33_eda

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1 Exploratory Data Analysis

1.0.1 Important Steps

Three important steps to keep in mind 1. Understand the data 2. Clean the data 3. Find a relationship between data

1.1 Exploring Data

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use({'figure.facecolor':'white'})
```

[ ]:
```
ks = sns.load_dataset('titanic')
```

[ ]:
```
ks.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    category
 9   who          891 non-null    object
 10  adult_male   891 non-null    bool
```

```
 11  deck         203 non-null    category
 12  embark_town  889 non-null    object
 13  alive        891 non-null    object
 14  alone        891 non-null    bool
dtypes: bool(2), category(2), float64(2), int64(4), object(5)
memory usage: 80.7+ KB
```

[ ]:
```
ks.head()
```

[ ]:
```
   survived  pclass     sex   age  sibsp  parch     fare embarked  class  \
0         0       3    male  22.0      1      0   7.2500        S  Third
1         1       1  female  38.0      1      0  71.2833        C  First
2         1       3  female  26.0      0      0   7.9250        S  Third
3         1       1  female  35.0      1      0  53.1000        S  First
4         0       3    male  35.0      0      0   8.0500        S  Third

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

[ ]:
```
ks.shape
```

[ ]:
```
(891, 15)
```

[ ]:
```
ks.describe()
```

[ ]:
```
         survived      pclass         age       sibsp       parch        fare
count  891.000000  891.000000  714.000000  891.000000  891.000000  891.000000
mean     0.383838    2.308642   29.699118    0.523008    0.381594   32.204208
std      0.486592    0.836071   14.526497    1.102743    0.806057   49.693429
min      0.000000    1.000000    0.420000    0.000000    0.000000    0.000000
25%      0.000000    2.000000   20.125000    0.000000    0.000000    7.910400
50%      0.000000    3.000000   28.000000    0.000000    0.000000   14.454200
75%      1.000000    3.000000   38.000000    1.000000    0.000000   31.000000
max      1.000000    3.000000   80.000000    8.000000    6.000000  512.329200
```

[ ]:
```
# Exploring data by using unique method to explore unique values in a DataFrame
ks.nunique()
```

[ ]:
```
survived         2
pclass           3
sex              2
age             88
sibsp            7
parch            7
```

```
fare            248
embarked          3
class             3
who               3
adult_male        2
deck              7
embark_town       3
alive             2
alone             2
dtype: int64
```

[ ]:
```
ks.columns
```

[ ]:
```
Index(['survived', 'pclass', 'sex', 'age', 'sibsp', 'parch', 'fare',
       'embarked', 'class', 'who', 'adult_male', 'deck', 'embark_town',
       'alive', 'alone'],
      dtype='object')
```

[ ]:
```
ks['age'].unique()
```

[ ]:
```
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.  ])
```

[ ]:
```
type(ks['age'])
```

[ ]:
```
pandas.core.series.Series
```

[ ]:
```
test = [ks['survived'],ks['class'],ks['who'], ks['embarked']]
```

[ ]:
```
# assignment:
# get unique values from more than 1 columns

# Solution to the assignment
# pd.concat, is doing nothing, instead, returning a panda's Series
 ↪DataType(pandas.core.series.Series) from this list
# so we can use panda's Series method(pandas.core.series.Series.unique) on it.
# https://pandas.pydata.org/docs/reference/api/pandas.Series.unique.html#
pd.concat([ks['survived'],ks['class'],ks['who'], ks['embarked']]).unique()
```

```
[ ]: array([0, 1, 'Third', 'First', 'Second', 'man', 'woman', 'child', 'S',
            'C', 'Q', nan], dtype=object)
```

```
[ ]: std_of_age = ks['age'].std()
     std_of_age
```

```
[ ]: 14.526497332334042
```

1.2 Cleaning and Filtering the data

```
[ ]: # find missing values
     ks.isnull()
```

```
[ ]:      survived  pclass    sex    age  sibsp  parch   fare  embarked  class  \
     0       False   False  False  False  False  False  False     False  False
     1       False   False  False  False  False  False  False     False  False
     2       False   False  False  False  False  False  False     False  False
     3       False   False  False  False  False  False  False     False  False
     4       False   False  False  False  False  False  False     False  False
     ..        …       …     …      …     …      …     …        …      …
     886     False   False  False  False  False  False  False     False  False
     887     False   False  False  False  False  False  False     False  False
     888     False   False  False   True  False  False  False     False  False
     889     False   False  False  False  False  False  False     False  False
     890     False   False  False  False  False  False  False     False  False

            who  adult_male   deck  embark_town  alive  alone
     0    False       False   True        False  False  False
     1    False       False  False        False  False  False
     2    False       False   True        False  False  False
     3    False       False  False        False  False  False
     4    False       False   True        False  False  False
     ..     …           …      …           …      …      …
     886  False       False   True        False  False  False
     887  False       False  False        False  False  False
     888  False       False   True        False  False  False
     889  False       False  False        False  False  False
     890  False       False   True        False  False  False

     [891 rows x 15 columns]
```

```
[ ]: # finding total null values summary
     ks.isnull().sum()
```

```
[ ]: 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
```

[ ]:
```python
# Dropping column with more null values
df = ks.copy()
ks_clean = df.drop(columns=['deck'])
ks_clean
```

[ ]:
```
     survived  pclass     sex   age  sibsp  parch     fare embarked   class  \
0           0       3    male  22.0      1      0   7.2500        S   Third
1           1       1  female  38.0      1      0  71.2833        C   First
2           1       3  female  26.0      0      0   7.9250        S   Third
3           1       1  female  35.0      1      0  53.1000        S   First
4           0       3    male  35.0      0      0   8.0500        S   Third
..        …     …     …     …    …      …       …      …
886         0       2    male  27.0      0      0  13.0000        S  Second
887         1       1  female  19.0      0      0  30.0000        S   First
888         0       3  female   NaN      1      2  23.4500        S   Third
889         1       1    male  26.0      0      0  30.0000        C   First
890         0       3    male  32.0      0      0   7.7500        Q   Third

       who  adult_male  embark_town alive  alone
0      man        True  Southampton    no  False
1    woman       False    Cherbourg   yes  False
2    woman       False  Southampton   yes   True
3    woman       False  Southampton   yes  False
4      man        True  Southampton    no   True
..     …          …          …    …     …
886    man        True  Southampton    no   True
887  woman       False  Southampton   yes   True
888  woman       False  Southampton    no  False
889    man        True    Cherbourg   yes   True
890    man        True   Queenstown    no   True

[891 rows x 14 columns]
```

[ ]:
```python
ks_clean.isnull().sum()
```

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

[ ]:
```python
891 - 177 - 2
```

[ ]:
```
712
```

[ ]:
```python
ks.loc[ks['deck'] == np.nan]
```

[ ]:
```
Empty DataFrame
Columns: [survived, pclass, sex, age, sibsp, parch, fare, embarked, class, who,
adult_male, deck, embark_town, alive, alone]
Index: []
```

[ ]:
```python
ks_clean['embarked']
```

[ ]:
```
0      S
1      C
2      S
3      S
4      S
      ..
886    S
887    S
888    S
889    C
890    Q
Name: embarked, Length: 891, dtype: object
```

[ ]:
```python
# filtering data
ks_clean.loc[ks_clean['embarked'].isnull()][['embarked', 'embark_town']]
```

[ ]:
```
    embarked embark_town
61       NaN         NaN
829      NaN         NaN
```

[ ]:
```
ks_clean.shape
```

[ ]:
```
(891, 14)
```

[ ]:
```
ks_clean.isnull().sum()
```

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

[ ]:
```
ks_clean.dropna(inplace=True)
```

[ ]:
```
ks_clean.shape
```

[ ]:
```
(712, 14)
```

[ ]:
```
ks_clean['age'].value_counts()
```

[ ]:
```
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: age, Length: 88, dtype: int64
```

[ ]:
```
ks_clean.isnull().sum()
```

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

[ ]:
```
ks.describe()
```

[ ]:

	survived	pclass	age	sibsp	parch	fare
count	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

[ ]:
```
ks_clean.describe()
```

[ ]:

	survived	pclass	age	sibsp	parch	fare
count	712.000000	712.000000	712.000000	712.000000	712.000000	712.000000
mean	0.404494	2.240169	29.642093	0.514045	0.432584	34.567251
std	0.491139	0.836854	14.492933	0.930692	0.854181	52.938648
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	1.000000	20.000000	0.000000	0.000000	8.050000
50%	0.000000	2.000000	28.000000	0.000000	0.000000	15.645850
75%	1.000000	3.000000	38.000000	1.000000	1.000000	33.000000
max	1.000000	3.000000	80.000000	5.000000	6.000000	512.329200

1.3 How to check outliers visually

[ ]:
```
ks_clean['age'].mean()
```

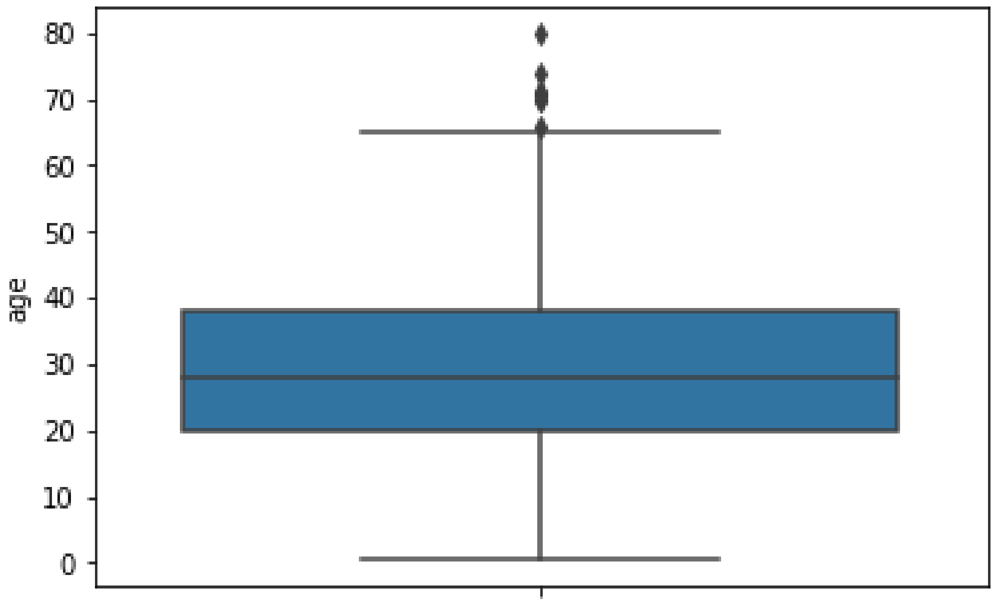
[ ]:
```
29.64209269662921
```

[ ]:
```
ks_clean.columns
```

[ ]: Index(['survived', 'pclass', 'sex', 'age', 'sibsp', 'parch', 'fare',
       'embarked', 'class', 'who', 'adult_male', 'embark_town', 'alive',
       'alone'],
      dtype='object')

[ ]:
```
sns.boxplot(y="age", data=ks_clean)
```

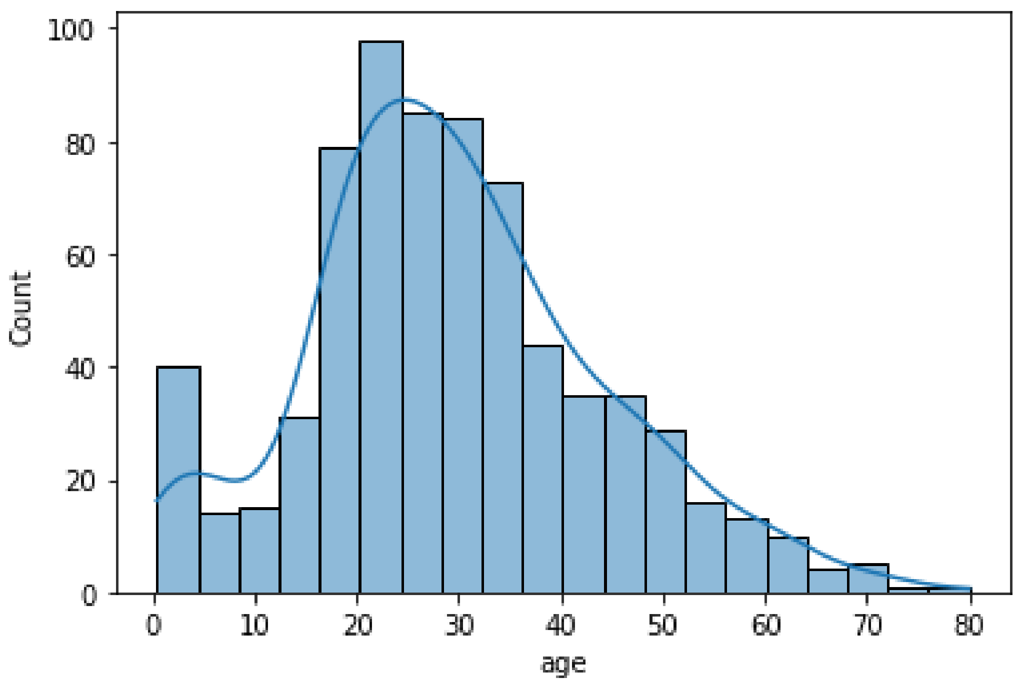
[ ]: <AxesSubplot:ylabel='age'>



above figures shows that the value above 68 is creating outliers, so lets remove those records having age more than 68

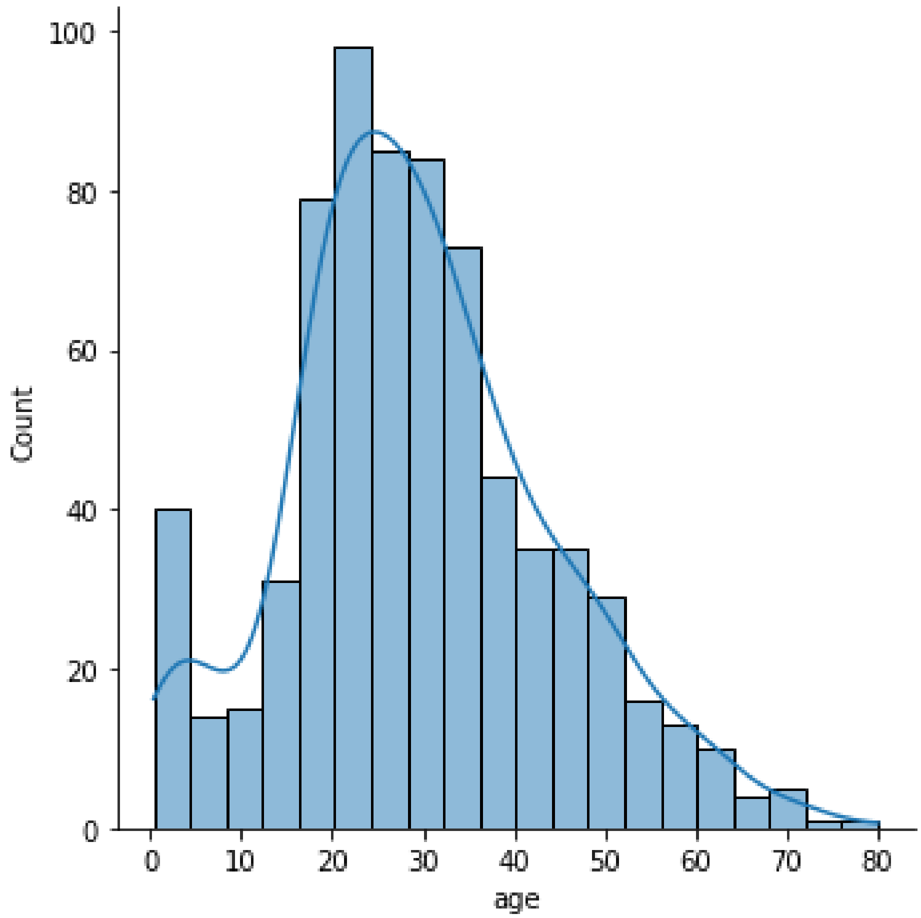
[ ]:
```
sns.histplot(ks_clean['age'], kde=True)
```

[ ]: <AxesSubplot:xlabel='age', ylabel='Count'>



[ ]:
```
sns.displot(ks_clean['age'], kde=True)
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x212422779d0>




```
[ ]: ks_clean = ks_clean.loc[ks_clean['age']<68]
```

```
[ ]: ks_clean
```

```
[ ]:      survived  pclass     sex   age  sibsp  parch     fare embarked   class  \
     0           0       3    male  22.0      1      0   7.2500        S   Third
     1           1       1  female  38.0      1      0  71.2833        C   First
     2           1       3  female  26.0      0      0   7.9250        S   Third
     3           1       1  female  35.0      1      0  53.1000        S   First
     4           0       3    male  35.0      0      0   8.0500        S   Third
     ..        …       …      …    …    …      …      …      …       …
     885         0       3  female  39.0      0      5  29.1250        Q   Third
     886         0       2    male  27.0      0      0  13.0000        S  Second
     887         1       1  female  19.0      0      0  30.0000        S   First
     889         1       1    male  26.0      0      0  30.0000        C   First
     890         0       3    male  32.0      0      0   7.7500        Q   Third

            who  adult_male  embark_town alive  alone
```

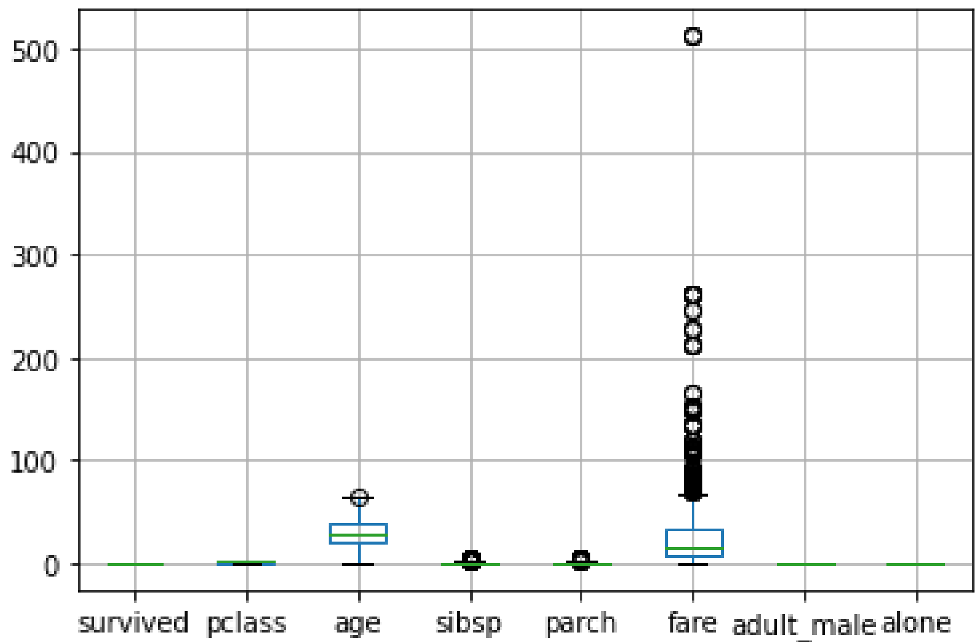
```
0      man        True  Southampton   no  False
1    woman       False    Cherbourg  yes  False
2    woman       False  Southampton  yes   True
3    woman       False  Southampton  yes  False
4      man        True  Southampton   no   True
..     …          …           …    …     …
885  woman       False   Queenstown   no  False
886    man        True  Southampton   no   True
887  woman       False  Southampton  yes   True
889    man        True    Cherbourg  yes   True
890    man        True   Queenstown   no   True

[705 rows x 14 columns]
```

[ ]:
```
ks_clean['age'].mean()
```

[ ]: 29.21797163120567

[ ]:
```
ks_clean.boxplot()
```

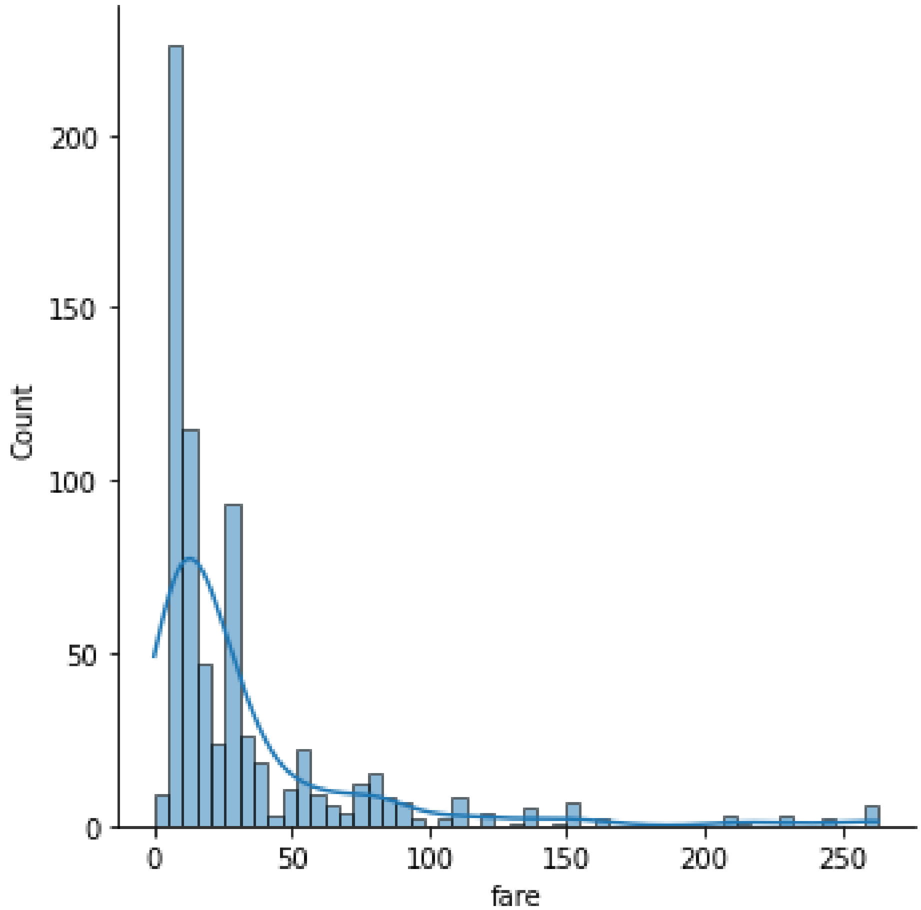
[ ]: <AxesSubplot:>



[ ]:
```
ks_clean = ks_clean.loc[ks_clean['fare'] < 300]
```

[ ]:
```
sns.displot(ks_clean['fare'], kde=True)
```

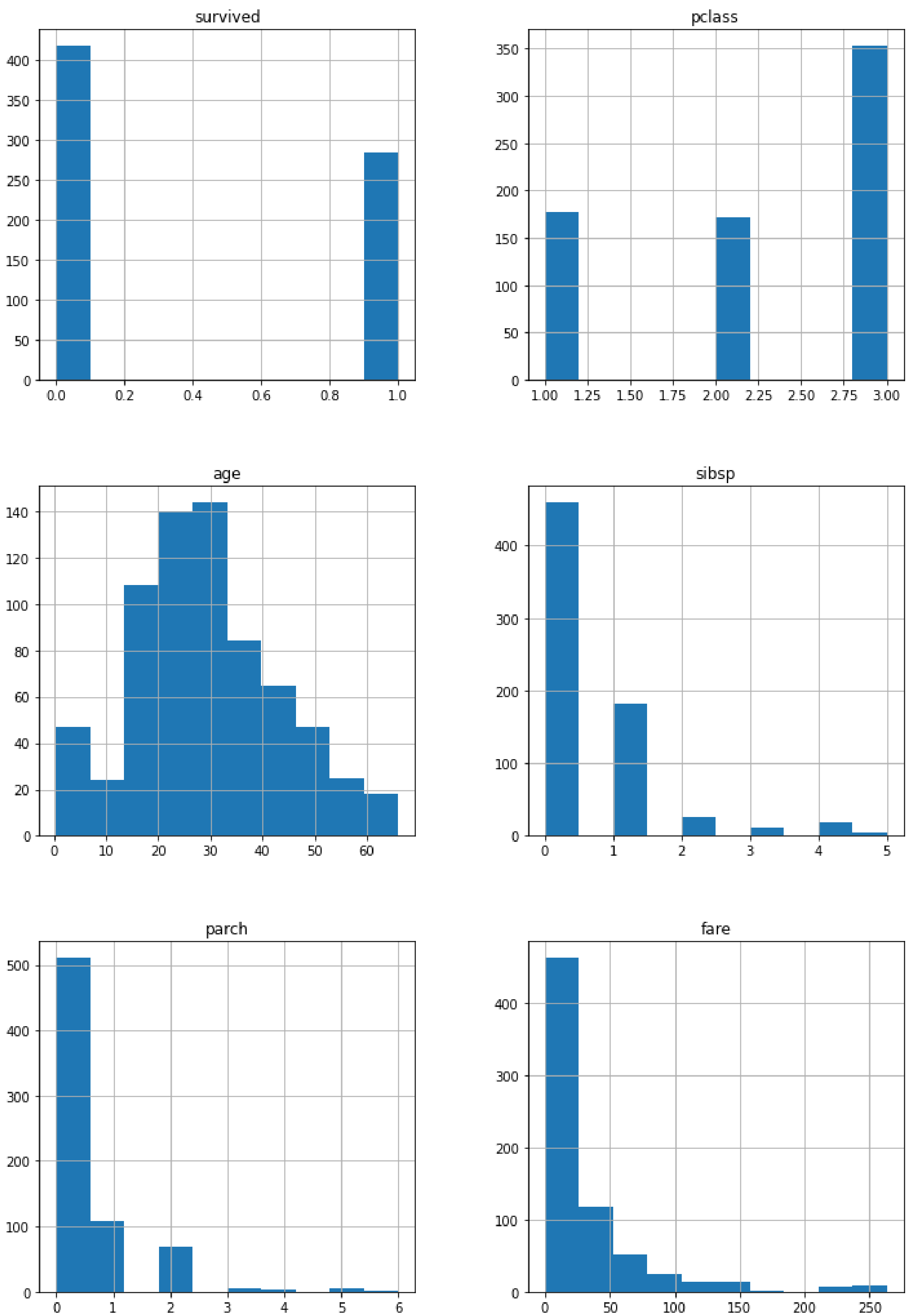
[ ]: <seaborn.axisgrid.FacetGrid at 0x2124243ed70>



Here we can see the data is not in ideal format. This problem needs the `Normalization` of data. Which we will see later.

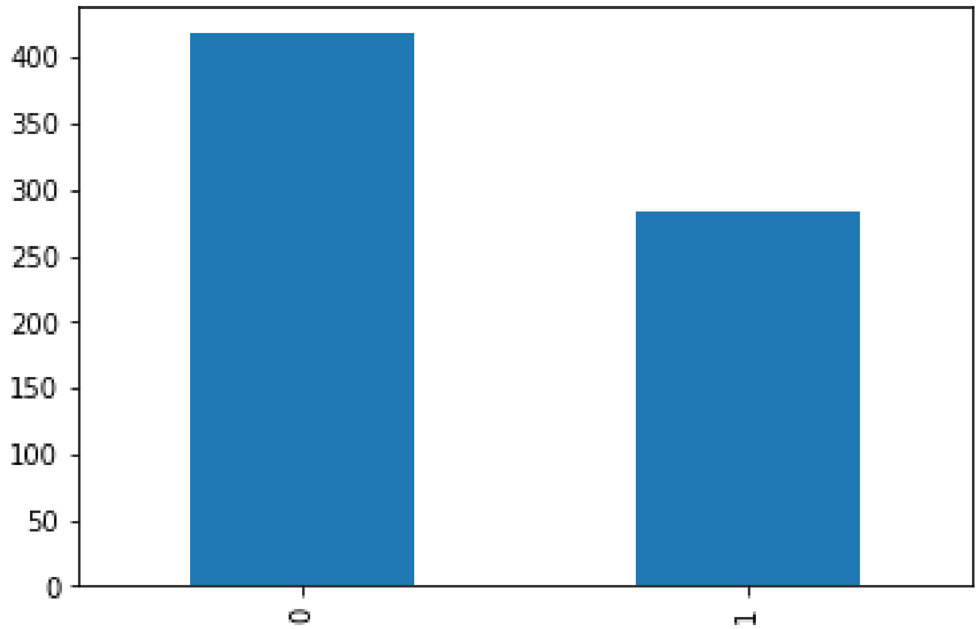
[ ]:
```
ks_clean.hist(figsize=(12.0, 18.0))
```

[ ]:
```
array([[<AxesSubplot:title={'center':'survived'}>,
         <AxesSubplot:title={'center':'pclass'}>],
        [<AxesSubplot:title={'center':'age'}>,
         <AxesSubplot:title={'center':'sibsp'}>],
        [<AxesSubplot:title={'center':'parch'}>,
         <AxesSubplot:title={'center':'fare'}>]], dtype=object)
```


survived
0.0
0.2
0.4
0.6
0.8
1.0
0
50
100
150
200
250
300
350
400
pclass
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
0
50
100
150
200
250
300
350
age
0
10
20
30
40
50
60
0
20
40
60
80
100
120
140
sibsp
0
1
2
3
4
5
0
100
200
300
400
parch
0
1
2
3
4
5
6
0
100
200
300
400
500
fare
0
50
100
150
200
250
0
100
200
300
400

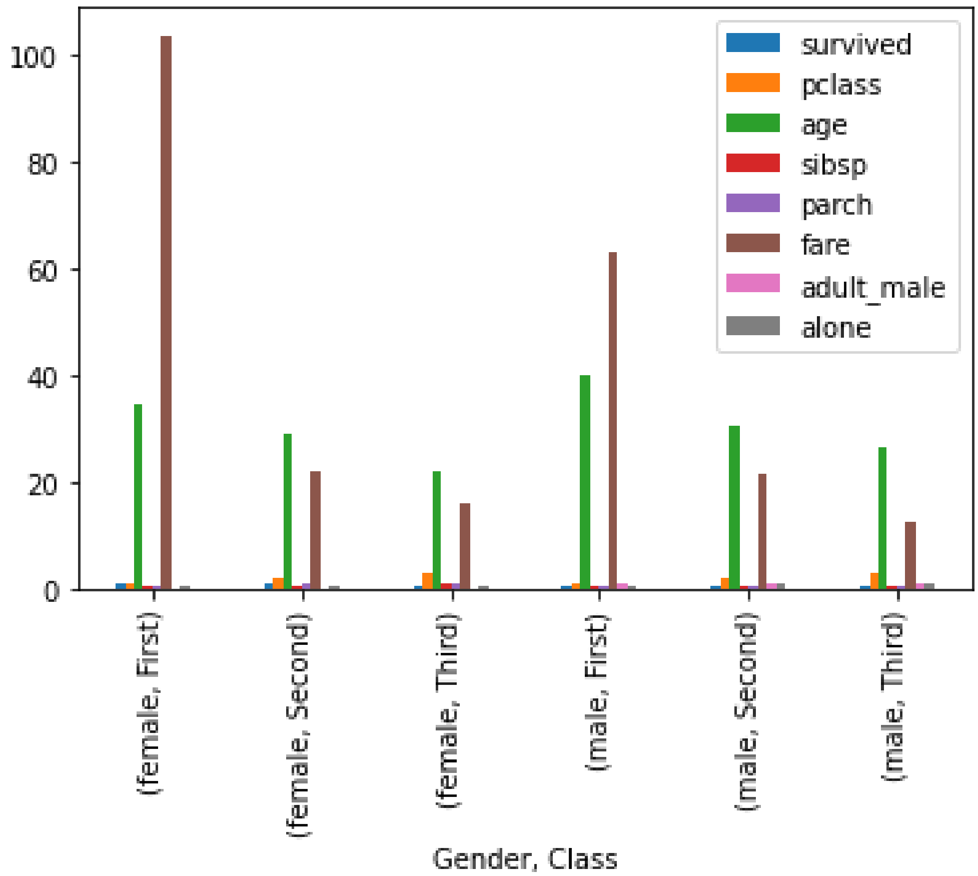
[ ]:
```
pd.value_counts(ks_clean['survived']).plot.bar()
```

[ ]: <AxesSubplot:>



[ ]:
```
ks_clean.groupby(['sex', 'class']).mean().plot.bar()
plt.xlabel('Gender, Class')
```

[ ]: Text(0.5, 0, 'Gender, Class')



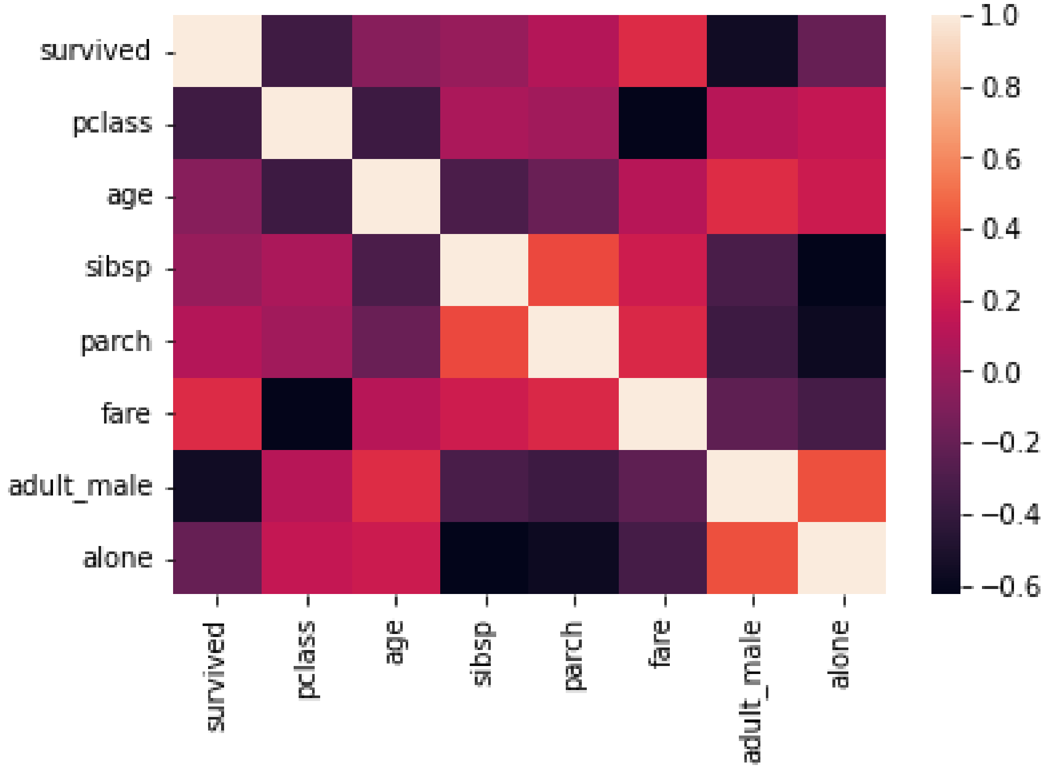
1.4 Correlation

a mutual relationship or connection between two or more things. - "research showed a clear correlation between recession and levels of property crime"

[ ]:
```
corr_ks_clean = ks_clean.corr()
```

[ ]:
```
sns.heatmap(corr_ks_clean)
```

[ ]: <AxesSubplot:>



[ ]:
```
plt.figure(figsize=(10.0, 10.0))
sns.heatmap(data=corr_ks_clean, annot=True)
```

[ ]: <AxesSubplot:>

[ ]:
```
help(sns.heatmap)
```

```
Help on function heatmap in module seaborn.matrix:

heatmap(data, *, vmin=None, vmax=None, cmap=None, center=None, robust=False,
annot=None, fmt='.2g', annot_kws=None, linewidths=0, linecolor='white',
cbar=True, cbar_kws=None, cbar_ax=None, square=False, xticklabels='auto',
yticklabels='auto', mask=None, ax=None, **kwargs)
    Plot rectangular data as a color-encoded matrix.

    This is an Axes-level function and will draw the heatmap into the
    currently-active Axes if none is provided to the ``ax`` argument.  Part of
    this Axes space will be taken and used to plot a colormap, unless ``cbar``
```

```
is False or a separate Axes is provided to ``cbar_ax``.

Parameters
----------
data : rectangular dataset
    2D dataset that can be coerced into an ndarray. If a Pandas DataFrame
    is provided, the index/column information will be used to label the
    columns and rows.
vmin, vmax : floats, optional
    Values to anchor the colormap, otherwise they are inferred from the
    data and other keyword arguments.
cmap : matplotlib colormap name or object, or list of colors, optional
    The mapping from data values to color space. If not provided, the
    default will depend on whether ``center`` is set.
center : float, optional
    The value at which to center the colormap when plotting divergant data.
    Using this parameter will change the default ``cmap`` if none is
    specified.
robust : bool, optional
    If True and ``vmin`` or ``vmax`` are absent, the colormap range is
    computed with robust quantiles instead of the extreme values.
annot : bool or rectangular dataset, optional
    If True, write the data value in each cell. If an array-like with the
    same shape as ``data``, then use this to annotate the heatmap instead
    of the data. Note that DataFrames will match on position, not index.
fmt : str, optional
    String formatting code to use when adding annotations.
annot_kws : dict of key, value mappings, optional
    Keyword arguments for :meth:`matplotlib.axes.Axes.text` when ``annot``
    is True.
linewidths : float, optional
    Width of the lines that will divide each cell.
linecolor : color, optional
    Color of the lines that will divide each cell.
cbar : bool, optional
    Whether to draw a colorbar.
cbar_kws : dict of key, value mappings, optional
    Keyword arguments for :meth:`matplotlib.figure.Figure.colorbar`.
cbar_ax : matplotlib Axes, optional
    Axes in which to draw the colorbar, otherwise take space from the
    main Axes.
square : bool, optional
    If True, set the Axes aspect to "equal" so each cell will be
    square-shaped.
xticklabels, yticklabels : "auto", bool, list-like, or int, optional
    If True, plot the column names of the dataframe. If False, don't plot
    the column names. If list-like, plot these alternate labels as the
    xticklabels. If an integer, use the column names but plot only every
```

```
    n label. If "auto", try to densely plot non-overlapping labels.
mask : bool array or DataFrame, optional
    If passed, data will not be shown in cells where ``mask`` is True.
    Cells with missing values are automatically masked.
ax : matplotlib Axes, optional
    Axes in which to draw the plot, otherwise use the currently-active
    Axes.
kwargs : other keyword arguments
    All other keyword arguments are passed to
    :meth:`matplotlib.axes.Axes.pcolormesh`.

Returns
-------
ax : matplotlib Axes
    Axes object with the heatmap.

See Also
--------
clustermap : Plot a matrix using hierachical clustering to arrange the
             rows and columns.

Examples
--------

Plot a heatmap for a numpy array:

.. plot::
    :context: close-figs

    >>> import numpy as np; np.random.seed(0)
    >>> import seaborn as sns; sns.set_theme()
    >>> uniform_data = np.random.rand(10, 12)
    >>> ax = sns.heatmap(uniform_data)

Change the limits of the colormap:

.. plot::
    :context: close-figs

    >>> ax = sns.heatmap(uniform_data, vmin=0, vmax=1)

Plot a heatmap for data centered on 0 with a diverging colormap:

.. plot::
    :context: close-figs

    >>> normal_data = np.random.randn(10, 12)
    >>> ax = sns.heatmap(normal_data, center=0)
```

Plot a dataframe with meaningful row and column labels:

```
.. plot::
    :context: close-figs

    >>> flights = sns.load_dataset("flights")
    >>> flights = flights.pivot("month", "year", "passengers")
    >>> ax = sns.heatmap(flights)
```

Annotate each cell with the numeric value using integer formatting:

```
.. plot::
    :context: close-figs

    >>> ax = sns.heatmap(flights, annot=True, fmt="d")
```

Add lines between each cell:

```
.. plot::
    :context: close-figs

    >>> ax = sns.heatmap(flights, linewidths=.5)
```

Use a different colormap:

```
.. plot::
    :context: close-figs

    >>> ax = sns.heatmap(flights, cmap="YlGnBu")
```

Center the colormap at a specific value:

```
.. plot::
    :context: close-figs

    >>> ax = sns.heatmap(flights, center=flights.loc["Jan", 1955])
```

Plot every other column label and don't plot row labels:

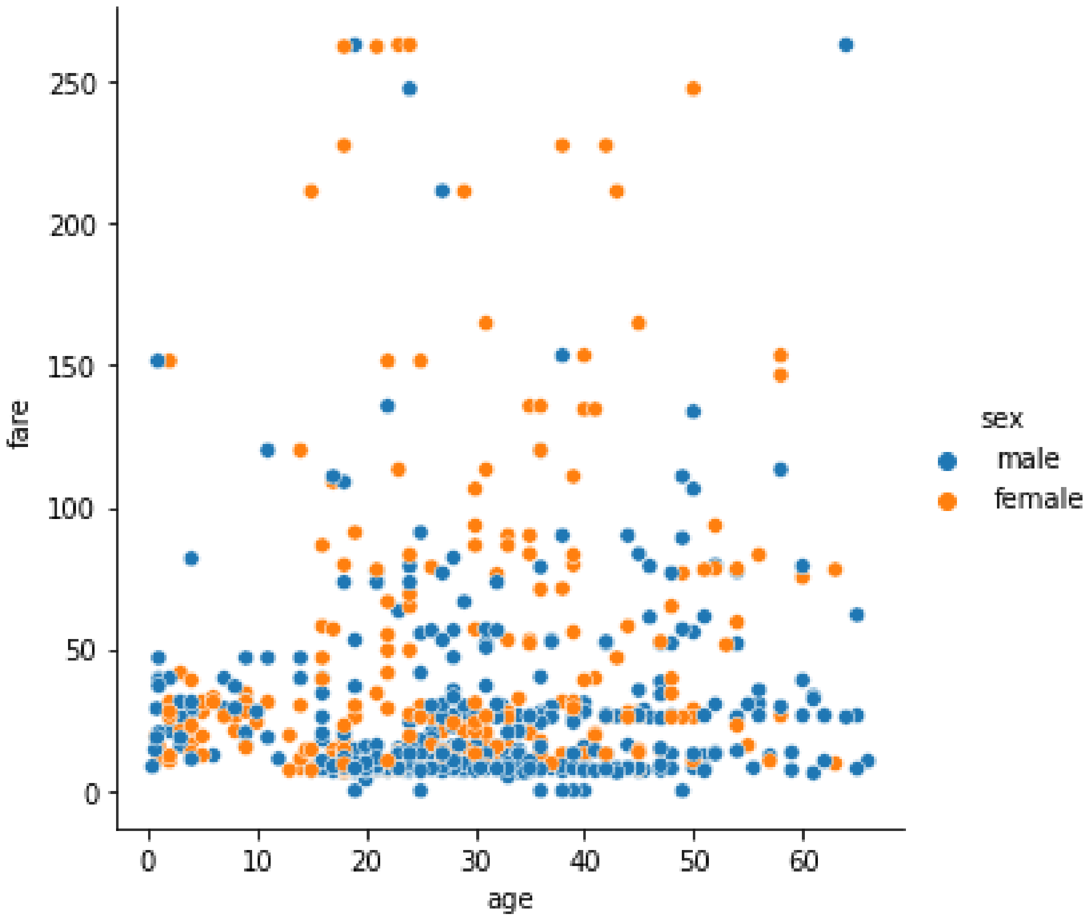
```
.. plot::
    :context: close-figs

    >>> data = np.random.randn(50, 20)
    >>> ax = sns.heatmap(data, xticklabels=2, yticklabels=False)
```

Don't draw a colorbar:

```
.. plot::
    :context: close-figs

    >>> ax = sns.heatmap(flights, cbar=False)

Use different axes for the colorbar:

.. plot::
    :context: close-figs

    >>> grid_kws = {"height_ratios": (.9, .05), "hspace": .3}
    >>> f, (ax, cbar_ax) = plt.subplots(2, gridspec_kw=grid_kws)
    >>> ax = sns.heatmap(flights, ax=ax,
    …                    cbar_ax=cbar_ax,
    …                    cbar_kws={"orientation": "horizontal"})

Use a mask to plot only part of a matrix

.. plot::
    :context: close-figs

    >>> corr = np.corrcoef(np.random.randn(10, 200))
    >>> mask = np.zeros_like(corr)
    >>> mask[np.triu_indices_from(mask)] = True
    >>> with sns.axes_style("white"):
    …     f, ax = plt.subplots(figsize=(7, 5))
    …     ax = sns.heatmap(corr, mask=mask, vmax=.3, square=True)
```

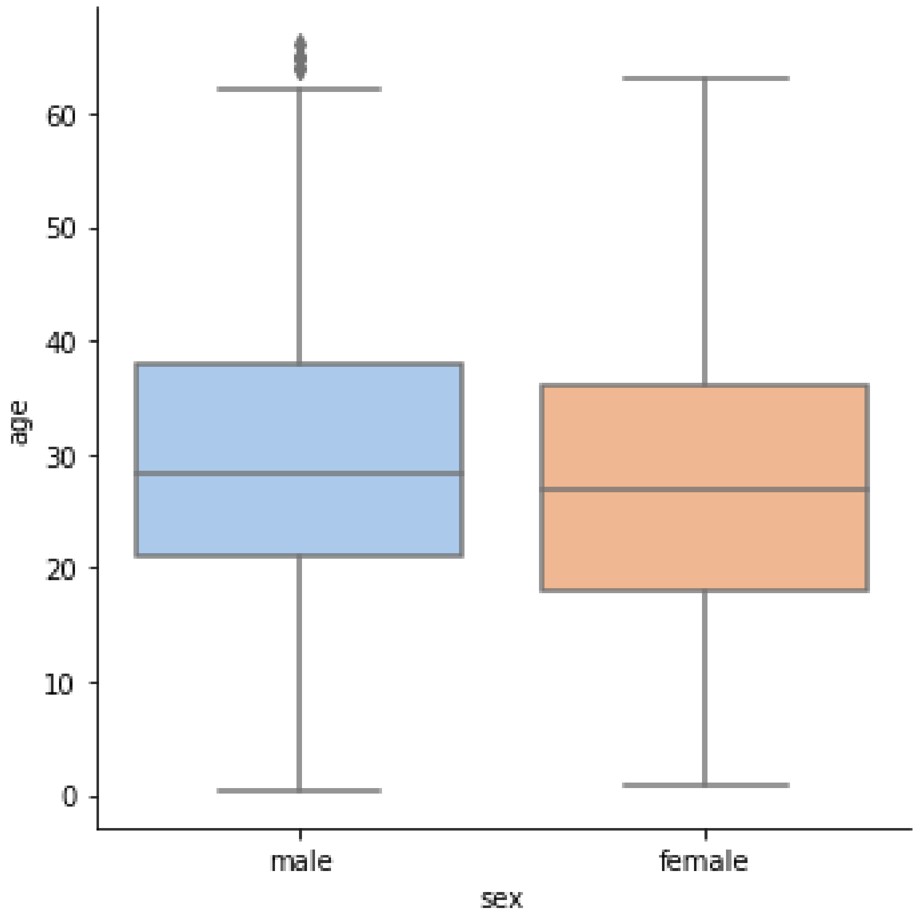
[ ]:
```
sns.relplot(x='age', y='fare', hue='sex', data=ks_clean)
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x21242868a60>




```
[ ]: sns.catplot(x='sex', y='age', data=ks_clean, kind='box', palette='pastel')
```

```
[ ]: <seaborn.axisgrid.FacetGrid at 0x21242c21a50>
```



[ ]:
```
# log transformation
ks_clean['fare_log'] = np.log(ks_clean['fare'])
ks_clean[['fare', 'fare_log']].head()
```

```
C:\Python310\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarning:
divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
C:\Users\hp\AppData\Local\Temp\ipykernel_13432\2123111376.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  ks_clean['fare_log'] = np.log(ks_clean['fare'])
```

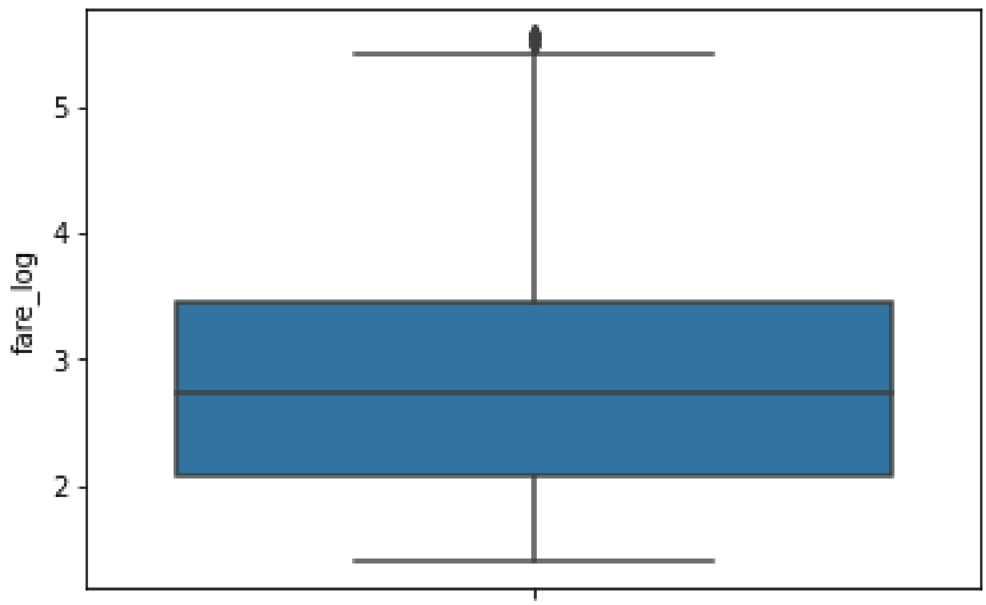
[ ]:

	fare	fare_log
0	7.2500	1.981001

```
1  71.2833  4.266662
2   7.9250  2.070022
3  53.1000  3.972177
4   8.0500  2.085672
```

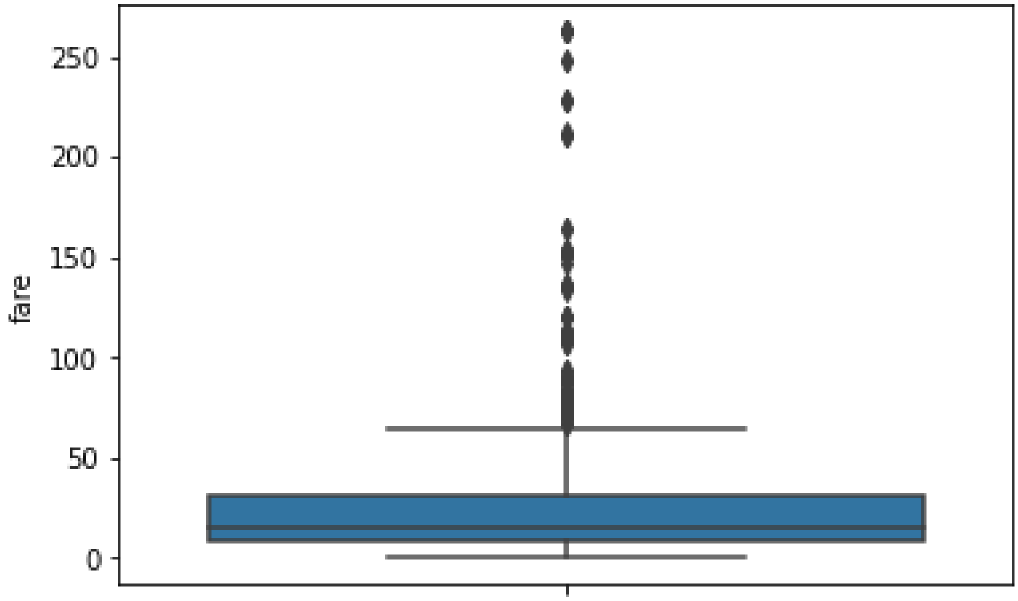
[ ]:
```
sns.boxplot(data=ks_clean, y='fare_log')
```

[ ]: <AxesSubplot:ylabel='fare_log'>



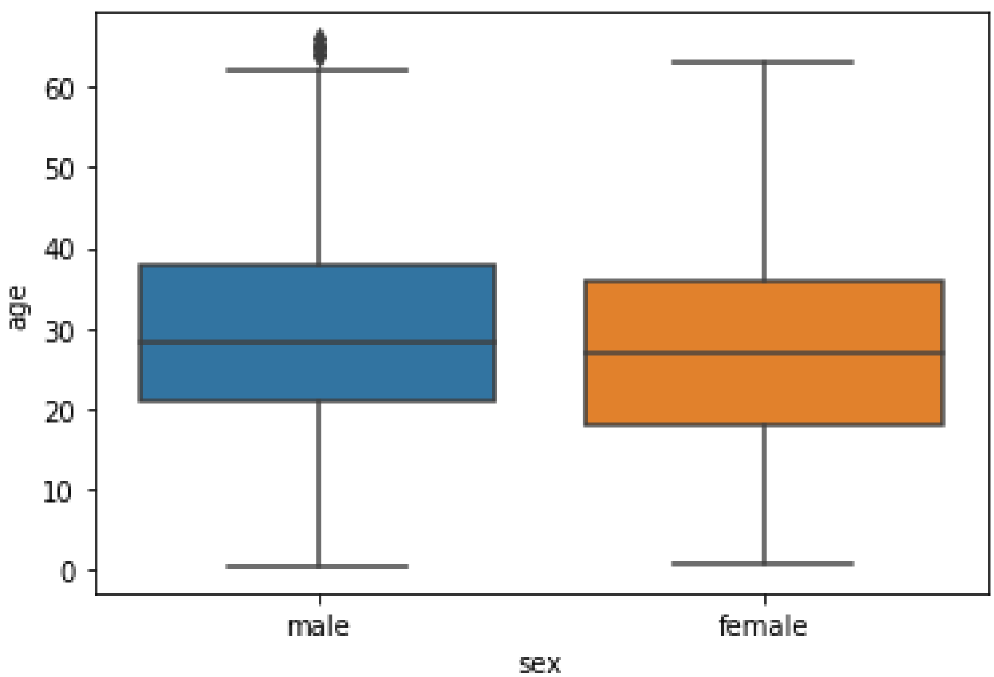
[ ]:
```
sns.boxplot(data=ks_clean, y='fare')
```

[ ]: <AxesSubplot:ylabel='fare'>



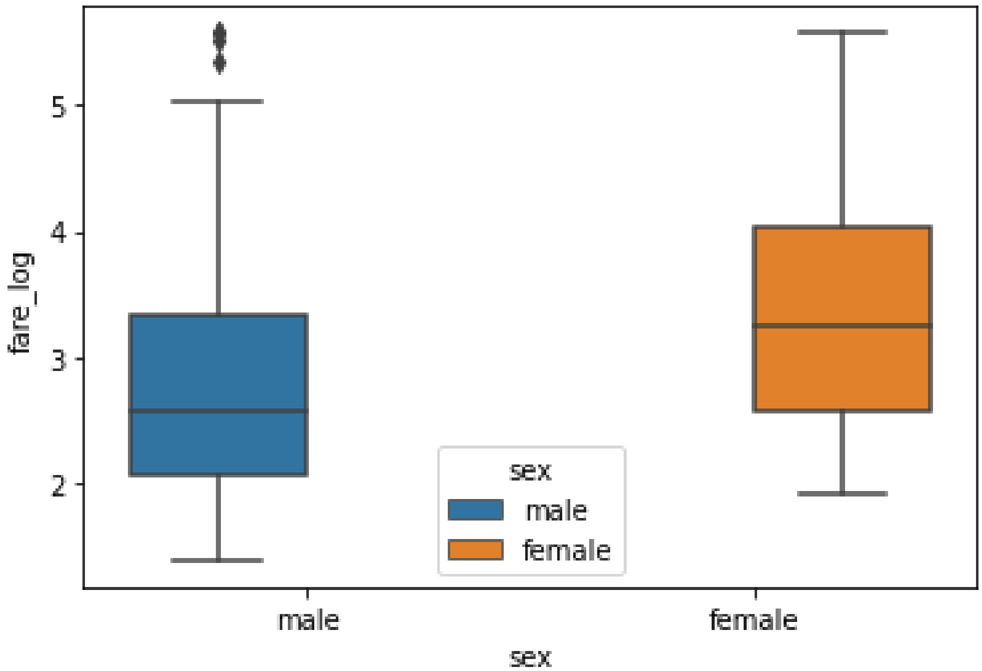

```
[ ]: sns.boxplot(data=ks_clean, x='sex', y='age')
```

[ ]: <AxesSubplot:xlabel='sex', ylabel='age'>



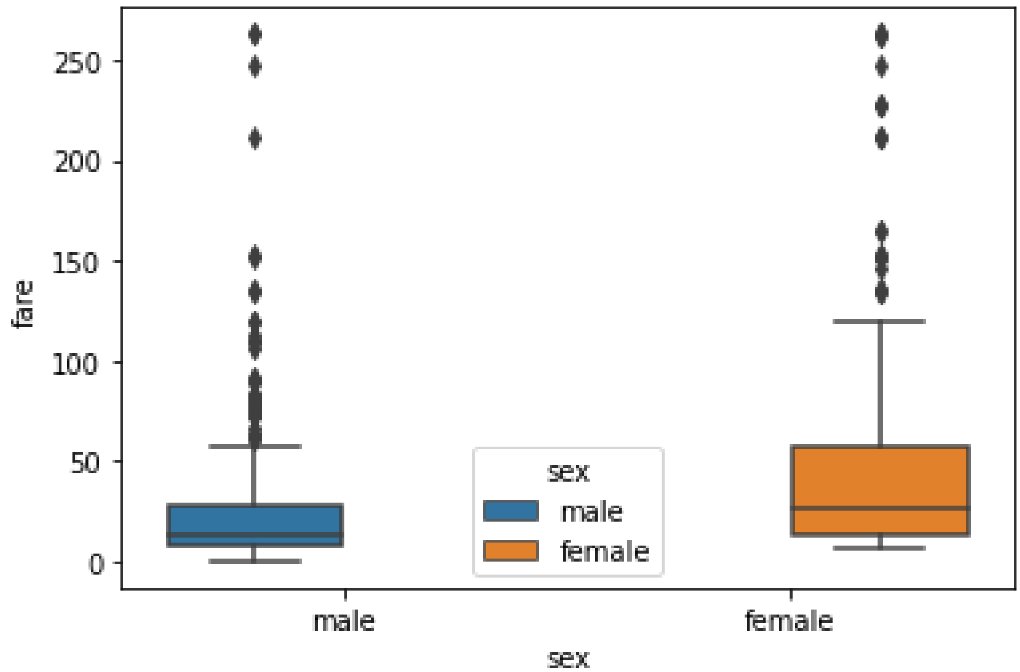
[ ]:
```
sns.boxplot(data=ks_clean, x='sex', y='fare_log', hue='sex')
```

[ ]: <AxesSubplot:xlabel='sex', ylabel='fare_log'>



[ ]:
```
sns.boxplot(data=ks_clean, x='sex', y='fare', hue='sex')
```

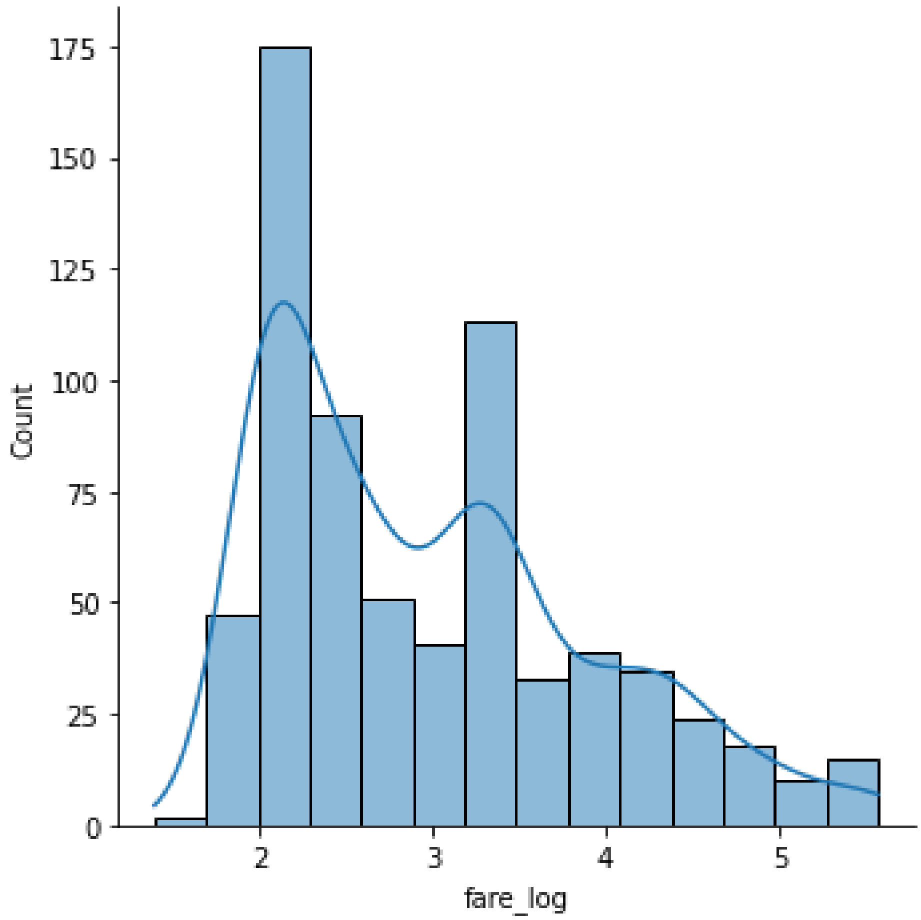
[ ]: <AxesSubplot:xlabel='sex', ylabel='fare'>



[ ]:

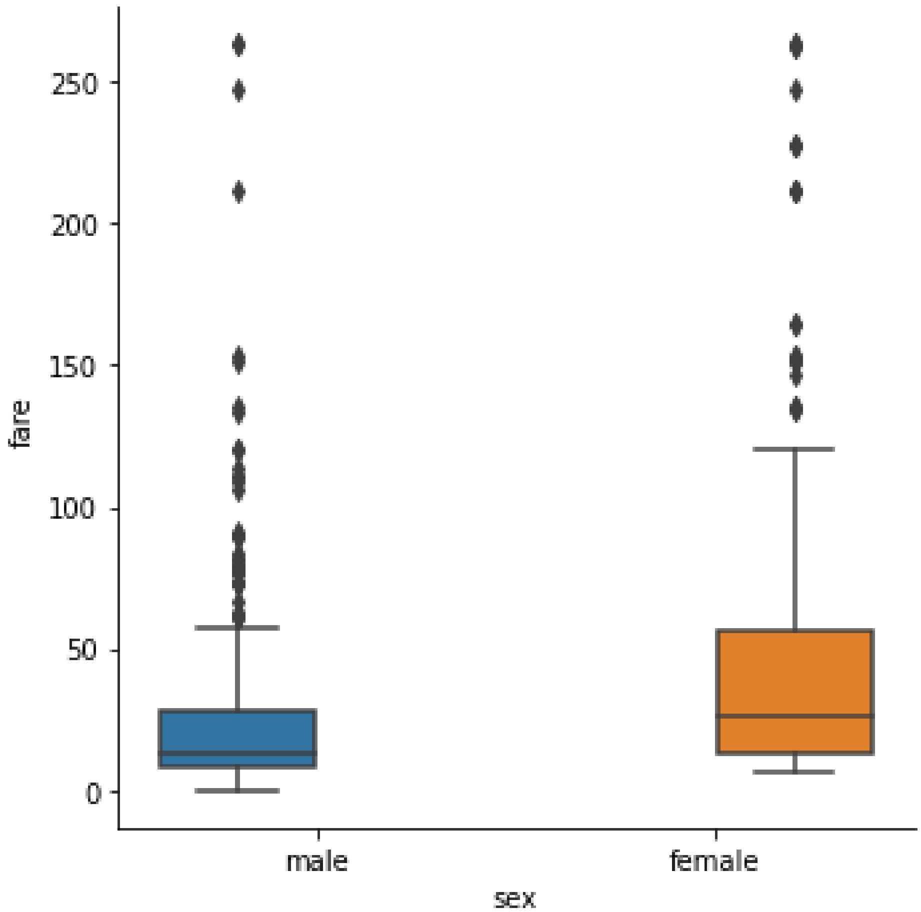
```
[ ]: sns.displot(ks_clean['fare_log'], kde=True)
```

```
[ ]: <seaborn.axisgrid.FacetGrid at 0x21242973d90>
```



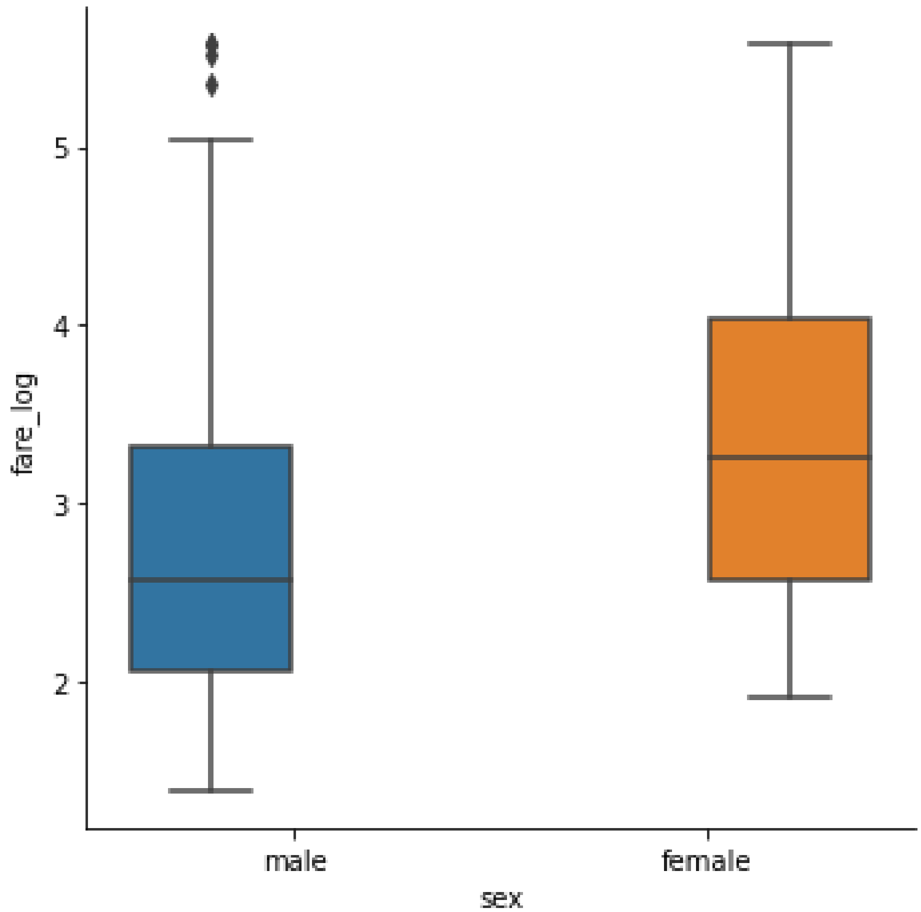

```
[ ]: sns.catplot(x='sex', y='fare', hue='sex', data=ks_clean, kind='box')
```

```
[ ]: <seaborn.axisgrid.FacetGrid at 0x2124272ca90>
```




```
[ ]: sns.catplot(x='sex', y='fare_log', hue='sex', data=ks_clean, kind='box')
```

```
[ ]: <seaborn.axisgrid.FacetGrid at 0x2124254fd00>
```



[ ]:
```
ks_clean.describe()
```

[ ]:
```
         survived      pclass         age       sibsp       parch        fare  \
count  702.000000  702.000000  702.000000  702.000000  702.000000  702.000000
mean     0.404558    2.250712   29.191838    0.519943    0.435897   32.569390
std      0.491156    0.832536   13.941519    0.935297    0.858469   43.087326
min      0.000000    1.000000    0.420000    0.000000    0.000000    0.000000
25%      0.000000    1.000000   20.000000    0.000000    0.000000    8.050000
50%      0.000000    3.000000   28.000000    0.000000    0.000000   15.500000
75%      1.000000    3.000000   38.000000    1.000000    1.000000   31.387500
max      1.000000    3.000000   66.000000    5.000000    6.000000  263.000000

         fare_log
count  702.000000
mean         -inf
std           NaN
min          -inf
25%      2.085672
```

```
50%        2.740840
75%        3.446410
max        5.572154
```