Titanic ¶

Business Understanding

Predict the Survival of Titanic Passengers

In [1]:
```
import warnings
warnings.filterwarnings('ignore')

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

In [2]:
```
df = pd.read_csv('train.csv')
df.head(2)
```

Out[2]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C

In [3]:
```
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
```

In [4]:
```
df.columns
```

Out[4]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

Data Understanding

- Survival (0=No, 1 =Yes)
- pclass (1st=Upper, 2nd = Middle, 3rd=Lower)
- Ticket class (1 = 1st, 2=2nd, 3=3rd)
- Age in years
- SibSp (# of sibling/ spouses abroad the Titanic)
- Parch (# of children/ children abroad the Titanic)
- fare (passenger fare)
- embarked (C = Cherbourg, Q = Queenstown, S = Southampton)

age: Age is fractional if less than 1. If the age is estimated, is it in the form of xx.5

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.

In [5]:
```
df['PassengerId'].nunique()
```

Out[5]:
```
891
```

In [6]:
```
#df.drop(columns = ['PassengerId'], inplace=True)
```

we can't drop this PassengerId column because in test.csv we are reuqired this column and it column should match from test.csv file that's why I am keeping this column

In [7]:
```
df['Survived'].unique()
```

Out[7]:
```
array([0, 1], dtype=int64)
```

In [8]:
```
df['Survived'].value_counts()
```

Out[8]:
```
Survived
0    549
1    342
Name: count, dtype: int64
```

In [9]:
```
df['Pclass'].unique()
```

Out[9]:
```
array([3, 1, 2], dtype=int64)
```

In [10]:
```
df['Pclass'].value_counts()
```

Out[10]:
```
Pclass
3    491
1    216
2    184
Name: count, dtype: int64
```

In [11]:
```
df['Sex'].unique()
```

Out[11]:
```
array(['male', 'female'], dtype=object)
```

In [12]:
```
df['Sex'].value_counts()
```

Out[12]:
```
Sex
male      577
female    314
Name: count, dtype: int64
```

In [13]:
```
df['Age'].unique()
```

Out[13]:
```
array([22.  , 38.  , 26.  , 35.  ,   nan, 54.  ,  2.  , 27.  , 14.  ,
        4.  , 58.  , 20.  , 39.  , 55.  , 31.  , 34.  , 15.  , 28.  ,
        8.  , 19.  , 40.  , 66.  , 42.  , 21.  , 18.  ,  3.  ,  7.  ,
       49.  , 29.  , 65.  , 28.5 ,  5.  , 11.  , 45.  , 17.  , 32.  ,
       16.  , 25.  ,  0.83, 30.  , 33.  , 23.  , 24.  , 46.  , 59.  ,
       71.  , 37.  , 47.  , 14.5 , 70.5 , 32.5 , 12.  ,  9.  , 36.5 ,
       51.  , 55.5 , 40.5 , 44.  ,  1.  , 61.  , 56.  , 50.  , 36.  ,
       45.5 , 20.5 , 62.  , 41.  , 52.  , 63.  , 23.5 ,  0.92, 43.  ,
       60.  , 10.  , 64.  , 13.  , 48.  ,  0.75, 53.  , 57.  , 80.  ,
       70.  , 24.5 ,  6.  ,  0.67, 30.5 ,  0.42, 34.5 , 74.  ])
```

In [14]:
```
df['Age'].value_counts()
```

Out[14]:
```
Age
24.00    30
22.00    27
18.00    26
19.00    25
28.00    25
         ..
36.50     1
55.50     1
0.92      1
23.50     1
74.00     1
Name: count, Length: 88, dtype: int64
```

In [15]:
```
df['SibSp'].unique()
```

Out[15]:
```
array([1, 0, 3, 4, 2, 5, 8], dtype=int64)
```

In [16]:
```
df['SibSp'].value_counts()
```

Out[16]:
```
SibSp
0    608
1    209
2     28
4     18
3     16
8      7
5      5
Name: count, dtype: int64
```

In [17]:
```
df['Parch'].unique()
```

Out[17]:
```
array([0, 1, 2, 5, 3, 4, 6], dtype=int64)
```

In [18]:
```
df['Parch'].value_counts()
```

Out[18]:
```
Parch
0    678
1    118
2     80
5      5
3      5
4      4
6      1
Name: count, dtype: int64
```

In [19]:
```python
df['Ticket'].unique()
```

Out[19]:
```
array(['A/5 21171', 'PC 17599', 'STON/O2. 3101282', '113803', '373450',
       '330877', '17463', '349909', '347742', '237736', 'PP 9549',
       '113783', 'A/5. 2151', '347082', '350406', '248706', '382652',
       '244373', '345763', '2649', '239865', '248698', '330923', '113788',
       '347077', '2631', '19950', '330959', '349216', 'PC 17601',
       'PC 17569', '335677', 'C.A. 24579', 'PC 17604', '113789', '2677',
       'A./5. 2152', '345764', '2651', '7546', '11668', '349253',
       'SC/Paris 2123', '330958', 'S.C./A.4. 23567', '370371', '14311',
       '2662', '349237', '3101295', 'A/4. 39886', 'PC 17572', '2926',
       '113509', '19947', 'C.A. 31026', '2697', 'C.A. 34651', 'CA 2144',
       '2669', '113572', '36973', '347088', 'PC 17605', '2661',
       'C.A. 29395', 'S.P. 3464', '3101281', '315151', 'C.A. 33111',
       'S.O.C. 14879', '2680', '1601', '348123', '349208', '374746',
       '248738', '364516', '345767', '345779', '330932', '113059',
       'SO/C 14885', '3101278', 'W./C. 6608', 'SOTON/OQ 392086', '343275',
       '343276', '347466', 'W.E.P. 5734', 'C.A. 2315', '364500', '374910',
       'PC 17754', 'PC 17759', '231919', '244367', '349245', '349215',
       '35281', '7540', '3101276', '349207', '343120', '312991', '349249',
       '371110', '110465', '2665', '324669', '4136', '2627',
```

In [20]:
```python
df['Ticket'].value_counts()
```

Out[20]:
```
Ticket
347082      7
CA. 2343    7
1601        7
3101295     6
CA 2144     6
           ..
9234        1
19988       1
2693        1
PC 17612    1
370376      1
Name: count, Length: 681, dtype: int64
```

In [21]:
```python
df['Fare'].value_counts()
```

Out[21]:
```
Fare
8.0500     43
13.0000    42
7.8958     38
7.7500     34
26.0000    31
           ..
35.0000     1
28.5000     1
6.2375      1
14.0000     1
10.5167     1
Name: count, Length: 248, dtype: int64
```

- 8.0500: This fare price was paid by 43 passengers.
- 13.0000: This fare price was paid by 42 passengers.

> ---- so on

In [22]:
```
df['Cabin'].unique()
```

Out[22]:
```
array([nan, 'C85', 'C123', 'E46', 'G6', 'C103', 'D56', 'A6',
       'C23 C25 C27', 'B78', 'D33', 'B30', 'C52', 'B28', 'C83', 'F33',
       'F G73', 'E31', 'A5', 'D10 D12', 'D26', 'C110', 'B58 B60', 'E101',
       'F E69', 'D47', 'B86', 'F2', 'C2', 'E33', 'B19', 'A7', 'C49', 'F4',
       'A32', 'B4', 'B80', 'A31', 'D36', 'D15', 'C93', 'C78', 'D35',
       'C87', 'B77', 'E67', 'B94', 'C125', 'C99', 'C118', 'D7', 'A19',
       'B49', 'D', 'C22 C26', 'C106', 'C65', 'E36', 'C54',
       'B57 B59 B63 B66', 'C7', 'E34', 'C32', 'B18', 'C124', 'C91', 'E40',
       'T', 'C128', 'D37', 'B35', 'E50', 'C82', 'B96 B98', 'E10', 'E44',
       'A34', 'C104', 'C111', 'C92', 'E38', 'D21', 'E12', 'E63', 'A14',
       'B37', 'C30', 'D20', 'B79', 'E25', 'D46', 'B73', 'C95', 'B38',
       'B39', 'B22', 'C86', 'C70', 'A16', 'C101', 'C68', 'A10', 'E68',
       'B41', 'A20', 'D19', 'D50', 'D9', 'A23', 'B50', 'A26', 'D48',
       'E58', 'C126', 'B71', 'B51 B53 B55', 'D49', 'B5', 'B20', 'F G63',
       'C62 C64', 'E24', 'C90', 'C45', 'E8', 'B101', 'D45', 'C46', 'D30',
       'E121', 'D11', 'E77', 'F38', 'B3', 'D6', 'B82 B84', 'D17', 'A36',
       'B102', 'B69', 'E49', 'C47', 'D28', 'E17', 'A24', 'C50', 'B42',
       'C148'], dtype=object)
```

In [23]:
```
df['Cabin'].value_counts()
```

Out[23]:
```
Cabin
B96 B98        4
G6             4
C23 C25 C27    4
C22 C26        3
F33            3
              ..
E34            1
C7             1
C54            1
E36            1
C148           1
Name: count, Length: 147, dtype: int64
```

In [24]:
```
df['Embarked'].unique()
```

Out[24]:
```
array(['S', 'C', 'Q', nan], dtype=object)
```

In [25]:
```
df['Embarked'].value_counts()
```

Out[25]:
```
Embarked
S    644
C    168
Q     77
Name: count, dtype: int64
```

In [26]:
```
df.head(2)
```

Out[26]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C

In [27]:
```
continuous = ['PassengerId', 'Survived', 'Age', 'Fare']
discrete_count = ['Pclass', 'SibSp', 'Parch']
discrete_categorical = ['Name', 'Sex', 'Embarked', 'Ticket', 'Cabin']
```

by the way remember 'Survided' column is a binary categorical varible so it should come under categorical varibale but I keep this inside continuous because in order to get summary

Exploratory Data Analysis (EDA)

EDA for continuous variables

In [28]:
```
df[continuous].describe()
```

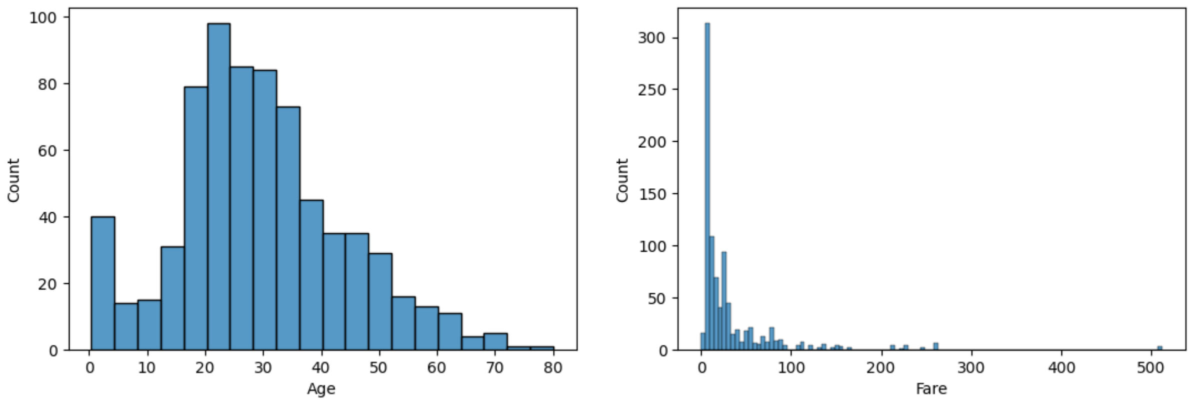
Out[28]:

	PassengerId	Survived	Age	Fare
count	891.000000	891.000000	714.000000	891.000000
mean	446.000000	0.383838	29.699118	32.204208
std	257.353842	0.486592	14.526497	49.693429
min	1.000000	0.000000	0.420000	0.000000
25%	223.500000	0.000000	20.125000	7.910400
50%	446.000000	0.000000	28.000000	14.454200
75%	668.500000	1.000000	38.000000	31.000000
max	891.000000	1.000000	80.000000	512.329200

when age = 0.420000 mean 5 month

This could indicate that the passenger was an infant or a very young child at the time of the Titanic's voyage.

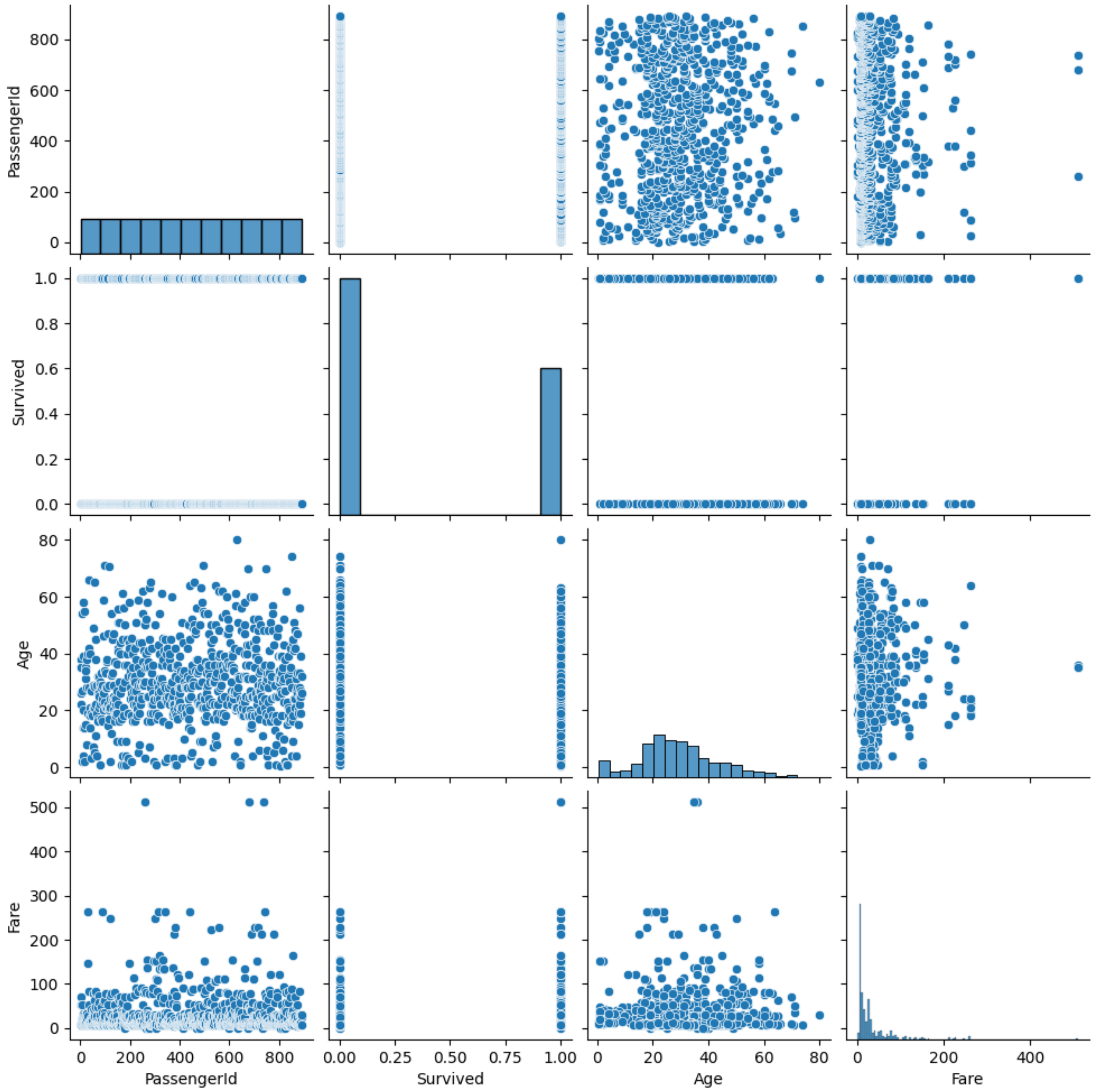
In [29]:
```
plt.rcParams['figure.figsize'] = (13, 4)
plt.subplot(1, 2, 1)
sns.histplot(df['Age'])

plt.subplot(1, 2, 2)
sns.histplot(df['Fare'])

plt.show()
```



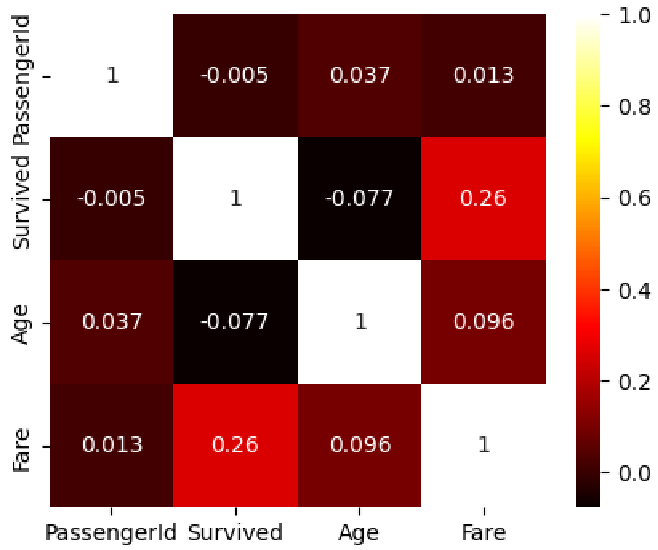
In [30]:
```
df[continuous].skew()
```

Out[30]:
```
PassengerId    0.000000
Survived       0.478523
Age            0.389108
Fare           4.787317
dtype: float64
```

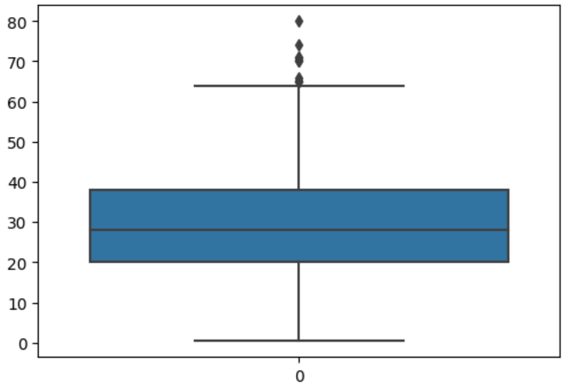
In [31]:
```python
plt.rcParams['figure.figsize'] = (13, 4)
sns.pairplot(df[continuous])
plt.show()
```

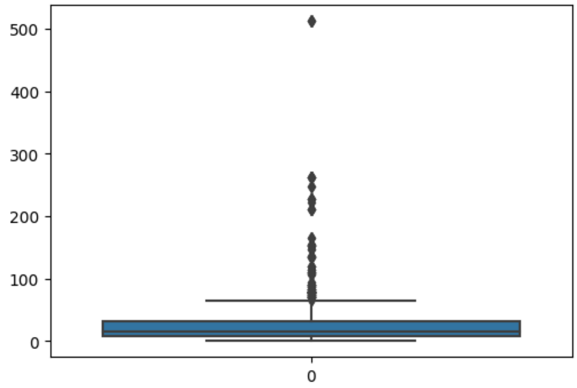


In [32]:
```python
plt.figure(figsize=(5, 4))
sns.heatmap(df[continuous].corr(), annot=True, cmap='hot')
plt.show()
```



In [33]:
```
plt.rcParams['figure.figsize'] = (13, 4)
plt.subplot(1, 2, 1)
sns.boxplot(df['Age'])

plt.subplot(1, 2, 2)
sns.boxplot(df['Fare'])

plt.show()
```





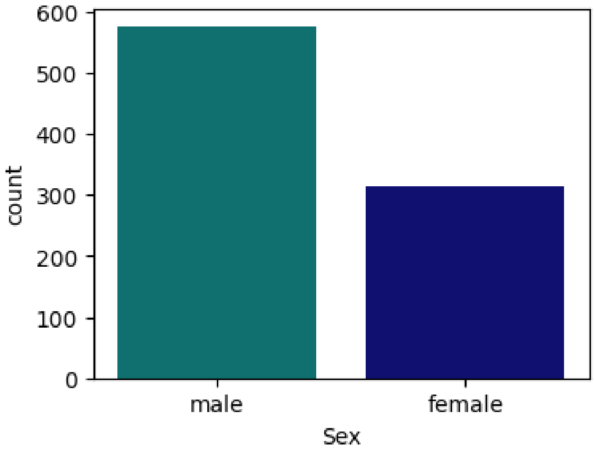
EDA for discrete variables

In [34]:
```
df[discrete_categorical].describe()
```

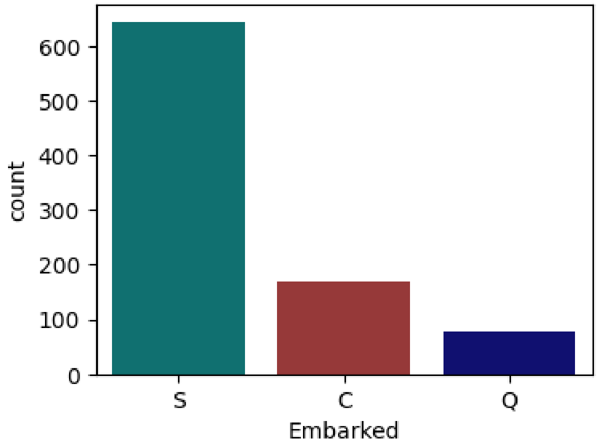
Out[34]:

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

In [35]:
```
plt.figure(figsize=(4, 3))
sns.countplot(data=df, x='Sex', palette=['teal', 'navy'])
plt.show()
```



In [36]:
```
plt.figure(figsize=(4, 3))
sns.countplot(data=df, x='Embarked', palette=['teal', 'brown', 'navy'])
plt.show()
```



Data Preparation

'SciSp' and 'Parch' both columns are family column so I combined it.

In [37]:
```
df['SibSp'].unique()
```

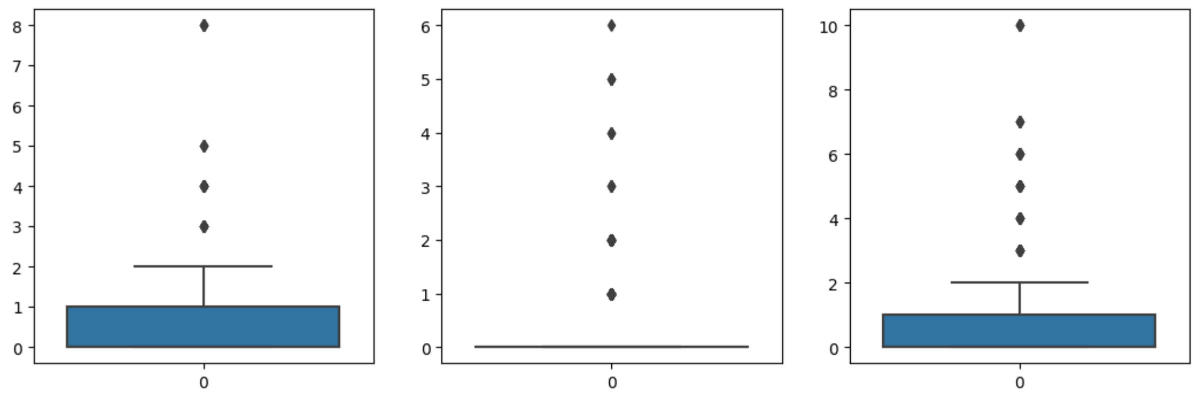
Out[37]:
```
array([1, 0, 3, 4, 2, 5, 8], dtype=int64)
```

In [38]:
```
df['Parch'].unique()
```

Out[38]:
```
array([0, 1, 2, 5, 3, 4, 6], dtype=int64)
```

In [39]:
```
df['Family'] = df['SibSp'] + df['Parch']
```

In [40]:
```
plt.rcParams['figure.figsize'] = (13, 4)
plt.subplot(1, 3, 1)
sns.boxplot(df['SibSp'])

plt.subplot(1, 3, 2)
sns.boxplot(df['Parch'])

plt.subplot(1, 3, 3)
sns.boxplot(df['Family'])
plt.show()
```



In [41]:
```
df.drop(columns= ['SibSp', 'Parch'], inplace=True)
```

In [42]:
```
df['Family'].unique()
```

Out[42]:
```
array([ 1,  0,  4,  2,  6,  5,  3,  7, 10], dtype=int64)
```

In [43]:
```
df['Family'].value_counts()
```

Out[43]:
```
Family
0     537
1     161
2     102
3      29
5      22
4      15
6      12
10      7
7       6
Name: count, dtype: int64
```

Missing value treatment

In [44]:
```
df.isnull().sum()
```

Out[44]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
Ticket           0
Fare             0
Cabin          687
Embarked         2
Family           0
dtype: int64
```

In [45]:
```
df['Age'].fillna(df['Age'].mean(), inplace=True)
```

as we know when we have missing values more than 30% so drop that but here as we can see our cabin column have 77% missing values so we will drop entire column

In [46]:
```
df.drop(columns = 'Cabin', inplace=True)
```

In [47]:
```
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)
```

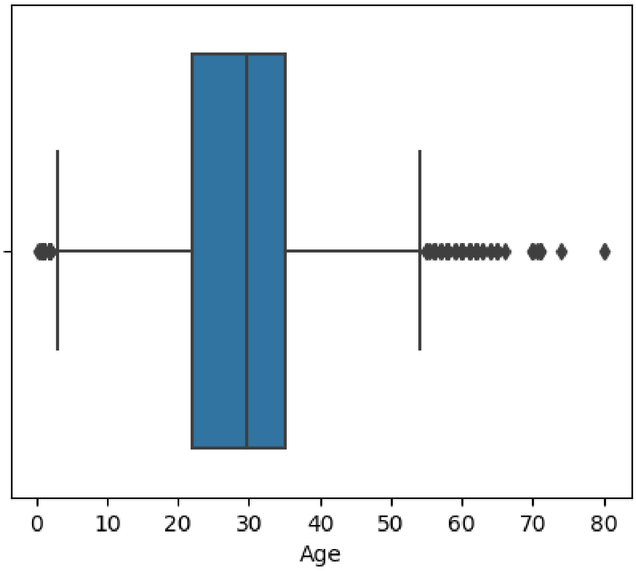
drop unimportant column

In [48]:
```
df.drop(columns = ['Name', 'Ticket'], inplace=True)
```

Outliers Treatment

AGE

In [49]:
```
plt.figure(figsize=(5, 4))
sns.boxplot(x=df['Age'])
plt.show()
```



In [50]:
```
# Calculate Q1
Q1 = df['Age'].quantile(0.25)
print("Q1: ", Q1)

# Calculate Q2
Q3 = df['Age'].quantile(0.75)
print("Q3: ", Q3)

# Calculate IQR
IQR = Q3 - Q1
print('IQR:', IQR)

# Calculate lower limit of outliers
lower_limit = Q1 - (IQR * 1.5)
print('lower_limit', lower_limit)

# Calculate upper limit of outliers
upper_limit = Q3 + (IQR * 1.5)
print('upper_limit', upper_limit)
```

```
Q1:  22.0
Q3:  35.0
IQR: 13.0
lower_limit 2.5
upper_limit 54.5
```

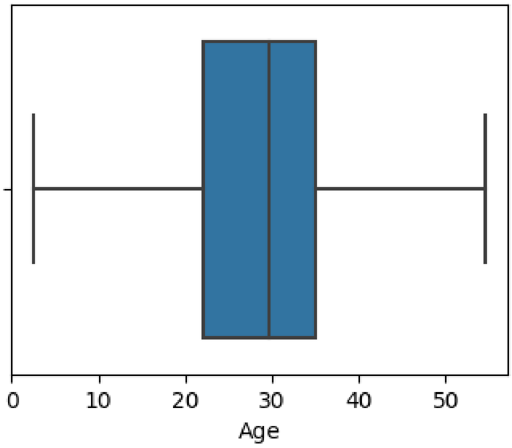
In [51]:
```
# list of outliers
df[(df['Age'] < lower_limit) | (df['Age'] > upper_limit)].index
```

Out[51]:
```
Index([  7,  11,  15,  16,  33,  54,  78,  94,  96, 116, 119, 152, 164, 170,
       172, 174, 183, 195, 205, 232, 252, 268, 275, 280, 297, 305, 326, 340,
       366, 381, 386, 438, 456, 467, 469, 479, 483, 487, 492, 493, 530, 545,
       555, 570, 587, 625, 626, 630, 642, 644, 647, 659, 672, 684, 694, 745,
       755, 772, 788, 803, 824, 827, 829, 831, 851, 879],
      dtype='int64')
```

In [52]:
```
# winsorization technqiue (for replacing outliers)
df['Age'] = df['Age'].clip(lower=2.5, upper=54.5)
df['Age']
```

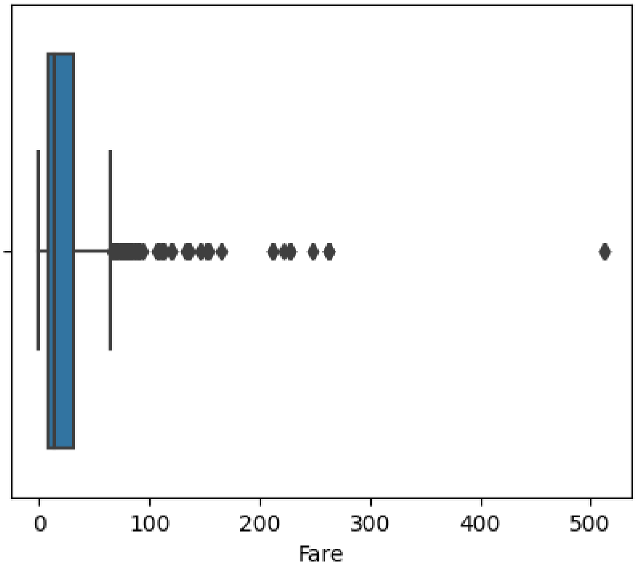
Out[52]:
```
0      22.000000
1      38.000000
2      26.000000
3      35.000000
4      35.000000
         ...
886    27.000000
887    19.000000
888    29.699118
889    26.000000
890    32.000000
Name: Age, Length: 891, dtype: float64
```

In [53]:
```
plt.figure(figsize=(4, 3))
sns.boxplot(x=df['Age'])
plt.show()
```



FARE

In [54]:
```
plt.figure(figsize=(5, 4))
sns.boxplot(x=df['Fare'])
plt.show()
```



In [55]:
```
# Calculate Q1
Q1 = df['Fare'].quantile(0.25)
print("Q1: ", Q1)

# Calculate Q2
Q3 = df['Fare'].quantile(0.75)
print("Q3: ", Q3)

# Calculate IQR
IQR = Q3 - Q1
print('IQR:', IQR)

# Calculate lower limit of outliers
lower_limit = Q1 - (IQR * 1.5)
print('lower_limit', lower_limit)

# Calculate upper limit of outliers
upper_limit = Q3 + (IQR * 1.5)
print('upper_limit', upper_limit)
```

```
Q1:  7.9104
Q3:  31.0
IQR: 23.0896
lower_limit -26.724
upper_limit 65.6344
```

In [56]:
```
len(df[(df['Fare'] < lower_limit) | (df['Fare'] > upper_limit)])
```

Out[56]: 116

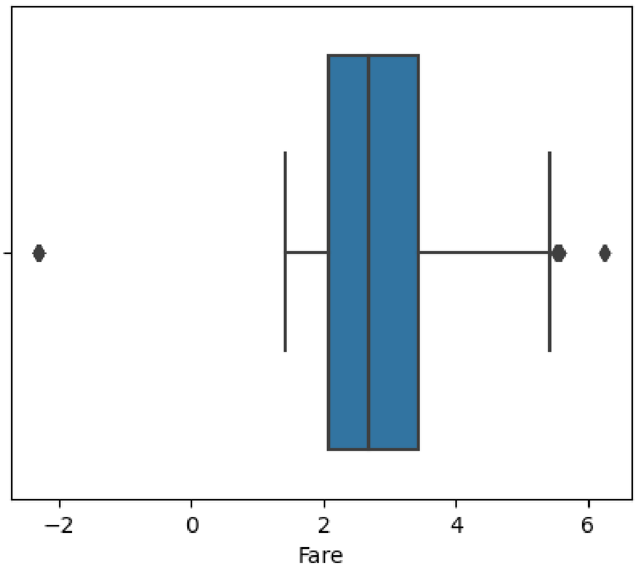
Logarithmic transformation

In [57]:
```
import numpy as np
df['Fare'] = np.log(df['Fare']+0.1)
df['Fare'].skew()
```

Out[57]: -0.9166865254725971

even after using lof transformation, I still have outliers so, I can use winsorization technique

In [58]:
```
plt.figure(figsize=(5, 4))
sns.boxplot(x=df['Fare'])
plt.show()
```



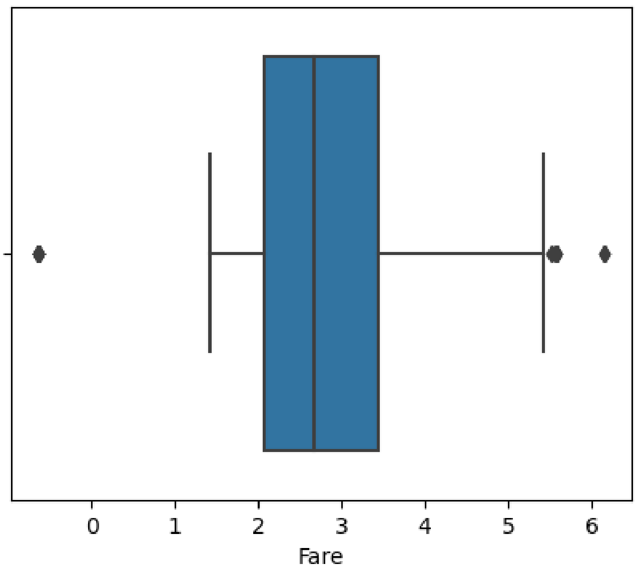
In [59]:
```
# Calculate Q1
Q1 = df['Fare'].quantile(0.25)
print("Q1: ", Q1)

# Calculate Q2
Q3 = df['Fare'].quantile(0.75)
print("Q3: ", Q3)

# Calculate IQR
IQR = Q3 - Q1
print('IQR:', IQR)

# Calculate lower limit of outliers
lower_limit = Q1 - (IQR * 2)
print('lower_limit', lower_limit)

# Calculate upper limit of outliers
upper_limit = Q3 + (IQR * 2)
print('upper_limit', upper_limit)
```

```
Q1:  2.0807390364175813
Q3:  3.4372078191851885
IQR: 1.3564687827676072
lower_limit -0.6321985291176331
upper_limit 6.150145384720403
```

In [60]:
```
# winsorization technqiue (for replacing outliers)
df['Fare'] = df['Fare'].clip(lower=-0.63, upper=6.15)
df['Fare']
```

Out[60]:
```
0      1.994700
1      4.268064
2      2.082562
3      3.974058
4      2.098018
         ...
886    2.572612
887    3.404525
888    3.159126
889    3.404525
890    2.060514
Name: Fare, Length: 891, dtype: float64
```

In [61]:
```
plt.figure(figsize=(5, 4))
sns.boxplot(x=df['Fare'])
plt.show()
```



In [62]:
```
len(df[(df['Fare'] < lower_limit) | (df['Fare'] > upper_limit)])
```

Out[62]:
```
0
```

for handling outliers in **'Fare'** column, I used two technique:

1. **Logarithmic Transformation:** Apply the logarithmic transformation to the 'Fare' column to reduce the skewness caused by outliers.
2. **Winsorization (IQR Method):** After applying the logarithmic transformation, calculate the interquartile range (IQR) of the transformed 'Fare' column.

In [63]:
```
df.head()
```

Out[63]:

	PassengerId	Survived	Pclass	Sex	Age	Fare	Embarked	Family
0	1	0	3	male	22.0	1.994700	S	1
1	2	1	1	female	38.0	4.268064	C	1
2	3	1	3	female	26.0	2.082562	S	0
3	4	1	1	female	35.0	3.974058	S	1
4	5	0	3	male	35.0	2.098018	S	0

Encoding

In [64]:
```
df['Sex'] = df['Sex'].replace({'male':1, 'female':0}).astype('int')
df['Embarked'] = df['Embarked'].replace({'S':2, 'Q':1, 'C':0}).astype('int')
```

In [65]:
```
df.head()
```

Out[65]:

	PassengerId	Survived	Pclass	Sex	Age	Fare	Embarked	Family
0	1	0	3	1	22.0	1.994700	2	1
1	2	1	1	0	38.0	4.268064	0	1
2	3	1	3	0	26.0	2.082562	2	0
3	4	1	1	0	35.0	3.974058	2	1
4	5	0	3	1	35.0	2.098018	2	0

These are the steps that I followed for Data Preparation

1. **Transformation of Categorical Variables:**

- The 'Sex' column has been transformed into a binary variable ('male' -> 1, 'female' -> 0).
- The 'Embarked' column has been transformed into numerical values (e.g., 'S' -> 2), presumably through label encoding or one-hot encoding.

2. **Feature Engineering:**

- A new feature 'Family' has been introduced, possibly representing the total number of family members on board (sum of 'SibSp' and 'Parch' columns).

3. **Normalization of Continuous Variables:**

- The 'Age' and 'Fare' columns seem to have been normalized or scaled, as the values are different from the original dataset.

4. **Dropping of Irrelevant Columns:**

- Columns such as 'PassengerId', 'Name', 'SibSp', 'Parch', and 'Ticket' have been dropped, presumably because they are deemed irrelevant for the analysis or modeling.

X & y

In [66]:
```
X = df.drop('Survived', axis=1)
y = df['Survived']
```

Identify the best random state number

In [67]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score


Train = []
Test = []
CV = []

for i in range(0, 100):
    X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.8, random_state=i)
    model = LogisticRegression()
    model.fit(X_train, y_train)

    ypred_train = model.predict(X_train)
    ypred_test = model.predict(X_test)

    Train.append(model.score(X_train, y_train))
    Test.append(model.score(X_test, y_test))

    CV.append(cross_val_score(model, X_train, y_train, cv=5,scoring= "accuracy").mean())

em = pd.DataFrame({'Train':Train, 'Test':Test, 'CV':CV})
gm = em[(abs(em['Train']-em['Test']) <= 0.05) & (abs(em['Test']-em['CV']) <=0.05)]
rs = gm[gm['CV']==gm['CV'].max()].index.to_list()
print('best random state number:', rs)
```

```
best random state number: [57]
```

In [68]:
```
rs = int(rs[0])
rs
```

Out[68]:
```
57
```

In [69]:
```
df.head()
```

Out[69]:

	PassengerId	Survived	Pclass	Sex	Age	Fare	Embarked	Family
0	1	0	3	1	22.0	1.994700	2	1
1	2	1	1	0	38.0	4.268064	0	1
2	3	1	3	0	26.0	2.082562	2	0
3	4	1	1	0	35.0	3.974058	2	1
4	5	0	3	1	35.0	2.098018	2	0

train-test split

In [70]:
```
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=rs)
```

Modeling & Evaluation

1. Logistic Regressiom

In [71]:
```
from sklearn.linear_model import LogisticRegression
log_model = LogisticRegression()
log_model.fit(X_train, y_train)

ypred_train = log_model.predict(X_train)
ypred_test = log_model.predict(X_test)

print('Train Accuracy:', accuracy_score(y_train, ypred_train))
print('Cross Validation Score:', cross_val_score(log_model, X_train, y_train, cv=5, scoring='accura
print('Test Accuracy:', accuracy_score(y_test, ypred_test))
```

```
Train Accuracy: 0.800561797752809
Cross Validation Score: 0.8076036639416921
Test Accuracy: 0.7877094972067039
```

2. KNN

In [72]:
```
# scaling
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [73]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
estimator = KNeighborsClassifier()
param_grid = {'n_neighbors' : list(range(1, 50))}

knn_model = GridSearchCV(estimator, param_grid, cv=5, scoring='accuracy')
knn_model.fit(X_train, y_train)
knn_model.best_params_
```

Out[73]:
```
{'n_neighbors': 11}
```

In [74]:
```
from sklearn.neighbors import KNeighborsClassifier
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(X_train, y_train)

ypred_train = knn_model.predict(X_train)
ypred_test = knn_model.predict(X_test)

print('Train Accuracy:', accuracy_score(y_train, ypred_train))
print('Cross Validation Score:', cross_val_score(knn_model, X_train, y_train, cv=5, scoring='accura
print('Test Accuracy:', accuracy_score(y_test, ypred_test))
```

```
Train Accuracy: 0.8623595505617978
Cross Validation Score: 0.8019304639022948
Test Accuracy: 0.7821229050279329
```

3. SVM

In [75]:
```
# scaling
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [76]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC
estimator = SVC()
param_grid = {'C':[0.01, 0.1, 1], 'kernel':['linear', 'rbf', 'sigmoid', 'poly']}

svm_model_ = GridSearchCV(estimator, param_grid, cv=5, scoring='accuracy')
svm_model_.fit(X_train, y_train)
svm_model_.best_params_
```

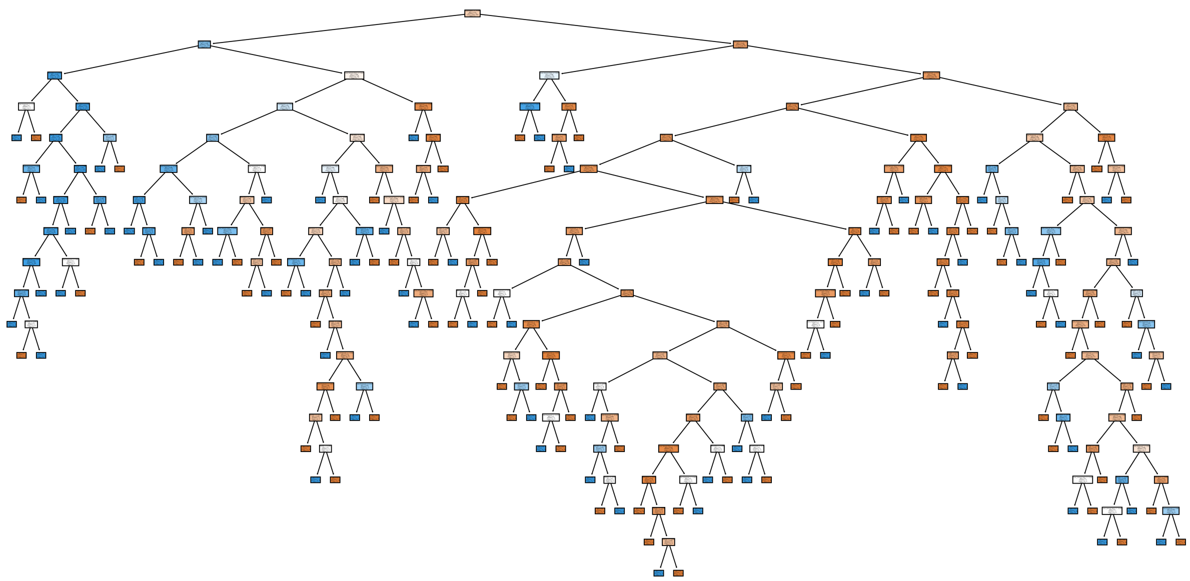
Out[76]:
```
{'C': 1, 'kernel': 'poly'}
```

In [77]:
```
from sklearn.svm import SVC
svm_model = SVC(C=1, kernel='poly')
svm_model.fit(X_train, y_train)

ypred_train = svm_model.predict(X_train)
ypred_test = svm_model.predict(X_test)

print('Train Accuracy:', accuracy_score(y_train, ypred_train))
print('Cross Validation Score:', cross_val_score(svm_model, X_train, y_train, cv=5, scoring='accura
print('Test Accuracy:', accuracy_score(y_test, ypred_test))
```

```
Train Accuracy: 0.8441011235955056
Cross Validation Score: 0.8188318723529993
Test Accuracy: 0.7932960893854749
```

4. Decision Tree Classifier

In [78]:
```
# Modelling
from sklearn.tree import DecisionTreeClassifier
dt_model_ = DecisionTreeClassifier()
dt_model_.fit(X_train, y_train)

from sklearn.tree import plot_tree
plt.figure(figsize=(24, 12), dpi=300)
plot_tree(dt_model_, filled=True, feature_names=['Gender', 'Married', 'Dependents', 'Education', 'S
       'LoanAmount', 'Loan_Amount_Term', 'Credit_History', 'Property_Area',
       'Income'], class_names=['1', '0'])
plt.show()
```



In [79]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
estimator = DecisionTreeClassifier()
param_grid = {'criterion':['gini', 'entropy'],
              'max_depth':list(range(1, 21))}

dt_grid = GridSearchCV(estimator, param_grid, cv=5, scoring='accuracy')
dt_grid.fit(X_train, y_train)
dt_grid.best_params_
```

Out[79]:
```
{'criterion': 'entropy', 'max_depth': 4}
```

In [80]:
```
dt_grid.best_estimator_
```

Out[80]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=4)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [81]:
```
# Feature importance
data = dt_grid.best_estimator_.feature_importances_
feats = pd.DataFrame(data, index=X.columns, columns=['Feature Importance'])
feats_imp = feats[feats['Feature Importance']>0]
importance_features_list = feats_imp.index.to_list()
importance_features_list
```

Out[81]: ['PassengerId', 'Pclass', 'Sex', 'Age', 'Fare', 'Embarked', 'Family']

In [82]:
```
len(importance_features_list)
```

Out[82]: 7

In [83]:
```
X_imp = X[importance_features_list]
X_train_dt, X_test_dt, y_train_dt, y_test_dt = train_test_split(X_imp, y, test_size=0.2, random_st
dt_model = DecisionTreeClassifier(criterion='entropy', max_depth=4)
dt_model.fit(X_train_dt, y_train_dt)

ypred_train = dt_model.predict(X_train_dt)
ypred_test = dt_model.predict(X_test_dt)

print('Train Accuracy:', accuracy_score(y_train_dt, ypred_train))
print('Cross Validation Score:', cross_val_score(dt_model, X_train_dt, y_train_dt, cv=5, scoring='
print('Test Accuracy:', accuracy_score(y_test_dt, ypred_test))
```

```
Train Accuracy: 0.8441011235955056
Cross Validation Score: 0.8216290751502019
Test Accuracy: 0.8044692737430168
```

5. Random Forest Classifier

In [84]:
```
# GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
estimator = RandomForestClassifier(random_state=70)
param_grid = {'n_estimators':list(range(1, 101))}
rf_grid = GridSearchCV(estimator, param_grid, cv=5, scoring='accuracy')
rf_grid.fit(X_train, y_train)
rf_grid.best_params_
```

Out[84]: {'n_estimators': 98}

In [85]:
```
rf_grid.best_estimator_
```

Out[85]: RandomForestClassifier(n_estimators=98, random_state=70)

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [86]:
```
# Feature importance
data = rf_grid.best_estimator_.feature_importances_
feats = pd.DataFrame(data, index=X.columns, columns=['Feature Importance'])
feats_imp = feats[feats['Feature Importance']>0]
importance_features_list = feats_imp.index.to_list()
importance_features_list
```

Out[86]: ['PassengerId', 'Pclass', 'Sex', 'Age', 'Fare', 'Embarked', 'Family']

In [87]:
```
len(importance_features_list)
```

Out[87]: 7

In [100]:
```
# rf --> model
# X_train_rf --> best_model_
X_imp = X[importance_features_list]
X_train_rf, X_test_rf, y_train_rf, y_test_rf = train_test_split(X_imp, y, test_size=0.2, random_st
rf_model = RandomForestClassifier(n_estimators=500, random_state=rs)
rf_model.fit(X_train_rf, y_train_rf)

ypred_train = rf_model.predict(X_train_rf)
ypred_test = rf_model.predict(X_test_rf)

print('Train Accuracy:', accuracy_score(y_train_rf, ypred_train))
print('Cross Validation Score:', cross_val_score(rf_model, X_train_rf, y_train_rf, cv=5, scoring='
print('Test Accuracy:', accuracy_score(y_test_rf, ypred_test))
```

```
Train Accuracy: 1.0
Cross Validation Score: 0.8089924160346695
Test Accuracy: 0.8156424581005587
```

6. AdaBoost Classifier

In [101]:
```
# GridSearchCV
from sklearn.ensemble import AdaBoostClassifier
from sklearn.model_selection import GridSearchCV
estimator_ab = AdaBoostClassifier(random_state=70)
param_grid = {'n_estimators':list(range(1, 51))}
ab_grid = GridSearchCV(estimator_ab, param_grid, cv=5, scoring='accuracy')
ab_grid.fit(X_train, y_train)
ab_grid.best_params_
```

Out[101]:
```
{'n_estimators': 3}
```

In [102]:
```
# Feature importance
data = ab_grid.best_estimator_.feature_importances_
feats = pd.DataFrame(data, index=X.columns, columns=['Feature Importance'])
feats_imp = feats[feats['Feature Importance']>0]
importance_features_list = feats_imp.index.to_list()
importance_features_list
```

Out[102]:
```
['Pclass', 'Sex', 'Family']
```

In [103]:
```
len(importance_features_list)
```

Out[103]:
```
3
```

In [104]:
```
ab_grid.best_estimator_
```

Out[104]:
```
AdaBoostClassifier(n_estimators=3, random_state=70)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [106]:
```
X_imp = X[importance_features_list]
X_train_ab, X_test_ab, y_train_ab, y_test_ab = train_test_split(X_imp, y, test_size=0.2, random_st
ab_model = AdaBoostClassifier(n_estimators=3, random_state=70)
ab_model.fit(X_train_ab, y_train_ab)

ypred_train = ab_model.predict(X_train_ab)
ypred_test = ab_model.predict(X_test_ab)

print('Train Accuracy:', accuracy_score(y_train_ab, ypred_train))
print('Cross Validation Score:', cross_val_score(ab_model, X_train_ab, y_train_ab, cv=5, scoring='
print('Test Accuracy:', accuracy_score(y_test_ab, ypred_test))
```

```
Train Accuracy: 0.8132022471910112
Cross Validation Score: 0.8104304146557668
Test Accuracy: 0.7988826815642458
```

7. GradientBoost Classifier

In [107]:
```
# GridSearchCV
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV
estimator_gb = GradientBoostingClassifier(random_state=70)
param_grid = {'n_estimators':list(range(1, 51)), 'learning_rate':[0.1, 0.2, 0.3, 0.4, 0.5, 1]}
gb_grid = GridSearchCV(estimator_gb, param_grid, cv=5, scoring='accuracy')
gb_grid.fit(X_train, y_train)
gb_grid.best_params_
```

Out[107]:
```
{'learning_rate': 0.2, 'n_estimators': 22}
```

In [108]:
```
# Feature importance
data = gb_grid.best_estimator_.feature_importances_
feats = pd.DataFrame(data, index=X.columns, columns=['Feature Importance'])
feats_imp = feats[feats['Feature Importance']>0]
importance_features_list = feats_imp.index.to_list()
importance_features_list
```

Out[108]:
```
['PassengerId', 'Pclass', 'Sex', 'Age', 'Fare', 'Embarked', 'Family']
```

In [109]:
```
len(importance_features_list)
```

Out[109]:
```
7
```

In [110]:
```
gb_grid.best_estimator_
```

Out[110]:
```
GradientBoostingClassifier(learning_rate=0.2, n_estimators=22, random_state=70)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [113]:
```
X_imp = X[importance_features_list]
X_train_gb, X_test_gb, y_train_gb, y_test_gb = train_test_split(X_imp, y, test_size=0.2, random_st
gb_model = AdaBoostClassifier(n_estimators=22, random_state=70, learning_rate=0.2)
gb_model.fit(X_train_gb, y_train_gb)

ypred_train = gb_model.predict(X_train_gb)
ypred_test = gb_model.predict(X_test_gb)

print('Train Accuracy:', accuracy_score(y_train_gb, ypred_train))
print('Cross Validation Score:', cross_val_score(gb_model, X_train_gb, y_train_gb, cv=5, scoring='
print('Test Accuracy:', accuracy_score(y_test_gb, ypred_test))
```

```
Train Accuracy: 0.8132022471910112
Cross Validation Score: 0.8061952132374668
Test Accuracy: 0.8044692737430168
```

8. XGBoost Classifier

In [112]:
```
# GridSearchCV
from xgboost import XGBClassifier
from sklearn.model_selection import GridSearchCV
estimator_xgb = XGBClassifier(random_state=70)
param_grid = {'n_estimators':list(range(1, 51)),
             'max_depth':list(range(1, 15)),
             'gamma':[0, 0, 15, 0.3, 0.5, 1]}
xgb_grid = GridSearchCV(estimator_xgb, param_grid, cv=5, scoring='accuracy')
xgb_grid.fit(X_train, y_train)
xgb_grid.best_params_
```

Out[112]:
```
{'gamma': 1, 'max_depth': 5, 'n_estimators': 10}
```

In [114]:
```
# Feature importance
data = xgb_grid.best_estimator_.feature_importances_
feats = pd.DataFrame(data, index=X.columns, columns=['Feature Importance'])
feats_imp = feats[feats['Feature Importance']>0]
importance_features_list = feats_imp.index.to_list()
importance_features_list
```

Out[114]:
```
['PassengerId', 'Pclass', 'Sex', 'Age', 'Fare', 'Embarked', 'Family']
```

In [115]:
```
len(importance_features_list)
```

Out[115]: 7

In [116]:
```
xgb_grid.best_estimator_
```

Out[116]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=1, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=5, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=10, n_jobs=None,
              num_parallel_tree=None, random_state=70, ...)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [117]:
```
X_imp = X[importance_features_list]
X_train_xgb, X_test_xgb, y_train_xgb, y_test_xgb = train_test_split(X_imp, y, test_size=0.2, rando
xgb_model = XGBClassifier(gamma = 1, n_estimators=10, max_depth=5, random_state=rs)
xgb_model.fit(X_train_xgb, y_train_xgb)

ypred_train = xgb_model.predict(X_train_xgb)
ypred_test = xgb_model.predict(X_test_xgb)

print('Train Accuracy:', accuracy_score(y_train_xgb, ypred_train))
print('Cross Validation Score:', cross_val_score(xgb_model, X_train_xgb, y_train_xgb, cv=5, scorin
print('Test Accuracy:', accuracy_score(y_test_xgb, ypred_test))
```

```
Train Accuracy: 0.8876404494382022
Cross Validation Score: 0.8356446370530879
Test Accuracy: 0.8212290502793296
```

Final model

Titanic Dataset (Kaggle Project)					
Model Name	Test Accuracy	CV	Train Accuracy	No. of Features	Comment
Logistic Regression	78.77	80.76	80.05	8	# Good
KNN	78.21	80.19	86.23	8	# Bad (overfitting)
SVM	79.32	81.88	84.41	8	# Good
Decision Tree	80.44	82.16	84.41	7	# Good
Random Forest	81.56	80.89	1	7	# Bad (overfitting)
Adaboost	79.88	81.04	81.32	3	# Good
Gradient Boost	80.44	80.61	81.32	7	# Good
XGBoost	82.12	83.56	88.76	7	# Good

Prediction

In [120]:
```
df1 = pd.read_csv('test.csv')
df1.head(2)
```

Out[120]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S

In [121]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  418 non-null    int64  
 1   Pclass       418 non-null    int64  
 2   Name         418 non-null    object 
 3   Sex          418 non-null    object 
 4   Age          332 non-null    float64
 5   SibSp        418 non-null    int64  
 6   Parch        418 non-null    int64  
 7   Ticket       418 non-null    object 
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object 
 10  Embarked     418 non-null    object 
dtypes: float64(2), int64(4), object(5)
memory usage: 36.1+ KB
```

In [122]:
```
df1.columns
```

Out[122]:
```
Index(['PassengerId', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp', 'Parch',
       'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

In [123]:
```
df1['Pclass'].unique()
```

Out[123]:
```
array([3, 2, 1], dtype=int64)
```

In [124]:
```
df1['Pclass'].value_counts()
```

Out[124]:
```
Pclass
3    218
1    107
2     93
Name: count, dtype: int64
```

In [125]:
```
df1['Sex'].unique()
```

Out[125]:
```
array(['male', 'female'], dtype=object)
```

In [126]:
```
df1['Age'].unique()
```

Out[126]:
```
array([34.5 , 47.  , 62.  , 27.  , 22.  , 14.  , 30.  , 26.  , 18.  ,
       21.  ,   nan, 46.  , 23.  , 63.  , 24.  , 35.  , 45.  , 55.  ,
        9.  , 48.  , 50.  , 22.5 , 41.  , 33.  , 18.5 , 25.  , 39.  ,
       60.  , 36.  , 20.  , 28.  , 10.  , 17.  , 32.  , 13.  , 31.  ,
       29.  , 28.5 , 32.5 ,  6.  , 67.  , 49.  ,  2.  , 76.  , 43.  ,
       16.  ,  1.  , 12.  , 42.  , 53.  , 26.5 , 40.  , 61.  , 60.5 ,
        7.  , 15.  , 54.  , 64.  , 37.  , 34.  , 11.5 ,  8.  ,  0.33,
       38.  , 57.  , 40.5 ,  0.92, 19.  , 36.5 ,  0.75,  0.83, 58.  ,
        0.17, 59.  , 14.5 , 44.  ,  5.  , 51.  ,  3.  , 38.5 ])
```

In [127]:
```
df1['SibSp'].unique()
```

Out[127]:
```
array([0, 1, 2, 3, 4, 5, 8], dtype=int64)
```

In [128]:
```
df1['Parch'].unique()
```

Out[128]:
```
array([0, 1, 3, 2, 4, 6, 5, 9], dtype=int64)
```

In [129]:
```
df1['Cabin'].unique()
```

Out[129]:
```
array([nan, 'B45', 'E31', 'B57 B59 B63 B66', 'B36', 'A21', 'C78', 'D34',
       'D19', 'A9', 'D15', 'C31', 'C23 C25 C27', 'F G63', 'B61', 'C53',
       'D43', 'C130', 'C132', 'C101', 'C55 C57', 'B71', 'C46', 'C116',
       'F', 'A29', 'G6', 'C6', 'C28', 'C51', 'E46', 'C54', 'C97', 'D22',
       'B10', 'F4', 'E45', 'E52', 'D30', 'B58 B60', 'E34', 'C62 C64',
       'A11', 'B11', 'C80', 'F33', 'C85', 'D37', 'C86', 'D21', 'C89',
       'F E46', 'A34', 'D', 'B26', 'C22 C26', 'B69', 'C32', 'B78',
       'F E57', 'F2', 'A18', 'C106', 'B51 B53 B55', 'D10 D12', 'E60',
       'E50', 'E39 E41', 'B52 B54 B56', 'C39', 'B24', 'D28', 'B41', 'C7',
       'D40', 'D38', 'C105'], dtype=object)
```

In [130]:
```
df1['Embarked'].unique()
```

Out[130]:
```
array(['Q', 'S', 'C'], dtype=object)
```

In [131]:
```
continuous = ['PassengerId', 'Age', 'Fare']
discrete_count = ['Pclass', 'SibSp', 'Parch']
discrete_categorical = ['Name', 'Sex', 'Embarked', 'Ticket', 'Cabin']
```

Exploratory Data Analysis (EDA)

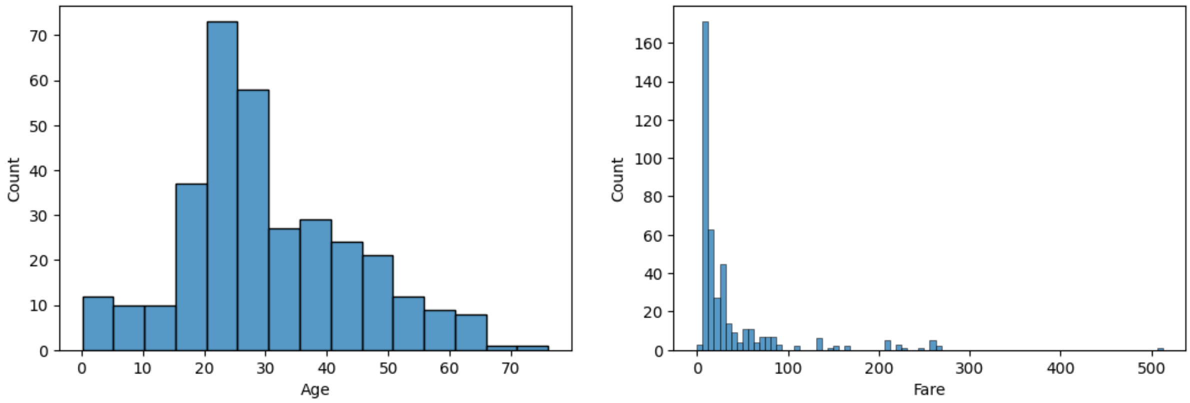
EDA for continuous variables

In [132]:
```
df1[continuous].describe()
```

Out[132]:

	PassengerId	Age	Fare
count	418.000000	332.000000	417.000000
mean	1100.500000	30.272590	35.627188
std	120.810458	14.181209	55.907576
min	892.000000	0.170000	0.000000
25%	996.250000	21.000000	7.895800
50%	1100.500000	27.000000	14.454200
75%	1204.750000	39.000000	31.500000
max	1309.000000	76.000000	512.329200

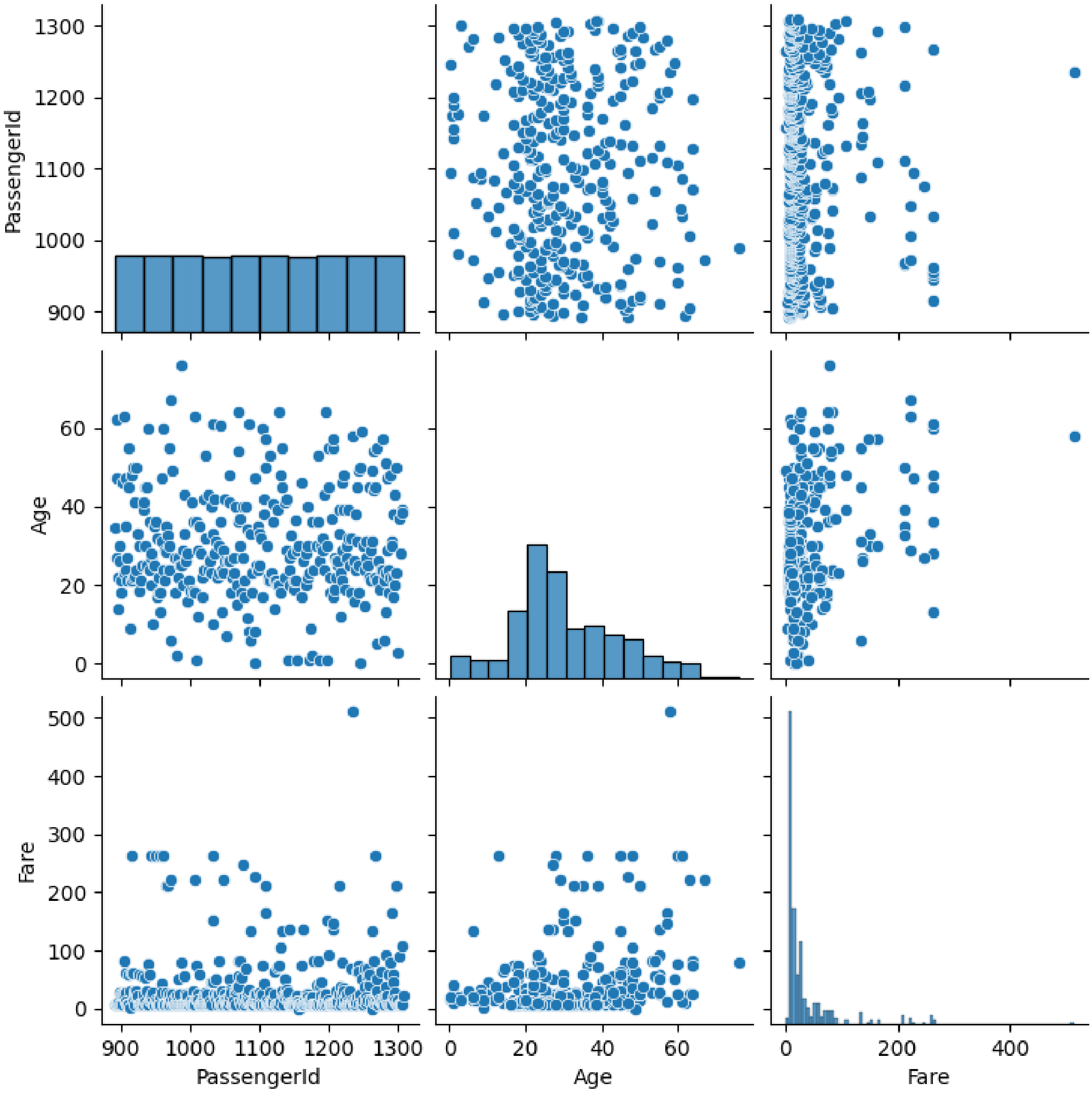
In [133]:
```
plt.rcParams['figure.figsize'] = (13, 4)
plt.subplot(1, 2, 1)
sns.histplot(df1['Age'])

plt.subplot(1, 2, 2)
sns.histplot(df1['Fare'])

plt.show()
```



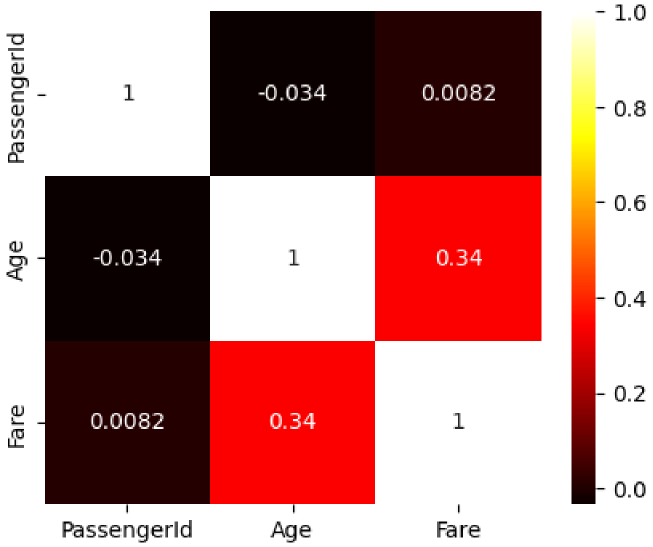
In [134]:
```
df1[continuous].skew()
```

Out[134]:
```
PassengerId    0.000000
Age            0.457361
Fare           3.687213
dtype: float64
```

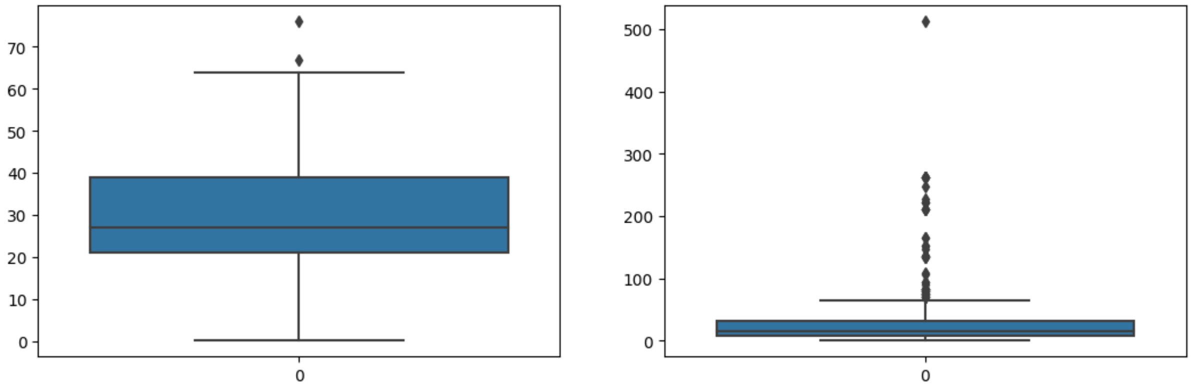
In [135]:
```
plt.rcParams['figure.figsize'] = (13, 4)
sns.pairplot(df1[continuous])
plt.show()
```



In [136]:
```
plt.figure(figsize=(5, 4))
sns.heatmap(df1[continuous].corr(), annot=True, cmap='hot')
plt.show()
```



In [137]:
```
plt.rcParams['figure.figsize'] = (13, 4)
plt.subplot(1, 2, 1)
sns.boxplot(df1['Age'])

plt.subplot(1, 2, 2)
sns.boxplot(df1['Fare'])

plt.show()
```



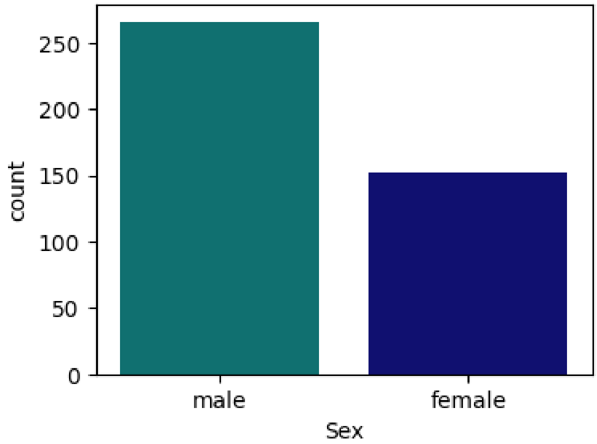
EDA for discrete variables

In [138]:
```
df1[discrete_categorical].describe()
```

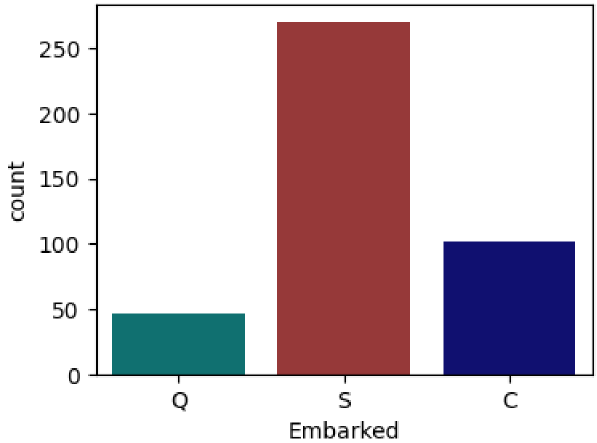
Out[138]:

	Name	Sex	Embarked	Ticket	Cabin
count	418	418	418	418	91
unique	418	2	3	363	76
top	Kelly, Mr. James	male	S	PC 17608	B57 B59 B63 B66
freq	1	266	270	5	3

In [139]:
```
plt.figure(figsize=(4, 3))
sns.countplot(data=df1, x='Sex', palette=['teal', 'navy'])
plt.show()
```



In [140]:
```
plt.figure(figsize=(4, 3))
sns.countplot(data=df1, x='Embarked', palette=['teal', 'brown', 'navy'])
plt.show()
```



Data Preparation

'SciSp' and 'Parch' both columns are family column so I combined it.

In [141]:
```
df1['SibSp'].unique()
```

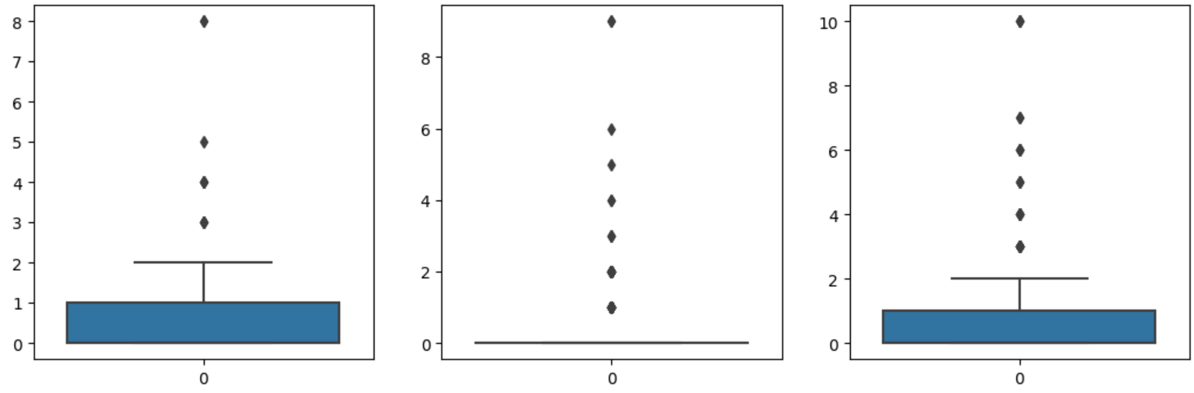
Out[141]:
```
array([0, 1, 2, 3, 4, 5, 8], dtype=int64)
```

In [142]:
```
df1['Parch'].unique()
```

Out[142]:
```
array([0, 1, 3, 2, 4, 6, 5, 9], dtype=int64)
```

In [143]:
```
df1['Family'] = df1['SibSp'] + df1['Parch']
```

In [144]:
```
plt.rcParams['figure.figsize'] = (13, 4)
plt.subplot(1, 3, 1)
sns.boxplot(df1['SibSp'])

plt.subplot(1, 3, 2)
sns.boxplot(df1['Parch'])

plt.subplot(1, 3, 3)
sns.boxplot(df1['Family'])
plt.show()
```



In [145]:
```
df1.drop(columns= ['SibSp', 'Parch'], inplace=True)
```

In [146]:
```
df1['Family'].unique()
```

Out[146]:
```
array([ 0,  1,  2,  4,  3,  5,  7,  6, 10], dtype=int64)
```

In [147]:
```
df1['Family'].value_counts()
```

Out[147]:
```
Family
0     253
1      74
2      57
3      14
4       7
6       4
10      4
5       3
7       2
Name: count, dtype: int64
```

Missing value treatment

In [148]:
```
df1.isnull().sum()
```

Out[148]:
```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
Ticket           0
Fare             1
Cabin          327
Embarked         0
Family           0
dtype: int64
```

In [149]:
```
df1['Age'].fillna(df1['Age'].mean(), inplace=True)
```

In [150]:
```
df1['Fare'].fillna(df1['Fare'].mean(), inplace=True)
```

In [151]:
```
df1.drop(columns = 'Cabin', inplace=True)
```

In [152]:
```
df1['Embarked'].fillna(df1['Embarked'].mode()[0], inplace=True)
```

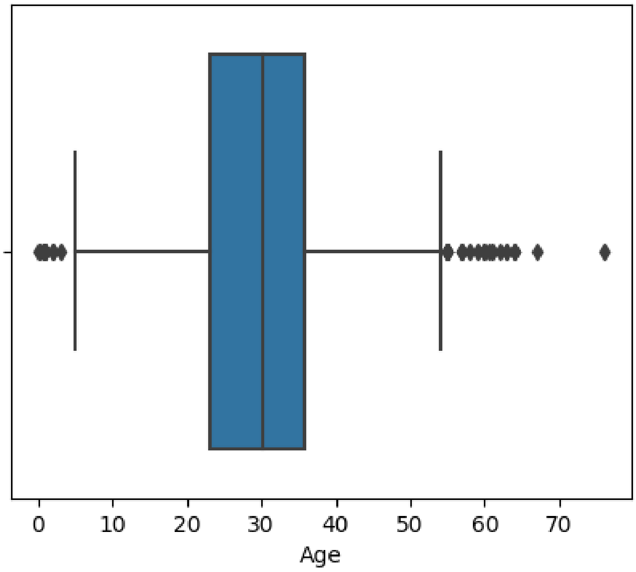
drop unimportant column

In [153]:
```
df1.drop(columns = ['Name', 'Ticket'], inplace=True)
```

Outliers Treatment

AGE

In [154]:
```
plt.figure(figsize=(5, 4))
sns.boxplot(x=df1['Age'])
plt.show()
```



In [155]:
```
# Calculate Q1
Q1 = df1['Age'].quantile(0.25)
print("Q1: ", Q1)

# Calculate Q2
Q3 = df1['Age'].quantile(0.75)
print("Q3: ", Q3)

# Calculate IQR
IQR = Q3 - Q1
print('IQR:', IQR)

# Calculate lower limit of outliers
lower_limit = Q1 - (IQR * 1.5)
print('lower_limit', lower_limit)

# Calculate upper limit of outliers
upper_limit = Q3 + (IQR * 1.5)
print('upper_limit', upper_limit)
```

```
Q1:  23.0
Q3:  35.75
IQR: 12.75
lower_limit 3.875
upper_limit 54.875
```

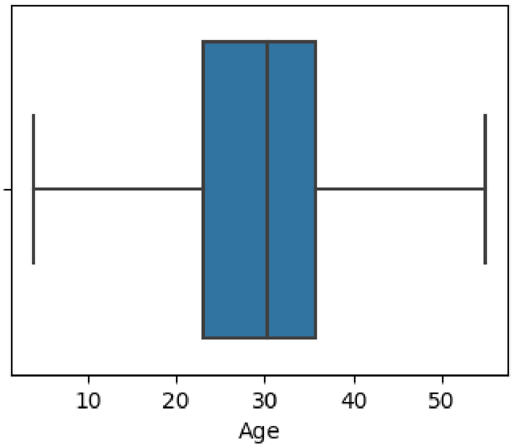
In [156]:
```python
# list of outliers
df1[(df1['Age'] < lower_limit) | (df1['Age'] > upper_limit)].index
```

Out[156]:
```
Index([  2,  13,  20,  48,  69,  77,  81,  89,  96, 114, 117, 142, 152, 179,
       193, 201, 213, 217, 236, 240, 250, 263, 281, 284, 296, 305, 307, 308,
       314, 316, 343, 354, 356, 378, 387, 409],
      dtype='int64')
```

In [157]:
```python
# winsorization technqiue (for replacing outliers)
df1['Age'] = df1['Age'].clip(lower=3.875, upper=54.875)
df1['Age']
```

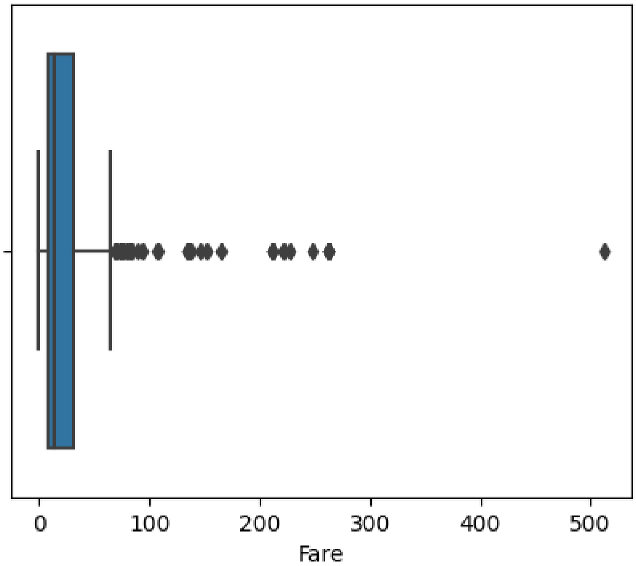
Out[157]:
```
0      34.50000
1      47.00000
2      54.87500
3      27.00000
4      22.00000
         ...
413    30.27259
414    39.00000
415    38.50000
416    30.27259
417    30.27259
Name: Age, Length: 418, dtype: float64
```

In [158]:
```python
plt.figure(figsize=(4, 3))
sns.boxplot(x=df1['Age'])
plt.show()
```



FARE

In [159]:
```
plt.figure(figsize=(5, 4))
sns.boxplot(x=df1['Fare'])
plt.show()
```



In [160]:
```
# Calculate Q1
Q1 = df1['Fare'].quantile(0.25)
print("Q1: ", Q1)

# Calculate Q2
Q3 = df1['Fare'].quantile(0.75)
print("Q3: ", Q3)

# Calculate IQR
IQR = Q3 - Q1
print('IQR:', IQR)

# Calculate lower limit of outliers
lower_limit = Q1 - (IQR * 1.5)
print('lower_limit', lower_limit)

# Calculate upper limit of outliers
upper_limit = Q3 + (IQR * 1.5)
print('upper_limit', upper_limit)
```

```
Q1:  7.8958
Q3:  31.5
IQR: 23.6042
lower_limit -27.5105
upper_limit 66.9063
```

In [161]:
```
len(df1[(df1['Fare'] < lower_limit) | (df1['Fare'] > upper_limit)])
```

Out[161]: 55

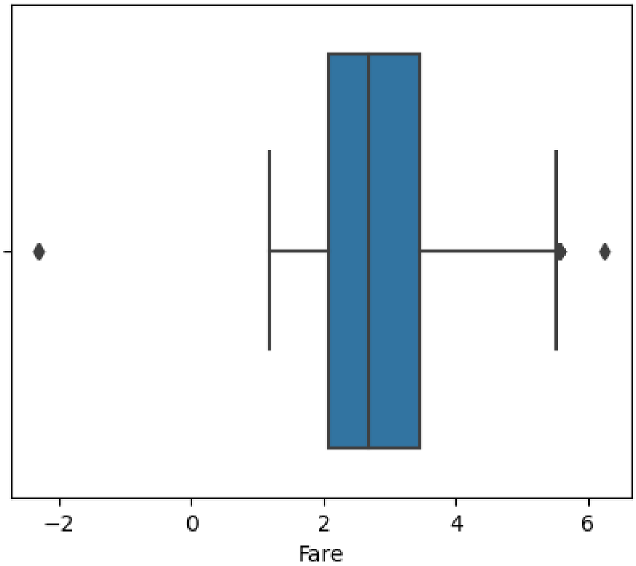
Logarithmic transformation

In [162]:
```
import numpy as np
df1['Fare'] = np.log(df1['Fare']+0.1)
df1['Fare'].skew()
```

Out[162]: 0.26397827672277474

even after using lof transformation, I still have outliers so, I can use winsorization technique

In [163]:
```
plt.figure(figsize=(5, 4))
sns.boxplot(x=df1['Fare'])
plt.show()
```



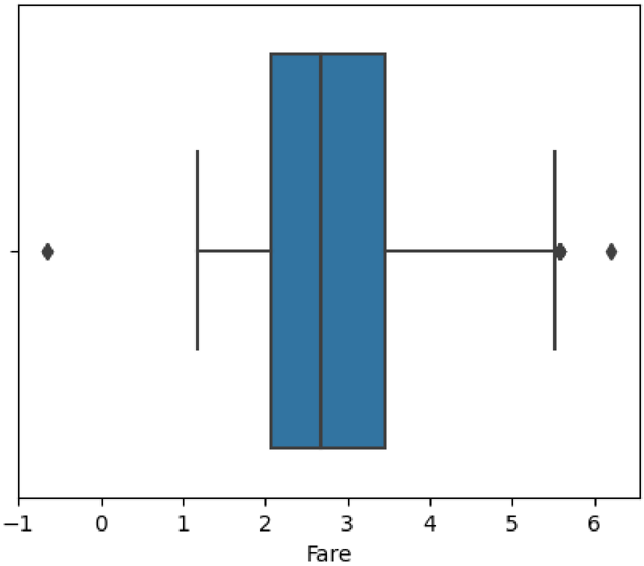
In [164]:
```
# Calculate Q1
Q1 = df1['Fare'].quantile(0.25)
print("Q1: ", Q1)

# Calculate Q2
Q3 = df1['Fare'].quantile(0.75)
print("Q3: ", Q3)

# Calculate IQR
IQR = Q3 - Q1
print('IQR:', IQR)

# Calculate lower limit of outliers
lower_limit = Q1 - (IQR * 2)
print('lower_limit', lower_limit)

# Calculate upper limit of outliers
upper_limit = Q3 + (IQR * 2)
print('upper_limit', upper_limit)
```

```
Q1:  2.0789164038190826
Q3:  3.4531571205928664
IQR: 1.3742407167737838
lower_limit -0.669565029728485
upper_limit 6.201638554140434
```

In [165]:
```
# winsorization technqiue (for replacing outliers)
df1['Fare'] = df1['Fare'].clip(lower=-0.66, upper=6.20)
df1['Fare']
```

Out[165]:
```
0      2.070552
1      1.960095
2      2.281106
3      2.170481
4      2.516688
         ...
413    2.098018
414    4.691348
415    1.994700
416    2.098018
417    3.111660
Name: Fare, Length: 418, dtype: float64
```

In [166]:
```
plt.figure(figsize=(5, 4))
sns.boxplot(x=df1['Fare'])
plt.show()
```



In [167]:
```
len(df1[(df1['Fare'] < lower_limit) | (df1['Fare'] > upper_limit)])
```

Out[167]: 0

In [168]:
```
df1.head()
```

Out[168]:

	PassengerId	Pclass	Sex	Age	Fare	Embarked	Family
0	892	3	male	34.500	2.070552	Q	0
1	893	3	female	47.000	1.960095	S	1
2	894	2	male	54.875	2.281106	Q	0
3	895	3	male	27.000	2.170481	S	0
4	896	3	female	22.000	2.516688	S	2

In [169]:
```
df1['Sex'] = df1['Sex'].replace({'male':1, 'female':0}).astype('int')
df1['Embarked'] = df1['Embarked'].replace({'S':2, 'Q':1, 'C':0}).astype('int')
```

In [170]:
```
df1.head()
```

Out[170]:

	PassengerId	Pclass	Sex	Age	Fare	Embarked	Family
0	892	3	1	34.500	2.070552	1	0
1	893	3	0	47.000	1.960095	2	1
2	894	2	1	54.875	2.281106	1	0
3	895	3	1	27.000	2.170481	2	0
4	896	3	0	22.000	2.516688	2	2

Modeling & Evaluation

for the future data there is no need of modeling because my model is already ready for the predicting on the unseen data

In [175]:
```
xgb_model
```

Out[175]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=1, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=5, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=10, n_jobs=None,
              num_parallel_tree=None, random_state=57, ...)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Predcition

In [176]:
```
final_model = np.array(xgb_model.predict(df1)).reshape(-1, 1)
final_model
```

Out[176]:
```
array([[0],
       [0],
       [0],
       [0],
       [1],
       [0],
       [0],
       [0],
       [1],
       [0],
       [0],
       [0],
       [1],
       [0],
       [1],
       [1],
       [0],
       [0],
       [0],
```

In [179]:
```
# Convert array to dataframe
df2 = pd.DataFrame(final_model, index = df1['PassengerId'], columns=['Survived'])
df2
```

PassengerId	
892	0
893	0
894	0
895	0
896	1
...	...
1305	0
1306	1
1307	0
1308	0
1309	0

418 rows × 1 columns

In [180]:
```
df2.to_csv('titanic_prediction.csv')
```

Save a model

In [174]:
```
from joblib import dump
dump(xgb_model, 'titanic.joblib')
```

Out[174]:
```
['titanic.joblib']
```