2vn17tlld

December 12, 2023

IMPORTING LIBRARIES

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sb

#display all columns and rows of the dataframe
pd.set_option('display.max_columns',None)
pd.set_option('display.max_rows', 150)
```

LOADING THE DATA

[ ]:
```
from google.colab import files
raw=files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving titanic.csv to titanic.csv
```

REVIEWING THE DATASET

[ ]:
```
rdata=pd.read_csv('titanic.csv')
```

[ ]:
```
ndata=rdata.copy()
ndata
```

[ ]:
```
     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           ...       ...     ...
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         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
..                                                ...     …   …    …
886                            Montvila, Rev. Juozas    male  27.0      0
887                     Graham, Miss. Margaret Edith  female  19.0      0
888         Johnston, Miss. Catherine Helen "Carrie"  female   NaN      1
889                            Behr, Mr. Karl Howell    male  26.0      0
890                              Dooley, Mr. Patrick    male  32.0      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
..     …               …      …   …      …
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q

[891 rows x 12 columns]
```

[ ]:
```
df=ndata.copy()
```

[ ]:
```
print("Column Names:", df.columns)
```

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

Survived —> This is basically our target.(We've to train our model on the basis of this data.)

PClass —> Ticket Class (1=Luxurious Class , 2=Modest Class, 3=Steerage Class(Basic))

Fare —> Passenger fare

Cabin —> Cabin Number

Emarked —> From where the people started their voyage (C=Cherbourg, S= Southampton, Q=Queenstown)

sibsp: The dataset defines family relations in this way…

Sibling = brother, sister, stepbrother, stepsister

Spouse = husband, wife (mistresses and fiancés were ignored)

parch: The dataset defines family relations in this way…

Parent = mother, father

Child = daughter, son, stepdaughter, stepson

Some children travelled only with a nanny, therefore parch=0 for them

EXPLORATORY DATA ANALYSIS

[ ]:
```
df.shape
```

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

[ ]:
```
df.head()# Display the first few rows
```

[ ]:
```
   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
```

[ ]:
```
df.tail()# Display the last few rows
```

[ ]:
```
     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
```

[ ]:
```
# Display data types of columns in the DataFrame
print(df.dtypes)
```

```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

[ ]:
```
# Display basic information about the dataset
print(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
None
```

[ ]:
```
# Display summary for categorical data
print(df.describe(include='object').T)
```

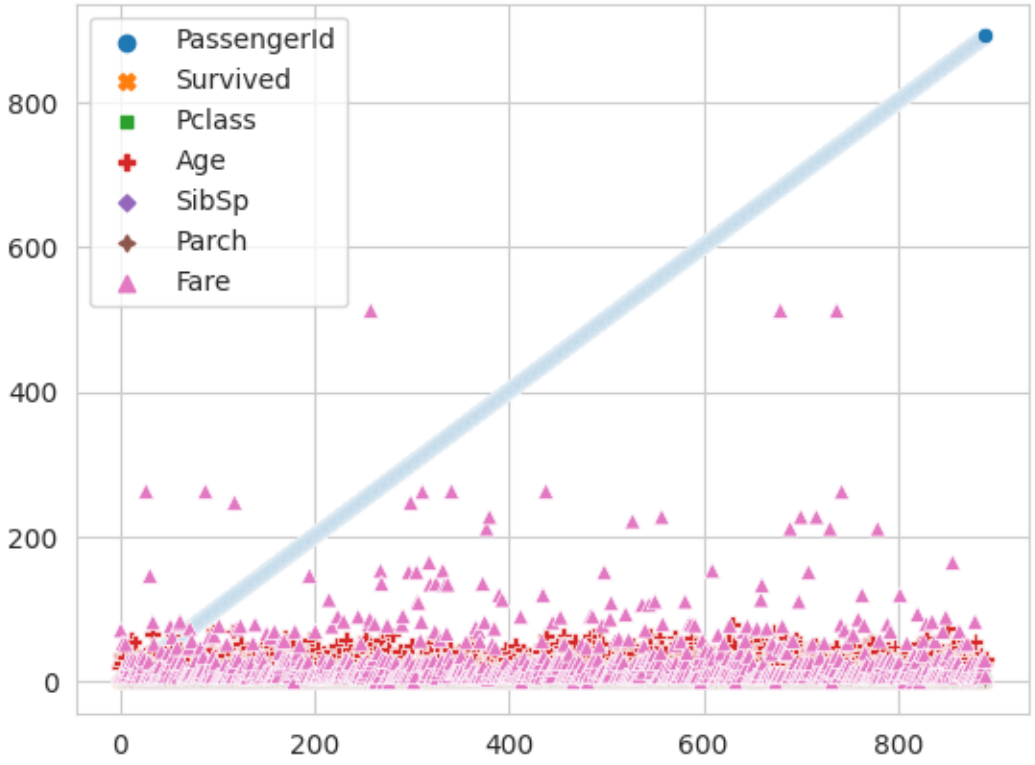
```
          count unique                      top freq
Name        891    891  Braund, Mr. Owen Harris    1
Sex         891      2                     male  577
Ticket      891    681                   347082    7
Cabin       204    147                 B96 B98    4
Embarked    889      3          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

1 Analyze survival rates by different factors

VISUALIZATION

[ ]:
```
sb.scatterplot(rdata)
```

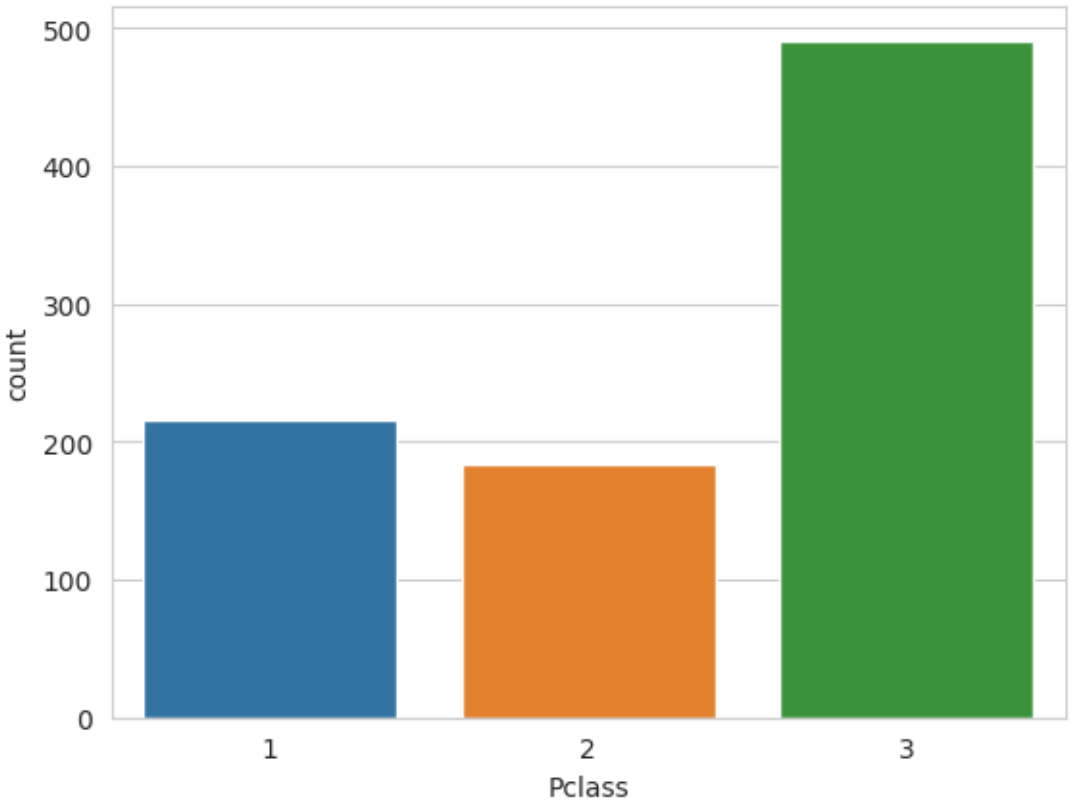
[ ]: <Axes: >



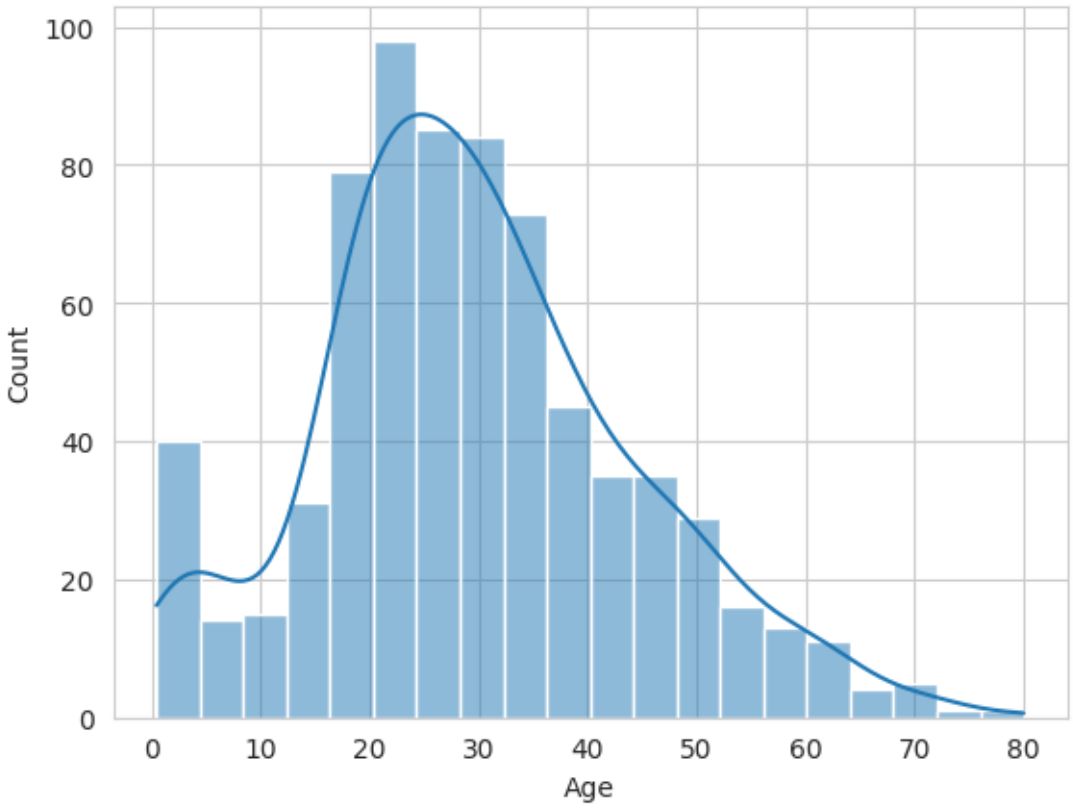
UNIVARIATE ANALYSIS

[ ]:
```
sb.countplot(x='Pclass', data=df)
```

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

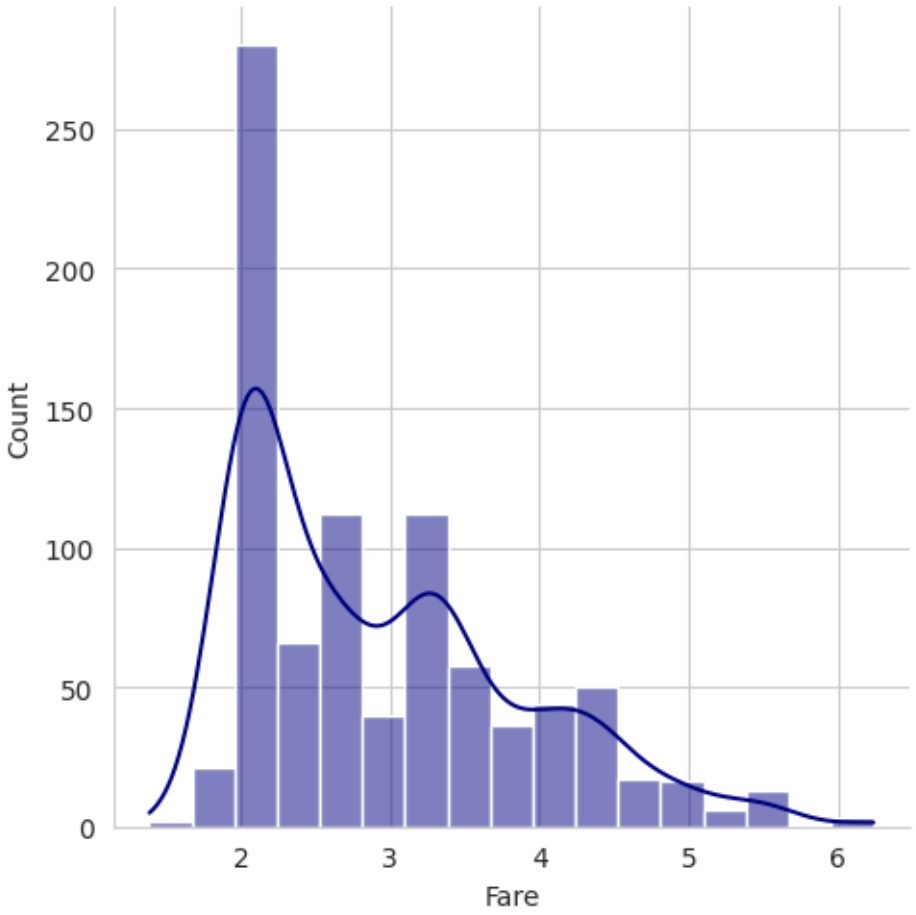


[ ]:
```
# Visualize distribution of a numerical column
sb.histplot(df['Age'], kde=True)
plt.show()
```



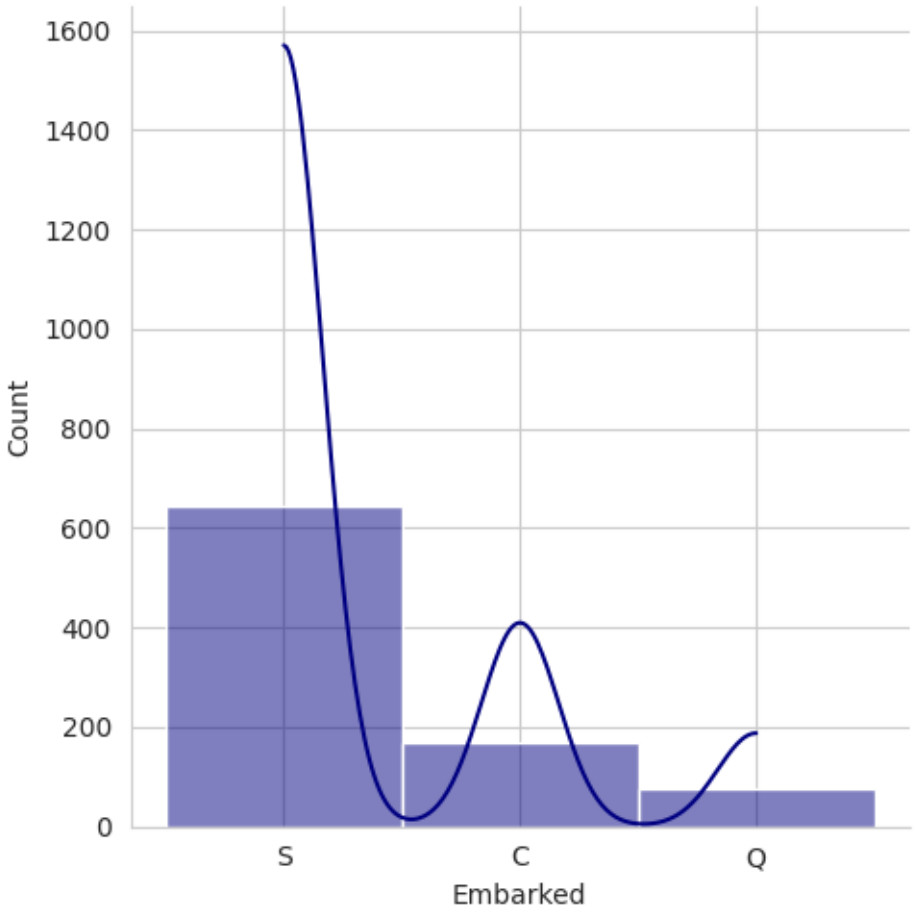
[ ]:
```
sb.displot(np.log(df['Fare']),kde=True, color='navy')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/pandas/core/arraylike.py:402:
RuntimeWarning: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

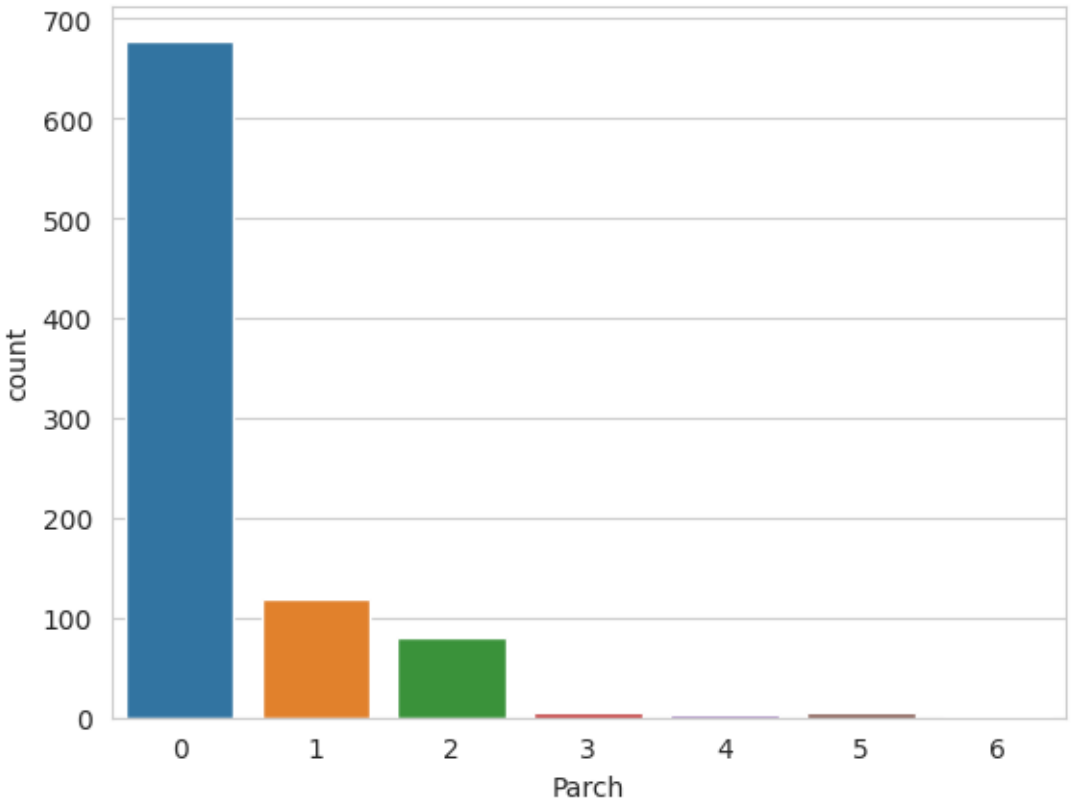


[ ]:
```
sb.displot(df['Embarked'], kde=True, color='navy')
plt.show
```

[ ]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



[ ]:
```
# Count plot for a categorical variable
sb.countplot(x='Parch', data=rdata)
plt.show()
```



BIVARAITE ANALYSIS

Selection of Relevant Data:

train[['Pclass', 'Survived']]: Choose only the 'Pclass' and 'Survived' columns from the 'train' DataFrame. Grouping by Passenger Class:

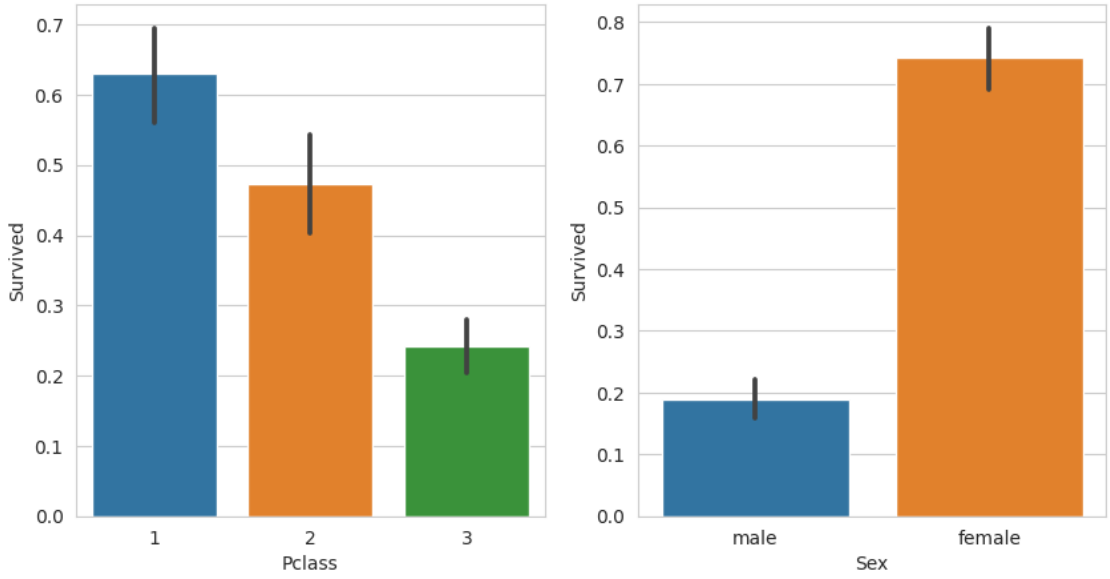
groupby(['Pclass'], as_index=False): Group the selected data based on the 'Pclass' column. The as_index=False part ensures that 'Pclass' doesn't become the index of the resulting grouped data. Calculating Average Survival Rate:

mean(): Calculate the mean (average) of the 'Survived' column for each group. This gives us the average survival rate for passengers in each passenger class. Printing the Result:

print(average_survival_rate): Display the resulting DataFrame that shows the average survival rate for each passenger class.

[ ]:
```
# Visualize survival rates
plt.figure(figsize=(10, 5))

# Bar plot for survival rates by Pclass
plt.subplot(1, 2, 1)
sb.barplot(x='Pclass', y='Survived', data=df)
```

```
# Bar plot for survival rates by Sex
plt.subplot(1, 2, 2)
sb.barplot(x='Sex', y='Survived', data=df)

plt.show()
```



[ ]:
```
# Select the 'Sex' and 'Survived' columns from the 'train' DataFrame
selected_data = df[['Sex', 'Survived']]

# Group the selected data by the 'Pclass' column
grouped_data = selected_data.groupby(['Sex'], as_index=False)

# Calculate the mean (average) of the 'Survived' column for each passenger class
average_survival_rate = grouped_data.mean()

# Print the result, showing the average survival rate for each passenger class
print(average_survival_rate)

 #on average,which gender had a higher survival rate
 #compared to those of male and female.
 #female survived more
```

```
      Sex  Survived
0  female  0.742038
1    male  0.188908
```

Relationship between age group and survived Define Bins and Labels:

bins = [0, 10, 20, 30, 40, 50, 60, 70, 80]: Specifies the bin edges. labels = ['0-9', '10-

19', '20-29', '30-39', '40-49', '50-59', '60-69', '70-79']: Assigns labels to the age groups. Create 'age_group' Column:

data['age_group'] = pd.cut(data['Age'], bins=bins, right=False, labels=labels, include_lowest=True): Creates a new column 'age_group' by cutting the 'Age' column into specified bins. Calculate Survival Rate:

survival_rate_by_age = data.groupby('age_group')['Survived'].mean(): Calculates the mean survival rate for each age group. Prepare Data for Seaborn:

survival_rate_by_age_group = survival_rate_by_age.reset_index(): Resets the index to make 'age_group' a column, which is helpful for Seaborn plotting. Plotting with Seaborn:

sns.barplot(x='age_group', y='Survived', data=survival_rate_by_age_group, palette='husl'): Plots a bar plot using Seaborn, showing the survival rate for each age group. Add Labels and Title:

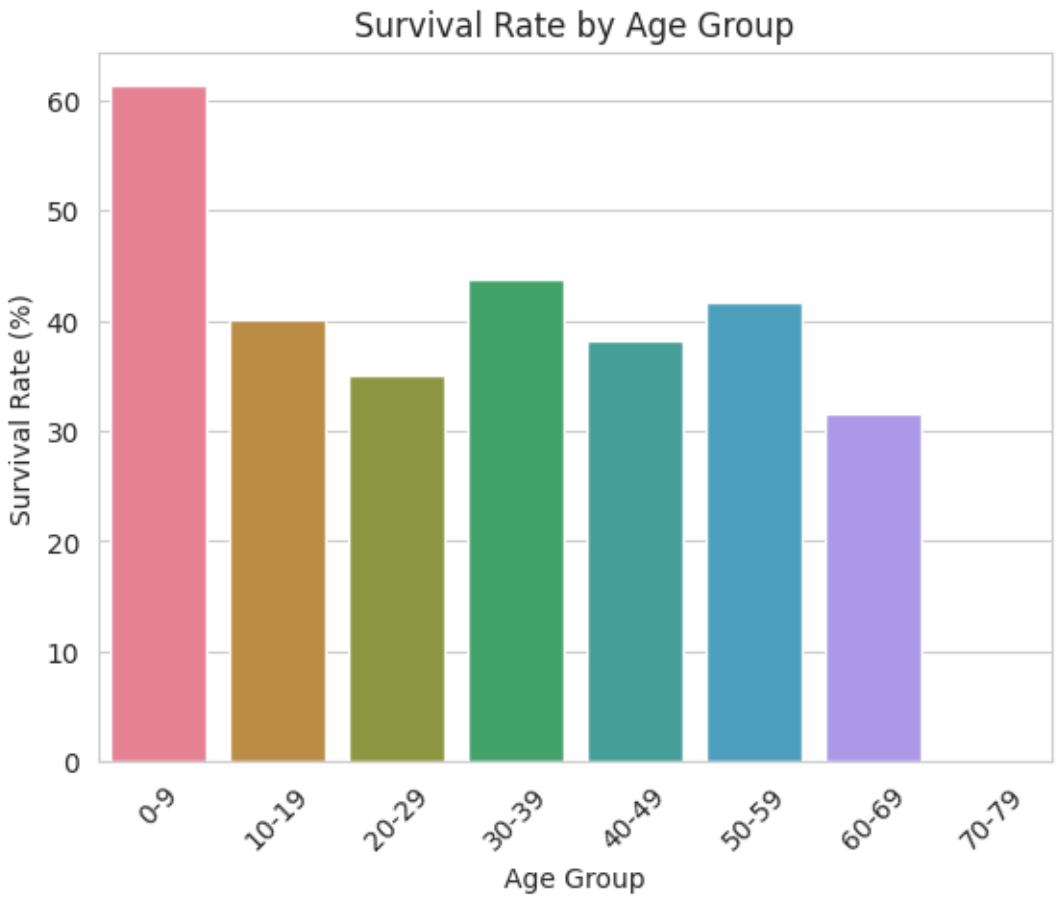
plt.xlabel('Age Group'): Adds a label to the x-axis. plt.ylabel('Survival Rate (%)'): Adds a label to the y-axis. plt.title('Survival Rate by Age Group'): Sets the title of the plot. Rotate X Labels:

plt.xticks(rotation=45): Rotates the x-axis labels for better readability. Show the Plot:

plt.show(): Displays the plot. This code produces a bar plot showing the survival rate for different age groups, providing insights into how age correlates with survival in the dataset.

[ ]:
```
# Define bin edges and labels for age groups
bins = [0, 10, 20, 30, 40, 50, 60, 70, 80]
labels = ['0-9', '10-19', '20-29', '30-39', '40-49', '50-59', '60-69', '70-79']

# Create a new column 'age_group' by cutting the data into bins
df['age_group'] = pd.cut(df['Age'], bins=bins, right=False, labels=labels,␣
 ↪include_lowest=True)

# Calculate the mean survival rate for each age group
survival_rate_by_age = df.groupby('age_group')['Survived'].mean()*100

# Reset index to make 'age_group' a column (helps with Seaborn plotting)
survival_rate_by_age_group = survival_rate_by_age.reset_index()

# Plotting with Seaborn
sb.barplot(x='age_group', y='Survived', data=survival_rate_by_age_group,␣
 ↪palette='husl')

# Add labels and title to the plot
plt.xlabel('Age Group')
plt.ylabel('Survival Rate (%)')
plt.title('Survival Rate by Age Group')

# Rotate the x labels for better readability
plt.xticks(rotation=45)
```

```
# Show the plot
plt.show()
```



Creates a new column 'Family' indicating whether a passenger had any family member aboard (1 if yes, 0 if no).

Drops the 'Parch' and 'SibSp' columns as they are no longer needed.

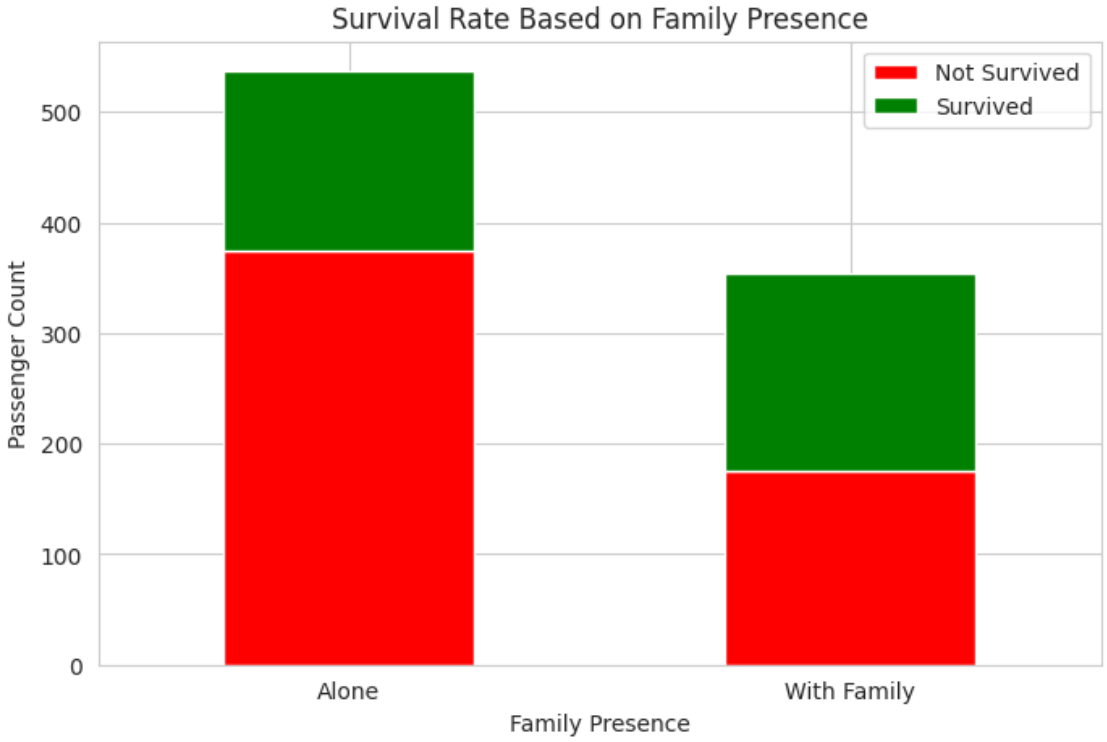
Plots two subplots:

The first subplot (axis1) is a count plot showing the distribution of passengers with and without family.

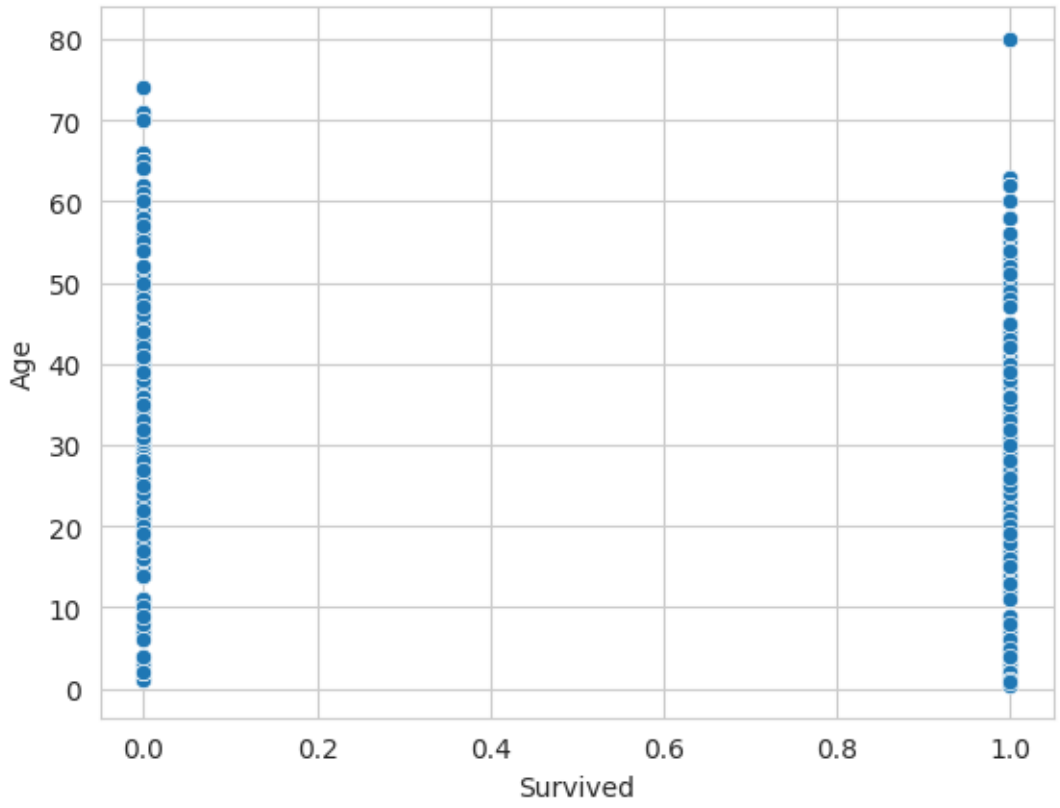
The second subplot (axis2) is a bar plot showing the average survival rate for passengers with and without family.

[ ]:
```
# Create a 'Family' column indicating whether a passenger had any family member␣
↪aboard
ndata['Family'] = (ndata['Parch'] + ndata['SibSp'] > 0).astype(int)
```

```
# Drop 'Parch' and 'SibSp' columns
ndata = ndata.drop(['Parch', 'SibSp'], axis=1)


# Create a stacked bar plot
family_survived = ndata.groupby(['Family', 'Survived']).size().unstack()
family_survived.columns = ['Not Survived', 'Survived']

# Plotting
family_survived.plot(kind='bar', stacked=True, color=['red', 'green'],␣
 ↪figsize=(8, 5))
plt.xticks([0, 1], ["Alone", "With Family"], rotation=0)
plt.title("Survival Rate Based on Family Presence")
plt.xlabel("Family Presence")
plt.ylabel("Passenger Count")

plt.show()
```



[ ]:
```
# Scatter plot
sb.scatterplot(x='Survived', y='Age', data=df)
plt.show()
```

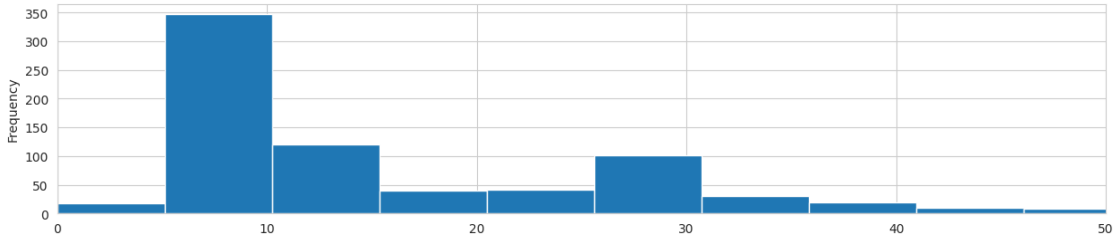


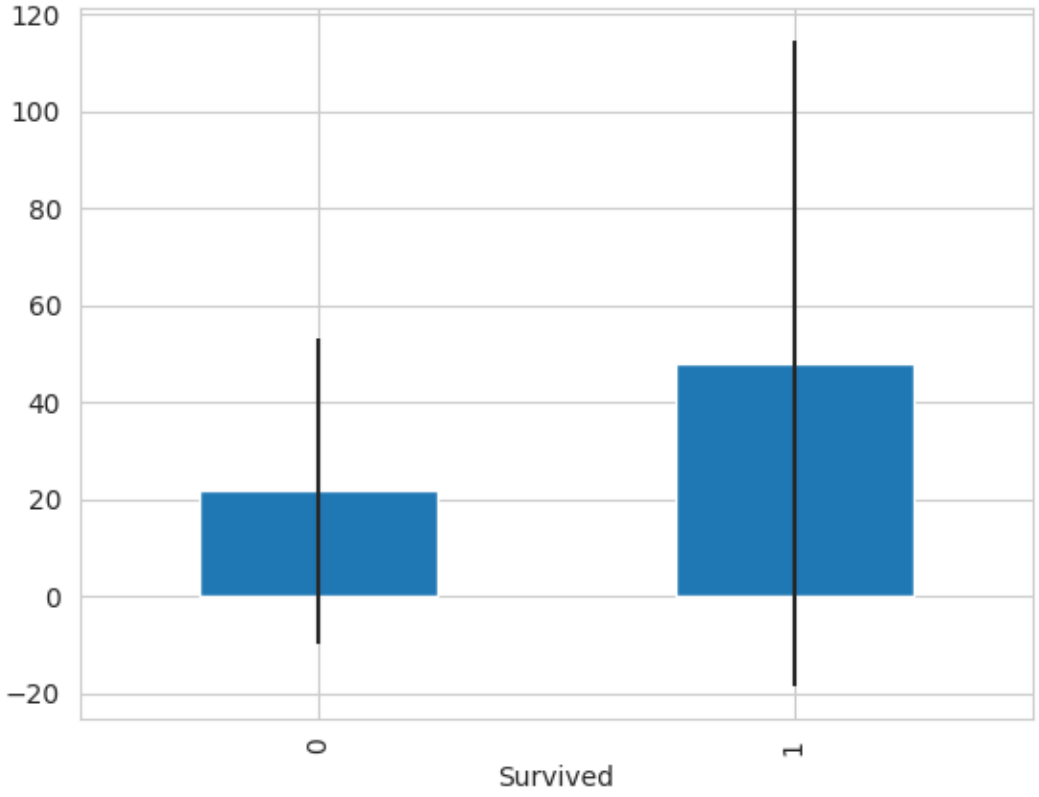
RELATIONSHIP BETWEEN FARE AND SURVIVED***

[ ]:
```
# Convert the 'Fare' column from float to integer for both DataFrames
df['Fare'] = df['Fare'].astype(int)

# Get the fare for survived and didn't survive passengers
fare_not_survived =df["Fare"][df["Survived"] == 0]
fare_survived = df["Fare"][df["Survived"] == 1]

# Calculate the average and standard deviation for fare of survived and not␣
 ↪survived passengers
average_fare = pd.DataFrame([fare_not_survived.mean(), fare_survived.mean()])
std_fare = pd.DataFrame([fare_not_survived.std(), fare_survived.std()])

# Plotting
df['Fare'].plot(kind='hist', figsize=(15, 3), bins=100, xlim=(0, 50))

# Set names for index in average_fare and std_fare DataFrames
average_fare.index.names = std_fare.index.names = ["Survived"]
```

```
# Plot a bar plot of average fare with error bars representing standard␣
  ↪deviation
average_fare.plot(yerr=std_fare, kind='bar', legend=False)
```

[ ]: <Axes: xlabel='Survived'>



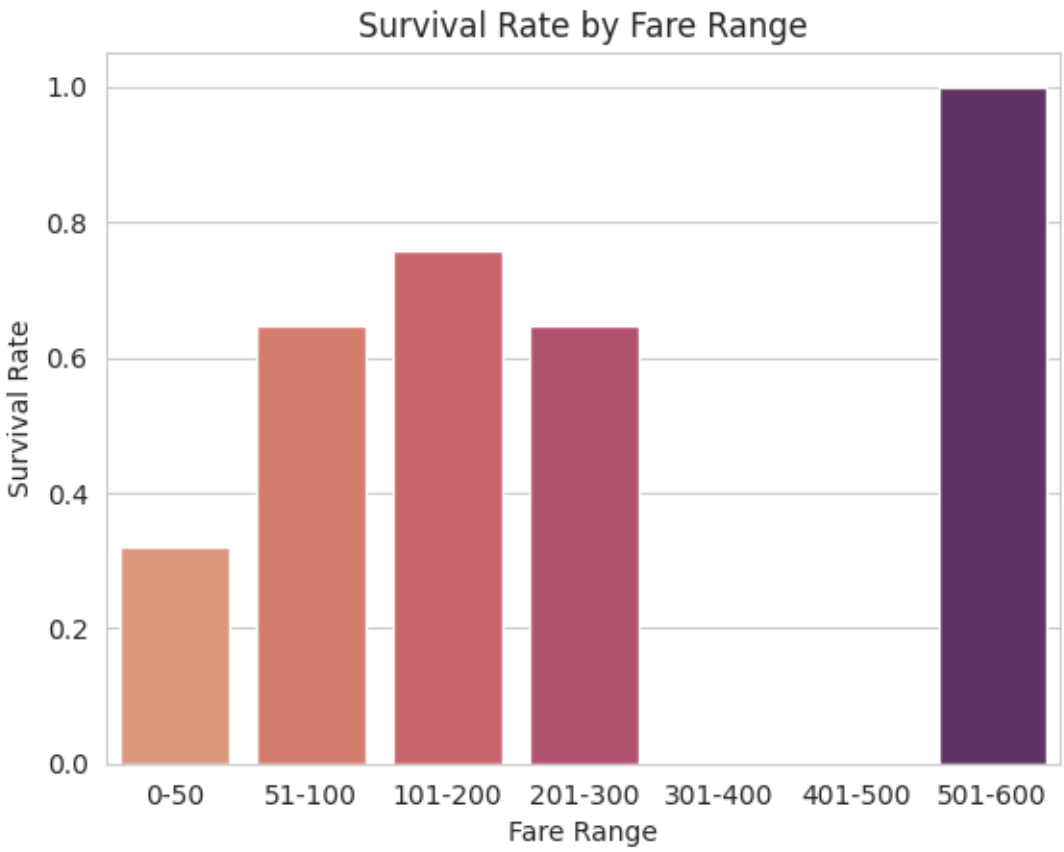


[ ]:
```
df['Fare'].unique()
```

[ ]:
```
array([  7,  71,  53,   8,  51,  21,  11,  30,  16,  26,  31,  29,  13,
        18,  35, 263,  27, 146,  10,  82,  52,   9,  41,  15,  17,  39,
        76,  61,  46,  80,  83,  73,  14,  56,  12,  47,  34,  20,  63,
```

```
 23,  77,  24, 247,  22,   6,  79,  36,  66,  69,  55,  25,  33,
 28,   0,  50, 113,  90,  86, 512, 153, 135,  19,  78,  91, 151,
110, 108, 262, 164, 134,  57, 133,  75, 211,   4, 227, 120,  32,
 81,  89,  38,  49,  59,  93, 221, 106,  40,  42,  65,  37,   5])
```

[ ]:
```
# Assuming 'data' is your DataFrame
# Define fare bins and labels
fare_bins = [0, 50, 100, 200, 300, 400, 500, 600]
fare_labels = ['0-50', '51-100', '101-200', '201-300', '301-400', '401-500',␣
 ↪'501-600']

# Create a new column 'FareRange' based on fare bins
df['FareRange'] = pd.cut(df['Fare'], bins=fare_bins, labels=fare_labels,␣
 ↪right=False, include_lowest=True)

# Calculate survival rate by fare range
survival_rate_by_fare = df.groupby('FareRange')['Survived'].mean().reset_index()

# Plotting
sb.barplot(data=survival_rate_by_fare, x='FareRange', y='Survived',␣
 ↪palette='flare')
plt.xlabel('Fare Range')
plt.ylabel('Survival Rate')
plt.title('Survival Rate by Fare Range')
plt.show()
```



[ ]:
```
#display summary for numerical data
df.describe().T
```

[ ]:

	count	mean	std	min	25%	50%	75%	max
PassengerId	891.0	446.000000	257.353842	1.00	223.500	446.0	668.5	891.0
Survived	891.0	0.383838	0.486592	0.00	0.000	0.0	1.0	1.0
Pclass	891.0	2.308642	0.836071	1.00	2.000	3.0	3.0	3.0
Age	714.0	29.699118	14.526497	0.42	20.125	28.0	38.0	80.0
SibSp	891.0	0.523008	1.102743	0.00	0.000	0.0	1.0	8.0
Parch	891.0	0.381594	0.806057	0.00	0.000	0.0	0.0	6.0
Fare	891.0	31.785634	49.703730	0.00	7.000	14.0	31.0	512.0

DATACLEANING:

Detecting missing values

[ ]:
```
rdata.isnull().sum()
```

[ ]:
```
PassengerId      0
Survived         0
Pclass           0
```

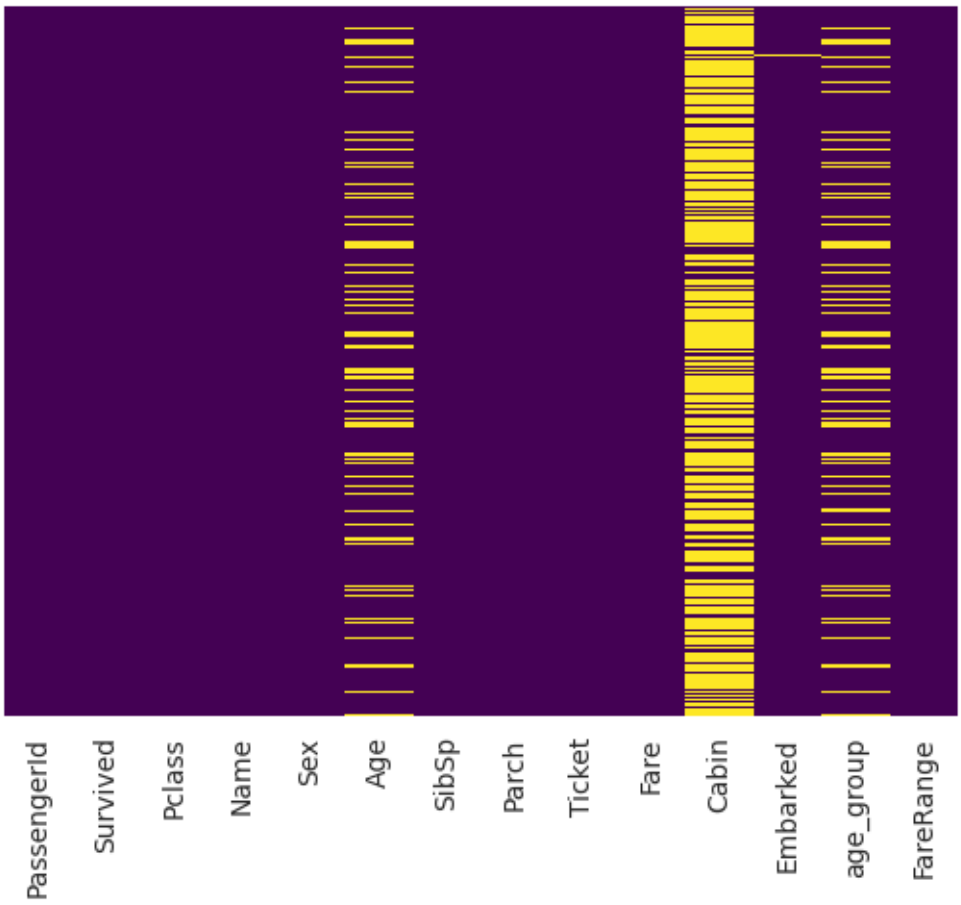
```
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

[ ]:
```
df.isna().sum()
```

[ ]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
age_group      178
FareRange        0
dtype: int64
```

[ ]:
```
sb.heatmap(df.isna(),yticklabels=False,cbar=False,cmap='viridis')
```

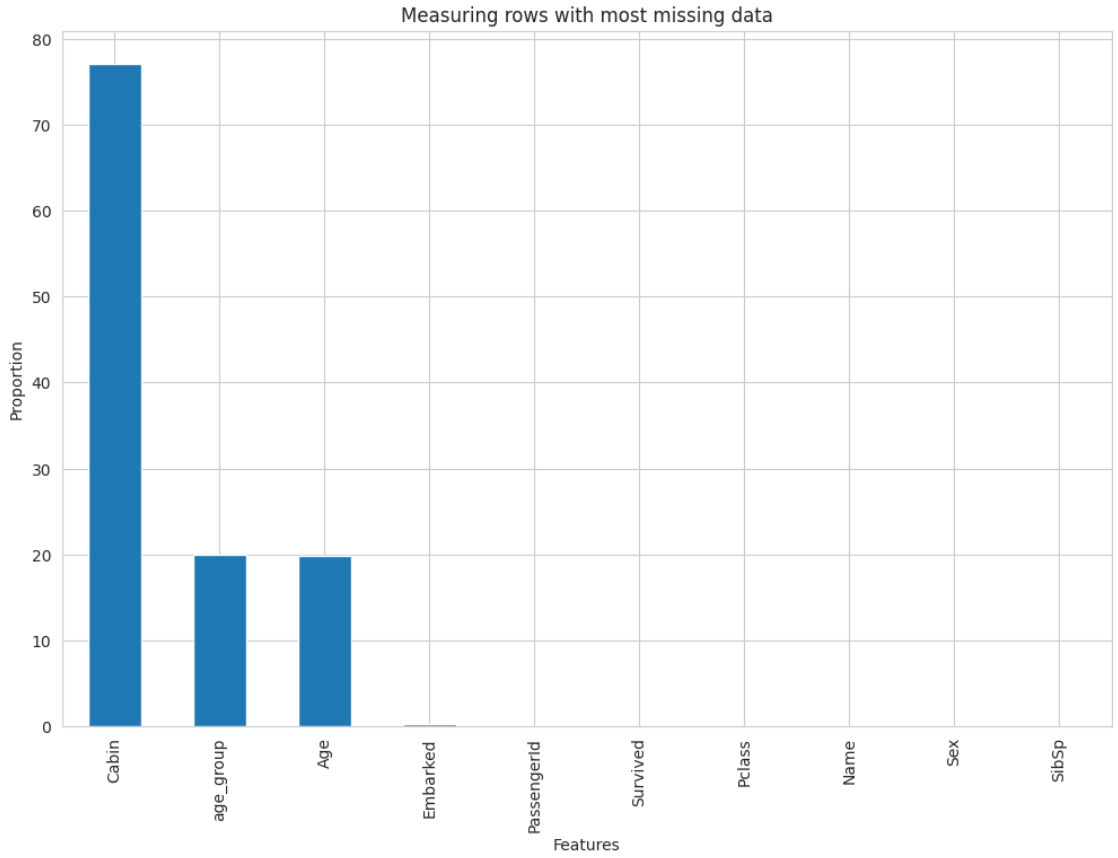
[ ]:
```
<Axes: >
```



[ ]:
```
(df.isna().sum()*100/df.shape[0]).sort_values(ascending=True)
```

[ ]:
```
PassengerId     0.000000
Survived        0.000000
Pclass          0.000000
Name            0.000000
Sex             0.000000
SibSp           0.000000
Parch           0.000000
Ticket          0.000000
Fare            0.000000
FareRange       0.000000
Embarked        0.224467
Age            19.865320
age_group      19.977553
Cabin          77.104377
dtype: float64
```

[ ]:
```
sb.set_style('whitegrid')
plt.figure(figsize=(12,8))
miss_values=df.isna().sum()*100/df.shape[0]
miss_values=miss_values.sort_values(ascending=False)[0:10]
ax=miss_values.plot(kind='bar')
ax.set_title('Measuring rows with most missing data')
ax.set_ylabel('Proportion')
ax.set_xlabel('Features')
ax.tick_params(axis='x',rotation=90)
```



[ ]:
```
df['Family']=df['SibSp']+df['Parch']+1
```

[ ]:
```
df.head(5)
```

[ ]:

	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 age_group FareRange  Family
0      0         A/5 21171     7   NaN        S     20-29      0-50       2
1      0          PC 17599    71   C85        C     30-39    51-100       2
2      0  STON/O2. 3101282     7   NaN        S     20-29      0-50       1
3      0            113803    53  C123        S     30-39    51-100       2
4      0            373450     8   NaN        S     30-39      0-50       1
```

[ ]:
```
df['Family']
```

[ ]:
```
0      2
1      2
2      1
3      2
4      1
      ..
886    1
887    1
888    4
889    1
890    1
Name: Family, Length: 891, dtype: int64
```

[ ]:
```
df.isna().sum()
```

[ ]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
age_group      178
FareRange        0
Family           0
```

```
dtype: int64
```

HANDLING MISSING VALUES

General Recommendations:

Always understand the nature of missing values before deciding on a strategy.

Consider the impact of missing data on your analysis and results.

Document any imputation or handling strategy for transparency.

[ ]:
```
df=df.
  ↪drop(['PassengerId','SibSp','Parch','age_group','FareRange','Cabin'],axis=1)
```

[ ]:
```
df.isna().sum()
```

[ ]:
```
Survived    0
Pclass      0
Name        0
Sex         0
Age         0
Ticket      0
Fare        0
Embarked    2
Family      0
dtype: int64
```

[ ]:
```
df['Age'].fillna(method='ffill',inplace=True)
```

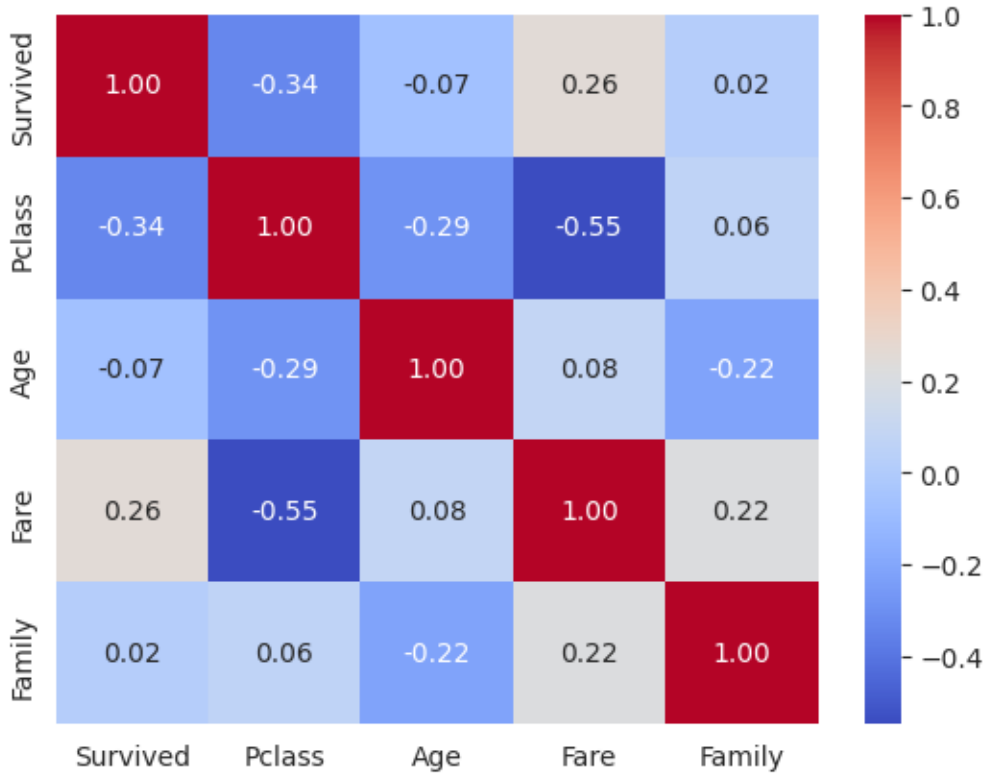
[ ]:
```
df.dropna(subset=['Embarked'], inplace=True)
```

[ ]:
```
df.isnull().sum()
```

[ ]:
```
Survived    0
Pclass      0
Name        0
Sex         0
Age         0
Ticket      0
Fare        0
Embarked    0
Family      0
dtype: int64
```

[ ]:
```
correlation=df.corr()
sb.heatmap(correlation, annot=True, cmap='coolwarm', fmt=".2f")
plt.show()
```

```
<ipython-input-155-c31ab5b310f0>:1: 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.
  correlation=df.corr()
```



[ ]:
```
print(correlation['Survived'].sort_values(ascending=False),'\n')
```

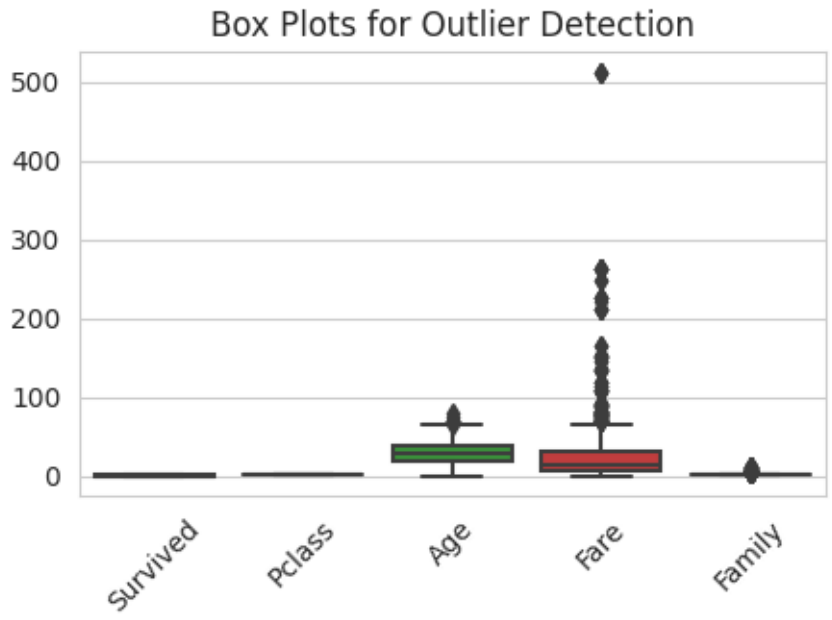
```
Survived    1.000000
Fare        0.255447
Family      0.018277
Age        -0.069907
Pclass     -0.335549
Name: Survived, dtype: float64
```

*** Likelihood of surviving the Titanic disaster***

Age, passenger class, embarkation point, gender, family status, and fare are all considered when analyzing survival rates.

2 OUTLIERS DETECTION AND REMOVAL

[ ]:
```
# Select numerical columns for outlier detection
numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns

# Create box plots for numerical columns
plt.figure(figsize=(5,3))
sb.boxplot(data=df[numerical_columns])
plt.title('Box Plots for Outlier Detection')
plt.xticks(rotation=45)
plt.show()

# Create scatter plots for pairs of numerical columns
#plt.figure(figsize=(12, 8))
#sb.pairplot(df[numerical_columns])
#plt.suptitle('Pair Plots for Outlier Detection', y=1.02)
#plt.show()
```



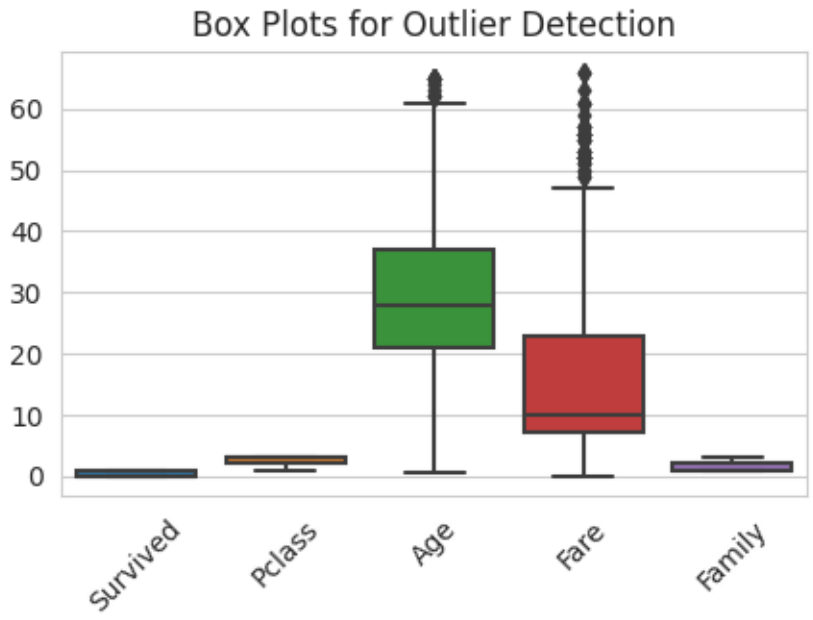
[ ]:
```
# Calculate IQR for each numerical column
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1

# Set a multiplier for IQR (adjust as needed)
iqr_multiplier = 1.5
```

```
# Identify and remove outliers based on IQR
df_no_outliers_iqr = df[~((df < (Q1 - iqr_multiplier * IQR)) | (df > (Q3 +␣
 ↪iqr_multiplier * IQR))).any(axis=1)]

# Display before and after
print("Before IQR Removal:")
print(df.describe())

print("\nAfter IQR Removal:")
print(df_no_outliers_iqr.describe())
```

```
Before IQR Removal:
         Survived      Pclass         Age        Fare      Family
count  889.000000  889.000000  889.000000  889.000000  889.000000
mean     0.382452    2.311586   29.535624   31.677165    1.906637
std      0.486260    0.834700   14.527483   49.706915    1.614703
min      0.000000    1.000000    0.420000    0.000000    1.000000
25%      0.000000    2.000000   20.000000    7.000000    1.000000
50%      0.000000    3.000000   28.000000   14.000000    1.000000
75%      1.000000    3.000000   38.000000   31.000000    2.000000
max      1.000000    3.000000   80.000000  512.000000   11.000000

After IQR Removal:
         Survived      Pclass         Age        Fare      Family
count  699.000000  699.000000  699.000000  699.000000  699.000000
mean     0.344778    2.450644   29.711488   16.165951    1.404864
std      0.475636    0.752310   13.298548   13.394967    0.685945
min      0.000000    1.000000    0.420000    0.000000    1.000000
25%      0.000000    2.000000   21.000000    7.000000    1.000000
50%      0.000000    3.000000   28.000000   10.000000    1.000000
75%      1.000000    3.000000   37.000000   23.000000    2.000000
max      1.000000    3.000000   65.000000   66.000000    3.000000
<ipython-input-158-131499712e54>:2: FutureWarning: The default value of
numeric_only in DataFrame.quantile 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.
  Q1 = df.quantile(0.25)
<ipython-input-158-131499712e54>:3: FutureWarning: The default value of
numeric_only in DataFrame.quantile 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.
  Q3 = df.quantile(0.75)
<ipython-input-158-131499712e54>:10: FutureWarning: Automatic reindexing on
DataFrame vs Series comparisons is deprecated and will raise ValueError in a
future version. Do `left, right = left.align(right, axis=1, copy=False)` before
e.g. `left == right`
  df_no_outliers_iqr = df[~((df < (Q1 - iqr_multiplier * IQR)) | (df > (Q3 +
```

```
iqr_multiplier * IQR))).any(axis=1)]
```

[ ]:
```
# Select numerical columns for outlier detection
numerical_columns = df_no_outliers_iqr.select_dtypes(include=['float64',␣
↪'int64']).columns

# Create box plots for numerical columns
plt.figure(figsize=(5,3))
sb.boxplot(data=df_no_outliers_iqr[numerical_columns])
plt.title('Box Plots for Outlier Detection')
plt.xticks(rotation=45)
plt.show()

# Create scatter plots for pairs of numerical columns
#plt.figure(figsize=(12, 8))
#sb.pairplot(df_no_outliers_iqr[numerical_columns])
#plt.suptitle('Pair Plots for Outlier Detection', y=1.02)
#plt.show()
```



[ ]:
```
df.dtypes
```

[ ]:
```
Survived      int64
Pclass        int64
Name         object
Sex          object
Age         float64
```

```
Ticket       object
Fare          int64
Embarked     object
Family        int64
dtype: object
```

[ ]:
```
df.shape
```

[ ]:
```
(889, 9)
```

[ ]:
```
data=df_no_outliers_iqr.copy()
```

[ ]:
```
data.isna().sum()
```

[ ]:
```
Survived    0
Pclass      0
Name        0
Sex         0
Age         0
Ticket      0
Fare        0
Embarked    0
Family      0
dtype: int64
```

3 *Ordinal Encoding*

[ ]:
```
from sklearn.preprocessing import LabelEncoder
# Select categorical columns for label encoding
categorical_columns = data.select_dtypes(include=['object']).columns

# Initialize the LabelEncoder
label_encoder = LabelEncoder()

# Apply label encoding to each categorical column
df_encoded = data.copy()
df_encoded[categorical_columns] = df_encoded[categorical_columns].apply(lambda␣
 ↪col: label_encoder.fit_transform(col))


#apply(lambda col: label_encoder.fit_transform(col)): This applies the label␣
 ↪encoding transformation to each column in the selected set of categorical␣
 ↪columns.
# Here's a breakdown of this part:
```

```
#lambda col: label_encoder.fit_transform(col): This lambda function takes each␣
 ↪column (col)
#and applies the label encoding transformation using label_encoder.
 ↪fit_transform. The fit_transform method fits the encoder to the unique␣
 ↪values in the column and transforms those values into numeric labels.

#The result is a DataFrame with the same structure as the original df_encoded,␣
 ↪but with the categorical columns replaced by their corresponding␣
 ↪label-encoded versions.
```

[ ]:
```
df_encoded.dtypes
```

[ ]:
```
Survived      int64
Pclass        int64
Name          int64
Sex           int64
Age         float64
Ticket        int64
Fare          int64
Embarked      int64
Family        int64
dtype: object
```

[ ]:
```
df_encoded.isna().sum()
```

[ ]:
```
Survived    0
Pclass      0
Name        0
Sex         0
Age         0
Ticket      0
Fare        0
Embarked    0
Family      0
dtype: int64
```

[ ]:
```
df_encoded.head()
```

[ ]:

	Survived	Pclass	Name	Sex	Age	Ticket	Fare	Embarked	Family
0	0	3	72	1	22.0	480	7	2	2
2	1	3	263	0	26.0	598	7	2	1
3	1	1	202	0	35.0	42	53	2	2
4	0	3	14	1	35.0	431	8	2	1
5	0	3	431	1	35.0	246	8	1	1