**Name:TBSVINEETH

REG.NO:20BIT0063

Campus:VELLORE

mail:bala.saivineeth2020@vitstudent.ac.in**

```
import pandas as pd

# Load the dataset
dataset_path = '/content/titanic.csv'
data = pd.read_csv(dataset_path)

# Print the first few rows to verify the dataset has been loaded correctly
print(data.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
```

Visualization

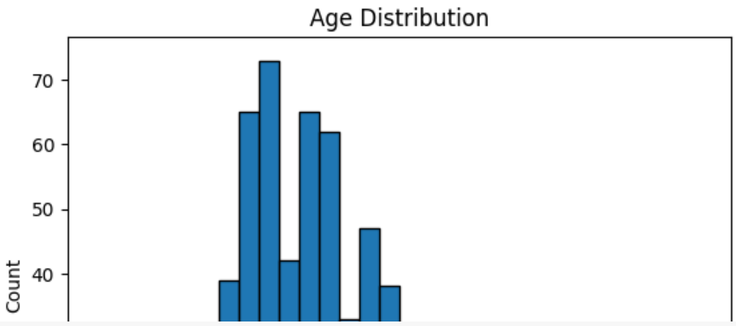
```
data.info()
```

```
<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    object
 9   who          891 non-null    object
 10  adult_male   891 non-null    bool
 11  deck         203 non-null    object
 12  embark_town  889 non-null    object
 13  alive        891 non-null    object
 14  alone        891 non-null    bool
dtypes: bool(2), float64(2), int64(4), object(7)
memory usage: 92.4+ KB
```

● Univariate Analysis

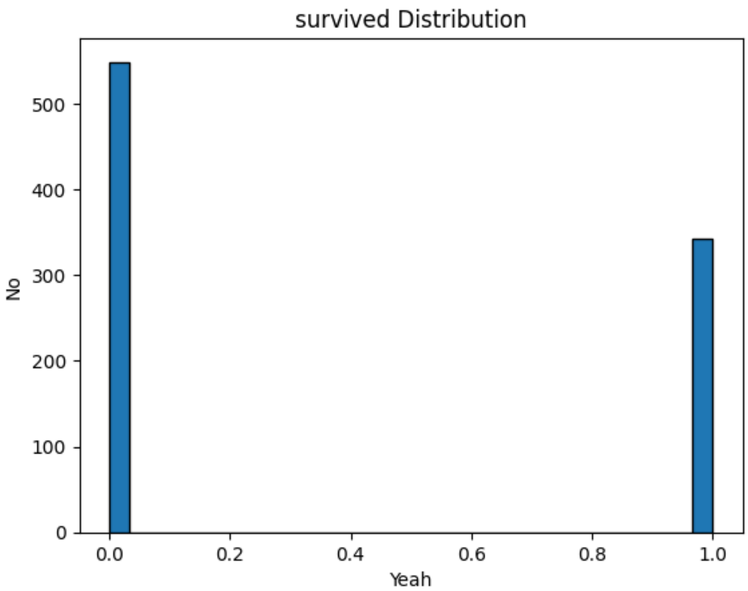
```
import matplotlib.pyplot as plt

# Histogram for age distribution
plt.hist(data['age'].dropna(), bins=30, edgecolor='k')
plt.xlabel('Age')
plt.ylabel('Count')
plt.title('Age Distribution')
plt.show()
```



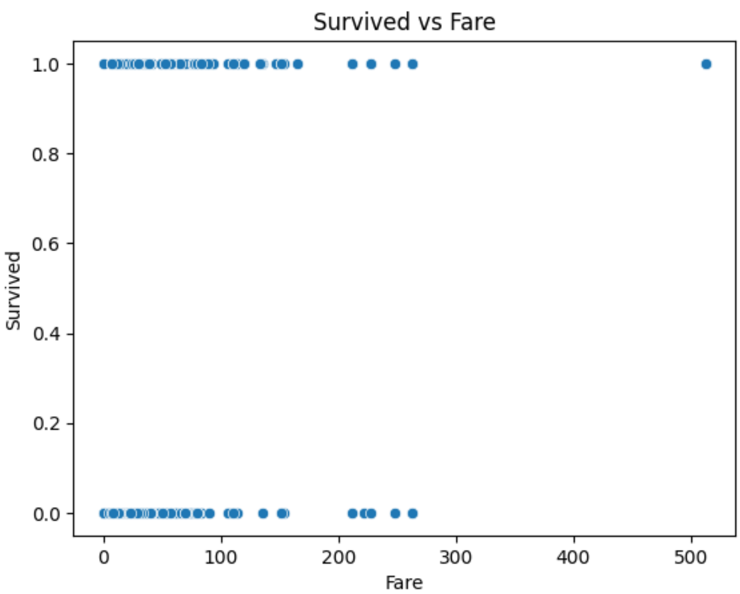

```
import matplotlib.pyplot as plt

# Histogram for age distribution
plt.hist(data['survived'].dropna(), bins=30, edgecolor='k')
plt.xlabel('Yeah')
plt.ylabel('No')
plt.title('survived Distribution')
plt.show()
```



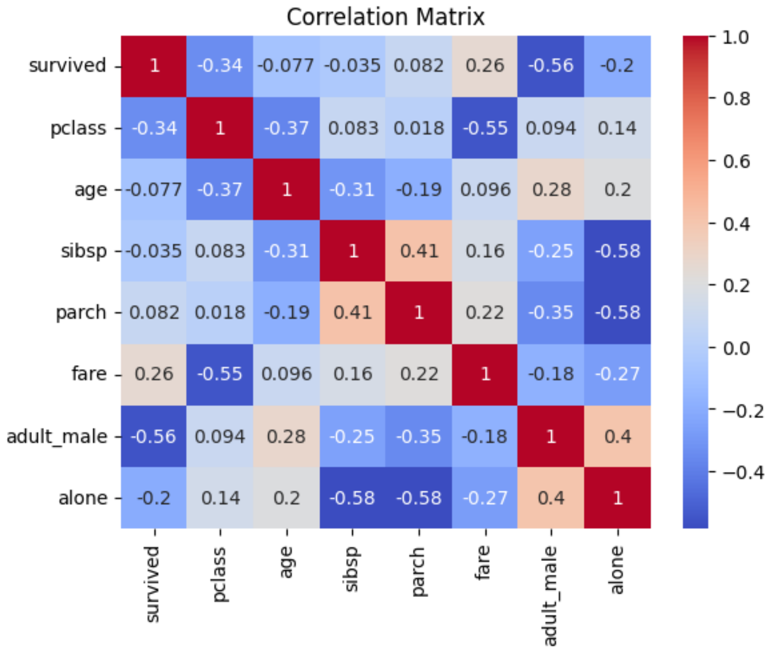

```
import seaborn as sns

# Scatter plot for Survived vs Fare
sns.scatterplot(data=data, x='fare', y='survived')
plt.xlabel('Fare')
plt.ylabel('Survived')
plt.title('Survived vs Fare')
plt.show()
```



```
# Correlation matrix
corr_matrix = data.corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```

```
<ipython-input-6-4a88ba0b1f3c>:2: FutureWarning: The default value of numeric_only in DataFrame.cor
  corr_matrix = data.corr()
```




```
print(data.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
```

```
# Fill missing values in Age column with median
data['age'].fillna(data['age'].median(), inplace=True)
```

```
# Fill missing values in sibsp column with median
data['sibsp'].fillna(data['sibsp'].median(), inplace=True)
```

```
# Fill missing values in Age column with median
data['fare'].fillna(data['fare'].median(), inplace=True)
```

7.

```
# Replace outliers in Fare column with median
Q1 = data['fare'].quantile(0.25)
Q3 = data['fare'].quantile(0.75)
IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

data['fare'] = data['fare'].apply(lambda x: data['fare'].median() if x < lower_bound or x > upper_bound else x)
```

```
import pandas as pd

# Load the dataset
dataset_path = '/content/titanic.csv'  # Update with the actual path to the dataset
data = pd.read_csv(dataset_path)

# Find outliers using IQR method for numeric columns
```

```
numeric_columns = ['age', 'fare']  # Update with the actual numeric columns in your dataset

for column in numeric_columns:
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1

    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    outliers = data[(data[column] < lower_bound) | (data[column] > upper_bound)]

    print(f"Outliers in {column}:")
    print(outliers)
```

```
Outliers in age:
     survived  pclass   sex   age  sibsp  parch     fare embarked   class  \
33          0       2  male  66.0      0      0  10.5000        S  Second
54          0       1  male  65.0      0      1  61.9792        C   First
96          0       1  male  71.0      0      0  34.6542        C   First
116         0       3  male  70.5      0      0   7.7500        Q   Third
280         0       3  male  65.0      0      0   7.7500        Q   Third
456         0       1  male  65.0      0      0  26.5500        S   First
493         0       1  male  71.0      0      0  49.5042        C   First
630         1       1  male  80.0      0      0  30.0000        S   First
672         0       2  male  70.0      0      0  10.5000        S  Second
745         0       1  male  70.0      1      1  71.0000        S   First
851         0       3  male  74.0      0      0   7.7750        S   Third

     who  adult_male deck  embark_town alive  alone
33   man        True  NaN  Southampton    no   True
54   man        True    B    Cherbourg    no  False
96   man        True    A    Cherbourg    no   True
116  man        True  NaN   Queenstown    no   True
280  man        True  NaN   Queenstown    no   True
456  man        True    E  Southampton    no   True
493  man        True  NaN    Cherbourg    no   True
630  man        True    A  Southampton   yes   True
672  man        True  NaN  Southampton    no   True
745  man        True    B  Southampton    no  False
851  man        True  NaN  Southampton    no   True
Outliers in fare:
     survived  pclass     sex   age  sibsp  parch      fare embarked  class  \
1           1       1  female  38.0      1      0   71.2833        C  First
27          0       1    male  19.0      3      2  263.0000        S  First
31          1       1  female   NaN      1      0  146.5208        C  First
34          0       1    male  28.0      1      0   82.1708        C  First
52          1       1  female  49.0      1      0   76.7292        C  First
..        ...     ...     ...   ...    ...    ...       ...      ...    ...
846         0       3    male   NaN      8      2   69.5500        S  Third
849         1       1  female   NaN      1      0   89.1042        C  First
856         1       1  female  45.0      1      1  164.8667        S  First
863         0       3  female   NaN      8      2   69.5500        S  Third
879         1       1  female  56.0      0      1   83.1583        C  First

       who  adult_male deck  embark_town alive  alone
1    woman       False    C    Cherbourg   yes  False
27     man        True    C  Southampton    no  False
31   woman       False    B    Cherbourg   yes  False
34     man        True  NaN    Cherbourg    no  False
52   woman       False    D    Cherbourg   yes  False
..     ...         ...  ...          ...   ...    ...
846    man        True  NaN  Southampton    no  False
849  woman       False    C    Cherbourg   yes  False
856  woman       False  NaN  Southampton   yes  False
863  woman       False  NaN  Southampton    no  False
879  woman       False    C    Cherbourg   yes  False

[116 rows x 15 columns]
```

```
# Replace outliers in age column with median
Q1 = data['age'].quantile(0.25)
Q3 = data['age'].quantile(0.75)
IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

data['age'] = data['age'].apply(lambda x: data['age'].median() if x < lower_bound or x > upper_bound else x)
```

Check for Categorical columns and perform encoding:

```
# One-hot encoding for Survived column
data = pd.get_dummies(data, columns=['survived'], drop_first=True)
```

```
import pandas as pd

# Define the mapping dictionary
sex_mapping = {'male': 0, 'female': 1}

# Apply max-min encoding to the 'Sex' column
data['Sex_encoded'] = data['sex'].map(sex_mapping)

# Print the updated 'Sex_encoded' column
print(data['Sex_encoded'])
```

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

```
from sklearn.preprocessing import LabelEncoder

# Create an instance of LabelEncoder
label_encoder = LabelEncoder()

# Perform label encoding on the 'alone' column
data['alone_encoded'] = label_encoder.fit_transform(data['alone'])
print(data['alone_encoded'])
```

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

```
data.describe()
```

	pclass	age	sibsp	parch	fare	survived_1	Sex_encoded	alone_enc
count	891.000000	714.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.00
mean	2.308642	29.055560	0.523008	0.381594	32.204208	0.383838	0.352413	0.60
std	0.836071	13.622807	1.102743	0.806057	49.693429	0.486592	0.477990	0.48
min	1.000000	0.420000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
25%	2.000000	20.125000	0.000000	0.000000	7.910400	0.000000	0.000000	0.00
50%	3.000000	28.000000	0.000000	0.000000	14.454200	0.000000	0.000000	1.00
75%	3.000000	37.000000	1.000000	0.000000	31.000000	1.000000	1.000000	1.00
max	3.000000	64.000000	8.000000	6.000000	512.329200	1.000000	1.000000	1.00

```
data['sex'] = data['sex'].map({'male': 1, 'female': 0})
```

```
# Split into dependent and independent variables
y = data['survived_1']
X = data.drop('survived_1', axis=1)
```

```
from sklearn.preprocessing import StandardScaler

# Standardize the independent variables
scaler = StandardScaler()
```

```
X_scaled = scaler.fit_transform(X)
```

```
from sklearn.model_selection import train_test_split

# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```