In [15]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [16]:

```
df=pd.read_csv('titanic.csv')
df
```

Out[16]:

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

891 rows × 15 columns

→

In [17]:

df.head()

Out[17]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_ma
0	0	3	male	22.0	1	0	7.2500	S	Third	man	Trı
1	1	1	female	38.0	1	0	71.2833	С	First	woman	Fals
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	Fals
3	1	1	female	35.0	1	0	53.1000	S	First	woman	Fals
4	0	3	male	35.0	0	0	8.0500	S	Third	man	Trı
4											>

In [18]:

```
df.tail()
```

Out[18]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_n
886	0	2	male	27.0	0	0	13.00	S	Second	man	1
887	1	1	female	19.0	0	0	30.00	S	First	woman	F
888	0	3	female	NaN	1	2	23.45	S	Third	woman	F
889	1	1	male	26.0	0	0	30.00	С	First	man	٦
890	0	3	male	32.0	0	0	7.75	Q	Third	man	٦
4											•

In [19]:

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	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
dtyn	es· hool(2)	float64(2) int6	4(4) object(

dtypes: bool(2), float64(2), int64(4), object(7)

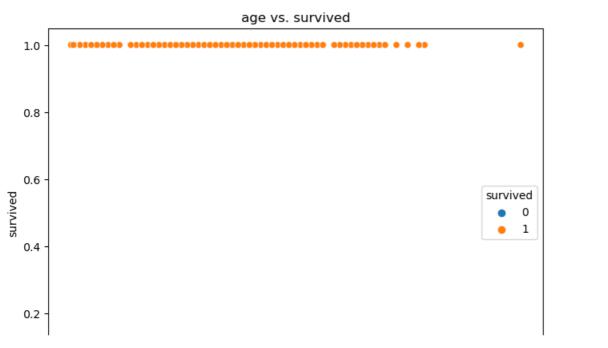
memory usage: 92.4+ KB

```
In [20]:
df['age']
Out[20]:
0
       22.0
1
       38.0
2
       26.0
3
       35.0
4
       35.0
886
       27.0
887
       19.0
888
        NaN
       26.0
889
890
       32.0
Name: age, Length: 891, dtype: float64
In [21]:
#Univariate Analysis
# Univariate analysis for numerical variables
numeric_vars = ['age', 'fare']
for var in numeric_vars:
    plt.figure(figsize=(8, 6))
    sns.histplot(data=df, x=var, kde=True)
    plt.title(f'Distribution of {var}')
    plt.show()
# Univariate analysis for categorical variables
categorical_vars = ['sex', 'embarked', 'pclass', 'survived']
for var in categorical_vars:
    plt.figure(figsize=(8, 6))
    sns.countplot(data=df, x=var)
    plt.title(f'Count of {var}')
    plt.show()
                    100
                                200
                                                        400
                                                                    500
                                            300
                                       fare
                                   Count of sex
   600
   500
   400
   300
```

In [22]:

```
#Bivariate Analysis
# Bivariate analysis for numerical variables
numeric_vars = ['age', 'fare']
for var in numeric_vars:
    plt.figure(figsize=(8, 6))
    sns.scatterplot(data=df, x=var, y='survived', hue='survived')
    plt.title(f'{var} vs. survived')
    plt.show()

# Bivariate analysis for categorical variables
categorical_vars = ['sex', 'embarked', 'pclass']
for var in categorical_vars:
    plt.figure(figsize=(8, 6))
    sns.countplot(data=df, x=var, hue='survived')
    plt.title(f'{var} vs. survived')
    plt.show()
```



In [23]:

```
#Multivariate Analysis
# Multivariate analysis using scatter plot matrix
numeric_vars = ['age', 'fare']
sns.pairplot(data=df, vars=numeric_vars, hue='survived')
plt.title('Pairwise Scatter Plot of Numeric Variables')
plt.show()
# Multivariate analysis using a heatmap of correlation matrix
corr_matrix = df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
# Multivariate analysis using a grouped bar plot
categorical_vars = ['sex', 'embarked', 'pclass']
for var in categorical_vars:
    plt.figure(figsize=(8, 6))
    sns.countplot(data=df, x=var, hue='survived')
    plt.title(f'{var} vs. survived')
    plt.show()
 parch
     0.082
             0.018
                     -0.19
                                             0.22
                                                              -0.58
                              0.41
                                                                          - 0.0
     0.26
             -0.55
                     0.096
                              0.16
                                      0.22
                                                     -0.18
                                                                           -0.2
 adult male
     -0.56
             0.094
                                             -0.18
                      0.28
                                                              0.4
                                                                           -0.4
             0.14
                      0.2
                                                      0.4
    survived
             pclass
                             sibsp
                                                   adult_male
                                                             alone
                                     parch
                                              fare
                      age
                                   sex vs. survived
                                                                       survived
                                                                          0
```

In [24]:

```
#Descriptive Statistics
# Compute descriptive statistics
statistics = df.describe()
# Display the descriptive statistics
print(statistics)
```

	survived	pclass	age	sibsp	parch	f
are						
count	891.000000	891.000000	714.000000	891.000000	891.000000	891.000
000						
mean	0.383838	2.308642	29.699118	0.523008	0.381594	32.204
208						
std	0.486592	0.836071	14.526497	1.102743	0.806057	49.693
429						
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000
000						
25%	0.000000	2.000000	20.125000	0.000000	0.000000	7.910
400						
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.454
200						
75%	1.000000	3.000000	38.000000	1.000000	0.000000	31.000
000						
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329
200						

In [25]:

```
#Descriptive Statistics
#Measures of central tendency
#Mean
```

df.mean()

C:\Users\vijay\AppData\Local\Temp\ipykernel_2076\1208449491.py:5: FutureWa
rning: The default value of numeric_only in DataFrame.mean is deprecated.
In a future version, it will default to False. In addition, specifying 'nu
meric_only=None' is deprecated. Select only valid columns or specify the v
alue of numeric_only to silence this warning.
 df.mean()

Out[25]:

survived	0.383838
pclass	2.308642
age	29.699118
sibsp	0.523008
parch	0.381594
fare	32.204208
adult_male	0.602694
alone	0.602694
dtype: float6	4

In [26]:

```
#Median
df.median()
```

C:\Users\vijay\AppData\Local\Temp\ipykernel_2076\863618092.py:2: FutureWar
ning: The default value of numeric_only in DataFrame.median is deprecated.
In a future version, it will default to False. In addition, specifying 'nu
meric_only=None' is deprecated. Select only valid columns or specify the v
alue of numeric_only to silence this warning.
 df.median()

Out[26]:

survived 0.0000 pclass 3.0000 28.0000 age 0.0000 sibsp parch 0.0000 14.4542 fare adult male 1.0000 alone 1.0000

dtype: float64

In [27]:

#Mode df.mode()

Out[27]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	decl
0	0	3	male	24.0	0	0	8.05	S	Third	man	True	(
4												•

In [28]:

```
#Skewness df.skew()
```

C:\Users\vijay\AppData\Local\Temp\ipykernel_2076\3944243432.py:2: FutureWa
rning: The default value of numeric_only in DataFrame.skew is deprecated.
In a future version, it will default to False. In addition, specifying 'nu
meric_only=None' is deprecated. Select only valid columns or specify the v
alue of numeric_only to silence this warning.
 df.skew()

Out[28]:

survived 0.478523 -0.630548 pclass 0.389108 age 3.695352 sibsp parch 2.749117 4.787317 fare adult_male -0.420431 alone -0.420431 dtype: float64

In [29]:

```
# Distplot
print(sns.distplot(df['age'],color='green'))
```

C:\Users\vijay\AppData\Local\Temp\ipykernel_2076\3882639869.py:2: UserWarn
ing:

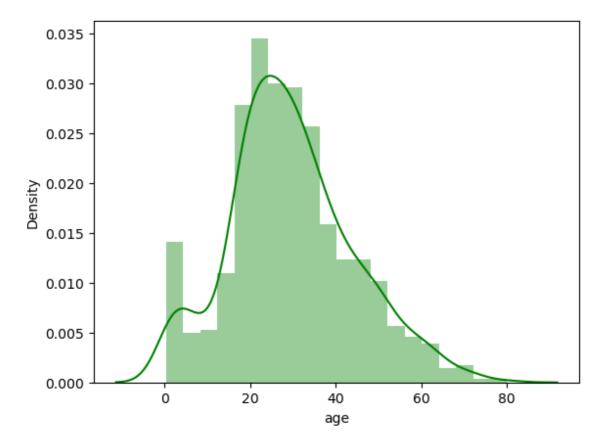
`distplot` is a deprecated function and will be removed in seaborn v0.14. 0.

Please adapt your code to use either `displot` (a figure-level function wi th similar flexibility) or `histplot` (an axes-level function for histogram s).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751 (https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751)

print(sns.distplot(df['age'],color='green'))

Axes(0.125,0.11;0.775x0.77)



In [30]:

```
print(sns.distplot(df['fare'],color='blue'))
```

C:\Users\vijay\AppData\Local\Temp\ipykernel_2076\925598583.py:1: UserWarni
ng:

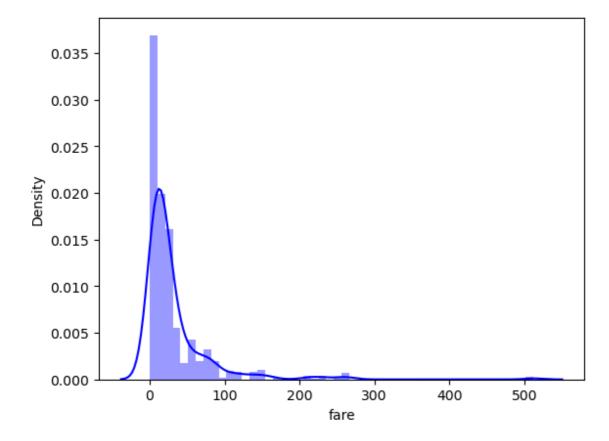
`distplot` is a deprecated function and will be removed in seaborn v0.14.

Please adapt your code to use either `displot` (a figure-level function wi th similar flexibility) or `histplot` (an axes-level function for histogram s).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751 (https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751)

print(sns.distplot(df['fare'],color='blue'))

Axes(0.125,0.11;0.775x0.77)



In [31]:

kurtosis df.kurt()

C:\Users\vijay\AppData\Local\Temp\ipykernel_2076\3536932851.py:2: FutureWa
rning: The default value of numeric_only in DataFrame.kurt is deprecated.
In a future version, it will default to False. In addition, specifying 'nu
meric_only=None' is deprecated. Select only valid columns or specify the v
alue of numeric_only to silence this warning.
 df.kurt()

Out[31]:

survived -1.775005 pclass -1.280015 0.178274 age sibsp 17.880420 parch 9.778125 fare 33.398141 adult_male -1.827345 -1.827345 alone

dtype: float64

#Range

df.max()

In [32]:

C:\Users\vijay\AppData\Local\Temp\ipykernel_2076\625711735.py:3: FutureWar
ning: The default value of numeric_only in DataFrame.max is deprecated. In
a future version, it will default to False. In addition, specifying 'numer
ic_only=None' is deprecated. Select only valid columns or specify the valu
e of numeric_only to silence this warning.
 df.max()

Out[32]:

survived 1 pclass 3 male sex 80.0 age 8 sibsp 6 parch 512.3292 fare Third class who woman True adult male alive yes alone True dtype: object

```
In [33]:
```

```
df.min()
```

C:\Users\vijay\AppData\Local\Temp\ipykernel_2076\3962516015.py:1: FutureWa
rning: The default value of numeric_only in DataFrame.min is deprecated. I
n a future version, it will default to False. In addition, specifying 'num
eric_only=None' is deprecated. Select only valid columns or specify the va
lue of numeric_only to silence this warning.
 df.min()

Out[33]:

```
0
survived
                    1
pclass
               female
sex
                 0.42
age
                    0
sibsp
parch
                    0
                  0.0
fare
class
                First
                child
who
adult_male
                False
alive
                   no
alone
                False
dtype: object
```

In [34]:

```
column = 'age'

# Find the range
column_range = df[column].max() - df[column].min()

# Print the range
print(f"The range for '{column}' is: {column_range}")
```

The range for 'age' is: 79.58

In [35]:

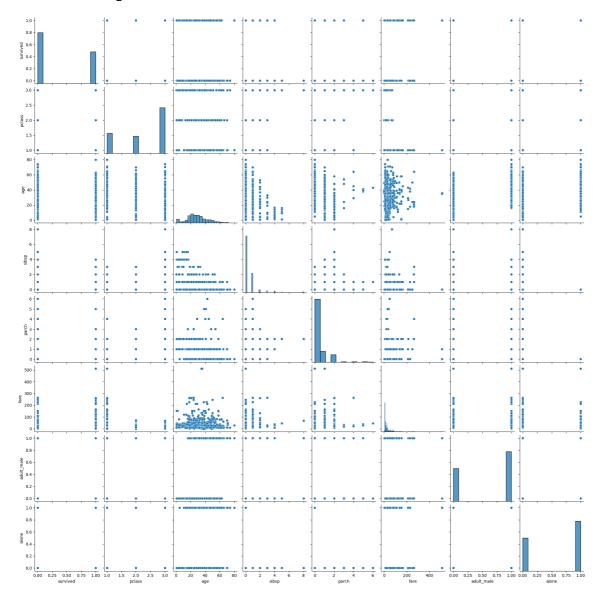
sns.pairplot(df)

<__array_function__ internals>:180: RuntimeWarning: Converting input from bool to <class 'numpy.uint8'> for compatibility. <__array_function__ internals>:180: RuntimeWarning: Converting input from

bool to <class 'numpy.uint8'> for compatibility.

Out[35]:

<seaborn.axisgrid.PairGrid at 0x1cc2ced02e0>



In [36]:

```
#Handling the Missing values

# Check for missing values
print(df.isnull().sum())

# Handling missing values for numerical columns
df['age'].fillna(df['age'].median(), inplace=True)
df['fare'].fillna(df['fare'].mean(), inplace=True)

# Handling missing values for categorical columns
df['embarked'].fillna(df['embarked'].mode()[0], inplace=True)

# Dropping rows with missing values
#data.dropna(inplace=True)

# Verify if missing values are handled
print(df.isnull().sum())
```

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

```
In [37]:
```

```
# Find the outliers and replace the outliers
# Identify outliers in numerical columns
numeric_vars = ['age', 'fare']
for var in numeric_vars:
   # Calculate the IQR (Interquartile Range)
   Q1 = df[var].quantile(0.25)
   Q3 = df[var].quantile(0.75)
   IQR = Q3 - Q1
   # Determine the upper and lower bounds for outliers
   lower_bound = Q1 - 1.5 * IQR
   upper_bound = Q3 + 1.5 * IQR
   # Identify outliers
   outliers = df[(df[var] < lower_bound) | (df[var] > upper_bound)]
   # Replace outliers with appropriate values
   df[var] = np.where((df[var] < lower_bound) | (df[var] > upper_bound), df[var].median
# Verify if outliers are replaced
for var in numeric_vars:
   # Calculate the IQR (Interquartile Range)
   Q1 = df[var].quantile(0.25)
   Q3 = df[var].quantile(0.75)
   IQR = Q3 - Q1
   # Determine the upper and lower bounds for outliers
   lower_bound = Q1 - 1.5 * IQR
   upper_bound = Q3 + 1.5 * IQR
   # Identify outliers
   outliers = df[(df[var] < lower_bound) | (df[var] > upper_bound)]
   # Print the outliers (should be empty if outliers are replaced)
   print(f"Outliers in '{var}':")
   print(outliers)
```

Outliers in 'age':										
		_	sex	age	sibsp	parch	fare	embarked	С	
lass \	١	•				•				
6	0	1	male	54.0	0	0	51.8625	S	F	
irst										
10	1	3	female	4.0	1	1	16.7000	S	Т	
hird										
24	0	3	female	8.0	3	1	21.0750	S	Т	
hird								_		
43	1	2	female	3.0	1	2	41.5792	С	Se	
cond		_	_			_		_	_	
50	0	3	male	7.0	4	1	39.6875	S	Т	
hird										
• •	• • •	• • •	• • •	• • •	• • •	• • •	• • •	• • •		
			,	E4 0	•	•	26 5500	-	_	
857	1	1	male	51.0	0	0	26.5500	S	F	
irst	4	4	C1-	40.0	0	0	25 0202	c	_	
862	1	1	female	48.0	0	0	25.9292	S	F	
irst										

```
#Check for Categorical columns and perform encoding.
# Check for categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns
print("Categorical columns:")
print(categorical_cols)
# Perform categorical encoding
#Label Encoding
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
for col in categorical_cols:
   df[col] = label_encoder.fit_transform(df[col])
#One-Hot Encoding
data = pd.get_dummies(df, columns=categorical_cols, drop_first=True)
# Display the encoded dataset
print(data.head())
Categorical columns:
Index(['sex', 'embarked', 'class', 'who', 'deck', 'embark_town', 'alive'],
dtype='object')
   survived pclass
                      age sibsp parch
                                             fare adult_male alone sex_1
\
                  3 22.0
                               1
                                          7.2500
                                                                          1
0
          0
                                      0
                                                         True False
1
          1
                  1 38.0
                               1
                                      0 14.4542
                                                        False False
                                                                          0
2
                  3 26.0
                                      0
                                                        False
                                                                          0
          1
                               0
                                         7.9250
                                                                True
3
          1
                  1 35.0
                               1
                                      0 53.1000
                                                        False False
                                                                          0
4
                  3 35.0
          0
                               0
                                      0
                                           8.0500
                                                         True
                                                                True
                                                                          1
   embarked_1 ... deck_2 deck_3 deck_4 deck_5 deck_6 deck_7 \
                                         0
0
                         0
                                 0
                                                  0
                                                          0
            0
1
            0
               . . .
                         1
                                 0
                                         0
                                                  0
                                                          0
                                                                  0
                                         0
                                                  0
                                                          0
2
            0
                         0
                                 0
                                                                  1
              . . .
3
            0
                         1
                                 0
                                         0
                                                  0
                                                          0
                                                                  0
              . . .
4
                         0
                                 0
                                         0
                                                  0
                                                                  1
               . . .
   embark_town_1 embark_town_2 embark_town_3
                                                 alive 1
0
               0
                              1
1
               0
                              0
                                              0
                                                       1
2
               0
                              1
                                              0
                                                       1
3
               0
                              1
                                              0
                                                       1
```

[5 rows x 26 columns]

```
In [39]:
```

```
# Split the data into dependent and independent variables
X = df.drop('survived', axis=1) # Independent variables (features)
y = df['survived'] # Dependent variable (target)

# Display the independent variables (features)
print("Independent variables (features):")
print(X.head())

# Display the dependent variable (target)
print("\nDependent variable (target):")
print(y.head())
```

Independent variables (features):

p	class	sex	age	sibsp	parch	fare	embarked	class	who	adult_m
ale	\									
0	3	1	22.0	1	0	7.2500	2	2	1	Т
rue										
1	1	0	38.0	1	0	14.4542	0	0	2	Fa
lse										
2	3	0	26.0	0	0	7.9250	2	2	2	Fa
lse										
3	1	0	35.0	1	0	53.1000	2	0	2	Fa
lse										
4	3	1	35.0	0	0	8.0500	2	2	1	Т
rue										

	deck	embark_town	alive	alone
0	7	2	0	False
1	2	0	1	False
2	7	2	1	True
3	2	2	1	False
4	7	2	0	True

Dependent variable (target):

0112131

0

Name: survived, dtype: int64

In [40]:

```
#Scale the independent variables
from sklearn.preprocessing import StandardScaler
# Split the data into dependent and independent variables
X = df.drop('survived', axis=1) # Independent variables (features)
y = df['survived'] # Dependent variable (target)
# Create a StandardScaler object
scaler = StandardScaler()
# Scale the independent variables
X_scaled = scaler.fit_transform(X)
# Convert the scaled variables back to a DataFrame (optional)
X_scaled = pd.DataFrame(X_scaled, columns=X.columns)
# Display the scaled variables
print(X_scaled.head())
     pclass
                                   sibsp
                                             parch
                                                        fare embarked
                 sex
                           age
0 0.827377 0.737695 -0.661724 0.432793 -0.473674 -0.797554
                                                              0.585954
1 -1.566107 -1.355574 0.972921 0.432793 -0.473674 -0.230556 -1.942303
 0.827377 -1.355574 -0.253063 -0.474545 -0.473674 -0.744429 0.585954
3 -1.566107 -1.355574 0.666425 0.432793 -0.473674 2.811012 0.585954
4 0.827377 0.737695 0.666425 -0.474545 -0.473674 -0.734591 0.585954
```

```
who adult_male
     class
                                     deck embark_town
                                                          alive
                                                                    alo
ne
                       0.811922 0.512048
                                              0.581114 -0.789272 -1.2316
  0.827377 -0.355242
0
45
1 -1.566107 1.328379
                       -1.231645 -1.914733
                                            -1.938460 1.266990 -1.2316
45
2 0.827377 1.328379
                       -1.231645 0.512048
                                              0.581114 1.266990 0.8119
22
3 -1.566107 1.328379
                       -1.231645 -1.914733
                                              0.581114 1.266990 -1.2316
45
                                              0.581114 -0.789272 0.8119
4 0.827377 -0.355242 0.811922 0.512048
22
```

In [42]:

```
from sklearn.model_selection import train_test_split
# Split the data into dependent and independent variables
X = df.drop('survived', axis=1) # Independent variables (features)
y = df['survived'] # Dependent variable (target)
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
# Display the shapes of the training and testing sets
print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)
Shape of X_train: (712, 14)
Shape of X_test: (179, 14)
Shape of y_train: (712,)
Shape of y_test: (179,)
In [ ]:
In [ ]:
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