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1. IMPORT THE LIBRARIES

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
```

2. IMPORT THE DATASET

```
df=pd.read_csv("Titanic-Dataset.csv")
```

```
df
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parcl
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	(
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	(
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	(
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May	female	35.0	1	(

```
df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0
1	2	1	1	Cumings, Mrs. John Bradley (Florence	female	38.0	1	0

```
df.tail()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0
887	888	1	1	Graham, Miss. .. .	female	19.0	0	0

```
df.shape
```

```
(891, 12)
```

```
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
```

```
df.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Pa
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000

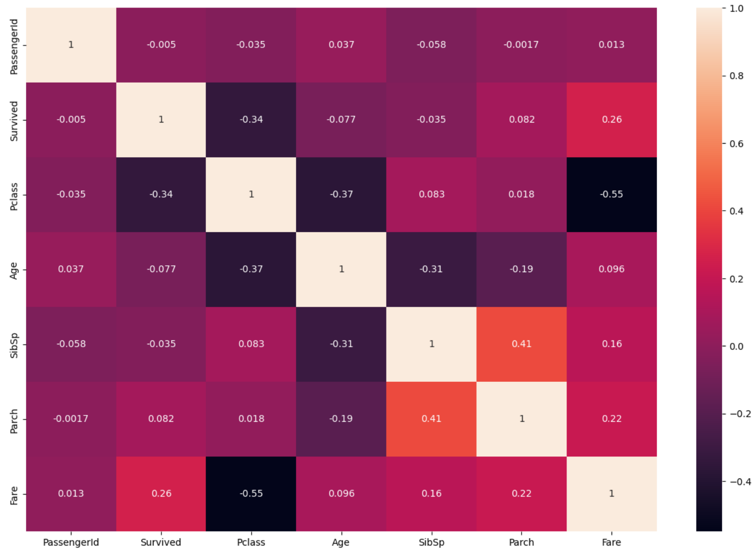
```
corr=df.corr()
corr
```

```
<ipython-input-13-7d5195e2bf4d>:1: FutureWarning: The default value
  corr=df.corr()
```

	PassengerId	Survived	Pclass	Age	SibSp	Par
PassengerId	1.000000	-0.005007	-0.035144	0.036847	-0.057527	-0.0016
Survived	-0.005007	1.000000	-0.338481	-0.077221	-0.035322	0.0816
Pclass	-0.035144	-0.338481	1.000000	-0.369226	0.083081	0.0184
Age	0.036847	-0.077221	-0.369226	1.000000	-0.308247	-0.1891
SibSp	-0.057527	-0.035322	0.083081	-0.308247	1.000000	0.4148
Parch	-0.001652	0.081629	0.018443	-0.189119	0.414838	1.0000
Fare	0.012658	0.257307	-0.549500	0.096067	0.159651	0.2162

```
plt.subplots(figsize=(15,10))
sns.heatmap(corr,annot=True)
```

```
<Axes: >
```




```
df.Survived.value_counts()
```

```
0    549
1    342
Name: Survived, dtype: int64
```

```
df.Sex.value_counts()
```

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

```
df.Embarked.value_counts()
```

```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

3. CHECK FOR NULL VALUES

```
df.isnull().any()
```

```
PassengerId    False
Survived       False
Pclass         False
Name           False
Sex            False
Age             True
SibSp          False
```

```
Parch          False
Ticket         False
Fare           False
Cabin           True
Embarked        True
dtype: bool
```

```
df.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
```

Fill null values in the 'Age' column with the mean age

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

Fill null values in the 'Embarked' column with the most common value

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

```
df.drop(['Cabin'],axis=1, inplace=True)
```

```
df.drop(['Ticket'],axis=1, inplace=True)
```

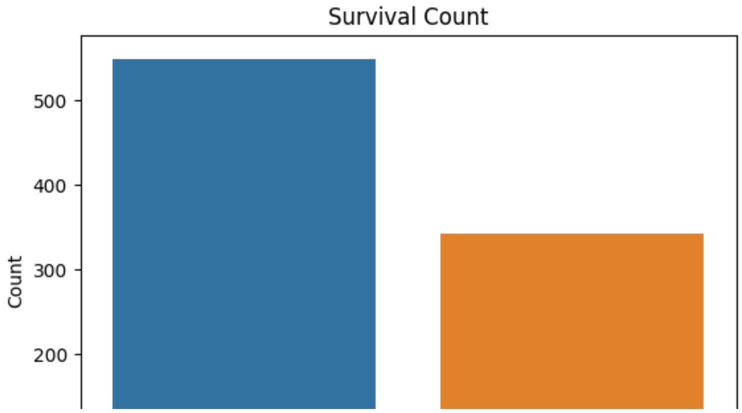
```
df.drop(['Name'],axis=1,inplace=True)
```

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

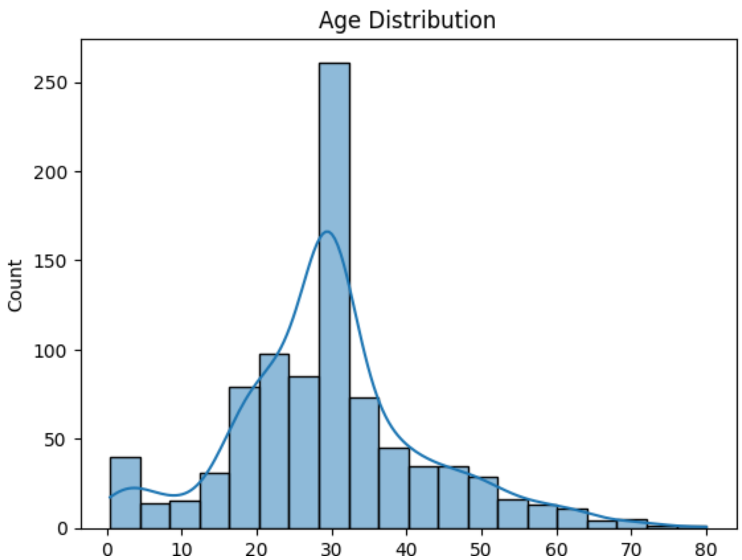
```
PassengerId    0
Survived       0
Pclass         0
Sex            0
Age            0
SibSp          0
Parch          0
Fare           0
Embarked       0
dtype: int64
```

4. Data Visualization

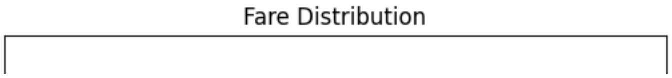
```
# Visualize the distribution of the 'Survived' column (0 = Not Survived, 1 = Survived)
sns.countplot(data=df, x='Survived')
plt.title('Survival Count')
plt.xlabel('Survived')
plt.ylabel('Count')
plt.show()
```



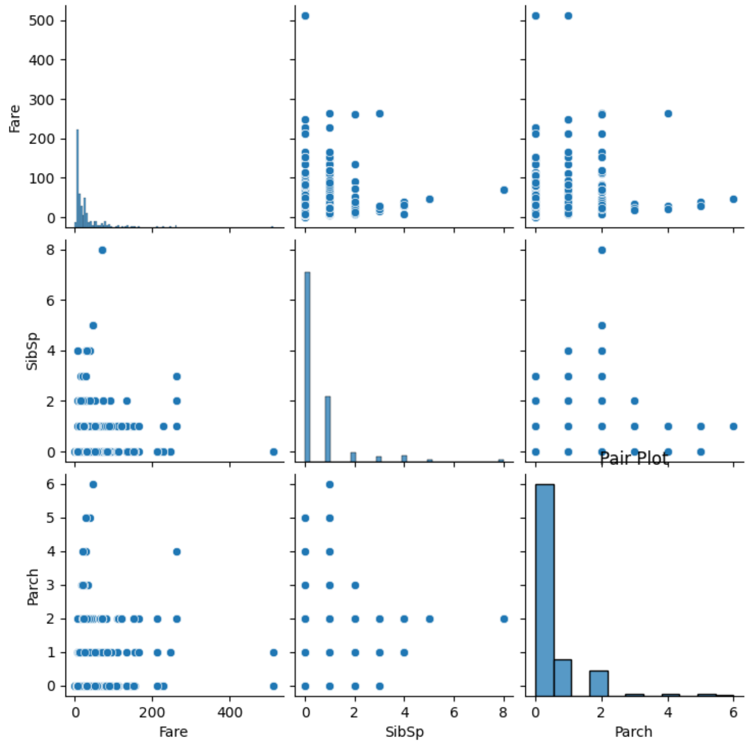

```
#Visualize the distribution of the 'Age' column
sns.histplot(data=df, x='Age', bins=20, kde=True)
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```




```
#Visualize the distribution of the 'Fare' column and detect outliers we will handle outliers in the next step
sns.boxplot(data=df, x='Fare')
plt.title('Fare Distribution')
plt.xlabel('Fare')
plt.show()
```

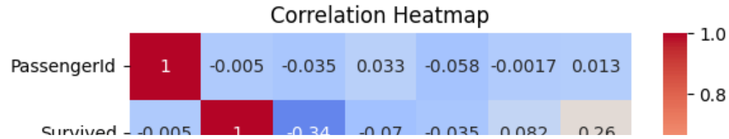



```
#Pair plot for selected numerical columns
sns.pairplot(data=df[['Fare', 'SibSp', 'Parch']])
plt.title('Pair Plot')
plt.show()
```




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

```
<ipython-input-30-8dcbd071fff3>:1: FutureWarning: The default value
  corr_matrix = df.corr()
```



5. Detect and Handle Outliers

```
z_scores = np.abs(stats.zscore(df['Age']))
max_threshold=3
outliers = df['Age'][z_scores > max_threshold]

# Print and visualize the outliers
print("Outliers detected using Z-Score:")
print(outliers)
```

```
Outliers detected using Z-Score:
96     71.0
116    70.5
493    71.0
630    80.0
672    70.0
745    70.0
851    74.0
Name: Age, dtype: float64
```

```
z_scores = np.abs(stats.zscore(df['Fare']))
max_threshold=3
outliers = df['Fare'][z_scores > max_threshold]

# Print and visualize the outliers
print("Outliers detected using Z-Score:")
print(outliers)
```

```
Outliers detected using Z-Score:
27     263.0000
88     263.0000
118    247.5208
258    512.3292
299    247.5208
311    262.3750
341    263.0000
377    211.5000
380    227.5250
438    263.0000
527    221.7792
557    227.5250
679    512.3292
689    211.3375
700    227.5250
716    227.5250
730    211.3375
737    512.3292
742    262.3750
779    211.3375
Name: Fare, dtype: float64
```

```
column_name = 'Fare'

# Calculate the first quartile (Q1) and third quartile (Q3)
Q1 = df[column_name].quantile(0.25)
Q3 = df[column_name].quantile(0.75)

# Calculate the IQR
IQR = Q3 - Q1

# Define the lower and upper bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter rows with values outside the IQR bounds
df_cleaned = df[(df[column_name] > lower_bound) & (df[column_name] <upper_bound)]
```

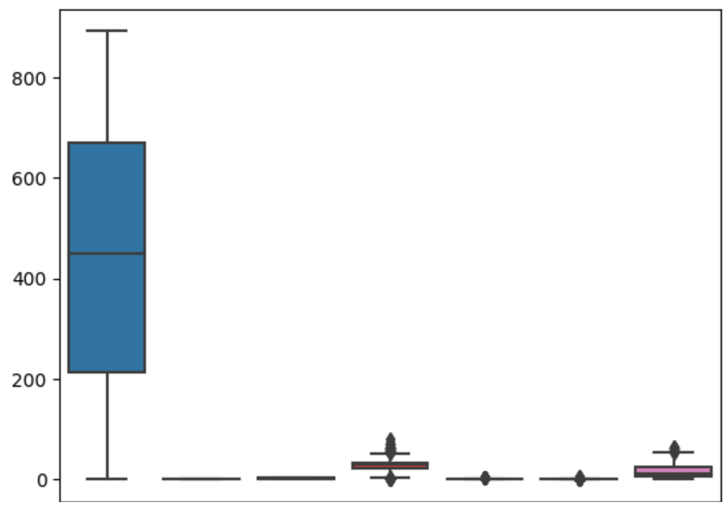
```
# Display the original and cleaned DataFrame sizes
print(f"Original DataFrame size: {df.shape}")
print(f"Cleaned DataFrame size: {df_cleaned.shape}")
df_cleaned
```

```
Original DataFrame size: (891, 9)
Cleaned DataFrame size: (775, 9)
```

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	
0	1	0	3	male	22.000000	1	0	7.
2	3	1	3	female	26.000000	0	0	7.
3	4	1	1	female	35.000000	1	0	53.
4	5	0	3	male	35.000000	0	0	8.
5	6	0	3	male	29.699118	0	0	8.
...	...	...	...	...	...	...	...	
886	887	0	2	male	27.000000	0	0	13.
887	888	1	1	female	19.000000	0	0	30.
888	889	0	3	female	29.699118	1	2	23.
889	890	1	1	male	26.000000	0	0	30.
890	891	0	3	male	32.000000	0	0	7.

```
sns.boxplot(df_cleaned)
```

```
<Axes: >
```




```
df=df_cleaned
```

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

```
x.head()
```

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Fare	Embark
0	1	3	male	22.000000	1	0	7.2500	
2	3	3	female	26.000000	0	0	7.9250	
3	4	1	female	35.000000	1	0	53.1000	
4	5	3	male	35.000000	0	0	8.0500	
5	6	3	male	29.699118	0	0	8.4583	

```
y.head()
```

```
0    0
2    1
3    1
4    0
5    0
Name: Survived, dtype: int64
```

7. Perform Encoding

```
en = LabelEncoder()
x['Sex'] = en.fit_transform(x['Sex'])
```

```
x.head()
```

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	3	1	22.000000	1	0	7.2500	S
2	3	3	0	26.000000	0	0	7.9250	S
3	4	1	0	35.000000	1	0	53.1000	S
4	5	3	1	35.000000	0	0	8.0500	S
5	6	3	1	29.699118	0	0	8.4583	Q

```
x = pd.get_dummies(x,columns=['Embarked'])
```

```
x.head()
```

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked_
0	1	3	1	22.000000	1	0	7.2500	
2	3	3	0	26.000000	0	0	7.9250	
3	4	1	0	35.000000	1	0	53.1000	
4	5	3	1	35.000000	0	0	8.0500	
5	6	3	1	29.699118	0	0	8.4583	

8. Feature Scaling

```
scale = StandardScaler()
x[['Age', 'Fare']] = scale.fit_transform(x[['Age', 'Fare']])
```

```
x.head()
```

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Fare	Embarke
0	1	3	1	-0.556219	1	0	-0.779117	
2	3	3	0	-0.243027	0	0	-0.729373	
3	4	1	0	0.461654	1	0	2.599828	
4	5	3	1	0.461654	0	0	-0.720161	
5	6	3	1	0.046606	0	0	-0.690071	

9. Splitting the data into Train and Test

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
```

```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(620, 10)
(155, 10)
(620,)
(155,)
```