Titanic Dataset Preprocessing Pipeline

This script preprocesses the Titanic dataset by:

1. Handling missing values
2. Removing outliers
3. Encoding categorical variables
4. Scaling numerical features

Output: Clean dataset ready for modeling

Step:1 Import libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
```

Step:2 Overview of dataset

```
# Load the dataset
titanic_df = sns.load_dataset('titanic')
titanic_df
```

```
     survived  pclass     sex   age  sibsp  parch     fare embarked  
class  \
0           0       3    male  22.0      1      0   7.2500        S  
Third
1           1       1  female  38.0      1      0  71.2833        C  
First
2           1       3  female  26.0      0      0   7.9250        S  
Third
3           1       1  female  35.0      1      0  53.1000        S  
First
4           0       3    male  35.0      0      0   8.0500        S  
Third
..        ...     ...     ...   ...    ...    ...      ...      ...  
...
886         0       2    male  27.0      0      0  13.0000        S  
Second
887         1       1  female  19.0      0      0  30.0000        S  
First
888         0       3  female   NaN      1      2  23.4500        S  
Third
889         1       1    male  26.0      0      0  30.0000        C  
First
890         0       3    male  32.0      0      0   7.7500        Q  
```

```
Third

       who  adult_male deck  embark_town alive  alone
0      man        True  NaN  Southampton    no  False
1    woman       False    C    Cherbourg   yes  False
2    woman       False  NaN  Southampton   yes   True
3    woman       False    C  Southampton   yes  False
4      man        True  NaN  Southampton    no   True
..     ...         ...  ...          ...   ...    ...
886    man        True  NaN  Southampton    no   True
887  woman       False    B  Southampton   yes   True
888  woman       False  NaN  Southampton    no  False
889    man        True    C    Cherbourg   yes   True
890    man        True  NaN   Queenstown    no   True

[891 rows x 15 columns]
```

Step:3 Understanding the Data

```python
print("Rows in the dataset:",[titanic_df.shape[0]])
print("Columns in the dataset:",[titanic_df.shape[1]])
```

```
Rows in the dataset: [891]
Columns in the dataset: [15]
```

```python
titanic_df.head()
```

```
   survived  pclass     sex   age  sibsp  parch     fare embarked
class  \
0         0       3    male  22.0      1      0   7.2500        S
Third
1         1       1  female  38.0      1      0  71.2833        C
First
2         1       3  female  26.0      0      0   7.9250        S
Third
3         1       1  female  35.0      1      0  53.1000        S
First
4         0       3    male  35.0      0      0   8.0500        S
Third

     who  adult_male deck  embark_town alive  alone
0    man        True  NaN  Southampton    no  False
1  woman       False    C    Cherbourg   yes  False
2  woman       False  NaN  Southampton   yes   True
3  woman       False    C  Southampton   yes  False
4    man        True  NaN  Southampton    no   True
```

```python
titanic_df.tail()
```

```
     survived  pclass     sex   age  sibsp  parch   fare embarked
class  \
```

```
886          0       2    male  27.0      0      0  13.00        S
Second
887          1       1  female  19.0      0      0  30.00        S
First
888          0       3  female   NaN      1      2  23.45        S
Third
889          1       1    male  26.0      0      0  30.00        C
First
890          0       3    male  32.0      0      0   7.75        Q
Third

       who  adult_male deck  embark_town alive  alone
886    man        True  NaN  Southampton    no   True
887  woman       False    B  Southampton   yes   True
888  woman       False  NaN  Southampton    no  False
889    man        True    C    Cherbourg   yes   True
890    man        True  NaN   Queenstown    no   True
```

```
titanic_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   survived     891 non-null    int64
 1   pclass       891 non-null    int64
 2   sex          891 non-null    object
 3   age          714 non-null    float64
 4   sibsp        891 non-null    int64
 5   parch        891 non-null    int64
 6   fare         891 non-null    float64
 7   embarked     889 non-null    object
 8   class        891 non-null    category
 9   who          891 non-null    object
 10  adult_male   891 non-null    bool
 11  deck         203 non-null    category
 12  embark_town  889 non-null    object
 13  alive        891 non-null    object
 14  alone        891 non-null    bool
dtypes: bool(2), category(2), float64(2), int64(4), object(5)
memory usage: 80.7+ KB
```

```
titanic_df.describe()
```

```
         survived      pclass         age       sibsp       parch
fare
count  891.000000  891.000000  714.000000  891.000000  891.000000
891.000000
mean     0.383838    2.308642   29.699118    0.523008    0.381594
```

```
32.204208
std      0.486592    0.836071   14.526497    1.102743    0.806057
49.693429
min      0.000000    1.000000    0.420000    0.000000    0.000000
0.000000
25%      0.000000    2.000000   20.125000    0.000000    0.000000
7.910400
50%      0.000000    3.000000   28.000000    0.000000    0.000000
14.454200
75%      1.000000    3.000000   38.000000    1.000000    0.000000
31.000000
max      1.000000    3.000000   80.000000    8.000000    6.000000
512.329200
```

Step4:Handling missing values

```
# Check for missing values
titanic_df.isnull().sum()

survived         0
pclass           0
sex              0
age            177
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64

# missing value percentage
print(titanic_df.isnull().sum()/len(titanic_df)*100)

survived        0.000000
pclass          0.000000
sex             0.000000
age            19.865320
sibsp           0.000000
parch           0.000000
fare            0.000000
embarked        0.224467
class           0.000000
who             0.000000
adult_male      0.000000
```

```
deck           77.216611
embark_town     0.224467
alive           0.000000
alone           0.000000
dtype: float64
```

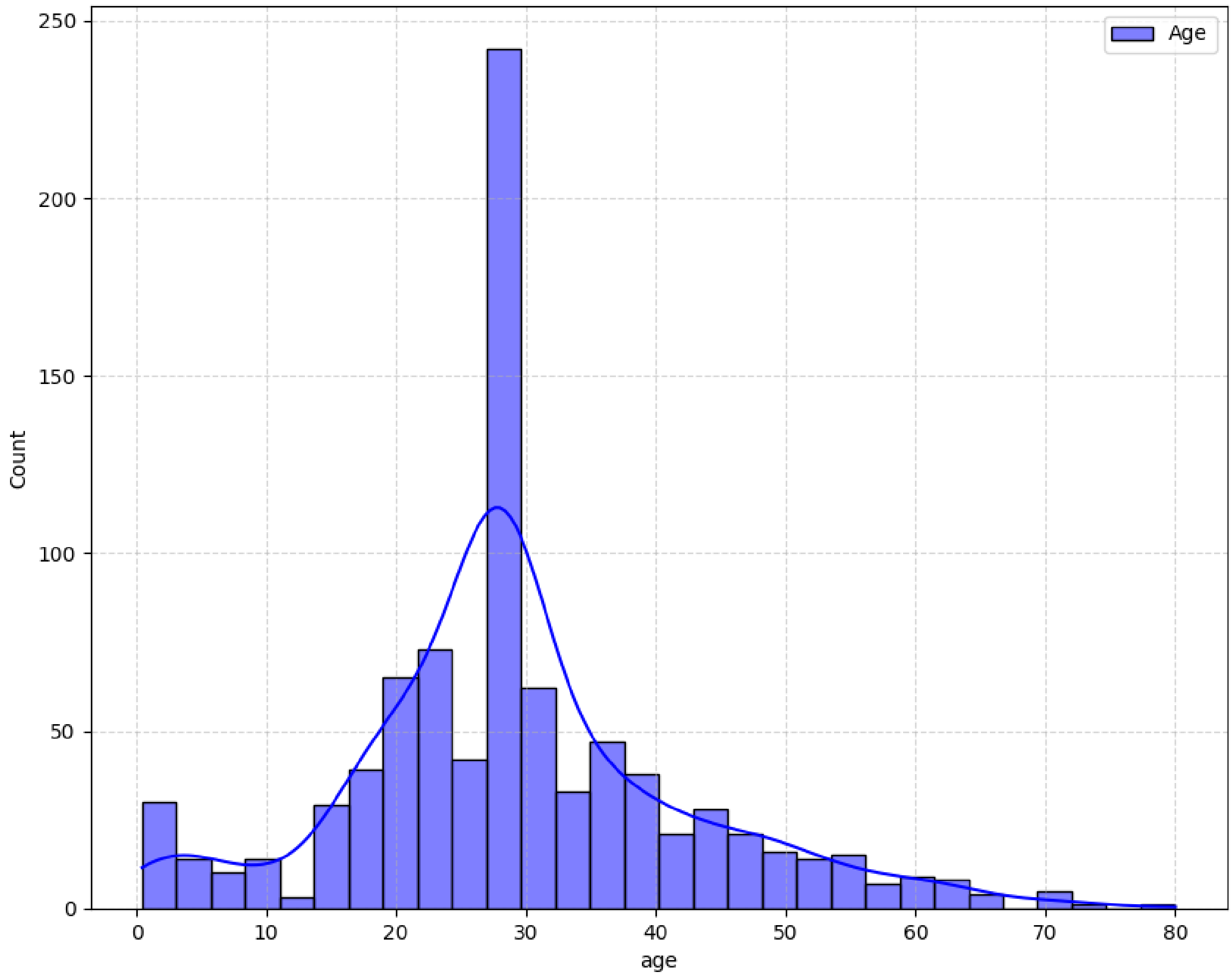
Missing values in columns like Age, Deck,Embarked and Embark_town

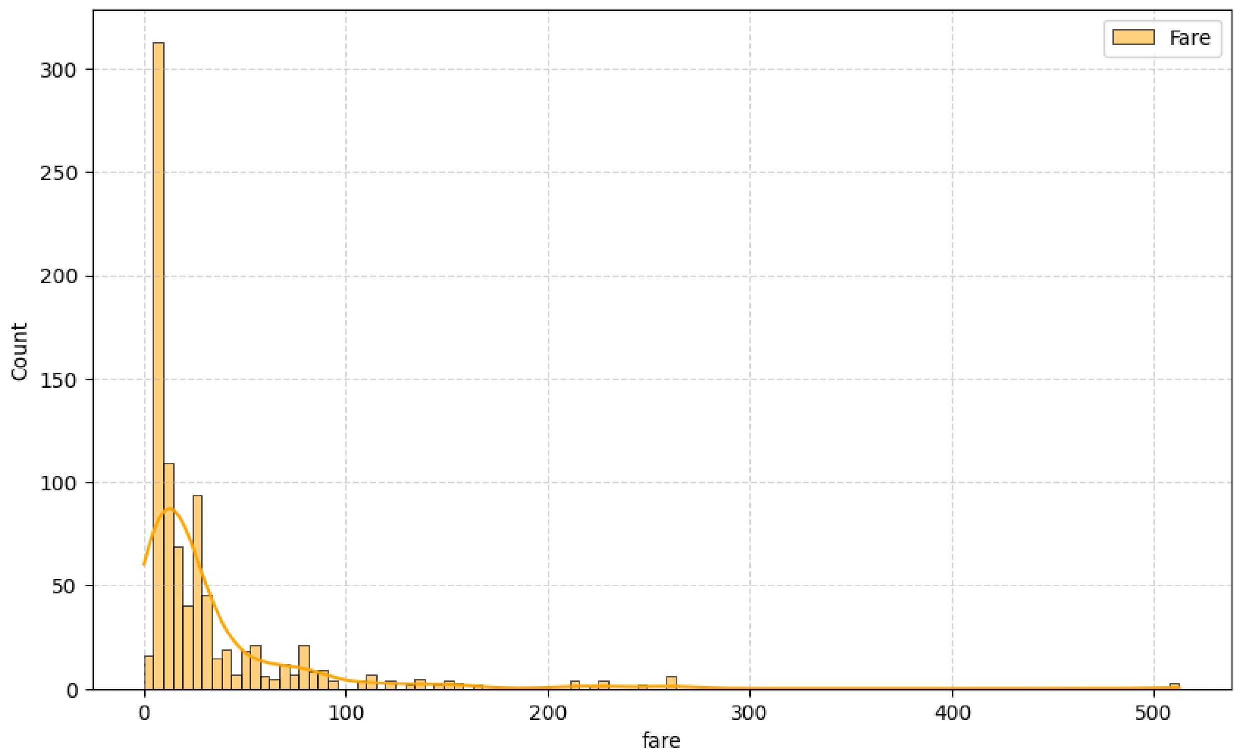
```
titanic_df['age'].fillna(titanic_df['age'].median(),inplace=True)

titanic_df.drop(columns=['deck'],inplace=True)

titanic_df['embarked'].fillna(titanic_df['embarked'].mode()
[0],inplace=True)

titanic_df['embark_town'].fillna(titanic_df['embark_town'].mode()
[0],inplace=True)
```

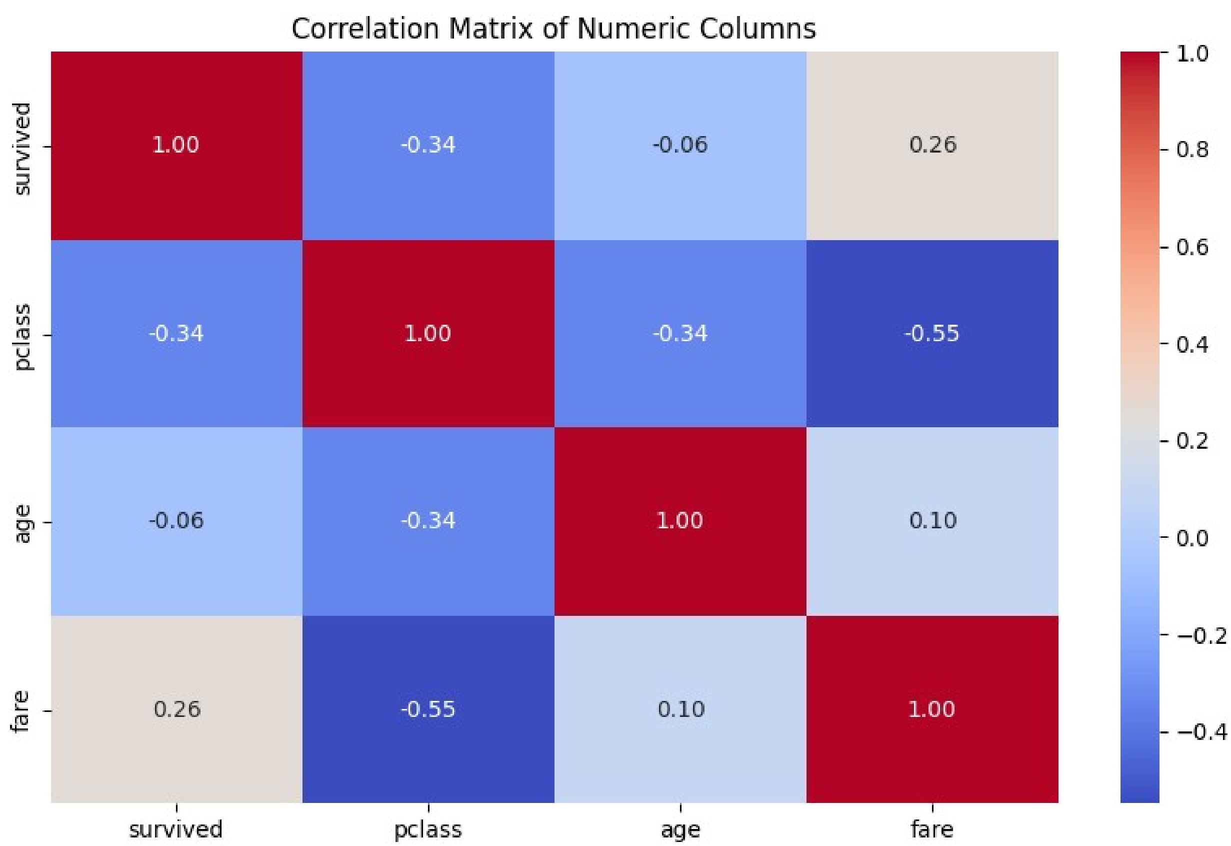
```
C:\Users\sanrkin\AppData\Local\Temp\ipykernel_9344\577215265.py:1:
FutureWarning: A value is trying to be set on a copy of a DataFrame or
Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  titanic_df['age'].fillna(titanic_df['age'].median(),inplace=True)
C:\Users\sanrkin\AppData\Local\Temp\ipykernel_9344\577215265.py:5:
FutureWarning: A value is trying to be set on a copy of a DataFrame or
Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  titanic_df['embarked'].fillna(titanic_df['embarked'].mode()
[0],inplace=True)
C:\Users\sanrkin\AppData\Local\Temp\ipykernel_9344\577215265.py:7:
FutureWarning: A value is trying to be set on a copy of a DataFrame or
Series through chained assignment using an inplace method.
```

```
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  titanic_df['embark_town'].fillna(titanic_df['embark_town'].mode()
[0],inplace=True)

titanic_df.isnull().sum()

survived       0
pclass         0
sex            0
age            0
sibsp          0
parch          0
fare           0
embarked       0
class          0
who            0
adult_male     0
embark_town    0
alive          0
alone          0
dtype: int64

# Drop irrelevant columns
titanic_df.drop(columns=['parch','sibsp'], inplace=True)


# Distribution of numerical features
plt.figure(figsize=(10, 8))
sns.histplot(data=titanic_df, x='age', kde=True, color='blue',
label='Age')
plt.grid(True, linestyle='--', alpha=0.5)
plt.legend()
plt.show()

# Plot histogram for 'fare'
plt.figure(figsize=(10, 6))
sns.histplot(data=titanic_df, x='fare', kde=True, color='orange',
label='Fare')
plt.grid(True, linestyle='--', alpha=0.5)
plt.legend()
plt.show()
```

```
numeric_df = titanic_df.select_dtypes(include=['number'])

# Plot the correlation matrix
plt.figure(figsize=(10, 6))
sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix of Numeric Columns')
plt.show()
```

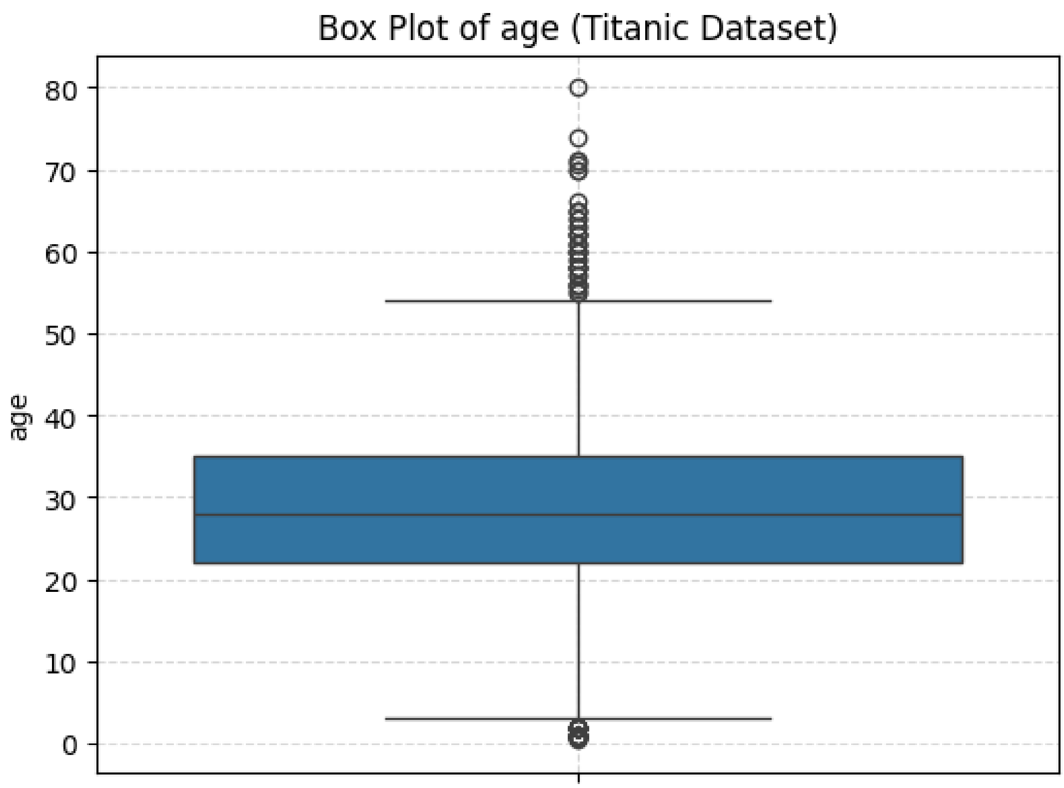


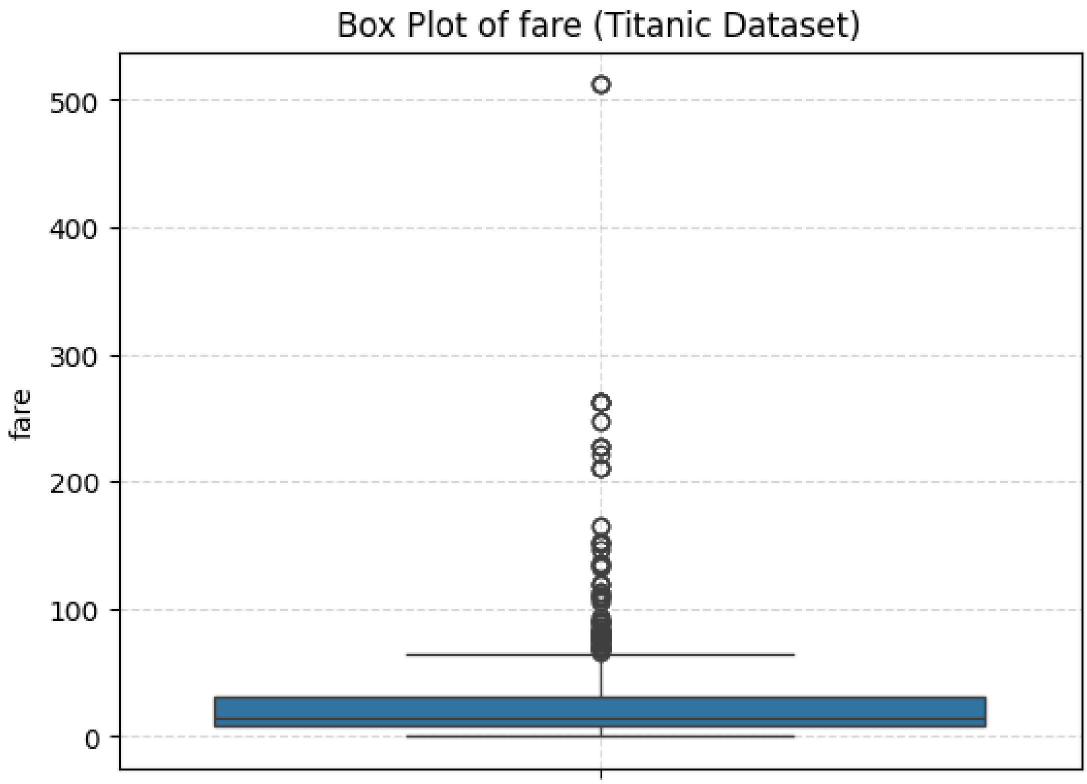

Fare
Count
fare
0
50
100
150
200
250
300
400
500


Correlation Matrix of Numeric Columns
survived
pclass
age
fare
1.00
-0.34
-0.06
0.26
-0.55
0.10
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

Step5:Handling outliers

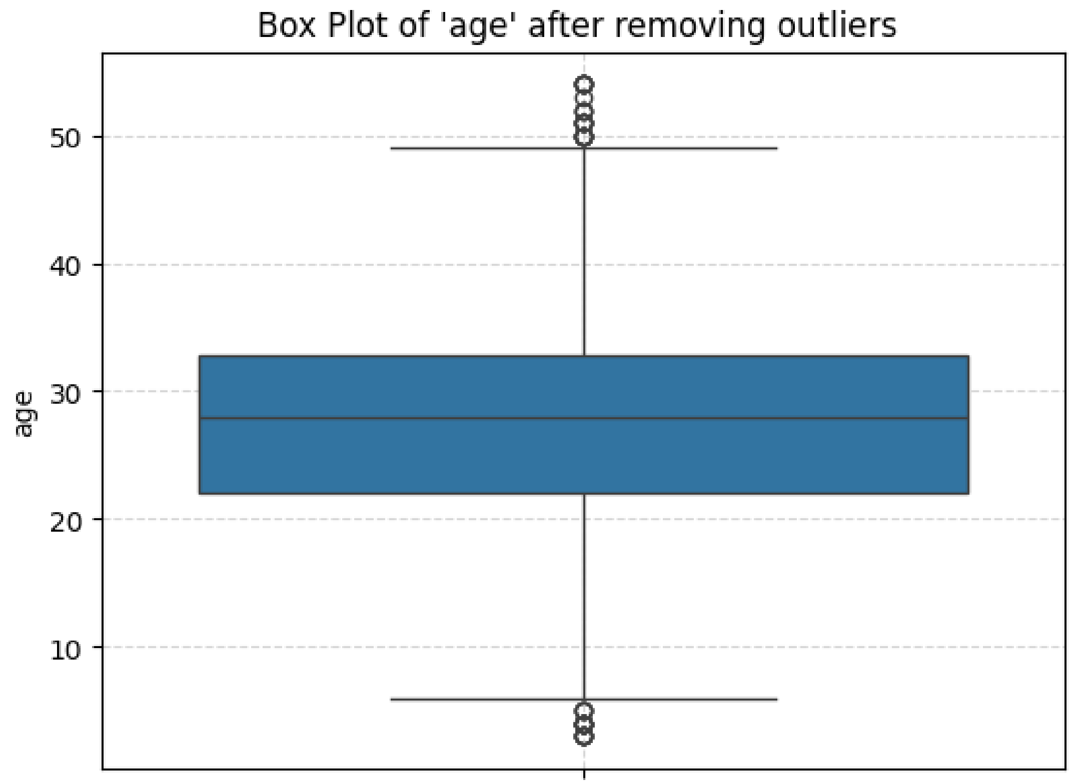
```
numerical_columns = ['age','fare']

for col in numerical_columns:
    sns.boxplot(data=titanic_df,y=col)
    plt.title(f"Box Plot of {col} (Titanic Dataset)")
    plt.grid(True,linestyle='--',alpha=0.5)
    plt.show()
```



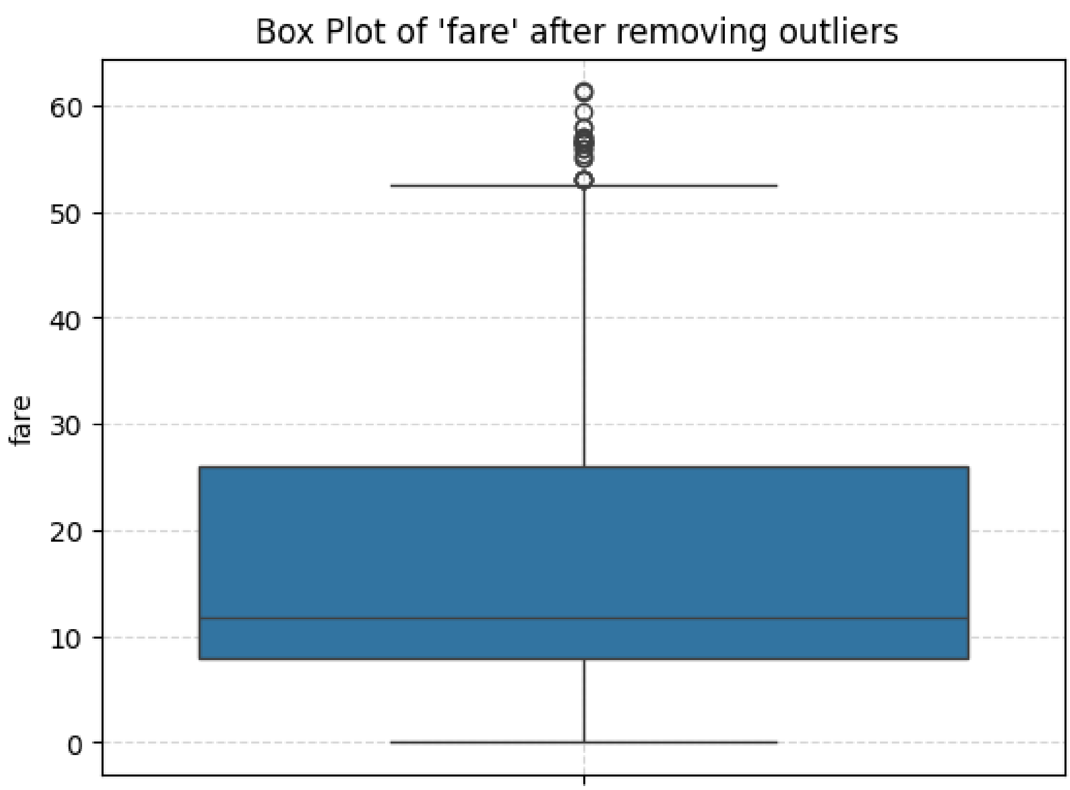


we can see there are outliers in the age and fare columns

```
def remove_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1

    # Define the bounds for filtering
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Filter the dataset to keep only non-outlier data
    df_filtered = df[(df[column] >= lower_bound) & (df[column] <=
upper_bound)]
    return df_filtered

titanic_data_cleaned = remove_outliers(titanic_df,'age')
titanic_data_cleaned = remove_outliers(titanic_data_cleaned,'fare')

for col in numerical_columns:
    sns.boxplot(data=titanic_data_cleaned,y=col)
    plt.title(f"Box Plot of '{col}' after removing outliers ")
    plt.grid(True,linestyle='--',alpha=0.5)
    plt.show()
```

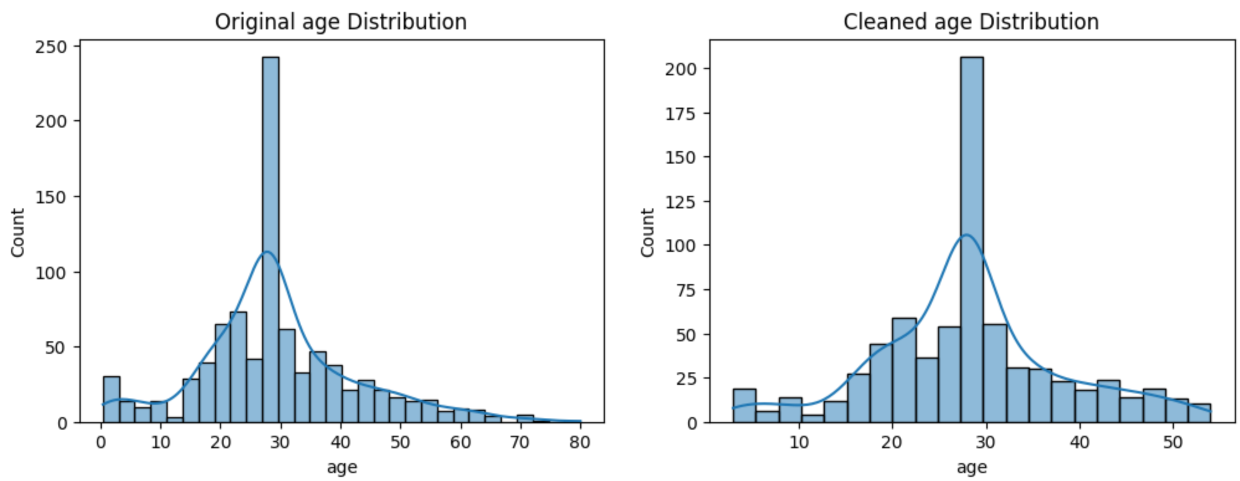


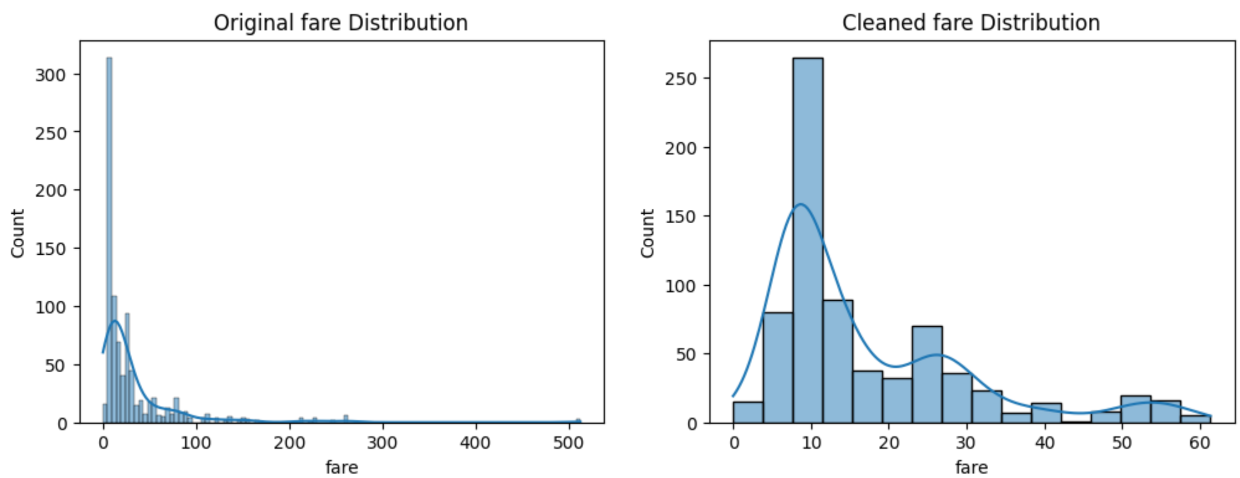
Box Plot of 'age' after removing outliers
age
50
40
30
20
10



Box Plot of 'fare' after removing outliers
fare
60
50
40
30
20
10
0

```python
def plot_distribution_comparison(df_original, df_cleaned, column):
    plt.figure(figsize=(12, 4))
    plt.subplot(1, 2, 1)
    sns.histplot(df_original[column], kde=True)
    plt.title(f'Original {column} Distribution')
    plt.subplot(1, 2, 2)
    sns.histplot(df_cleaned[column], kde=True)
    plt.title(f'Cleaned {column} Distribution')
    plt.show()

# Use for each numerical column
for col in numerical_columns:
    plot_distribution_comparison(titanic_df, titanic_data_cleaned,
col)
```





Step 6:Dealing with Categorical Data

```python
titanic_data_cleaned
```

```
     survived  pclass     sex   age     fare embarked   class
who  \
0           0       3    male  22.0   7.2500        S   Third    man

2           1       3  female  26.0   7.9250        S   Third  woman

3           1       1  female  35.0  53.1000        S   First  woman

4           0       3    male  35.0   8.0500        S   Third    man

5           0       3    male  28.0   8.4583        Q   Third    man

..        ...     ...     ...   ...      ...      ...     ...    ...

886         0       2    male  27.0  13.0000        S  Second    man

887         1       1  female  19.0  30.0000        S   First  woman

888         0       3  female  28.0  23.4500        S   Third  woman

889         1       1    male  26.0  30.0000        C   First    man

890         0       3    male  32.0   7.7500        Q   Third    man


     adult_male  embark_town alive  alone
0          True  Southampton    no  False
2         False  Southampton   yes   True
3         False  Southampton   yes  False
4          True  Southampton    no   True
5          True   Queenstown    no   True
..          ...          ...   ...    ...
886        True  Southampton    no   True
887       False  Southampton   yes   True
888       False  Southampton    no  False
889        True    Cherbourg   yes   True
890        True   Queenstown    no   True

[718 rows x 12 columns]

# Create separate encoders
le_sex = LabelEncoder()
le_who = LabelEncoder()

# Encode sex
titanic_data_cleaned['sex_encoded'] =
le_sex.fit_transform(titanic_data_cleaned['sex'])

# Encode who
titanic_data_cleaned['who_encoded'] =
le_who.fit_transform(titanic_data_cleaned['who'])
```

```
# If you need to know the mapping:
print("Sex categories:", le_sex.classes_)
print("Who categories:", le_who.classes_)
```

```
Sex categories: ['female' 'male']
Who categories: ['child' 'man' 'woman']
```

Step 7: Convert Categorical Columns into Numerical

```
# Initialize OneHotEncoder
ohe = OneHotEncoder(sparse_output=False)  # Use sparse=False for a
dense array

# Fit and transform the 'class' column
encoded_class = ohe.fit_transform(titanic_data_cleaned[['class']])
#2d

# Convert the encoded array to a DataFrame with proper column names
class_encoded_df = pd.DataFrame(encoded_class,
columns=ohe.get_feature_names_out(['class']))


# Ensure the encoded DataFrame has the same index as the original
DataFrame
class_encoded_df.index = titanic_data_cleaned.index

# Concatenate the encoded DataFrame with the original DataFrame
df_titanic = pd.concat([titanic_data_cleaned, class_encoded_df],
axis=1)

# Display the resulting DataFrame
df_titanic
```

```
     survived  pclass     sex   age     fare embarked   class
who  \
0           0       3    male  22.0   7.2500        S   Third    man

2           1       3  female  26.0   7.9250        S   Third  woman

3           1       1  female  35.0  53.1000        S   First  woman

4           0       3    male  35.0   8.0500        S   Third    man

5           0       3    male  28.0   8.4583        Q   Third    man

..        ...     ...     ...   ...      ...      ...     ...    ...

886         0       2    male  27.0  13.0000        S  Second    man
```

```
887          1        1  female  19.0  30.0000        S  First  woman
888          0        3  female  28.0  23.4500        S  Third  woman
889          1        1    male  26.0  30.0000        C  First    man
890          0        3    male  32.0   7.7500        Q  Third    man

     adult_male  embark_town alive  alone  sex_encoded  who_encoded  \
0          True  Southampton    no  False            1            1
2         False  Southampton   yes   True            0            2
3         False  Southampton   yes  False            0            2
4          True  Southampton    no   True            1            1
5          True   Queenstown    no   True            1            1
..          ...          ...   ...    ...          ...          ...
886        True  Southampton    no   True            1            1
887       False  Southampton   yes   True            0            2
888       False  Southampton    no  False            0            2
889        True    Cherbourg   yes   True            1            1
890        True   Queenstown    no   True            1            1

     class_First  class_Second  class_Third
0            0.0           0.0          1.0
2            0.0           0.0          1.0
3            1.0           0.0          0.0
4            0.0           0.0          1.0
5            0.0           0.0          1.0
..           ...           ...          ...
886          0.0           1.0          0.0
887          1.0           0.0          0.0
888          0.0           0.0          1.0
889          1.0           0.0          0.0
890          0.0           0.0          1.0

[718 rows x 17 columns]
```

Step 8: Feature Scaling

```
from sklearn.preprocessing import StandardScaler

# Initialize the scaler
scaler = StandardScaler()

# Scale Age and Fare columns
df_titanic[['Age', 'Fare']] = scaler.fit_transform(df_titanic[['age', 'fare']])

df_titanic.head()
```

```
   survived  pclass     sex   age     fare embarked  class    who
adult_male  \
0         0       3    male  22.0   7.2500        S  Third    man
True
2         1       3  female  26.0   7.9250        S  Third  woman
False
3         1       1  female  35.0  53.1000        S  First  woman
False
4         0       3    male  35.0   8.0500        S  Third    man
True
5         0       3    male  28.0   8.4583        Q  Third    man
True

   embark_town alive  alone  sex_encoded  who_encoded  class_First  \
0  Southampton    no  False            1            1          0.0
2  Southampton   yes   True            0            2          0.0
3  Southampton   yes  False            0            2          1.0
4  Southampton    no   True            1            1          0.0
5   Queenstown    no   True            1            1          0.0

   class_Second  class_Third       Age      Fare
0           0.0          1.0 -0.607611 -0.751265
2           0.0          1.0 -0.207827 -0.700265
3           0.0          0.0  0.691688  2.712961
4           0.0          1.0  0.691688 -0.690821
5           0.0          1.0 -0.007934 -0.659971
```