izrfdmleu

December 1, 2023

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

[ ]:
```
# IMPORT LIBRARY
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import␣
↪confusion_matrix,classification_report,accuracy_score
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
```

[ ]:
```
# CSV file and reads the data into a Pandas DataFrame object.
df=pd.read_csv('titanic.csv')
```

1 Exploratory data analysis(EDA) Python

[ ]:
```
# Shallow copy
df_copy=df.copy()
```

[ ]:
```
# The shape of a DataFrame.
df.shape
```

[ ]:
```
(891, 12)
```

[ ]:
```
# column labels of the Dataframe
df.columns
```

[ ]: Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')

[ ]:
```
# Returns a from the top.
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

                                                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
```

[ ]:
```
# Return the last 5 rows
df.tail()
```

[ ]:
```
     PassengerId  Survived  Pclass                                      Name  \
886          887         0       2                     Montvila, Rev. Juozas
887          888         1       1              Graham, Miss. Margaret Edith
888          889         0       3  Johnston, Miss. Catherine Helen "Carrie"
889          890         1       1                     Behr, Mr. Karl Howell
890          891         0       3                       Dooley, Mr. Patrick

        Sex   Age  SibSp  Parch      Ticket   Fare Cabin Embarked
886    male  27.0      0      0      211536  13.00   NaN        S
887  female  19.0      0      0      112053  30.00   B42        S
888  female   NaN      1      2  W./C. 6607  23.45   NaN        S
889    male  26.0      0      0      111369  30.00  C148        C
890    male  32.0      0      0      370376   7.75   NaN        Q
```

[ ]:
```
# specific rows of a DataFrame ( "integer location" Method)
df.iloc[100:200]
```

```
[ ]:      PassengerId  Survived  Pclass                                       Name  \
    100          101         0       3                  Petranec, Miss. Matilda
    101          102         0       3           Petroff, Mr. Pastcho ("Pentcho")
    102          103         0       1                 White, Mr. Richard Frasar
    103          104         0       3                Johansson, Mr. Gustaf Joel
    104          105         0       3             Gustafsson, Mr. Anders Vilhelm
    ..           …         …      …                                         …
    195          196         1       1                       Lurette, Miss. Elise
    196          197         0       3                       Mernagh, Mr. Robert
    197          198         0       3           Olsen, Mr. Karl Siegwart Andreas
    198          199         1       3           Madigan, Miss. Margaret "Maggie"
    199          200         0       2      Yrois, Miss. Henriette ("Mrs Harbeck")

            Sex   Age  SibSp  Parch     Ticket      Fare Cabin Embarked
    100  female  28.0      0      0     349245    7.8958   NaN        S
    101    male   NaN      0      0     349215    7.8958   NaN        S
    102    male  21.0      0      1      35281   77.2875   D26        S
    103    male  33.0      0      0       7540    8.6542   NaN        S
    104    male  37.0      2      0    3101276    7.9250   NaN        S
    ..     …   …    …    …        …     …   …      …
    195  female  58.0      0      0   PC 17569  146.5208   B80        C
    196    male   NaN      0      0     368703    7.7500   NaN        Q
    197    male  42.0      0      1       4579    8.4042   NaN        S
    198  female   NaN      0      0     370370    7.7500   NaN        Q
    199  female  24.0      0      0     248747   13.0000   NaN        S

    [100 rows x 12 columns]
```

```
[ ]: # describe() method gives us summary statistics for numerical columns in ␣
     ↪DataFrame.
     df.describe().T
```

```
[ ]:              count       mean         std   min       25%       50%    75%  \
    PassengerId  891.0  446.000000  257.353842  1.00  223.5000  446.0000  668.5
    Survived     891.0    0.383838    0.486592  0.00    0.0000    0.0000    1.0
    Pclass       891.0    2.308642    0.836071  1.00    2.0000    3.0000    3.0
    Age          714.0   29.699118   14.526497  0.42   20.1250   28.0000   38.0
    SibSp        891.0    0.523008    1.102743  0.00    0.0000    0.0000    1.0
    Parch        891.0    0.381594    0.806057  0.00    0.0000    0.0000    0.0
    Fare         891.0   32.204208   49.693429  0.00    7.9104   14.4542   31.0

                      max
    PassengerId  891.0000
    Survived       1.0000
    Pclass         3.0000
    Age           80.0000
    SibSp          8.0000
```

```
Parch          6.0000
Fare         512.3292
```

[ ]:
```
# prints information about the DataFrame. [number of columns, column labels,␣
↪column data types, memory usage, range index,]
df.info()
```

```
<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
```

[ ]:
```
# Including only string columns in a DataFrame description
df.describe(include=object)
```

[ ]:

	Name	Sex	Ticket	Cabin	Embarked
count	891	891	891	204	889
unique	891	2	681	147	3
top	Braund, Mr. Owen Harris	male	347082	B96 B98	S
freq	1	577	7	4	644

2 Data Cleaning

[ ]:
```
# To check for duplicate values in a  DataFrame
df.duplicated().sum()
```

[ ]: 0

[ ]:
```
df.drop(columns='PassengerId',inplace=True)
```

[ ]:
```
# returns the number of missing values.
df.isnull().sum()
```

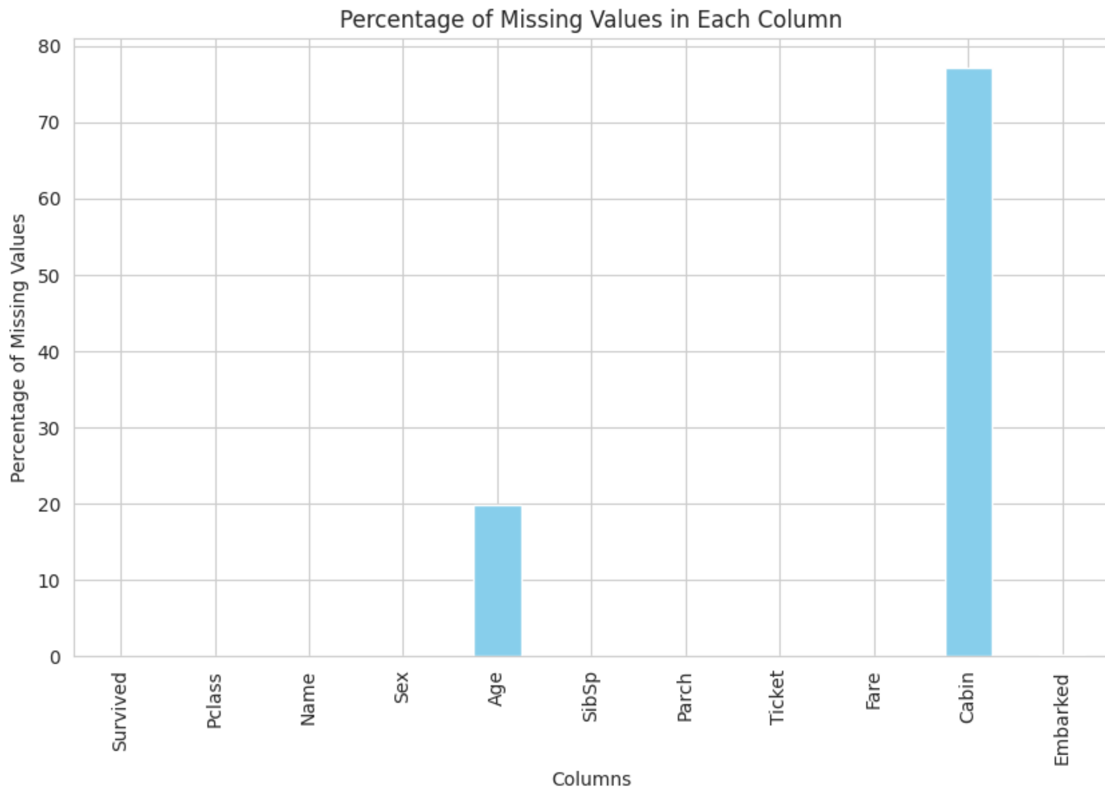
[ ]:
```
Survived      0
Pclass        0
Name          0
Sex           0
Age         177
SibSp         0
Parch         0
Ticket        0
Fare          0
Cabin       687
Embarked      2
dtype: int64
```

[ ]:
```
# Missing value percentage calculator
df.isnull().sum()*100/df.shape[0]
```

[ ]:
```
Survived     0.000000
Pclass       0.000000
Name         0.000000
Sex          0.000000
Age         19.865320
SibSp        0.000000
Parch        0.000000
Ticket       0.000000
Fare         0.000000
Cabin       77.104377
Embarked     0.224467
dtype: float64
```

[ ]:
```
# missing value percentage calculator plot
sns.set_style("whitegrid")
missing_percentage=df.isnull().sum()*100/df.shape[0]
plt.figure(figsize=(10, 6))
missing_percentage.plot(kind='bar', color='skyblue')
plt.xlabel('Columns')
plt.ylabel('Percentage of Missing Values')
plt.title('Percentage of Missing Values in Each Column')
```

[ ]:
```
Text(0.5, 1.0, 'Percentage of Missing Values in Each Column')
```



i'll drop capin because the null values are more than 40%

[ ]:
```
# removes columns that contains NULL values
df.drop(columns='Cabin',inplace=True)
```

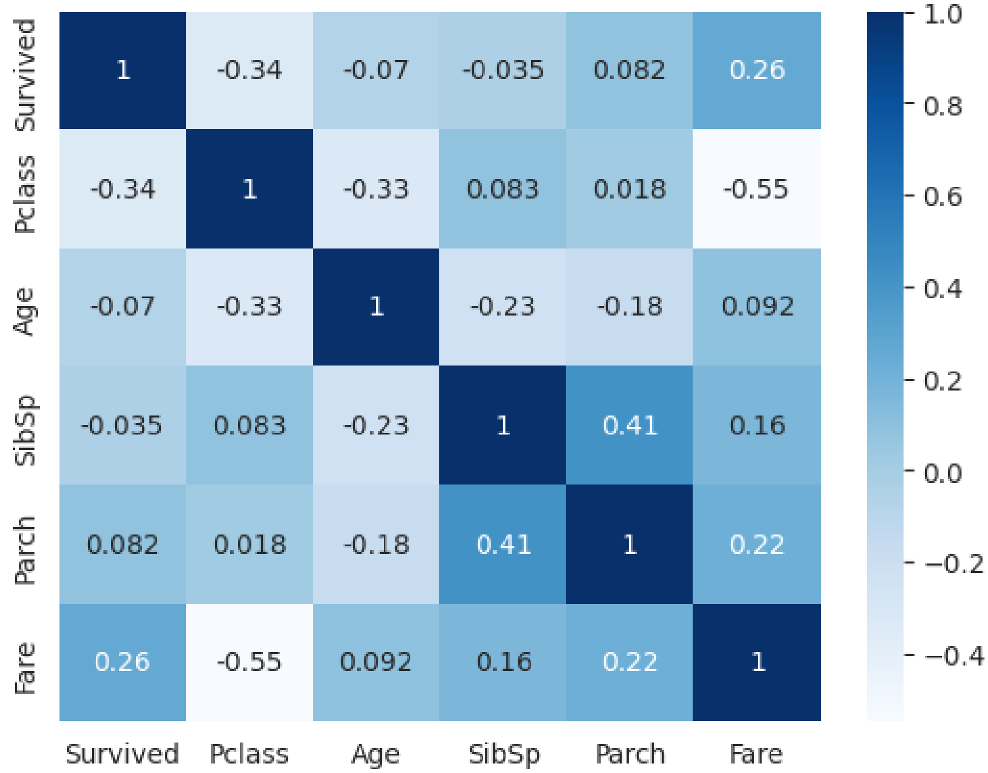
[ ]:
```
# replaces the NULL values with a specified value
df['Embarked'].fillna(method='ffill',inplace=True)
```

[ ]:
```
# The method of replacing NULL values with mean values.
df['Age'].fillna(df['Age'].mean(),inplace=True)
```

[ ]:
```
# used to plot rectangular data in the form of a color-coded matrix.

sns.heatmap(df.corr(),annot=True,cmap='Blues')
```

```
<ipython-input-22-f636f44a3637>:3: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sns.heatmap(df.corr(),annot=True,cmap='Blues')
```

[ ]: <Axes: >



[ ]:
```
# checks if there are any missing values in the DataFrame
df.isnull().sum().any()
```

[ ]:
```
False
```

[ ]:
```
# Numerical columns list
numerical_data=df.select_dtypes(include=['int64', 'float64']).columns.tolist()
```

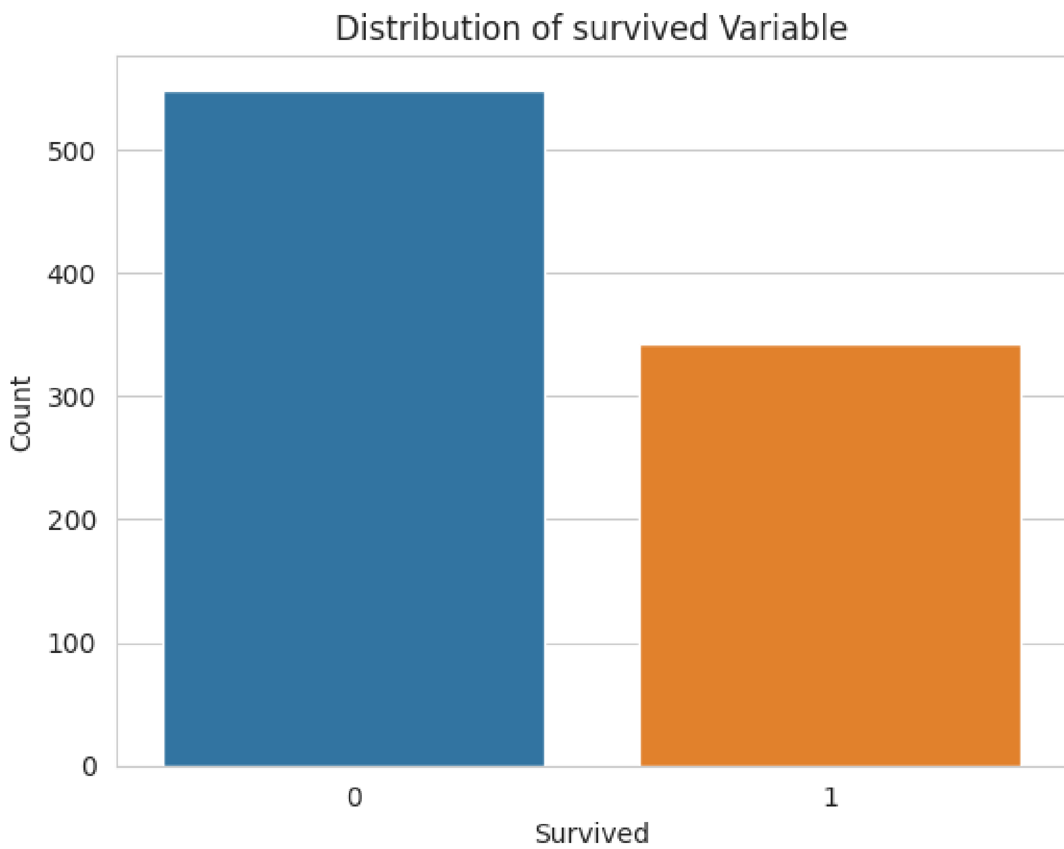
[ ]:
```
# Numerical columns list
object_data=df.select_dtypes(include=['object']).columns.tolist()
object_data
```

[ ]:
```
['Name', 'Sex', 'Ticket', 'Embarked']
```

3 visualization

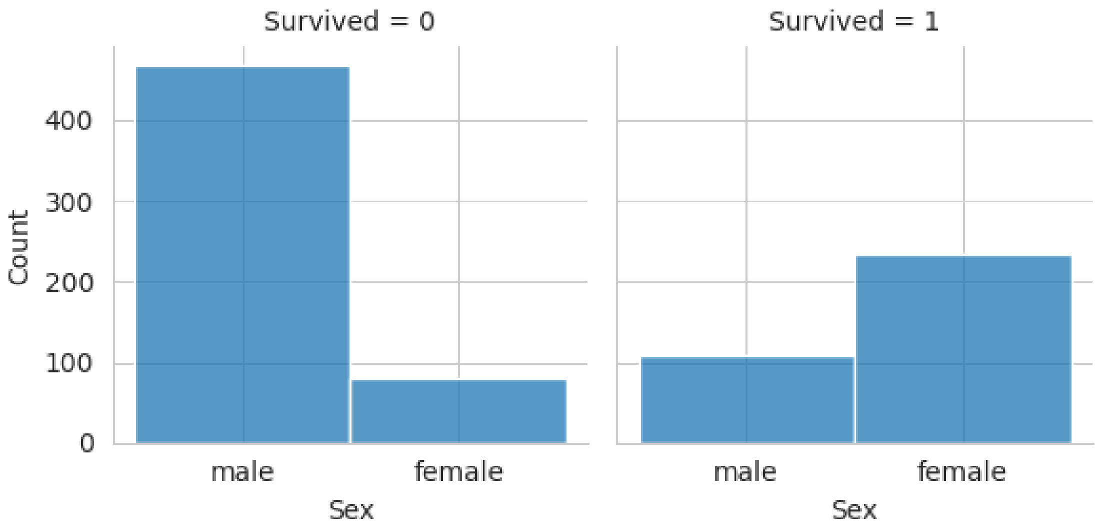
[ ]:
```
sns.countplot(x='Survived',data=df)
plt.title('Distribution of survived Variable')
plt.xlabel('Survived')
plt.ylabel('Count')
```

[ ]: Text(0, 0.5, 'Count')

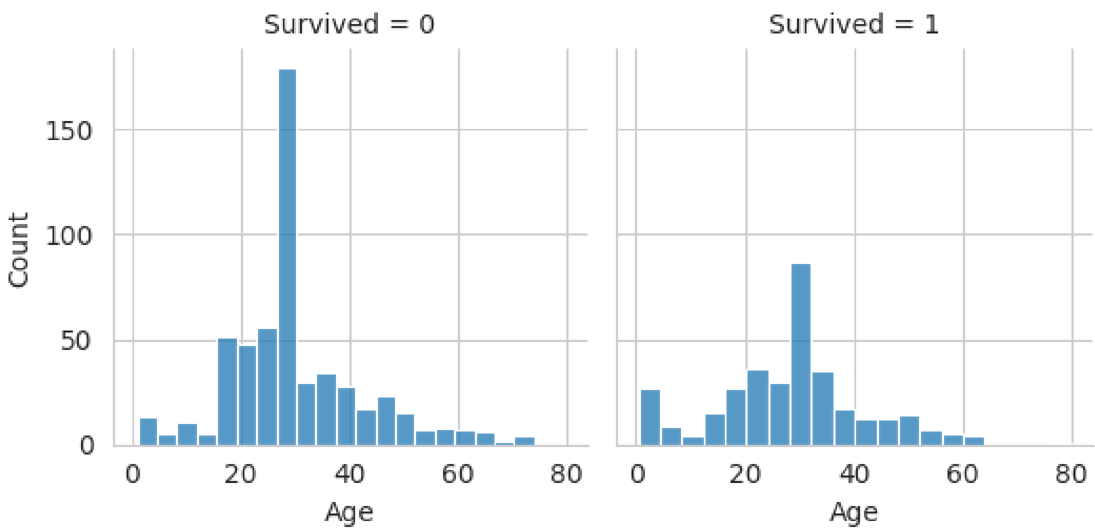


[ ]:
```
survied_fg=sns.FacetGrid(df, col="Survived")
survied_fg.map(sns.histplot, "Sex", bins=20)
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x7e1743a46260>

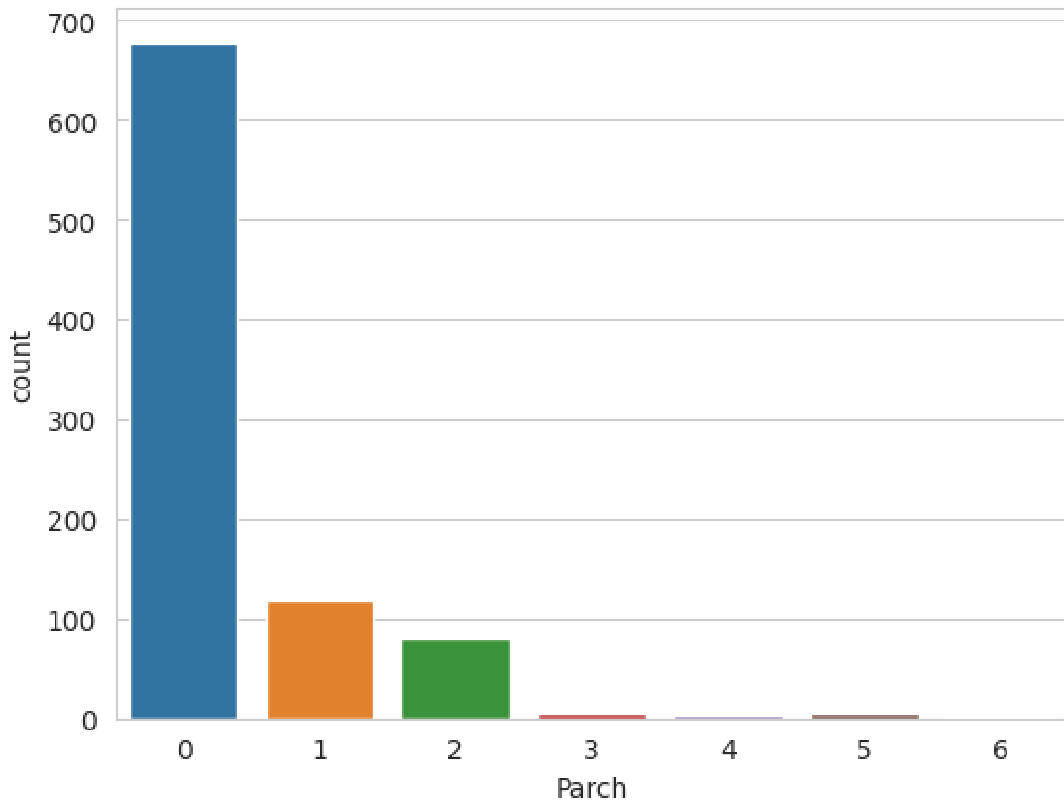



```
[ ]: survied_fg=sns.FacetGrid(df, col="Survived")
     survied_fg.map(sns.histplot,'Age',bins=20)
     plt.show()
```



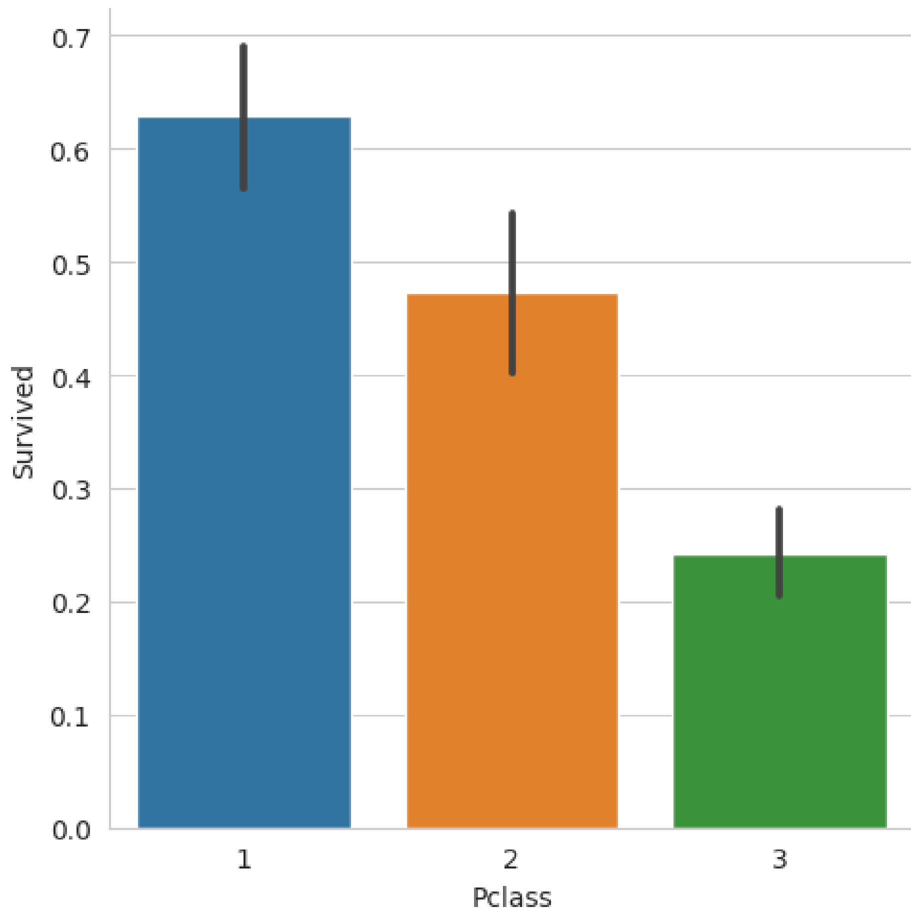

```
[ ]: sns.countplot(x='Parch',data=df)
```

```
[ ]: <Axes: xlabel='Parch', ylabel='count'>
```



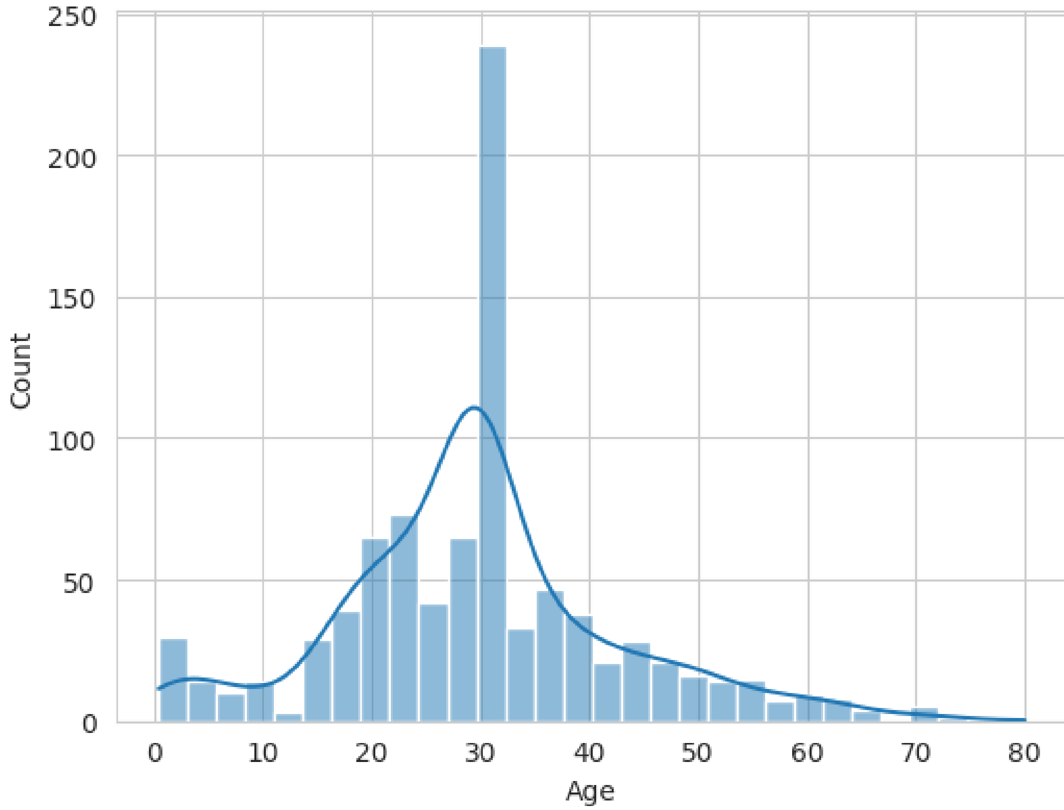
[ ]:
```
sns.catplot(x="Pclass", y="Survived", data=df, kind="bar")
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x7e170943b850>

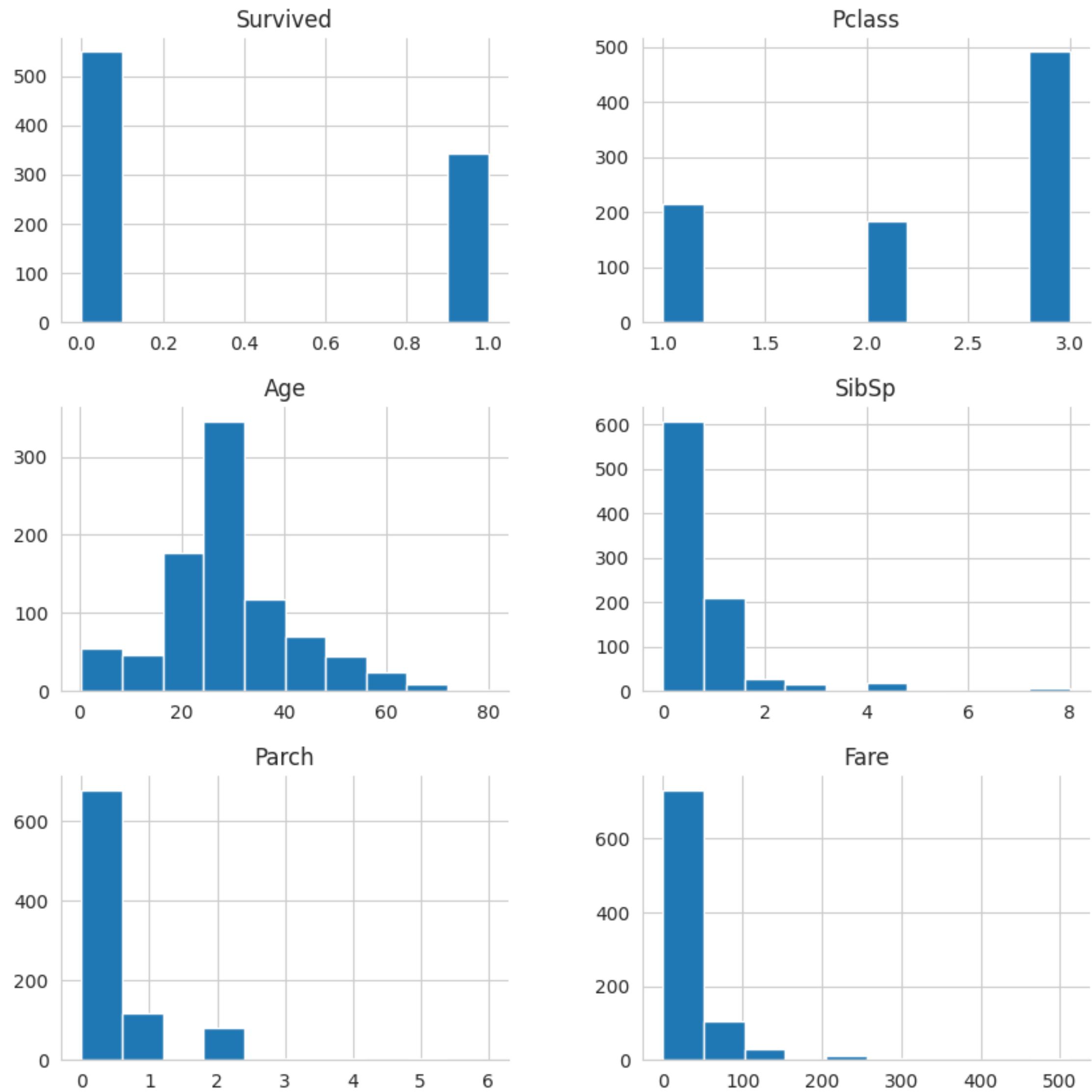


[ ]:
```
sns.histplot(df['Age'],kde=True)
```

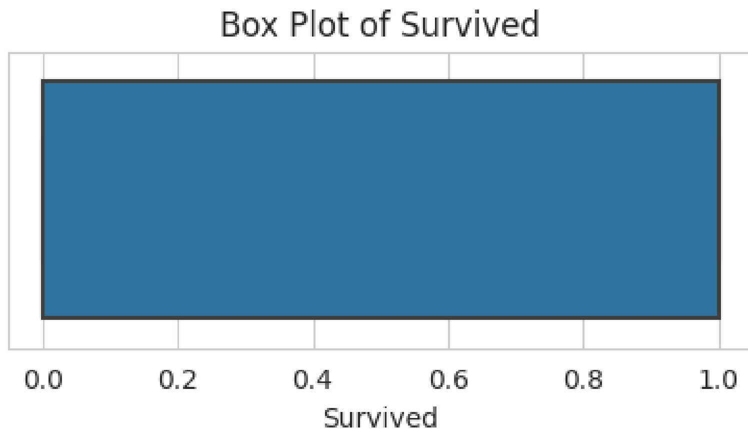
[ ]: <Axes: xlabel='Age', ylabel='Count'>

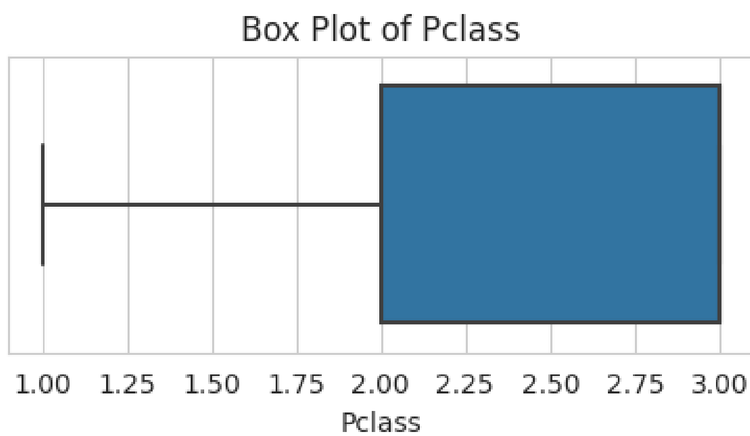


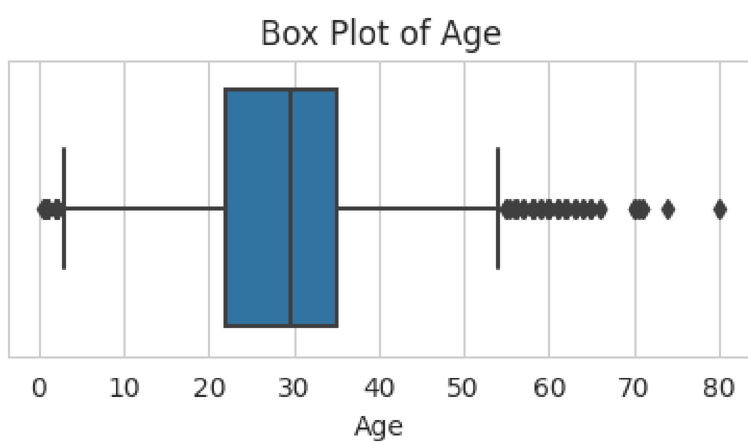

```
[ ]: df[numerical_data].hist(figsize=(10,10))
     sns.despine()
```



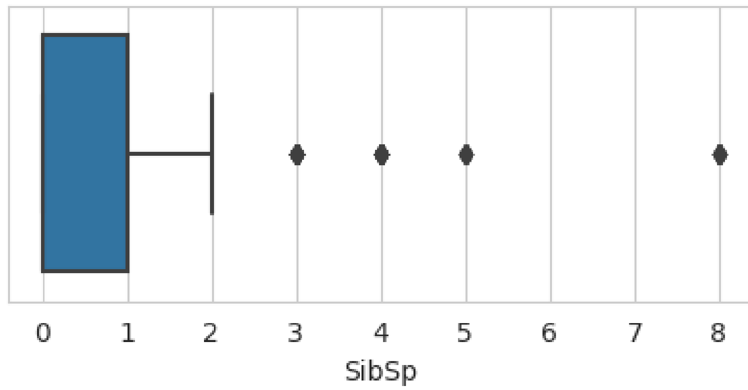
[ ]:
```
for column in df[numerical_data]:
    plt.figure(figsize=(5, 2))
    sns.boxplot(x=df[column])
    plt.title(f'Box Plot of {column}')
    plt.show()
```


Box Plot of Survived
0.0
0.2
0.4
0.6
0.8
1.0
Survived

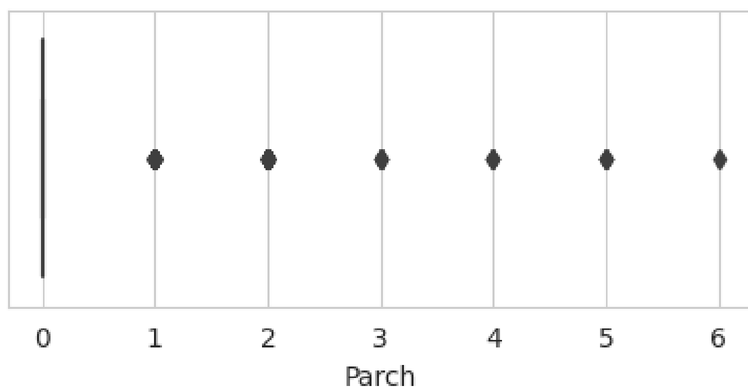

Box Plot of Pclass
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Pclass


Box Plot of Age
0
10
20
30
40
50
60
70
80
Age

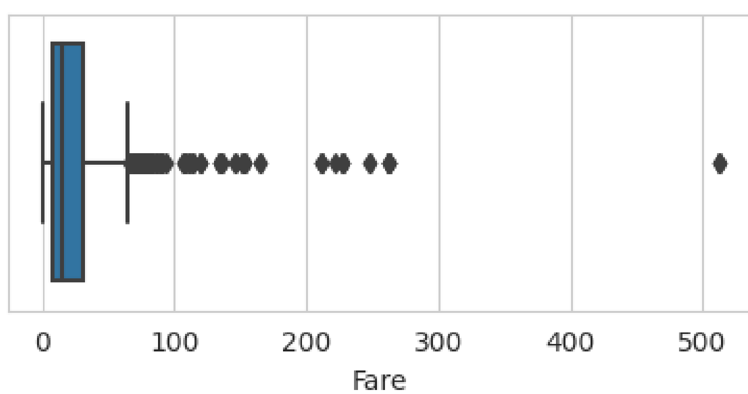
Box Plot of SibSp



Box Plot of Parch

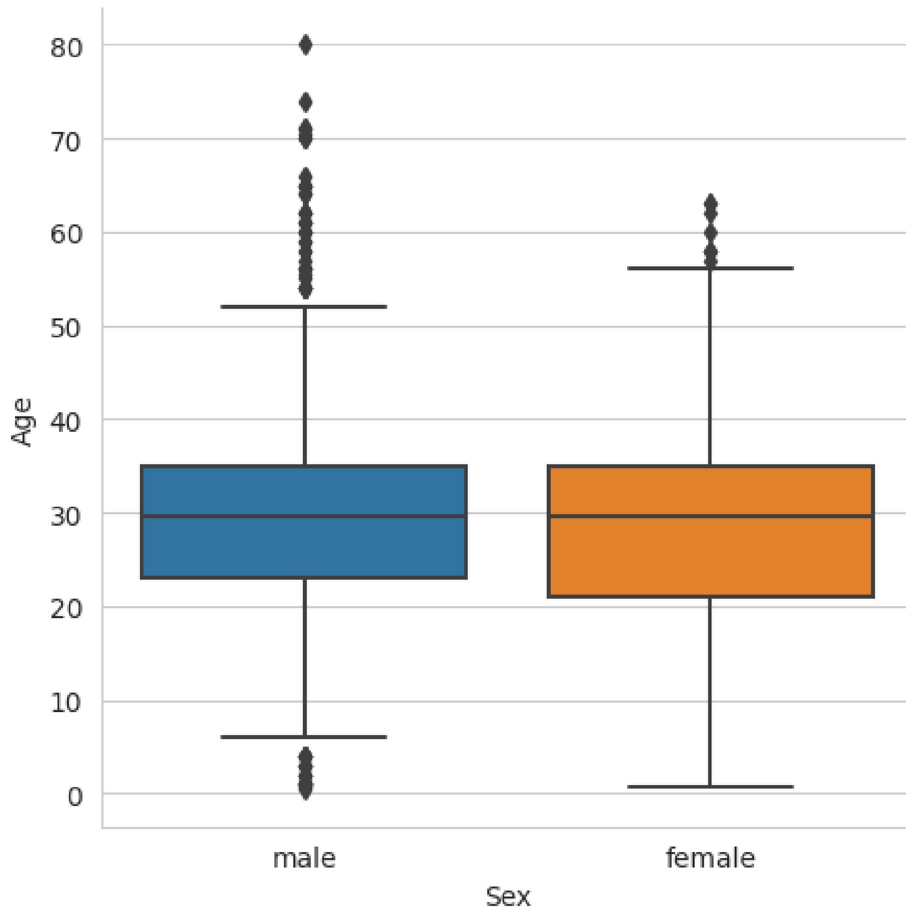


Box Plot of Fare



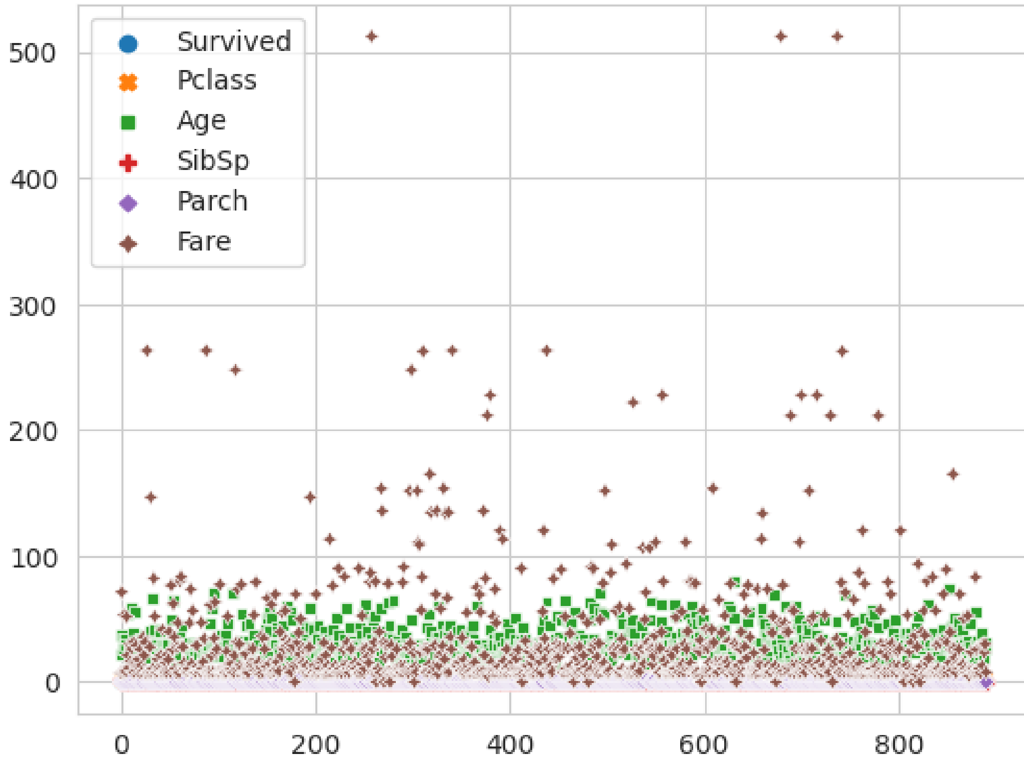
[ ]:
```
sns.catplot(data=df,x='Sex',y='Age',kind="box")
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x7e17094dd840>

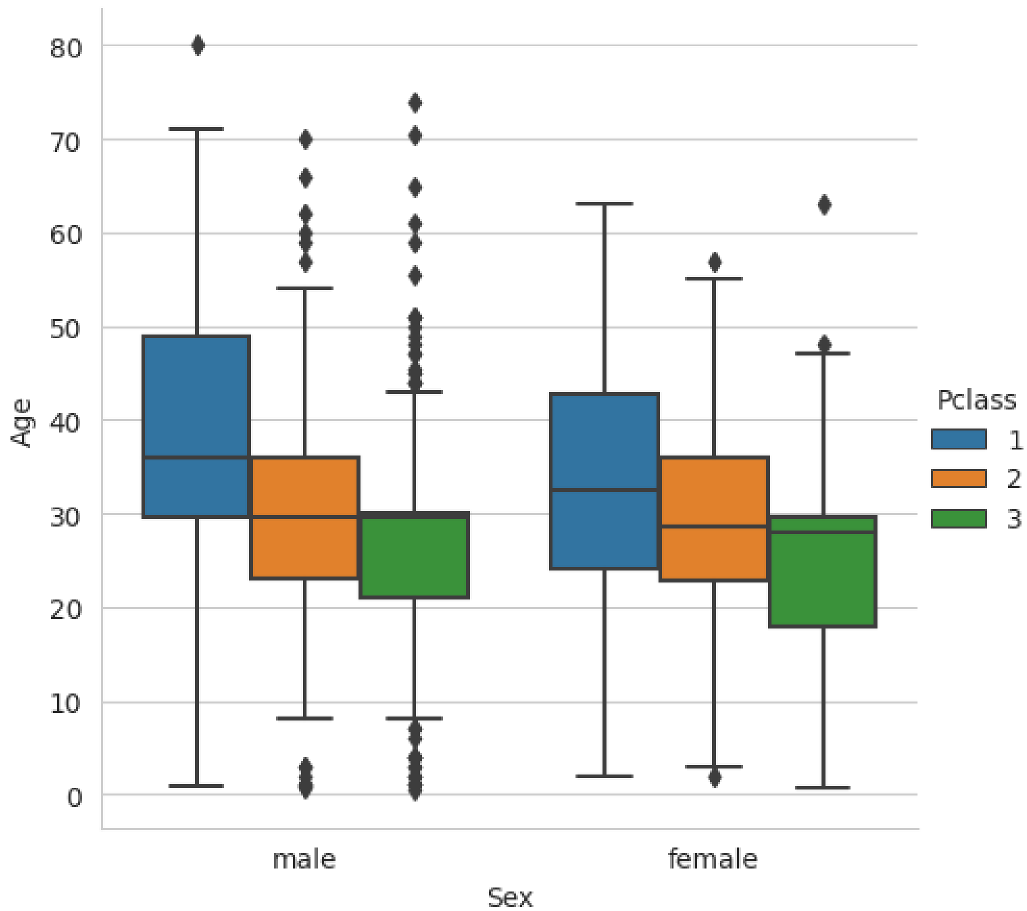


[ ]:
```
sns.scatterplot(df)
```

[ ]: <Axes: >

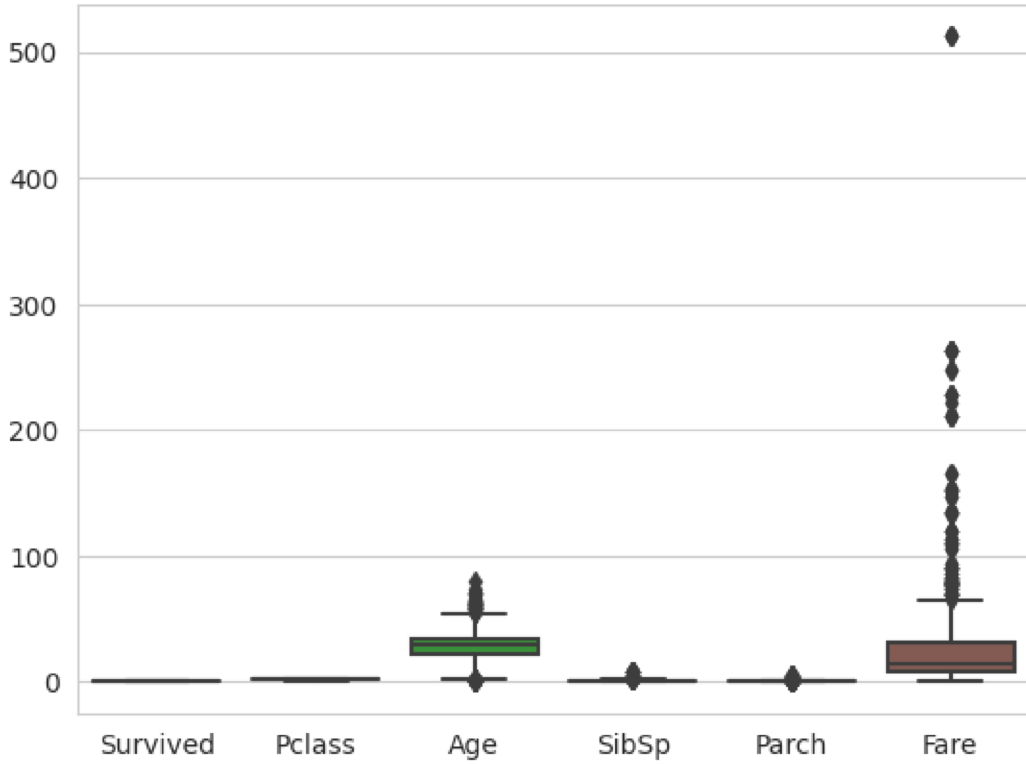


[ ]:
```
sns.catplot(x="Sex", y="Age", hue="Pclass", data=df, kind="box")
plt.show()
```



[ ]:
```
sns.boxplot(df[numerical_data])
```

[ ]: <Axes: >



4 LabelEncoder

[ ]:
```
lb=LabelEncoder()
df['Name']=lb.fit_transform(df['Name'])
df['Ticket']=lb.fit_transform(df['Ticket'])
```

[ ]:
```
df = pd.get_dummies(df, columns=['Embarked'])
df=pd.get_dummies(df,columns=['Sex'])
```

[ ]:
```
df
```

[ ]:
```
     Survived  Pclass  Name        Age  SibSp  Parch  Ticket     Fare  \
0           0       3   108  22.000000      1      0     523   7.2500
1           1       1   190  38.000000      1      0     596  71.2833
2           1       3   353  26.000000      0      0     669   7.9250
3           1       1   272  35.000000      1      0      49  53.1000
4           0       3    15  35.000000      0      0     472   8.0500
..        …     …   …        …    …   …     …      …
886         0       2   548  27.000000      0      0     101  13.0000
887         1       1   303  19.000000      0      0      14  30.0000
888         0       3   413  29.699118      1      2     675  23.4500
```

```
889          1        1     81  26.000000      0      0        8  30.0000
890          0        3    220  32.000000      0      0      466   7.7500

     Embarked_C  Embarked_Q  Embarked_S  Sex_female  Sex_male
0             0           0           1           0         1
1             1           0           0           1         0
2             0           0           1           1         0
3             0           0           1           1         0
4             0           0           1           0         1
..          …         …         …         …       …
886           0           0           1           0         1
887           0           0           1           1         0
888           0           0           1           1         0
889           1           0           0           0         1
890           0           1           0           0         1

[891 rows x 13 columns]
```

[ ]:
```
# x and y spilt
```

[ ]:
```
x=df.drop(columns='Survived',axis=1)
y=df['Survived']
```

5 StandardScaler

[ ]:
```
st=StandardScaler()
x=st.fit_transform(x)
```

6 Data Splitting

[ ]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
 ↪3,random_state=42)
```

7 Model building function

[ ]:
```
def train_evaluation_model(model,X_train,X_test,Y_train,Y_test):
  model.fit(X_train,Y_train)
  pred=model.predict(X_test)
  cm=confusion_matrix(Y_test,pred)
  acc=accuracy_score(Y_test,pred)*100
  cr=classification_report(Y_test,pred)
  print('confusion_matrix:\n',cm)
  print('accuracy_score:',acc)
  print('classification_report:\n',cr)
```

8 K-Nearest Neighbors(knn)

[ ]:
```
k=5
knn=KNeighborsClassifier(n_neighbors=k,p=2)
```

[ ]:
```
train_evaluation_model(knn,x_train,x_test,y_train,y_test)
```

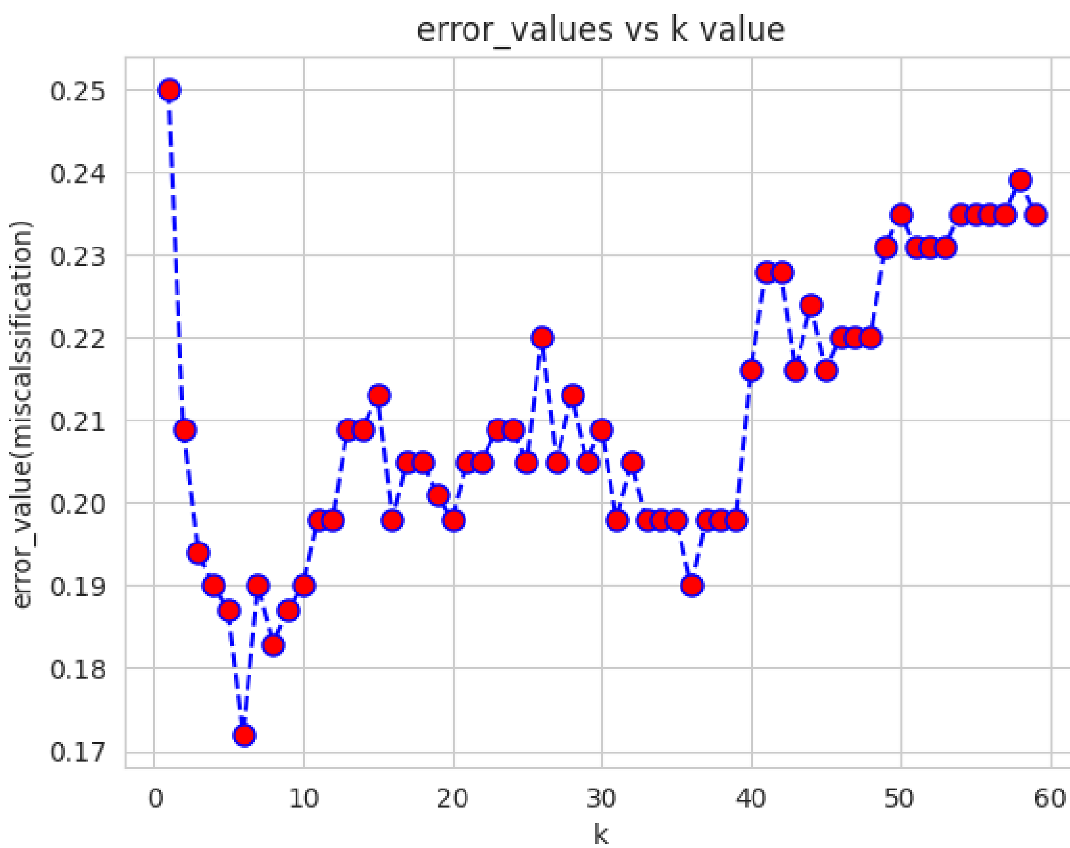
```
confusion_matrix:
 [[139  18]
 [ 32  79]]
accuracy_score: 81.34328358208955
classification_report:
               precision    recall  f1-score   support

           0       0.81      0.89      0.85       157
           1       0.81      0.71      0.76       111

    accuracy                           0.81       268
   macro avg       0.81      0.80      0.80       268
weighted avg       0.81      0.81      0.81       268
```

[ ]:
```
# K-Nearest Neighbors - Elbow Method Plot
```

[ ]:
```
error=[]
for i in range(1,60):
  knn_i=KNeighborsClassifier(n_neighbors=i)
  knn_i.fit(x_train,y_train)
  y_pred_knn_i=knn_i.predict(x_test)
  error.append(round(np.mean(y_pred_knn_i!=y_test),3))
```

[ ]:
```
# PLOT FOR ERROR VALUE
plt.
 ↪plot(range(1,60),error,color='blue',linestyle='dashed',marker='o',markerfacecolor='red',␣
 ↪markersize=8)
plt.title('error_values vs k value')
plt.xlabel('k')
plt.ylabel("error_value(miscalssification)")
```

[ ]:
```
Text(0, 0.5, 'error_value(miscalssification)')
```



9 Support Vector Machine(svm)

[ ]:
```
svm=SVC(kernel='linear')
```

[ ]:
```
train_evaluation_model(svm,x_train,x_test,y_train,y_test)
```

```
confusion_matrix:
 [[134  23]
 [ 33  78]]
accuracy_score: 79.1044776119403
classification_report:
              precision    recall  f1-score   support

           0       0.80      0.85      0.83       157
           1       0.77      0.70      0.74       111

    accuracy                           0.79       268
   macro avg       0.79      0.78      0.78       268
weighted avg       0.79      0.79      0.79       268
```

#Logistic Regression

[ ]:
```
lg=LogisticRegression()
```

[ ]:
```
train_evaluation_model(lg,x_train,x_test,y_train,y_test)
```

```
confusion_matrix:
 [[134  23]
 [ 29  82]]
accuracy_score: 80.59701492537313
classification_report:
               precision    recall  f1-score   support

           0       0.82      0.85      0.84       157
           1       0.78      0.74      0.76       111

    accuracy                           0.81       268
   macro avg       0.80      0.80      0.80       268
weighted avg       0.81      0.81      0.81       268
```

[55]:
```
# BY CHANDRASEKAR
```

[56]:
```
# Happy Coding!
```