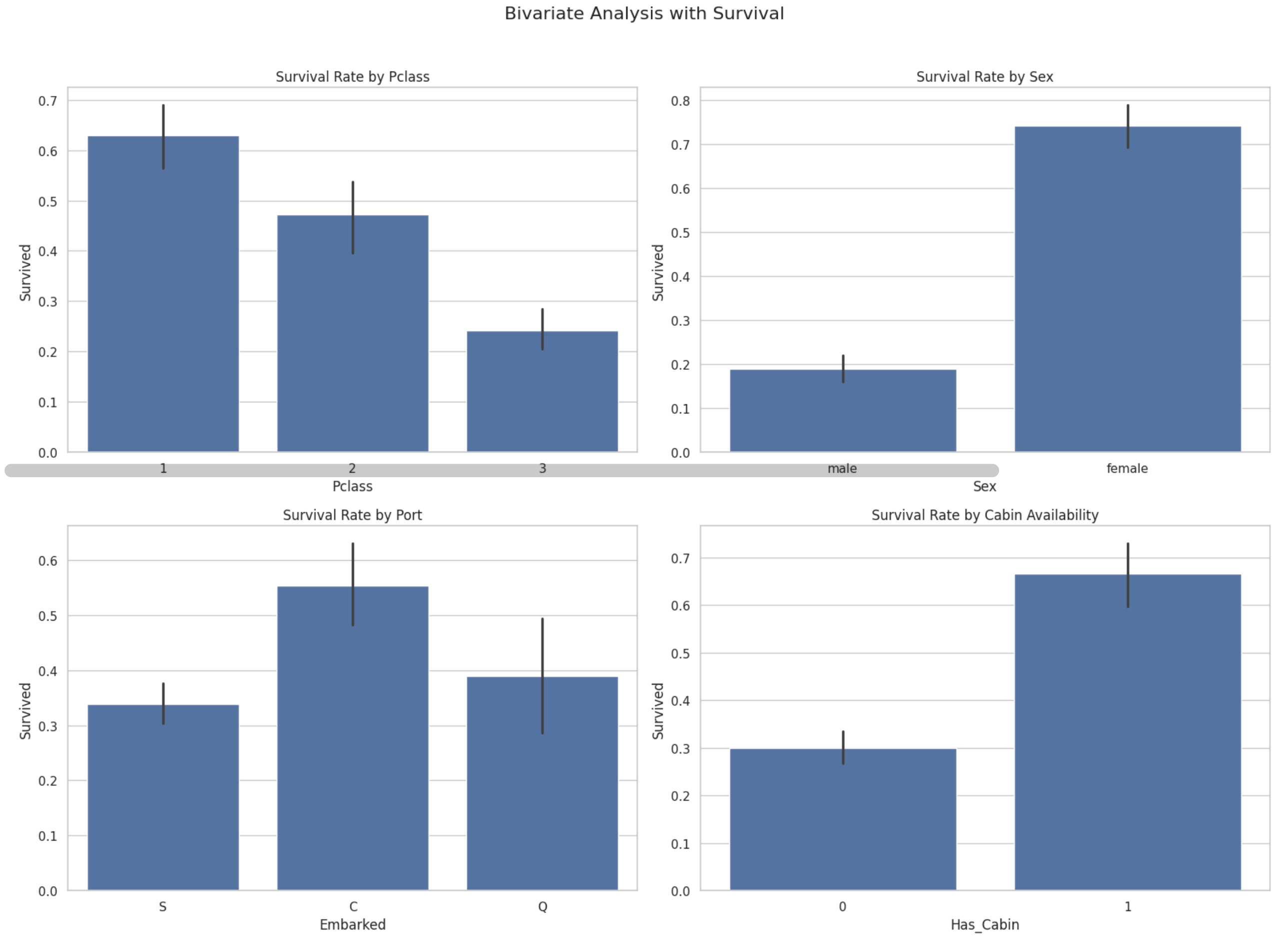
This type of analysis involves two different variables, and its main purpose is to find relationships between them.

- **Categorical vs. Numerical:** To compare a numerical variable across different categories, we often use bar plots (`barplot`) that show the mean (or another estimator) of the numerical variable for each category. We can also use box plots or violin plots.
- **Categorical vs. Categorical:** We can use stacked bar charts or contingency tables (crosstabs).
- **Numerical vs. Numerical:** A scatter plot is the standard choice, with a correlation matrix being used to quantify the relationship.

```
print("Bivariate Analysis: Feature vs. Survival")

fig, axes = plt.subplots(2, 2, figsize=(16, 12))
fig.suptitle('Bivariate Analysis with Survival', fontsize=16)

# Pclass vs. Survived
sns.barplot(ax=axes[0, 0], x='Pclass', y='Survived', data=titanic_df).set_title('Survival Rate I

# Sex vs. Survived
sns.barplot(ax=axes[0, 1], x='Sex', y='Survived', data=titanic_df).set_title('Survival Rate by !

# Embarked vs. Survived
sns.barplot(ax=axes[1, 0], x='Embarked', y='Survived', data=titanic_df).set_title('Survival Rat

# Has_Cabin vs. Survived
sns.barplot(ax=axes[1, 1], x='Has_Cabin', y='Survived', data=titanic_df).set_title('Survival Ra
```

```
plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
```

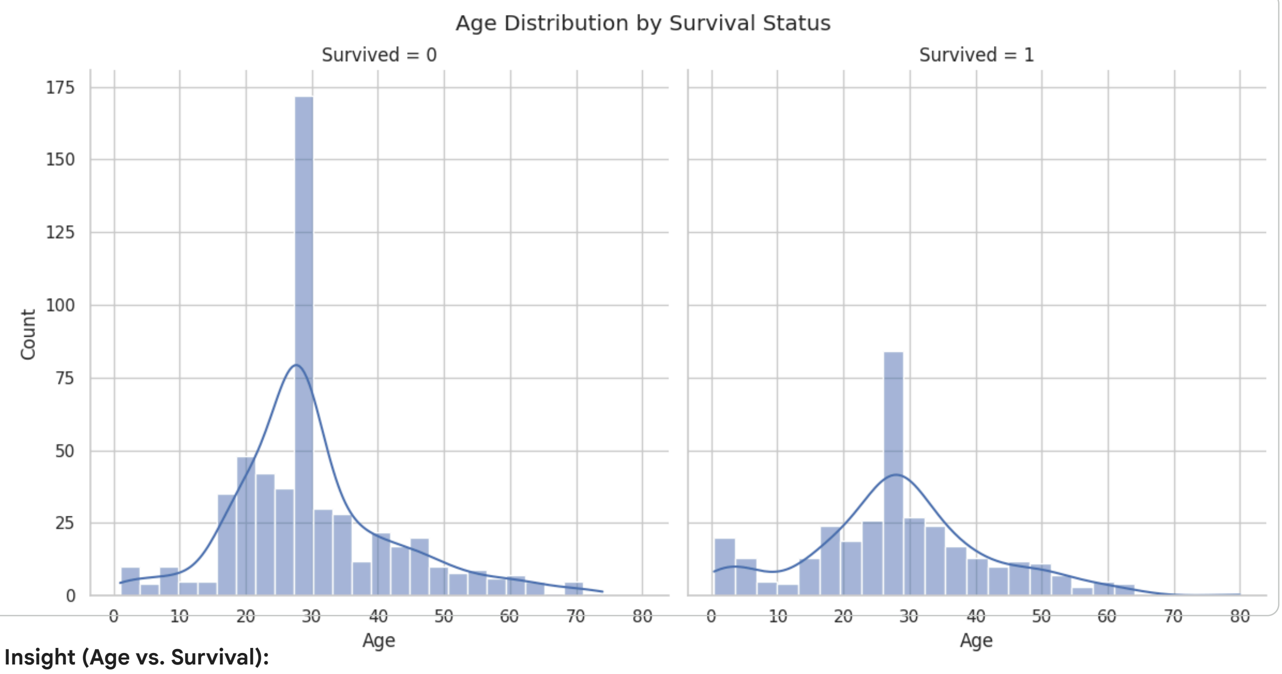
```
Bivariate Analysis: Feature vs. Survival
```



Key Insights (Bivariate):

- **Pclass:** A clear trend emerges: 1st class passengers had a >60% survival rate, while 3rd class passengers had less than 25%.
- **Sex:** This is the strongest predictor. Females had a survival rate of ~75%, while males had a rate below 20%.
- **Embarked:** Passengers embarking from Cherbourg ('C') had a higher survival rate than those from the other ports.
- **Has_Cabin:** Passengers with a registered cabin number had a much higher survival rate. This is likely correlated with being in 1st class.

```
# Age vs. Survival
g = sns.FacetGrid(titanic_df, col='Survived', height=6)
g.map(sns.histplot, 'Age', bins=25, kde=True)
plt.suptitle('Age Distribution by Survival Status', y=1.02)
plt.show()
```



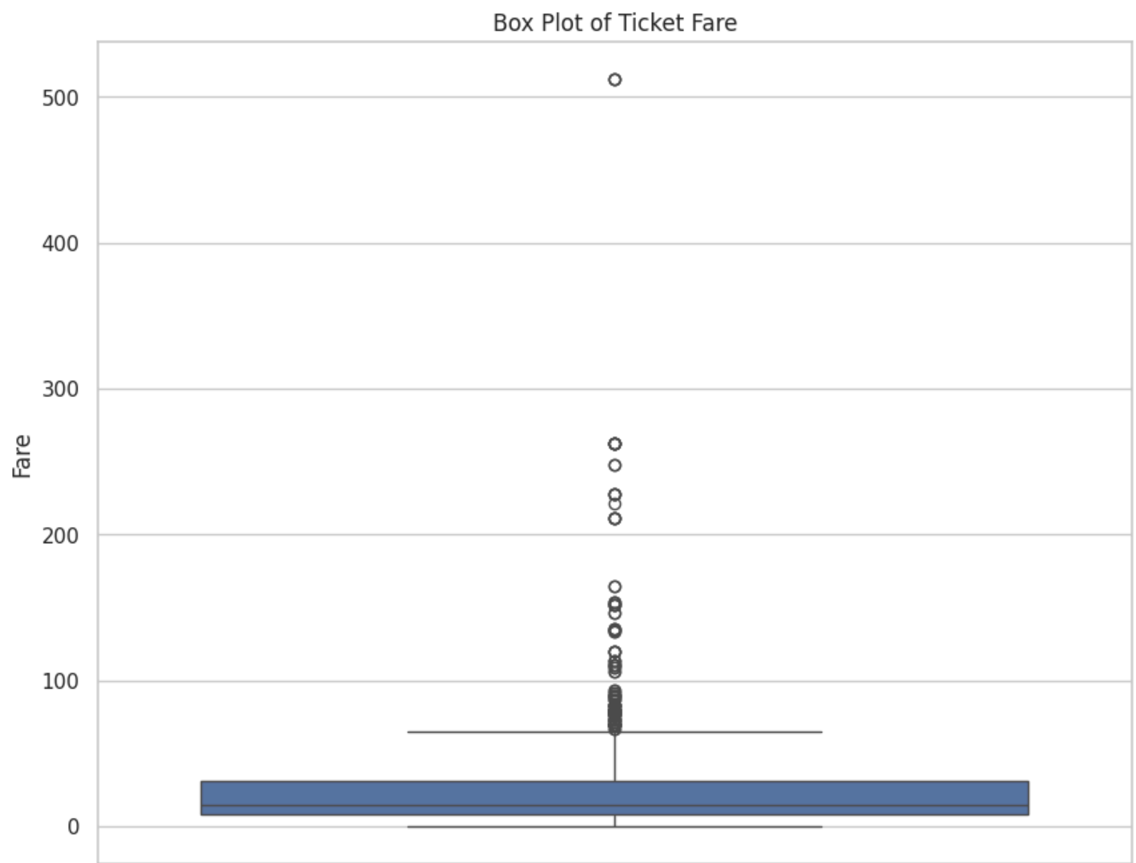
Key Insight (Age vs. Survival):

- Infants and young children had a higher probability of survival.
- A large portion of non-survivors were young adults (20-40).
- The oldest passengers (80 years) did not survive.

Deeper Dive: Outlier Analysis for 'Fare'

The `.describe()` function and histogram showed that `Fare` has extreme outliers. Let's visualize this clearly with a box plot.

```
plt.figure(figsize=(10, 8))
sns.boxplot(y='Fare', data=titanic_df)
plt.title('Box Plot of Ticket Fare')
plt.ylabel('Fare')
plt.show()
```



Observation: The box plot confirms the presence of significant outliers. Most fares are concentrated below $100, but there are several fares extending far beyond, with some even exceeding $500. These are likely first-class passengers who booked luxurious suites. For some machine learning models, handling these outliers (e.g., through log transformation) would be an important step.

Step 6: Feature Engineering

Now, we'll create new features from the existing ones to potentially uncover deeper insights and provide more useful information for a machine learning model.

Theoretical Concept: Feature Engineering

Feature engineering is the process of using domain knowledge to extract features (characteristics, properties, attributes) from raw data. A good feature should be relevant to the problem and easy for a model to understand.

Common Techniques:

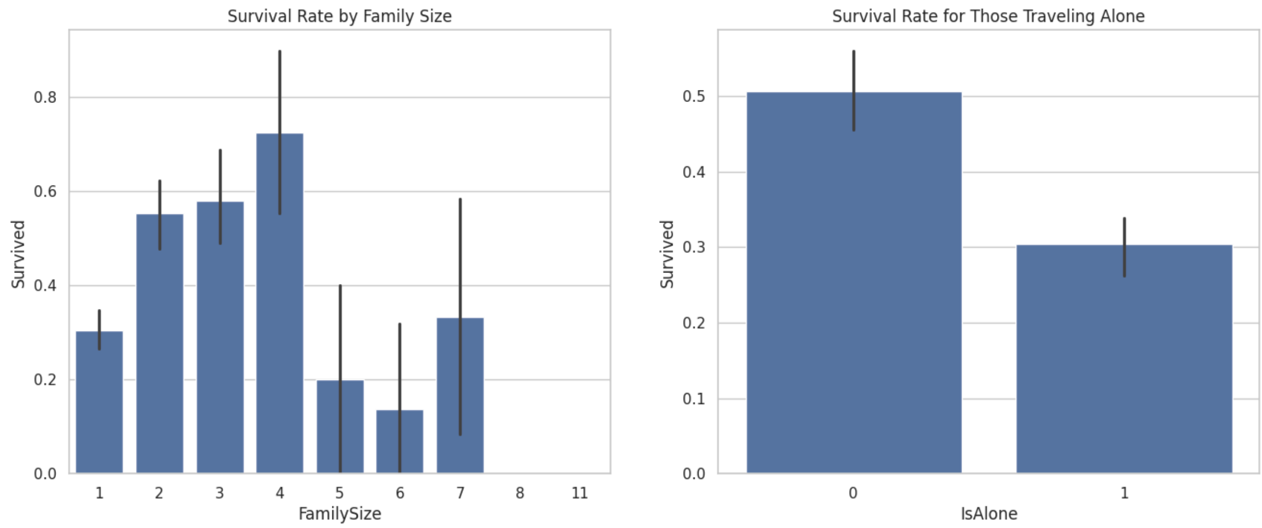
1. **Combining Features:** Creating a new feature by combining others (e.g., `SibSp` + `Parch` = `FamilySize`).
2. **Extracting from Text:** Pulling out specific information from a text feature (e.g., extracting titles from the `Name` column).
3. **Binning:** Converting a continuous numerical feature into a categorical one (e.g., binning `Age` into groups like 'Child', 'Adult', 'Senior').

```
# 1. Create a 'FamilySize' feature
titanic_df['FamilySize'] = titanic_df['SibSp'] + titanic_df['Parch'] + 1 # +1 for the person th

# 2. Create an 'IsAlone' feature
titanic_df['IsAlone'] = 0
titanic_df.loc[titanic_df['FamilySize'] == 1, 'IsAlone'] = 1

print("Created 'FamilySize' and 'IsAlone' features:")
titanic_df[['FamilySize', 'IsAlone']].head()
```

```
Created 'FamilySize' and 'IsAlone' features:
```

	FamilySize	IsAlone
0	2	0
1	2	0
2	1	1
3	2	0
4	1	1

```
# Analyze the new family-related features against survival
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Survival Rate by FamilySize
sns.barplot(ax=axes[0], x='FamilySize', y='Survived', data=titanic_df).set_title('Survival Rate

# Survival Rate by IsAlone
sns.barplot(ax=axes[1], x='IsAlone', y='Survived', data=titanic_df).set_title('Survival Rate fo

plt.show()
```



Insight:

- Passengers who were alone (`IsAlone=1`) had a lower survival rate (~30%) than those in small families.
- Small families of 2 to 4 members had the highest survival rates.
- Very large families (5 or more) had a very poor survival rate. This might be because it was harder for large families to stay together and evacuate.

- Matches a space.
- Titles in the names are usually preceded by a space. ([A-Za-z]+): This is the capturing group.
- [A-Za-z]+: Matches one or more uppercase or lowercase letters. This captures the title itself (like Mr, Mrs, Miss, etc.).
- .: Matches a literal dot (.) which usually follows the title.

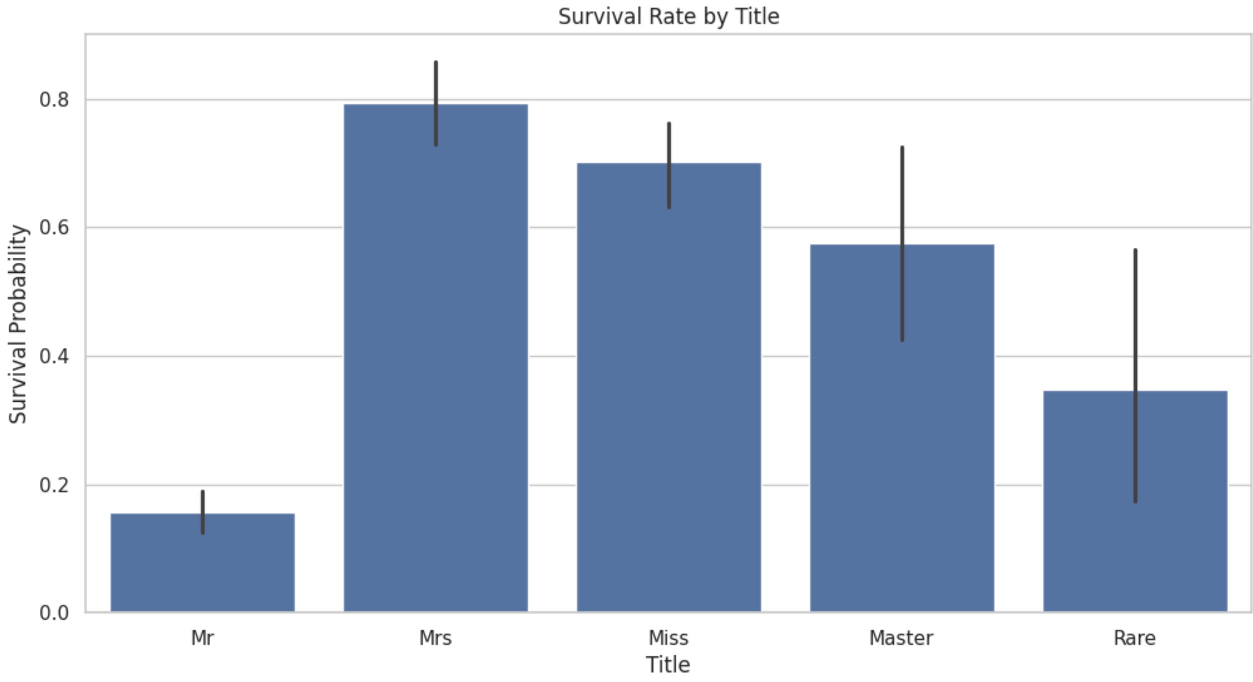
```
# 3. Extract 'Title' from the 'Name' column
titanic_df['Title'] = titanic_df['Name'].str.extract(r' ([A-Za-z]+)\.', expand=False)

# Let's see the different titles
print("Extracted Titles:")
titanic_df['Title'].value_counts()
```

```
Extracted Titles:
```

Title	count
Mr	517
Miss	182
Mrs	125
Master	40
Dr	7
Rev	6
Col	2
Mlle	2
Major	2
Ms	1
Mme	1
Don	1
Lady	1
Sir	1
Capt	1
Countess	1
Jonkheer	1

dtype: int64

```
# Simplify the titles by grouping rare ones into a 'Rare' category
titanic_df['Title'] = titanic_df['Title'].replace(['Lady', 'Countess','Capt', 'Col','Don', 'Dr'

titanic_df['Title'] = titanic_df['Title'].replace('Mlle', 'Miss')
titanic_df['Title'] = titanic_df['Title'].replace('Ms', 'Miss')
titanic_df['Title'] = titanic_df['Title'].replace('Mme', 'Mrs')

# Let's see the survival rate by the new, cleaned titles
plt.figure(figsize=(12, 6))
sns.barplot(x='Title', y='Survived', data=titanic_df)
plt.title('Survival Rate by Title')
plt.ylabel('Survival Probability')
plt.show()
```

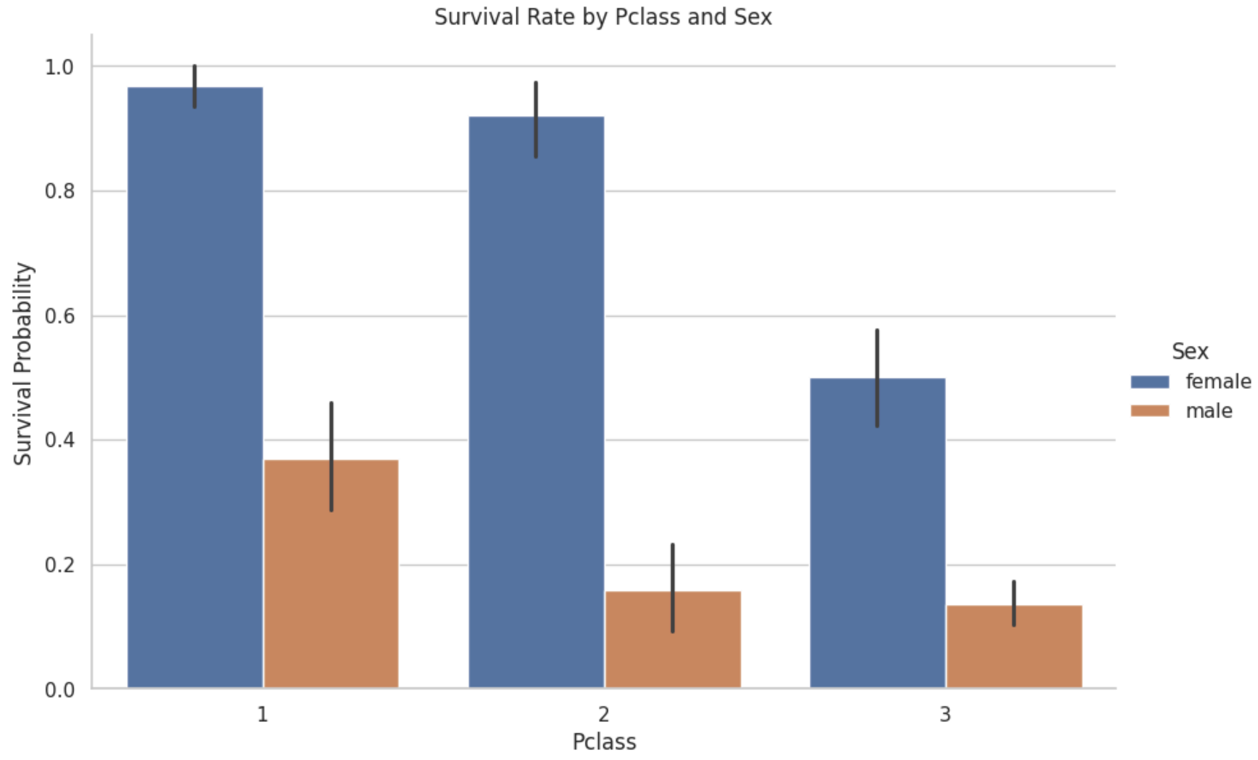


Insight: The `Title` feature gives us powerful information. 'Mrs' and 'Miss' (females) had high survival rates. 'Mr' (males) had a very low survival rate. 'Master' (young boys) had a significantly higher survival rate than 'Mr', reinforcing the 'children first' idea. The 'Rare' titles, often associated with nobility or status, also had a mixed but generally higher survival rate than common men.

Step 7: Multivariate Analysis

Now we explore interactions between multiple variables simultaneously, including our new engineered features.

```
# Survival rate by Pclass and Sex
sns.catplot(x='Pclass', y='Survived', hue='Sex', data=titanic_df, kind='bar', height=6, aspect=:
plt.title('Survival Rate by Pclass and Sex')
plt.ylabel('Survival Probability')
plt.show()

# Insights: Females in all classes had a significantly higher survival rate than males.
```



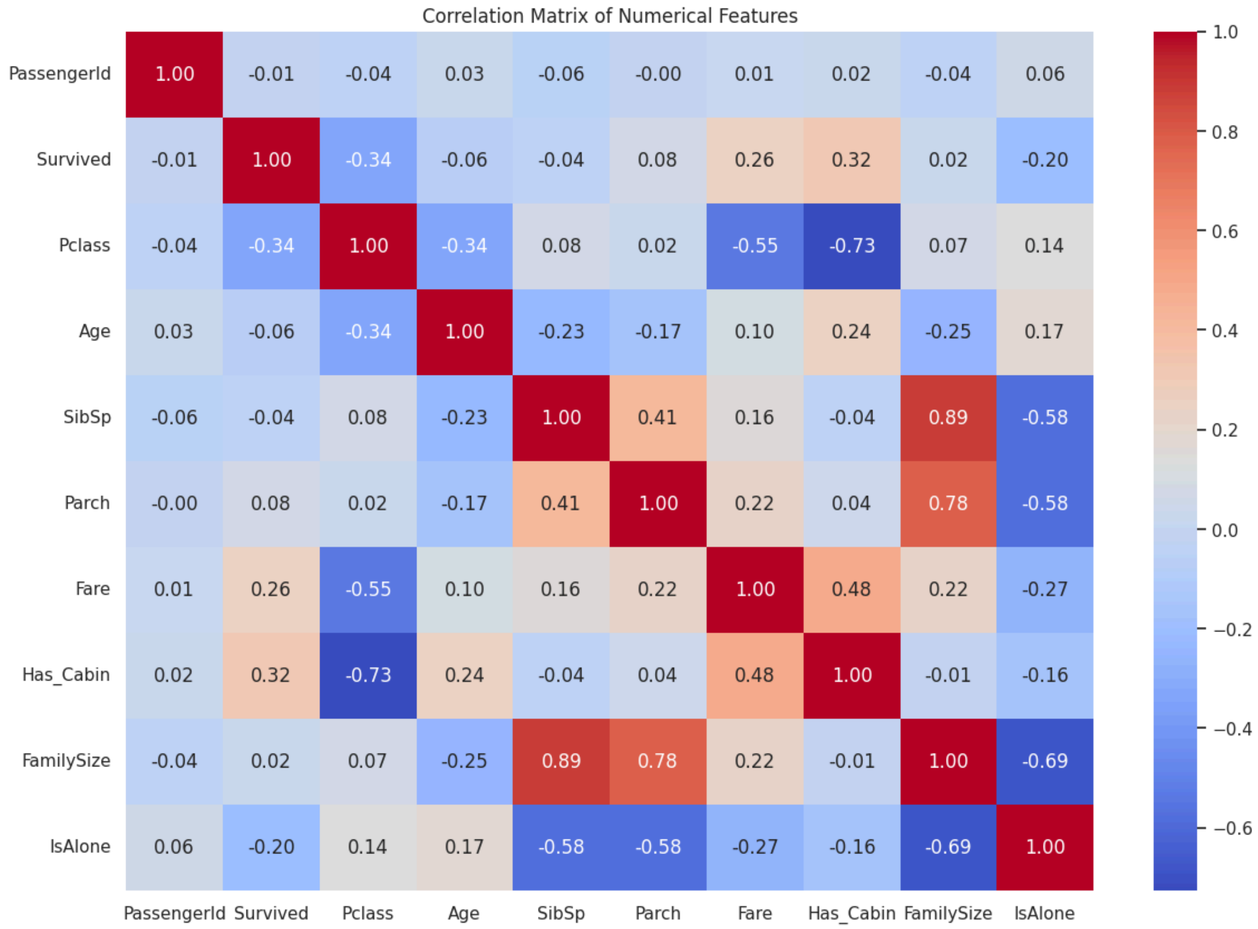

```
# Violin plot to see age distribution by sex and survival status
plt.figure(figsize=(14, 8))
sns.violinplot(x='Sex', y='Age', hue='Survived', data=titanic_df, split=True, palette={0: 'blue
plt.title('Age Distribution by Sex and Survival')
plt.show()
```

Insight from Violin Plot:

- For males, the peak of the distribution for survivors (orange) is at a very young age (children), while the peak for non-survivors is in the 20-30 range.
- For females, the distribution of survivors is much broader, indicating that females of most ages had a good chance of surviving.

Step 8: Correlation Analysis

```
# Correlation Heatmap for numerical features
plt.figure(figsize=(14, 10))
numeric_cols = titanic_df.select_dtypes(include=np.number)
correlation_matrix = numeric_cols.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix of Numerical Features')
plt.show()
```



	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare	Has_Cabin	FamilySize	IsAlone
PassengerId	1.00	-0.01	-0.04	0.03	-0.06	-0.00	0.01	0.02	-0.04	0.06
Survived	-0.01	1.00	-0.34	-0.06	-0.04	0.08	0.26	0.32	0.02	-0.20
Pclass	-0.04	-0.34	1.00	-0.34	0.08	0.02	-0.55	-0.73	0.07	0.14
Age	0.03	-0.06	-0.34	1.00	-0.23	-0.17	0.10	0.24	-0.25	0.17
SibSp	-0.06	-0.04	0.08	-0.23	1.00	0.41	0.16	-0.04	0.89	-0.58
Parch	-0.00	0.08	0.02	-0.17	0.41	1.00	0.22	0.04	0.78	-0.58
Fare	0.01	0.26	-0.55	0.10	0.16	0.22	1.00	0.48	0.22	-0.27
Has_Cabin	0.02	0.32	-0.73	0.24	-0.04	0.04	0.48	1.00	-0.01	-0.16
FamilySize	-0.04	0.02	0.07	-0.25	0.89	0.78	0.22	-0.01	1.00	-0.69
IsAlone	0.06	-0.20	0.14	0.17	-0.58	-0.58	-0.27	-0.16	-0.69	1.00

Interpretation of the Heatmap:

- `Survived` has a notable positive correlation with `Fare` and `Has_Cabin`, and a negative correlation with `Pclass` and our new `IsAlone` feature.
- `Pclass` and `Fare` are strongly negatively correlated, which makes sense (1st class = high fare).
- Our new `FamilySize` feature is composed of `SibSp` and `Parch`, so it's highly correlated with them by definition.

```
import pandas as pd

# Create a sample DataFrame
sample_data = {'col1': [1, 2, 3, 4],
               'col2': ['A', 'B', 'C', 'D'],
               'col3': [True, False, True, False]}
sample_df = pd.DataFrame(sample_data)
```

```
# Display the sample DataFrame
print("Sample DataFrame:")
display(sample df)
```

Sample DataFrame:

	col1	col2	col3
0	1	A	True
1	2	B	False
2	3	C	True
3	4	D	False

y-profiling of sample dataframe

```
# Install ydata-profiling
!pip install ydata-profiling -q
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 62.0/62.0 kB 4.6 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 400.1/400.1 kB 25.7 MB/s eta 0:00:00
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 296.5/296.5 kB 22.6 MB/s eta 0:00:00
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 679.7/679.7 kB 40.1 MB/s eta 0:00:00
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 37.3/37.3 MB 46.3 MB/s eta 0:00:00
```