

Exploratory Data Analysis (EDA) on Titanic Dataset

This notebook aims to extract insights using visual and statistical exploration.

Objective

Extract insights using visual and statistical exploration.

```
# Step 1: Import Required Libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style='whitegrid')

# Step 2: Load Dataset
df =
pd.read_csv('https://raw.githubusercontent.com/datasciencedojo/dataset
s/master/titanic.csv')
df.head()
```

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

	SibSp	\	Name	Sex	Age
0			Braund, Mr. Owen Harris	male	22.0
1					
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

Step 3: Basic Exploration

```
df.describe()
```

	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
max	6.000000	512.329200

Step 4: Info and Null Values

```
df.info()
```

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

```
<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
```

```
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
```

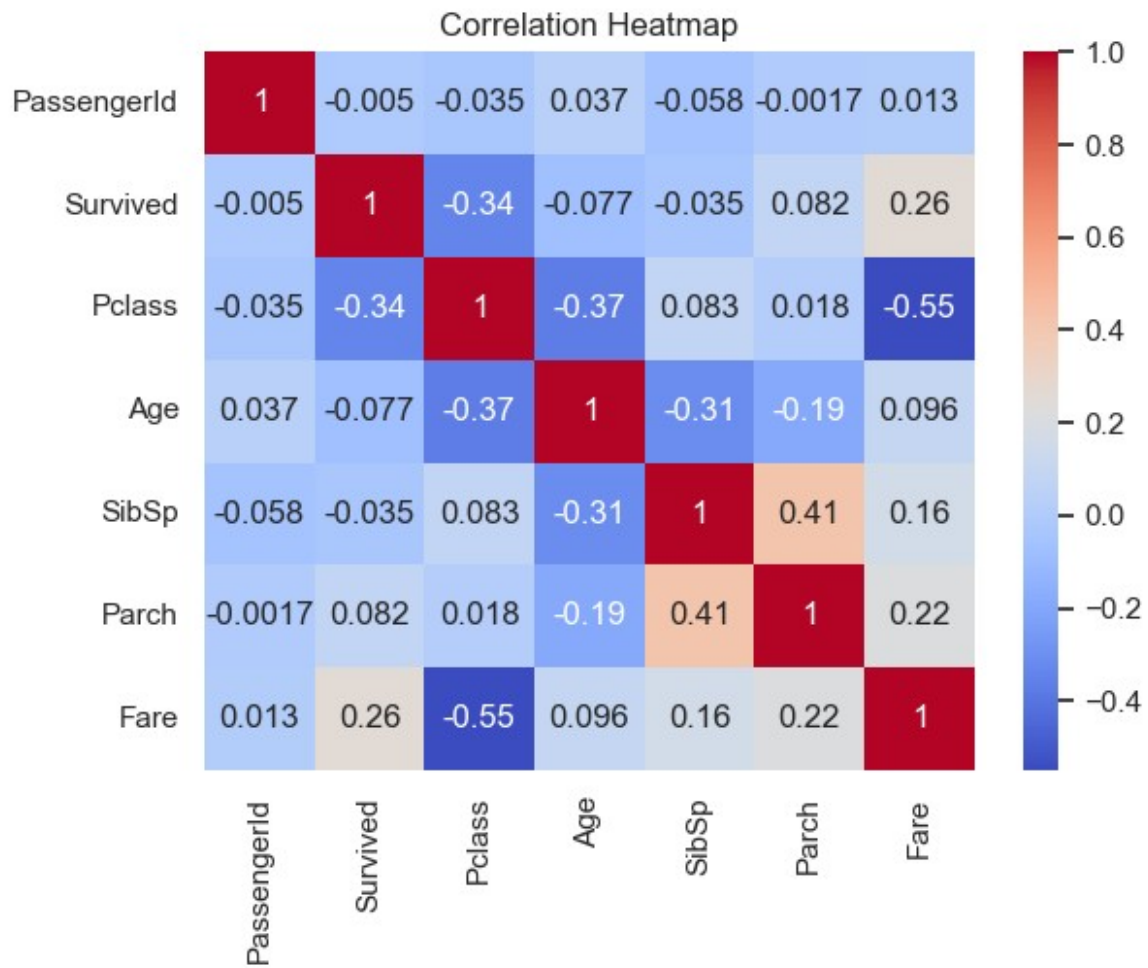
Step 5: Value Counts

```
df['Sex'].value_counts()
```

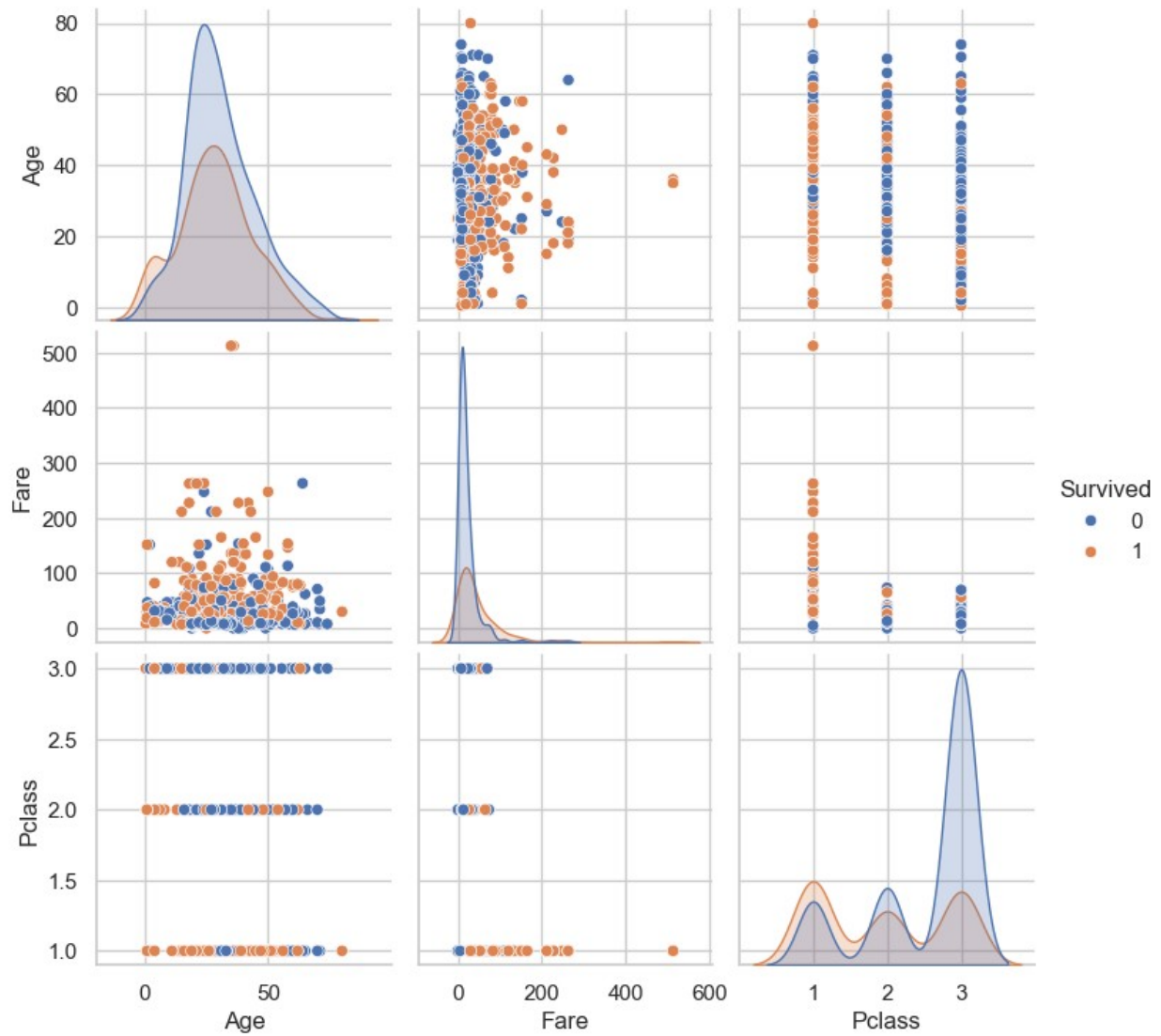
```
Sex
male      577
female    314
Name: count, dtype: int64
```

Step 6: Correlation and Heatmap

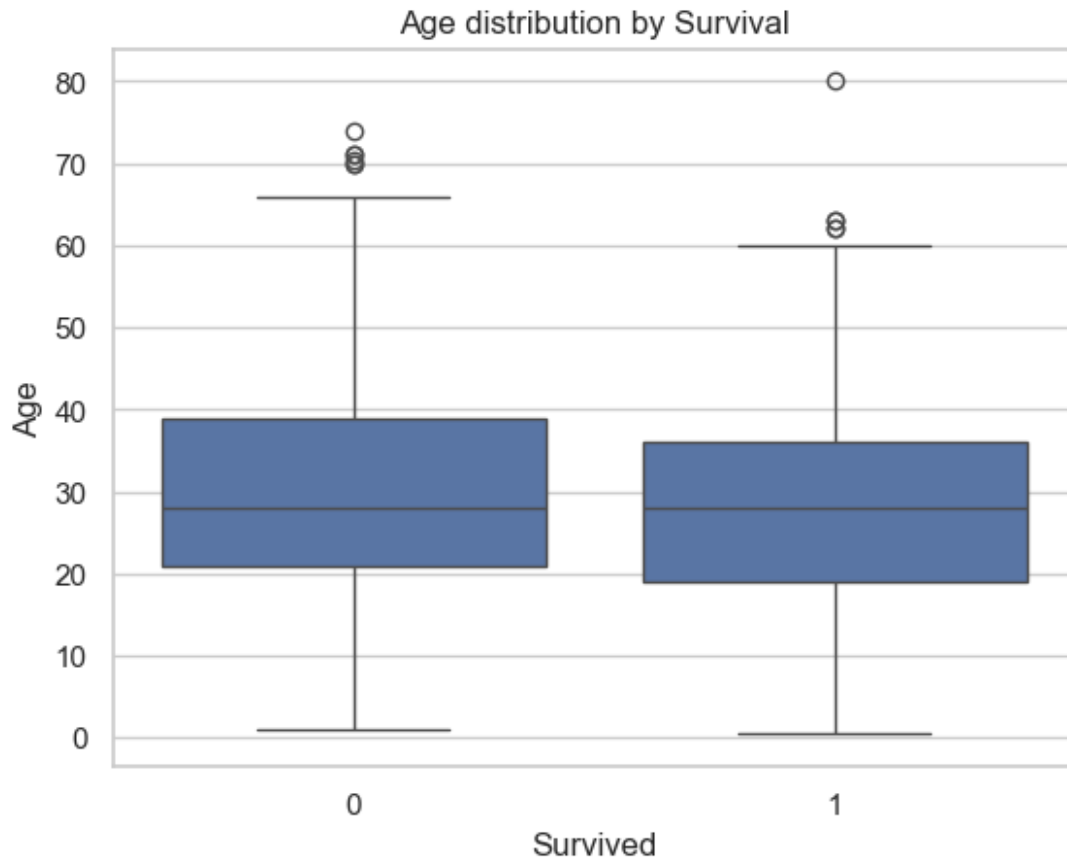
```
corr = df.corr(numeric_only=True)
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



```
# Step 7: Pairplot
sns.pairplot(df[['Survived', 'Age', 'Fare', 'Pclass']],
             hue='Survived')
<seaborn.axisgrid.PairGrid at 0x1c7fba96c30>
```



```
# Step 8: Boxplot
sns.boxplot(x='Survived', y='Age', data=df)
plt.title('Age distribution by Survival')
Text(0.5, 1.0, 'Age distribution by Survival')
```



Summary of Findings

- Females had higher survival rates than males.
- Younger passengers had slightly better survival odds.
- Higher class passengers had a higher survival rate.
- Fare paid positively correlates with survival.