Titanic Ship Case Study

ADS Assignment 2

Problem Description:

```
On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing
1502 out of 2224 passengers and crew. Translated 32% survival rate.
 One of the reasons that the shipwreck led to such loss of life was that there were not enough
lifeboats for the passengers and crew.
 Although there was some element of luck involved in surviving the sinking, some groups of people were
more likely to survive than others, such as women, children, and the upper- class.
The problem associated with the Titanic dataset is to predict whether a passenger survived the disaster
or not. The dataset contains various features such as passenger class, age, gender, cabin, fare, and
whether the passenger had any siblings or spouses on board. These features can be used to build a
predictive model to determine the likelihood of a passenger surviving the disaster. The dataset offers
opportunities for feature engineering, data visualization, and model selection, making it a valuable
resource for developing and testing data analysis and machine learning skills.

Perform Below Tasks to complete the assignment:-
```

1.Download the dataset: titanic.csv

2.Load the dataset

In [4]:
```
import pandas as pd
data=pd.read_csv("titanic.csv")
data
```

Out[4]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	False
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	True
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	True
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
886	0	2	male	27.0	0	0	13.0000	S	Second	man	True	NaN	Southampton	no	True
887	1	1	female	19.0	0	0	30.0000	S	First	woman	False	B	Southampton	yes	True
888	0	3	female	NaN	1	2	23.4500	S	Third	woman	False	NaN	Southampton	no	False
889	1	1	male	26.0	0	0	30.0000	C	First	man	True	C	Cherbourg	yes	True
890	0	3	male	32.0	0	0	7.7500	Q	Third	man	True	NaN	Queenstown	no	True

891 rows × 15 columns

In [5]:
```
data.shape
```

Out[5]: (891, 15)

In [6]:
```
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
```

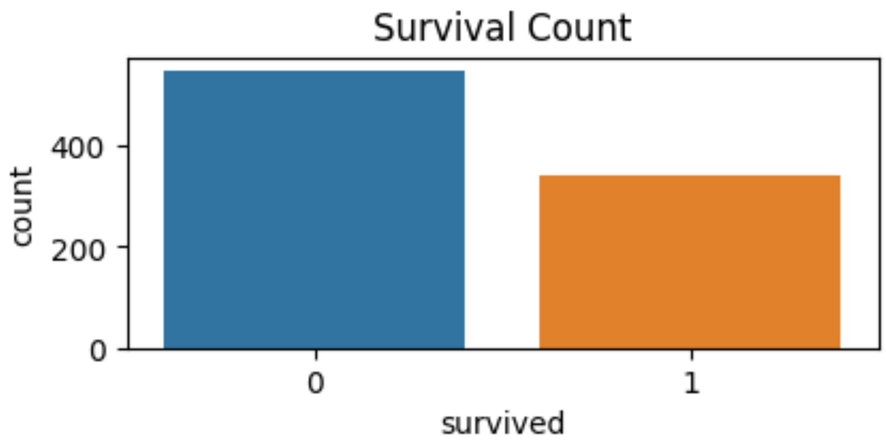
3. Perform Below Visualizations.

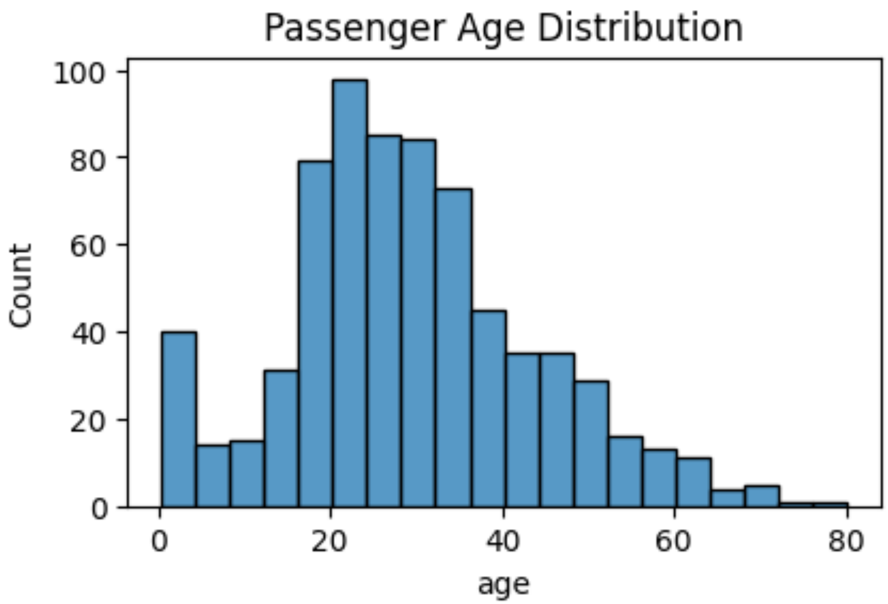
• Univariate Analysis

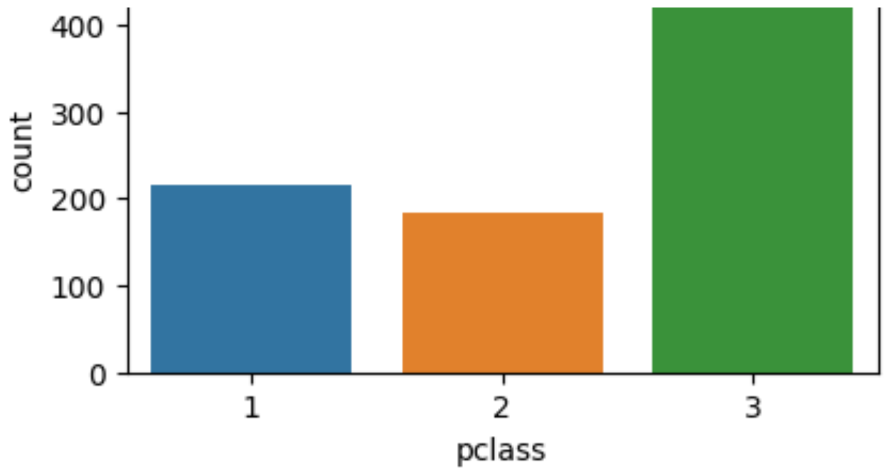
In [7]:

```
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(10,6))
# Plotting the count of passengers by their survival status
plt.subplot(3,2,1)
sns.countplot(x='survived', data=data)
plt.title('Survival Count')
# Plotting the distribution of passenger ages
plt.subplot(2,2,2)
sns.histplot(data['age'].dropna(), bins=20)
plt.title('Passenger Age Distribution')
# Plotting the count of passengers by passenger class
plt.subplot(2,2,3)
sns.countplot(x='pclass', data=data)
```

Out[7]: <AxesSubplot: xlabel='pclass', ylabel='count'>



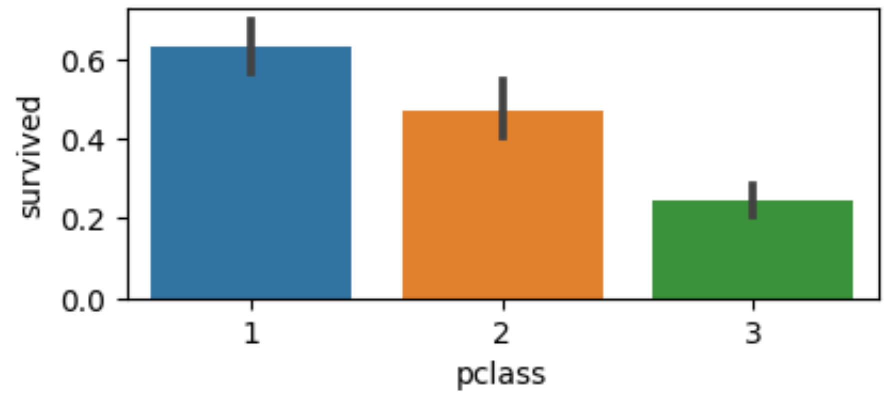


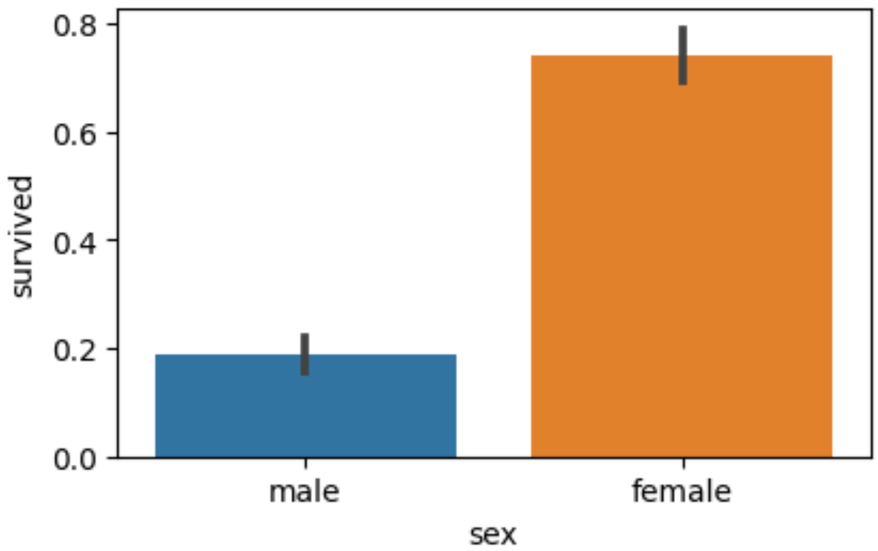


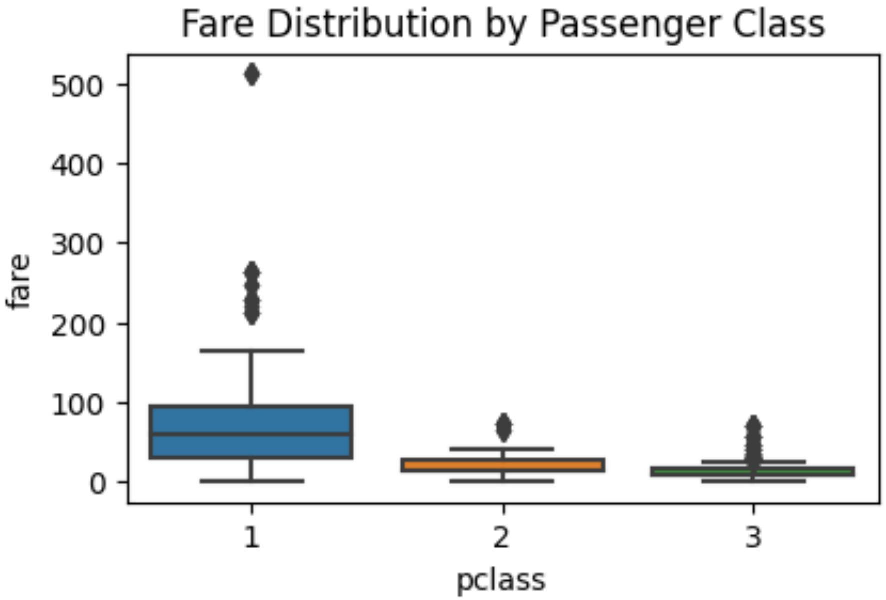
•Bivariate

In [8]:
```
plt.figure(figsize=(10,6))
# Plotting the survival rate by passenger class
plt.subplot(3,2,1)
sns.barplot(x='pclass', y='survived', data=data)
plt.title('Survival Rate by Passenger Class')
# Plotting the survival rate by gender
plt.subplot(2,2,2)
sns.barplot(x='sex', y='survived', data=data)
plt.title('Survival Rate by Gender')
# Plotting the fare distribution by passenger class
plt.subplot(2,2,3)
sns.boxplot(x='pclass', y='fare', data=data)
plt.title('Fare Distribution by Passenger Class')
```

Out[8]:
```
Text(0.5, 1.0, 'Fare Distribution by Passenger Class')
```

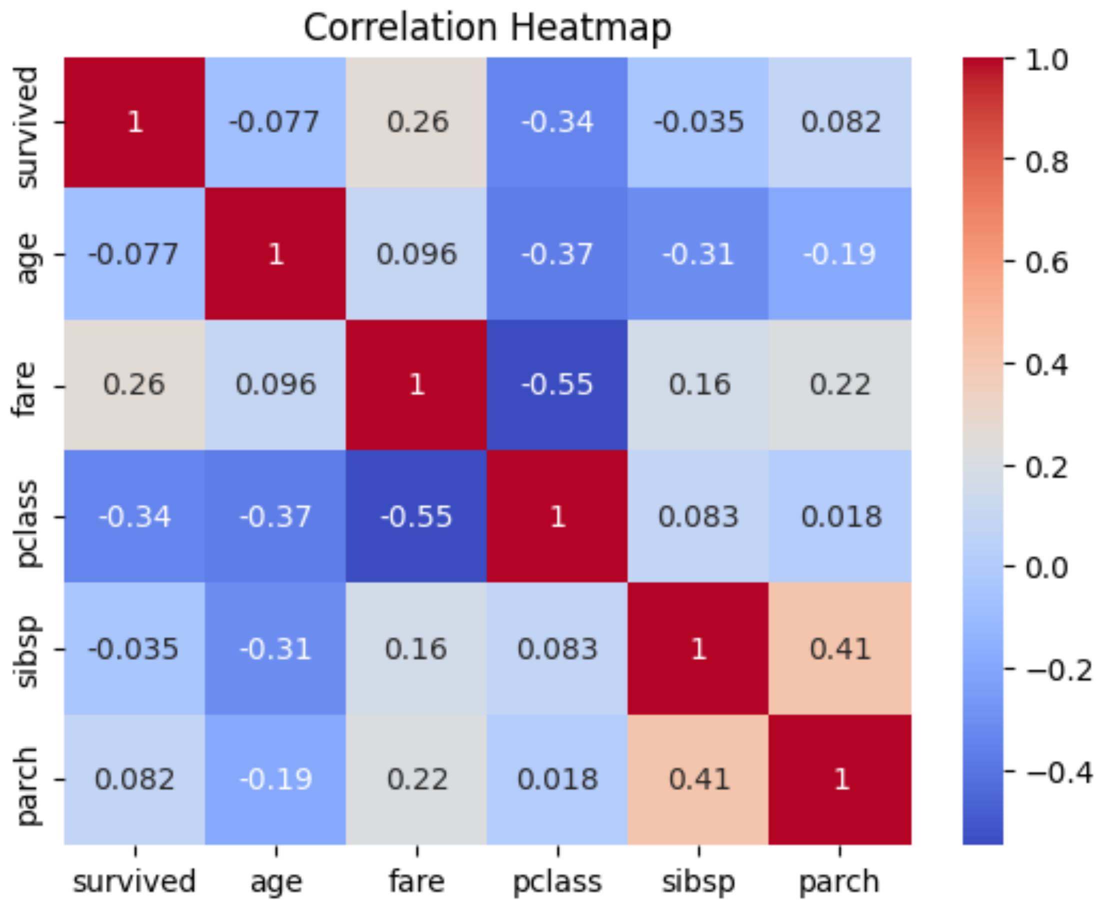






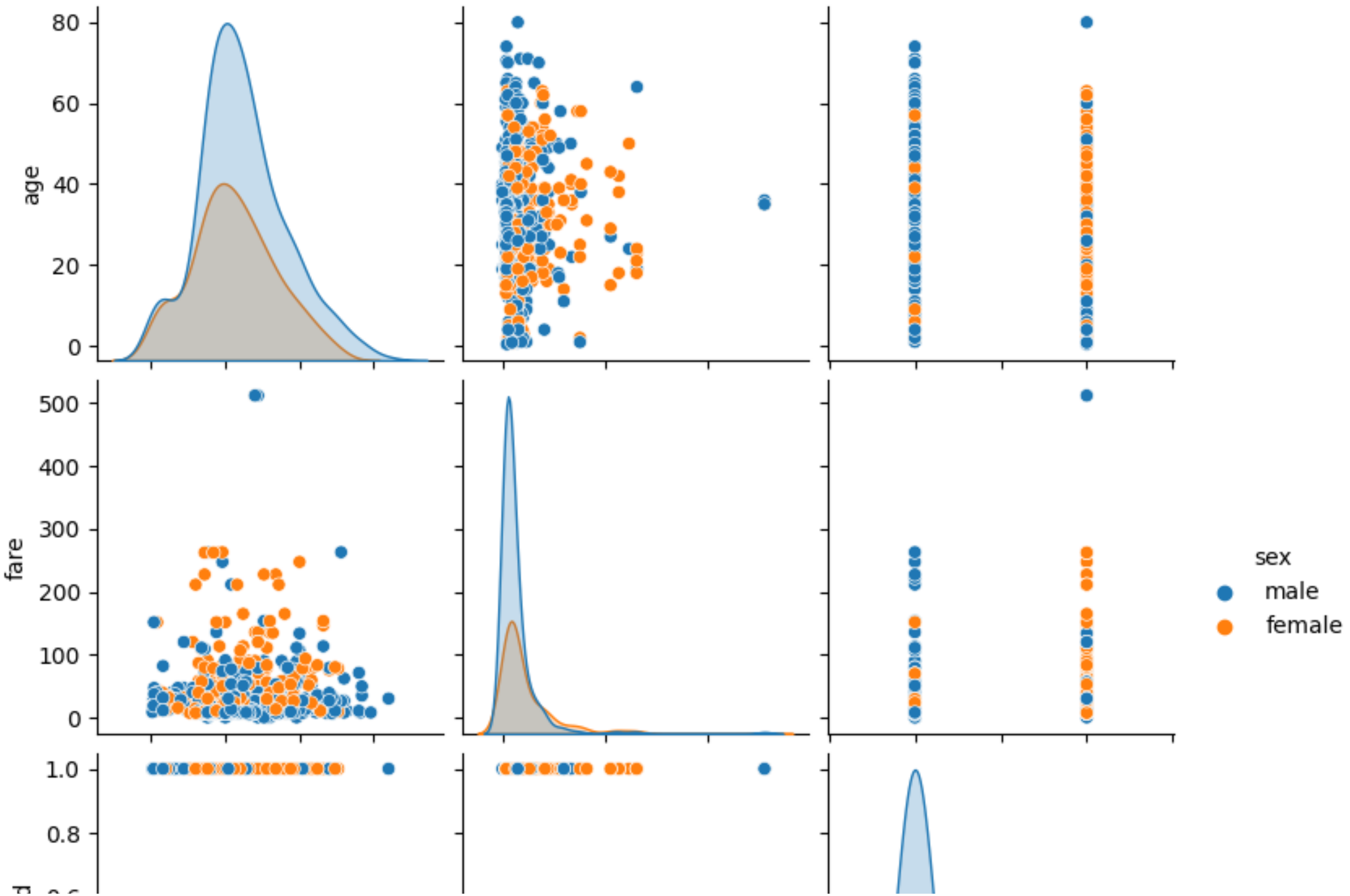
- **multivariate**

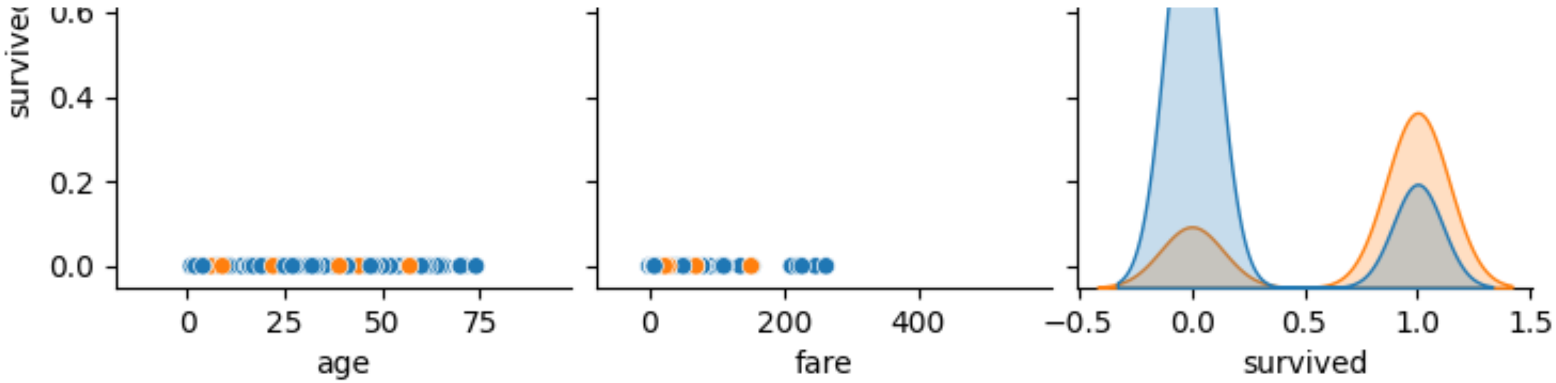
In [9]:
```
# Plotting the correlation heatmap of numeric variables
numeric_cols = ['survived', 'age', 'fare', 'pclass', 'sibsp', 'parch']
sns.heatmap(data[numeric_cols].corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



In [10]:

```
sns.pairplot(data=data, vars=['age', 'fare', 'survived'], hue='sex')
plt.show()
```





4. Perform descriptive statistics on the dataset.

In [83]:
```
data.describe()
```

Out[83]:

	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

5. Handle the Missing values.

In [84]:
```
data.isnull().sum()
```

Out[84]:
```
survived         0
pclass           0
sex              0
age            177
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

In [85]:
```
# Replacing the null values for the age,deck attribute
data['age'].fillna(data['age'].mean(),inplace=True)
# Replacing the null values for the deck attribute
data['deck'].fillna(data['deck'].mode()[0],inplace=True)
# Replacing the null values for the deck attribute
data['embarked'].fillna(data['embarked'].mode()[0],inplace=True )
# Replacing the null values for the deck attribute
data['embark_town'].fillna(data['embark_town'].mode()[0],inplace=True)
```

In [86]:
```
data.isnull().sum()
```

Out[86]:
```
survived         0
pclass           0
sex              0
age              0
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           687
embark_town      2
alive            0
alone            0
dtype: int64
```

In [87]:
```
data.head()
```

Out[87]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	C	Southampton	no	False
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	True
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	True

6. Find the outliers and replace the outliers

In [88]:
```
# numeric columns
numeric_cols = ['age', 'fare', 'sibsp', 'parch']
# Calculate the IQR for each column
Q1 = data[numeric_cols].quantile(0.25)
Q3 = data[numeric_cols].quantile(0.75)
IQR = Q3 - Q1
# Define the lower and upper bounds for outliers
lower_bound = Q1 - (1.5 * IQR)
upper_bound = Q3 + (1.5 * IQR)
# Replace outliers with the median value
for col in numeric_cols:
    data.loc[(data[col] < lower_bound[col]) | (data[col] > upper_bound[col]), col] = data[col].median()

# Verify if outliers have been replaced
outliers_replaced = data[(data[numeric_cols] < lower_bound) | (data[numeric_cols] > upper_bound)].any()
print(outliers_replaced)
```

```
survived       False
pclass         False
sex            False
age            False
sibsp          False
parch          False
fare           False
embarked       False
class          False
who            False
adult_male     False
deck           False
embark_town    False
alive          False
alone          False
dtype: bool
```

7. Check for Categorical columns and perform encoding.

In [89]:
```
# Identify categorical columns
categorical_cols = data.select_dtypes(include='object').columns
print(categorical_cols)
```

```
Index(['sex', 'embarked', 'class', 'who', 'deck', 'embark_town', 'alive'], dtype='object')
```

In [90]:
```
# Perform one-hot encoding
data_encoded = pd.get_dummies(data, columns=categorical_cols)
print(data_encoded.head())
```

```
   survived  pclass   age  sibsp  parch     fare  adult_male  alone  \
0         0       3  22.0      1      0   7.2500        True  False   
1         1       1  38.0      1      0  14.4542       False  False   
2         1       3  26.0      0      0   7.9250       False   True   
3         1       1  35.0      1      0  53.1000       False  False   
4         0       3  35.0      0      0   8.0500        True   True   

   sex_female  sex_male  ...  deck_C  deck_D  deck_E  deck_F  deck_G  \
0           0         1  ...       1       0       0       0       0   
1           1         0  ...       1       0       0       0       0   
2           1         0  ...       0       0       0       0       0   
3           1         0  ...       1       0       0       0       0   
4           0         1  ...       0       0       0       0       0   

   embark_town_Cherbourg  embark_town_Queenstown  embark_town_Southampton  \
0                      0                       0                        1   
1                      1                       0                        0   
2                      0                       0                        1   
3                      0                       0                        1   
4                      0                       0                        1   

   alive_no  alive_yes  
0         1          0  
1         0          1  
2         0          1  
3         0          1  
4         1          0  

[5 rows x 31 columns]
```

8. Split the data into dependent and independent variables.

In [91]:
```
x = data.drop('survived', axis=1)
# Independent variables
y = data['survived']
# Dependent variable
# Display the independent variables (features)
print("Independent values:\n",x.head())
# Display the dependent variable (target)
print("\nDependent variable:\n",y.head())
```

```
Independent values:
    pclass     sex   age  sibsp  parch     fare embarked  class    who  \
0       3    male  22.0      1      0   7.2500        S  Third    man
1       1  female  38.0      1      0  71.2833        C  First  woman
2       3  female  26.0      0      0   7.9250        S  Third  woman
3       1  female  35.0      1      0  53.1000        S  First  woman
4       3    male  35.0      0      0   8.0500        S  Third    man

   adult_male deck  embark_town alive  alone
0        True    C  Southampton    no  False
1       False    C    Cherbourg   yes  False
2       False  NaN  Southampton   yes   True
3       False    C  Southampton   yes  False
4        True  NaN  Southampton    no   True

Dependent variable:
 0    0
1    1
2    1
3    1
4    0
Name: survived, dtype: int64
```

9. Scale the independent variables

In [92]:
```
from sklearn.preprocessing import StandardScaler
scale = StandardScaler()
x_scaled = scale.fit_transform(data_encoded)
# Create a new DataFrame with the scaled independent variables
data_scaled = pd.DataFrame(x_scaled, columns=data_encoded.columns)
# Display the scaled independent variables
print(data_scaled.head())
```

```
   survived    pclass       age     sibsp  parch      fare  adult_male  \
0 -0.789272  0.827377 -0.708584  1.347605    0.0 -0.797554    0.811922
1  1.266990 -1.566107  0.924948  1.347605    0.0 -0.230556   -1.231645
2  1.266990  0.827377 -0.300201 -0.570472    0.0 -0.744429   -1.231645
3  1.266990 -1.566107  0.618661  1.347605    0.0  2.811012   -1.231645
4 -0.789272  0.827377  0.618661 -0.570472    0.0 -0.734591    0.811922

      alone  sex_female  sex_male  ...    deck_C    deck_D    deck_E  \
0 -1.231645   -0.737695  0.737695  ...  3.721559 -0.196116 -0.193009
1 -1.231645    1.355574 -1.355574  ...  3.721559 -0.196116 -0.193009
2  0.811922    1.355574 -1.355574  ... -0.268705 -0.196116 -0.193009
3 -1.231645    1.355574 -1.355574  ...  3.721559 -0.196116 -0.193009
4  0.811922   -0.737695  0.737695  ... -0.268705 -0.196116 -0.193009

     deck_F    deck_G  embark_town_Cherbourg  embark_town_Queenstown  \
0 -0.121681 -0.067153              -0.482043               -0.307562
1 -0.121681 -0.067153               2.074505               -0.307562
2 -0.121681 -0.067153              -0.482043               -0.307562
3 -0.121681 -0.067153              -0.482043               -0.307562
4 -0.121681 -0.067153              -0.482043               -0.307562

   embark_town_Southampton  alive_no  alive_yes
0                 0.619306  0.789272  -0.789272
```

```
1                -1.614710 -1.266990   1.266990
2                 0.619306 -1.266990   1.266990
3                 0.619306 -1.266990   1.266990
4                 0.619306  0.789272  -0.789272

[5 rows x 31 columns]
```

10. Split the data into training and testing

In [93]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=42)
```

In [94]:
```
x_train
```

Out[94]:

	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
331	1	male	45.500000	0	0	28.5000	S	First	man	True	C	Southampton	no	True
733	2	male	23.000000	0	0	13.0000	S	Second	man	True	NaN	Southampton	no	True
382	3	male	32.000000	0	0	7.9250	S	Third	man	True	NaN	Southampton	no	True
704	3	male	26.000000	1	0	7.8542	S	Third	man	True	NaN	Southampton	no	False
813	3	female	6.000000	0	0	31.2750	S	Third	child	False	NaN	Southampton	no	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
106	3	female	21.000000	0	0	7.6500	S	Third	woman	False	NaN	Southampton	yes	True
270	1	male	29.699118	0	0	31.0000	S	First	man	True	NaN	Southampton	no	True
860	3	male	41.000000	2	0	14.1083	S	Third	man	True	NaN	Southampton	no	False
435	1	female	14.000000	1	0	14.4542	S	First	child	False	B	Southampton	yes	False
102	1	male	21.000000	0	0	14.4542	S	First	man	True	D	Southampton	no	False

712 rows × 14 columns

In [95]:
```
y_train
```

Out[95]:
```
331    0
733    0
382    0
704    0
813    0
      ..
106    1
270    0
860    0
435    1
102    0
Name: survived, Length: 712, dtype: int64
```

In [96]:
```
x_test
```

Out[96]:

	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
709	3	male	29.699118	1	0	15.2458	C	Third	man	True	NaN	Cherbourg	yes	False
439	2	male	31.000000	0	0	10.5000	S	Second	man	True	NaN	Southampton	no	True
840	3	male	20.000000	0	0	7.9250	S	Third	man	True	NaN	Southampton	no	True
720	2	female	6.000000	0	0	33.0000	S	Second	child	False	NaN	Southampton	yes	False
39	3	female	14.000000	1	0	11.2417	C	Third	child	False	NaN	Cherbourg	yes	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
433	3	male	17.000000	0	0	7.1250	S	Third	man	True	NaN	Southampton	no	True
773	3	male	29.699118	0	0	7.2250	C	Third	man	True	NaN	Cherbourg	no	True
25	3	female	38.000000	1	0	31.3875	S	Third	woman	False	NaN	Southampton	yes	False
84	2	female	17.000000	0	0	10.5000	S	Second	woman	False	NaN	Southampton	yes	True
10	3	female	4.000000	1	0	16.7000	S	Third	child	False	G	Southampton	yes	False

179 rows × 14 columns

In [97]:
```
y_test
```

Out[97]:
```
709    1
439    0
840    0
720    1
39     1
      ..
433    0
773    0
25     1
84     1
10     1
Name: survived, Length: 179, dtype: int64
```