Task - 02

Perform data cleaning and exploratory data analysis (EDA) on a dataset of your choice, such as the Titanic dataset from Kaggle. Explore the relationships between variables and identify patterns and trends in the data.

Dataset:- https://www.kaggle.com/c/titanic/data?select=train.csv

The Titanic dataset is a classic dataset used in data science and machine learning for educational purposes. It contains information about the passengers who were aboard the RMS Titanic when it sank on its maiden voyage in April 1912. The goal of analyzing this dataset is often to predict which passengers survived the disaster based on various features.

The data has been split into two groups:

1.training set (train.csv)

2.test set (test.csv)

For data cleaning and exploratory data analysis (EDA), we typically use the train.csv file because it contains both the features and the target variable (Survived). The test.csv file is usually used for predictions.

```
#Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
#Load the dataset
df = pd.read_csv('/content/train.csv')
df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

Next steps: Generate code with df | View recommended plots

```
df.shape #Total no. of rows & cols
```

```
(891, 12)
```

```
df.info() #summary of df
```

```
<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
```

```
df.isnull().sum() #check for null values
```

```
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
```

Here Column Age, Cabin, embarked have missing values.

```
df.duplicated().sum() #check for duplicate values
```

```
0
```

Filling missing values in the 'Age' column with the median age.

```
df['Age'].fillna(df['Age'].median(), inplace=True)
```

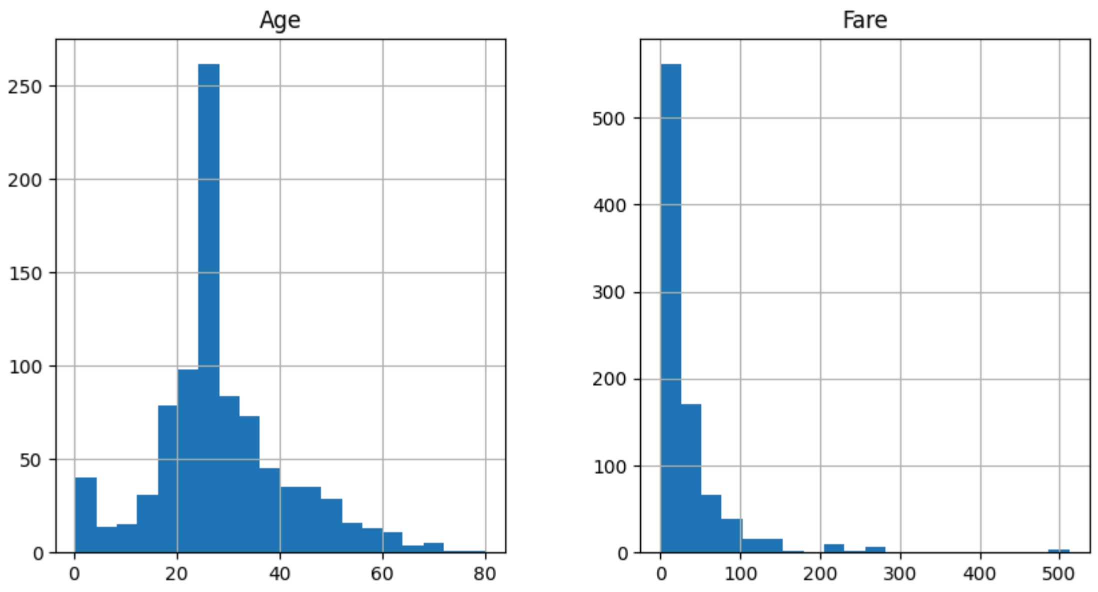
For 'Embarked', filling missing values with the most frequent value (mode).

```
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)
```

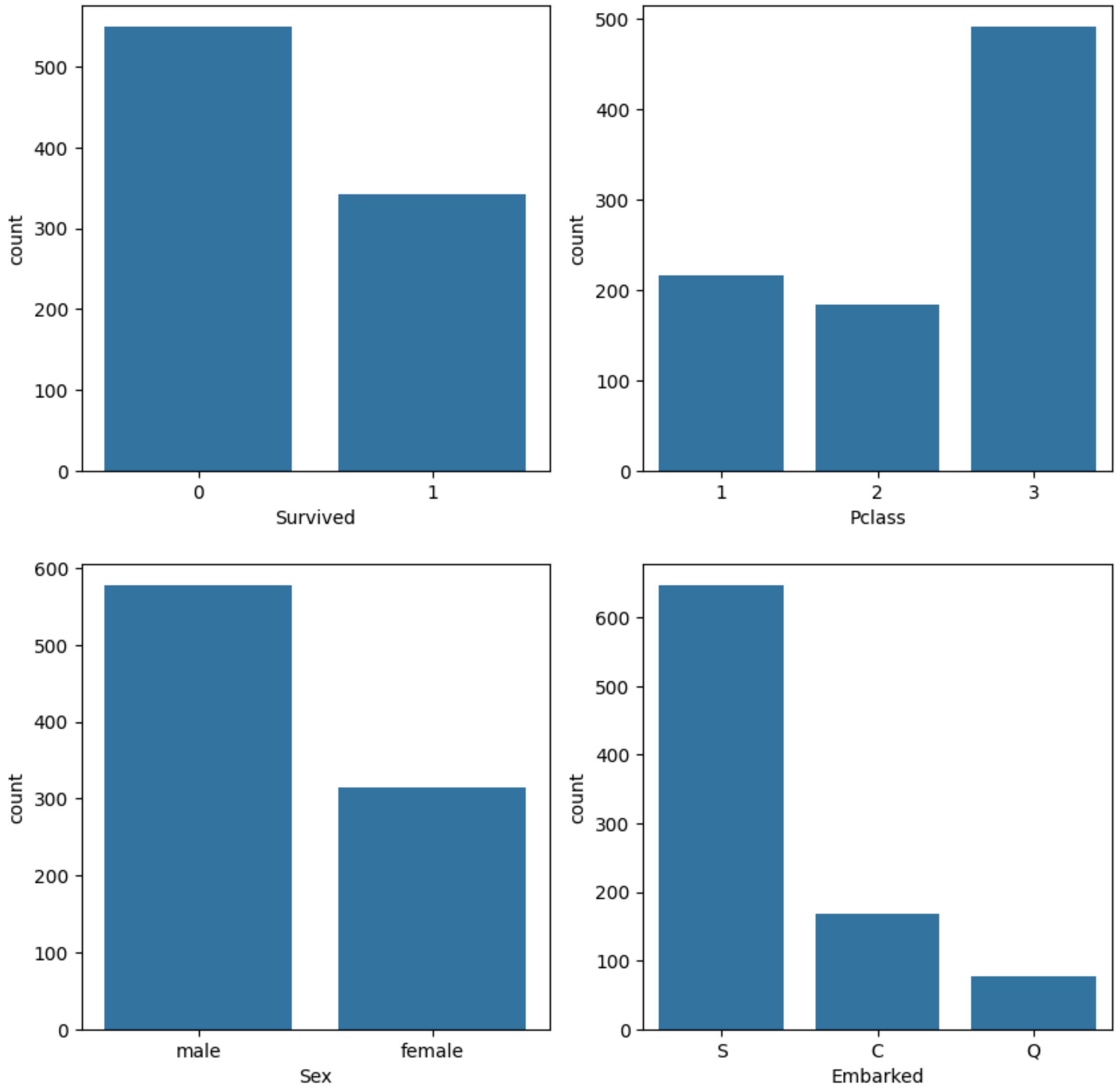
Fill missing values in 'Cabin' with 'Unknown'

```
df['Cabin'].fillna('Unknown', inplace=True)
```

```
# Histograms for numerical features
df.hist(['Age', 'Fare'], bins=20, figsize=(10, 5))
plt.show()
```

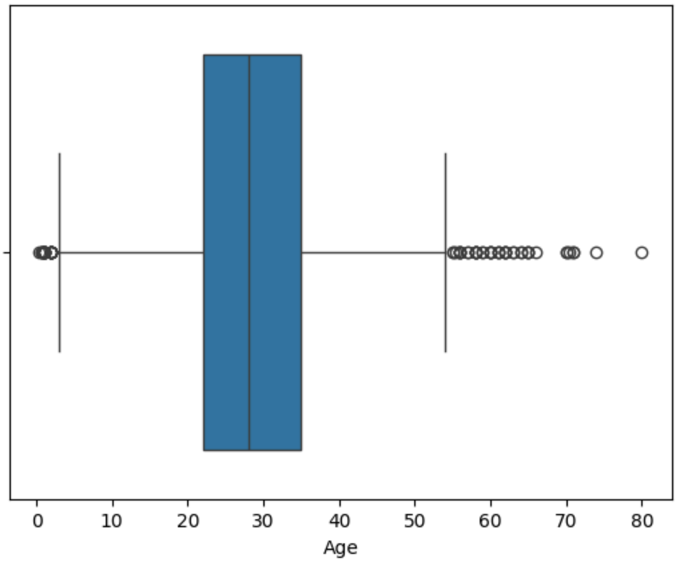


```
# Bar plots for categorical features
fig, axes = plt.subplots(2, 2, figsize=(10, 10))
sns.countplot(ax=axes[0, 0], x='Survived', data=df)
sns.countplot(ax=axes[0, 1], x='Pclass', data=df)
sns.countplot(ax=axes[1, 0], x='Sex', data=df)
sns.countplot(ax=axes[1, 1], x='Embarked', data=df)
plt.show()
```



```
sns.boxplot(x=df['Age'])
```

```
<Axes: xlabel='Age'>
```



```
q1 = df['Age'].quantile(0.25)
q3 = df['Age'].quantile(0.75)
iqr = q3-q1
```

```
q1, q3, iqr
```

```
(22.0, 35.0, 13.0)
```

```
upper_limit = q3 + (1.5 * iqr)   #calculating the upper and lower limit using the Interquartile Range (IQR)
lower_limit = q1 - (1.5 * iqr)
lower_limit, upper_limit
```

```
(2.5, 54.5)
```

```
# find the outliers
df.loc[(df['Age'] > upper_limit) | (df['Age'] < lower_limit)]
```

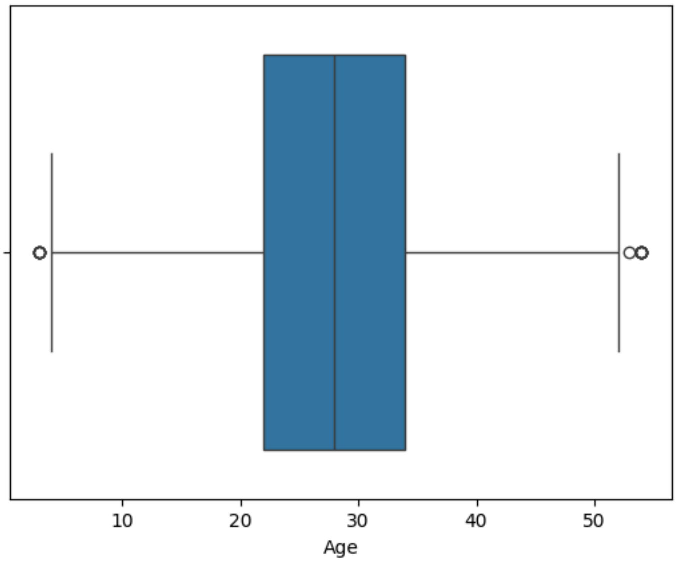
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.00	3	1	349909	21.0750	Unknown	S
11	12	1	1	Bonnell, Miss. Elizabeth	female	58.00	0	0	113783	26.5500	C103	S
15	16	1	2	Hewlett, Mrs. (Mary D Kingcome)	female	55.00	0	0	248706	16.0000	Unknown	S
16	17	0	3	Rice, Master. Eugene	male	2.00	4	1	382652	29.1250	Unknown	Q
33	34	0	2	Wheadon, Mr. Edward H	male	66.00	0	0	C.A. 24579	10.5000	Unknown	S
...	...	...	...	...	...	...	...	...	...	...	...	...
827	828	1	2	Mallet, Master. Andre	male	1.00	0	2	S.C./PARIS 2079	37.0042	Unknown	C
829	830	1	1	Stone, Mrs. George Nelson (Martha Evelyn)	female	62.00	0	0	113572	80.0000	B28	S
831	832	1	2	Richards, Master. George Sibley	male	0.83	1	1	29106	18.7500	Unknown	S
851	852	0	3	Svensson, Mr. Johan	male	74.00	0	0	347060	7.7750	Unknown	S

```
# trimming - delete the outlier data
new_df = df.loc[(df['Age'] <= upper_limit) & (df['Age'] >= lower_limit)]
print('before removing outliers:', len(df))
print('after removing outliers:',len(new_df))
print('outliers:', len(df)-len(new_df))
```

```
before removing outliers: 891
after removing outliers: 825
outliers: 66
```

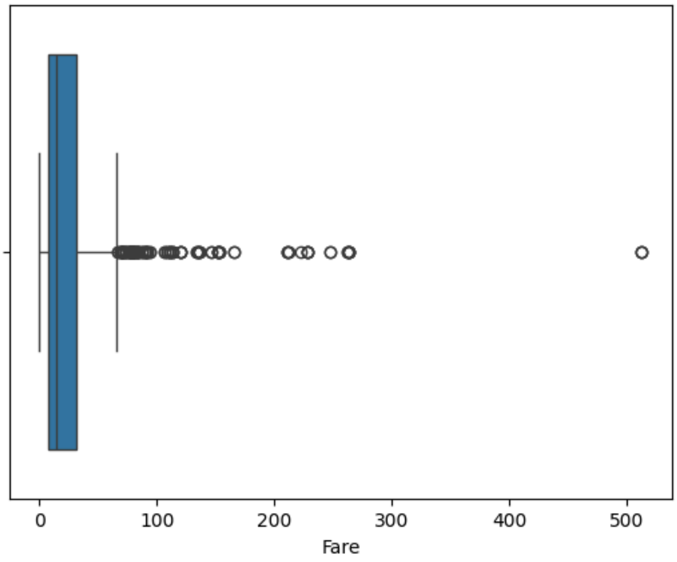
```
sns.boxplot(x=new_df['Age'])
```

```
<Axes: xlabel='Age'>
```



```
sns.boxplot(x=df['Fare'])
```

```
<Axes: xlabel='Fare'>
```



```
q1 = df['Fare'].quantile(0.25)
q3 = df['Fare'].quantile(0.75)
iqr = q3-q1
q1, q3, iqr
```

```
(7.9104, 31.0, 23.0896)
```

```
upper_limit = q3 + (1.5 * iqr)
lower_limit = q1 - (1.5 * iqr)
lower_limit, upper_limit
```

```
(-26.724, 65.6344)
```

```
# find the outliers
df.loc[(df['Fare'] > upper_limit) | (df['Fare'] < lower_limit)]
```

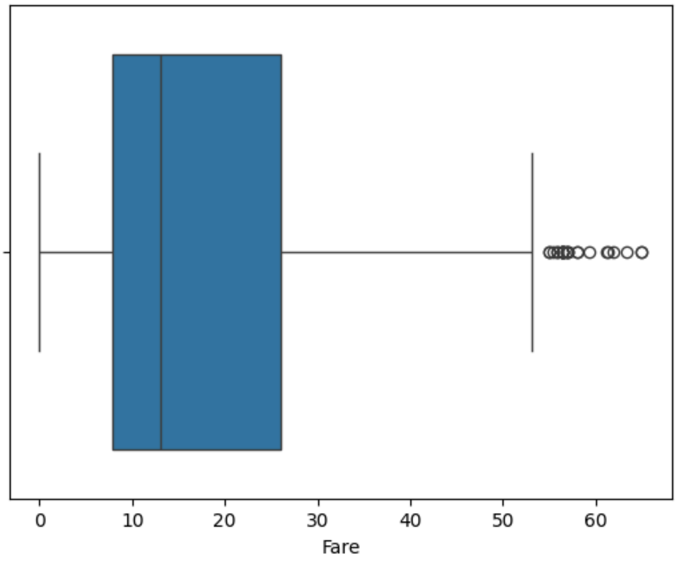
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
27	28	0	1	Fortune, Mr. Charles Alexander	male	19.0	3	2	19950	263.0000	C23 C25 C27	S
31	32	1	1	Spencer, Mrs. William Augustus (Marie Eugenie)	female	28.0	1	0	PC 17569	146.5208	B78	C
34	35	0	1	Meyer, Mr. Edgar Joseph	male	28.0	1	0	PC 17604	82.1708	Unknown	C
52	53	1	1	Harper, Mrs. Henry Sleeper (Myna Haxtun)	female	49.0	1	0	PC 17572	76.7292	D33	C
...	...	...	...	...	...	...	...	...	...	...	...	...
846	847	0	3	Sage, Mr. Douglas Bullen	male	28.0	8	2	CA. 2343	69.5500	Unknown	S
849	850	1	1	Goldenberg, Mrs. Samuel L (Edwiga Grabowska)	female	28.0	1	0	17453	89.1042	C92	C
856	857	1	1	Wick, Mrs. George Dennick (Mary Hitchcock)	female	45.0	1	1	36928	164.8667	Unknown	S
863	864	0	3	Sage, Miss. Dorothy Edith "Dolly"	female	28.0	8	2	CA. 2343	69.5500	Unknown	S
				Potter, Mrs. Thomas Jr (Lily								

```
# trimming - delete the outlier data
new_df = df.loc[(df['Fare'] <= upper_limit) & (df['Fare'] >= lower_limit)]
print('before removing outliers:', len(df))
print('after removing outliers:',len(new_df))
print('outliers:', len(df)-len(new_df))
```

```
before removing outliers: 891
after removing outliers: 775
outliers: 116
```

```
sns.boxplot(x=new_df['Fare'])
```

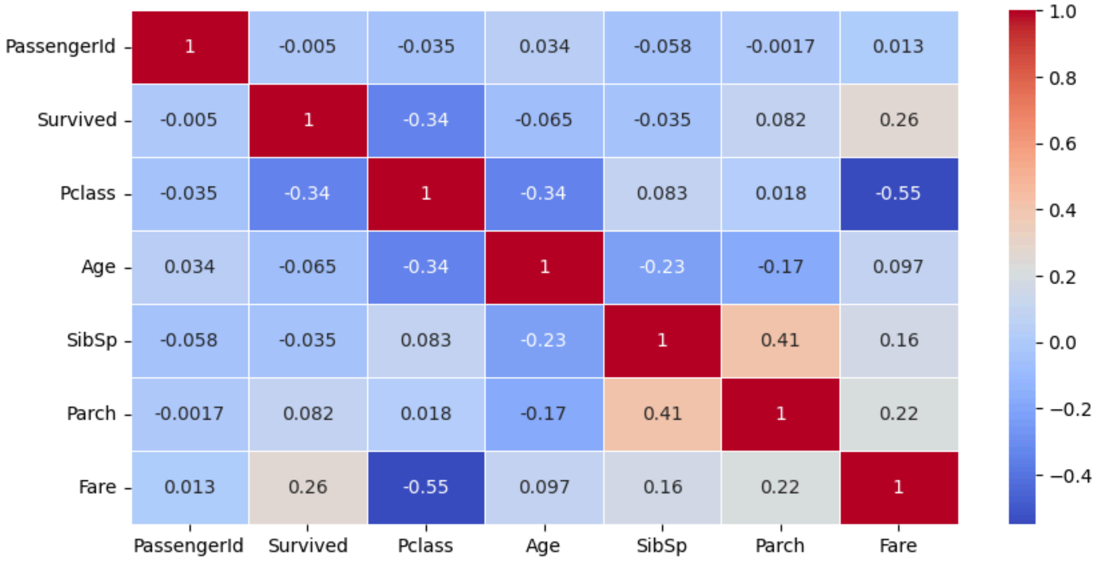
```
<Axes: xlabel='Fare'>
```



```
# Survival rates by gender
survival_by_gender = df.groupby('Sex')['Survived'].mean()
print(survival_by_gender)
```

```
Sex
female    0.742038
male      0.188908
Name: Survived, dtype: float64
```

```
# Correlation matrix for numerical features
plt.figure(figsize=(10, 5))
sns.heatmap(df.select_dtypes(include=['number']).corr(), annot=True, cmap='coolwarm', linewidths=0.5)
plt.show()
```



Pclass and Fare have a strong negative correlation (-0.55), which means that passengers in higher class generally paid more for their tickets.

Survived and Pclass have a moderate negative correlation (-0.34), which means that passengers in higher classes were less likely to survive.

Age and SibSp have a moderate negative correlation (-0.23), which means that passengers with more siblings or spouses tended to be younger.