I recently explored the Titanic dataset and practiced data cleaning, feature extraction, and visualization using Pandas, Seaborn, and Matplotlib. Here's a breakdown of what I did:

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

df = pd.read_csv('train.csv')
```

→ Load the Titanic training data using Pandas.

```
print(df.head(5))
print("\nmissing values before cleaning:")
print( df.isnull().sum())
print("duplicated rows before cleaning:")
print(df.duplicated().sum())
```

```
   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

missing values before cleaning:
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
duplicated rows before cleaning:
0
```

-> checking the missing and duplicated values.

```
print("filling missing values:")
df['Age'] = df['Age'].fillna(df['Age'].median())
df['Embarked'] = df['Embarked'].fillna(df['Embarked'].mode()[0
print("missing values after cleaning:")
print(df.isnull().sum())
print("duplicated rows after cleaning:")
print(df.duplicated().sum())
```

```
filling missing values:
missing values after cleaning:
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         0
dtype: int64
duplicated rows after cleaning:
0
```

-> filling the missing values and checking again.

cleaning steps:

-> Filled missing Age values with the median age.

-> Filled missing Embarked values with the most frequent port (mode).

```
df['Deck'] = df['Cabin'].str[0]
df['Deck'].fillna('Unknown', inplace=True)
df.drop('Cabin', axis=1, inplace=True)

df['Title'] = df['Name'].str.extract(r',\s*([^\.]+)\.')
```

```
df['FamilySize'] = df['SibSp'] + df['Parch']
```

Show hidden output

```
print(df.describe())
print(df.info())
print(df.value_counts())
```

```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  891.000000  891.000000
mean    446.000000    0.383838    2.308642   29.361582    0.523008
std     257.353842    0.486592    0.836071   13.019697    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   22.000000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   35.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare  FamilySize
count  891.000000  891.000000  891.000000
mean     0.381594   32.204208    0.904602
std      0.806057   49.693429    1.613459
min      0.000000    0.000000    0.000000
25%      0.000000    7.910400    0.000000
50%      0.000000   14.454200    0.000000
75%      0.000000   31.000000    1.000000
max      6.000000  512.329200   10.000000
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 14 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          891 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  Embarked     891 non-null    object 
 11  Deck         891 non-null    object 
 12  Title        891 non-null    object 
 13  FamilySize   891 non-null    int64  
dtypes: float64(2), int64(6), object(6)
memory usage: 97.6+ KB
None
PassengerId  Survived  Pclass  Name                                                 S
891          0         3       Dooley, Mr. Patrick                                  m
1            0         3       Braund, Mr. Owen Harris                              m
2            1         1       Cumings, Mrs. John Bradley (Florence Briggs Thayer)  f
3            1         3       Heikkinen, Miss. Laina                               f
4            1         1       Futrelle, Mrs. Jacques Heath (Lily May Peel)         f
```

```
16          1         2       Hewlett, Mrs. (Mary D Kingcome)                  f
15          0         3       Vestrom, Miss. Hulda Amanda Adolfina             f
14          0         3       Andersson, Mr. Anders Johan                      m
13          0         3       Saundercock, Mr. William Henry                   m
12          1         1       Bonnell, Miss. Elizabeth                         f
Name: count, Length: 891, dtype: int64
```

->Extracted Deck letter from the Cabin column and replaced missing with 'Unknown'.

->Extracted Title (like Mr, Miss, etc.) from the Name using regex.

->Created a new feature: FamilySize = SibSp + Parch (people the passenger traveled with).

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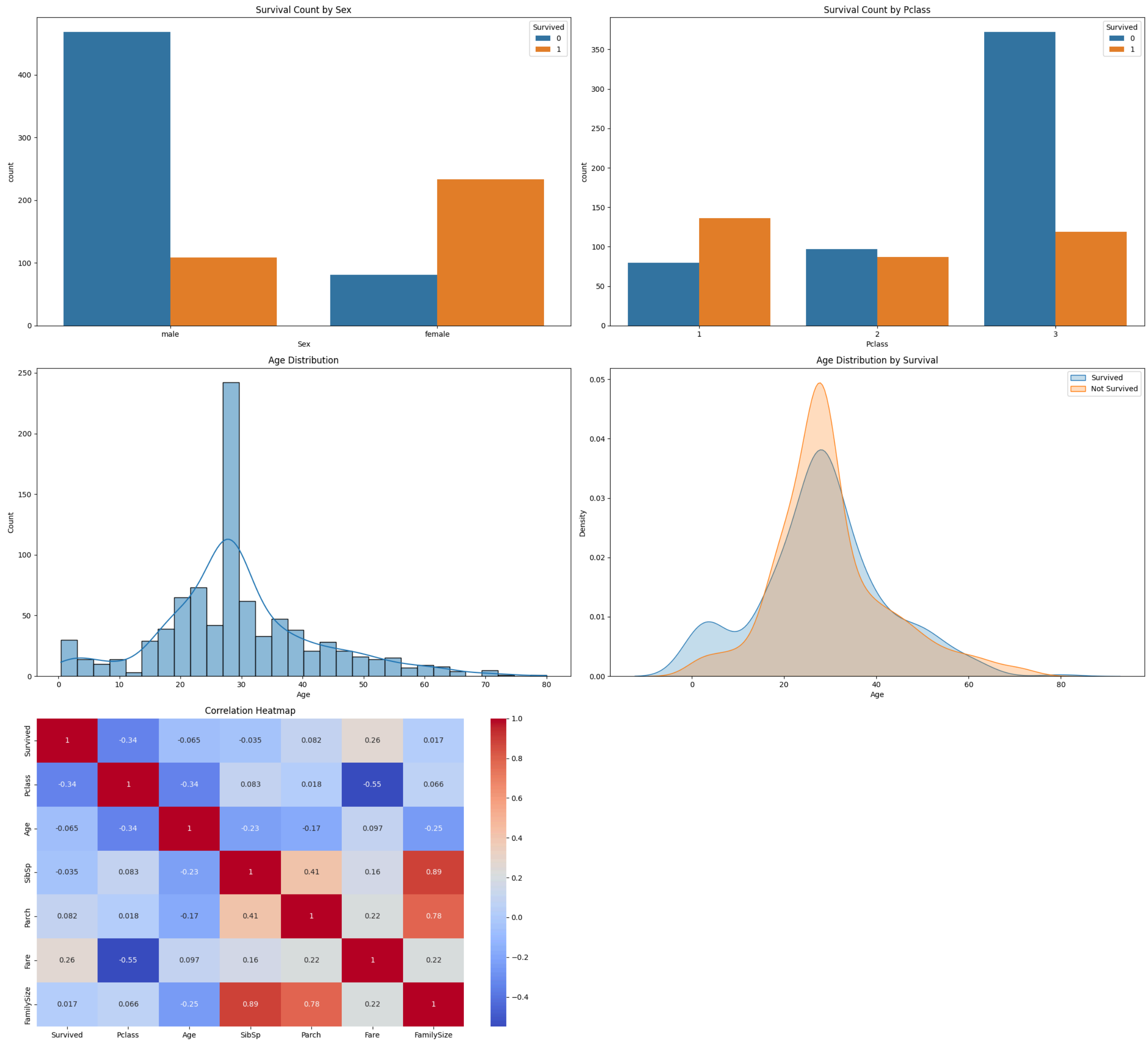
```
#Count plot: Survival by Sex
plt.figure(figsize=(22, 20))
plt.subplot(3,2,1)
sns.countplot(data=df, x='Sex', hue='Survived')
plt.title('Survival Count by Sex')
# Count plot: Survival by Pclass
plt.subplot(3,2,2)
sns.countplot(data=df, x='Pclass', hue='Survived')
plt.title('Survival Count by Pclass')
# Histogram: Age distribution
plt.subplot(3,2,3)
sns.histplot(data=df, x='Age', bins=30, kde=True)
plt.title('Age Distribution')

#kdeplot:age distribution by survival
plt.subplot(3,2,4)
sns.kdeplot(data=df[df['Survived'] == 1]['Age'], label='Survive
sns.kdeplot(data=df[df['Survived'] == 0]['Age'], label='Not Sur
plt.title('Age Distribution by Survival')
plt.legend()

numeric_features = ['Survived', 'Pclass', 'Age', 'SibSp', 'Parc
corr = df[numeric_features].corr()
plt.subplot(3,2,5)
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')

plt.tight_layout()
```

```
plt.show()
```

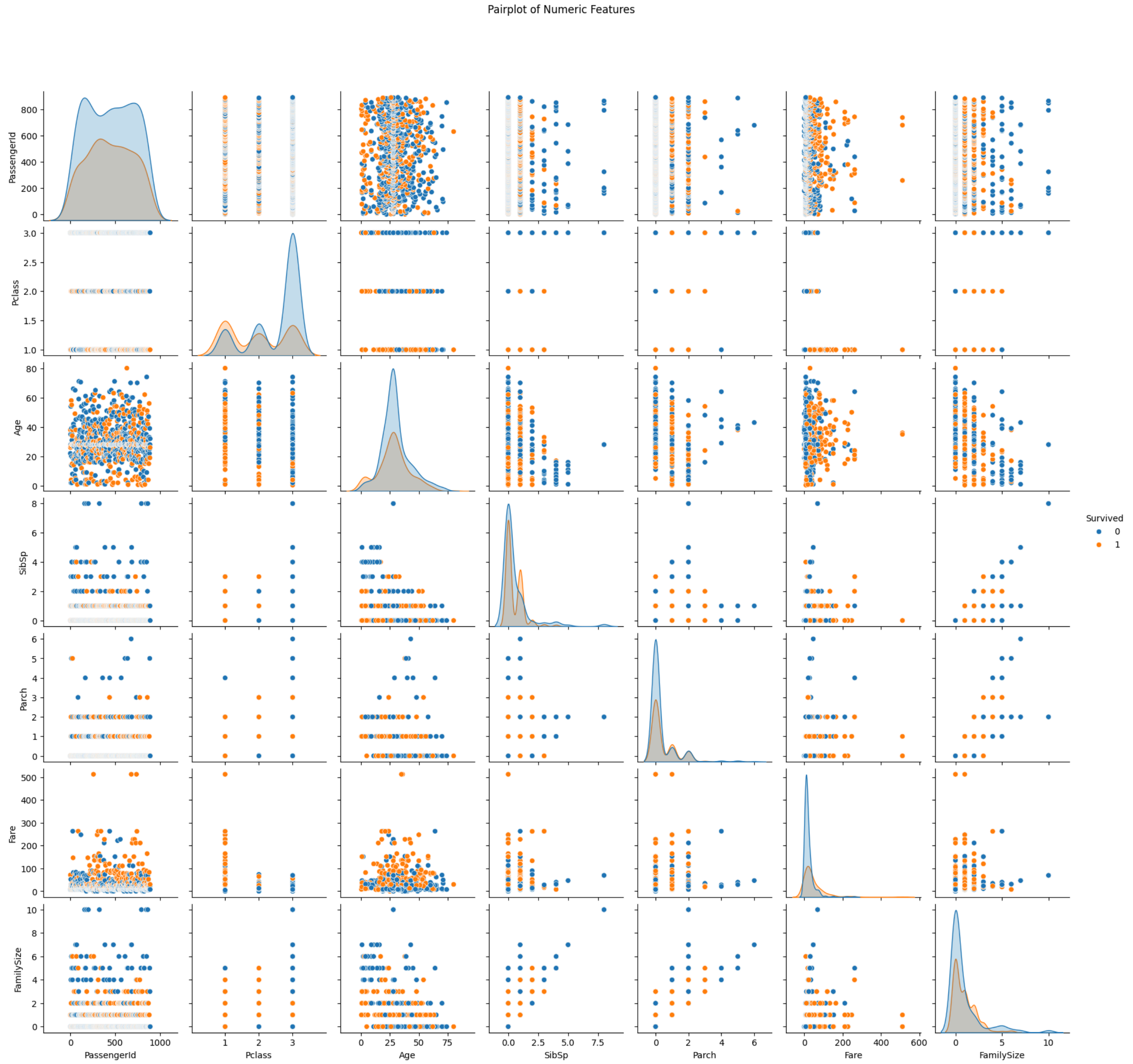



```
numeric_features = df.select_dtypes(include=['number']).columns

sns.pairplot(df[numeric_features], hue='Survived')
plt.subplots_adjust(top=0.9)
```

```
plt.suptitle('Pairplot of Numeric Features')
```

```
Text(0.5, 0.98, 'Pairplot of Numeric Features')
```



Visualizations and What They Mean

1. Count Plot (using Seaborn) A count plot shows the number of observations for each category in a feature.

   sns.countplot(x='Sex', hue='Survived')

🔎 Insight: More women survived than men. This aligns with "women and children first."

sns.countplot(x='Pclass', hue='Survived')

🔎 Insight: First-class passengers had the highest survival rate, while third class had the lowest.

2. KDE Plot (Kernel Density Estimate) A KDE plot shows a smoothed curve of the distribution of a variable (like Age). It's useful for spotting the overall shape and skewness.

   sns.histplot(x='Age', kde=True)

🔎 Insight: The Age distribution is right-skewed, meaning most passengers were young, with fewer older individuals.

sns.kdeplot(df[df['Survived'] == 1]['Age']) vs df[df['Survived'] == 0]['Age']

🔎 Insight:Survivors were mostly younger people Non-survivors were spread across all ages, especially older groups This gives a strong hint that youth improved survival odds.

3. Correlation Heatmap A heatmap visualizes correlations between numerical variables. Values close to 1 or -1 mean strong positive/negative correlation.

   sns.heatmap(df[numeric_cols].corr(), annot=True)

🔎 Insights: Pclass is negatively correlated with Survival (higher class → more survival)

Fare is positively correlated with Survival

FamilySize has a weak correlation, but still worth exploring

4.A pair plot (via sns.pairplot): It is a quick way to visualize the relationships and distributions of multiple numeric variables at once. Here's what it gives you:

Scatterplots for every pair On the off-diagonal, you get a grid of scatterplots showing how each feature relates to every other feature. This helps you spot correlations, clusters, or outliers.

Univariate distributions on the diagonal By default you see either histograms or kernel-density estimates of each variable along the diagonal—so you can check its distribution (e.g. skew, multimodality).

Hue grouping If you pass a hue argument (like 'Survived'), the points and distributions are colored by that categorical variable. That way you can immediately see, for example, how survivors vs. non-survivors differ across features.

Summary of pairwise structure Instead of manually plotting every scatter and histogram, one call to pairplot gives you the full matrix at once—making exploratory data analysis much faster.