Data_Wrangling

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0.0.1 Subject of this NoteBook: Data Wrangling (D_W)

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data munging, is the process of cleaning, transforming, and organizing data in a way that makes it more suitable for analysis. It is a crucial step in the data science process as real-world data is often messy and inconsistent.

0.1 Steps:

1. Geathering Data (Kia)
2. Tools to clean data (Kis sy clean)
3. How to da (Kiasy)
4.

[1]:
```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
```

[2]:
```
df = sns.load_dataset('titanic')
```

[3]:
```
df.head()
```

[3]:
```
   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
```

[4]:
```
df.describe()
```

[4]:

	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]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   survived     891 non-null    int64
 1   pclass       891 non-null    int64
 2   sex          891 non-null    object
 3   age          714 non-null    float64
 4   sibsp        891 non-null    int64
 5   parch        891 non-null    int64
 6   fare         891 non-null    float64
 7   embarked     889 non-null    object
 8   class        891 non-null    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
```

[6]:
```
df.isnull().sum()*100/len(df)
```

[6]:
```
survived      0.000000
pclass        0.000000
sex           0.000000
age          19.865320
sibsp         0.000000
parch         0.000000
fare          0.000000
embarked      0.224467
class         0.000000
```

```
who             0.000000
adult_male      0.000000
deck           77.216611
embark_town     0.224467
alive           0.000000
alone           0.000000
dtype: float64
```

[7]:
```
df.drop(columns='deck', inplace=True)
```

[8]:
```
# df = df.fillna(value =df['age'].mean())
df['age'] = df['age'].fillna(df['age'].mean())
```

[9]:
```
df['embarked'] = df.embarked.fillna(value = df['embarked'].mode()[0])
```

[10]:
```
df['embark_town'] = df.embark_town.fillna(value= df['embark_town'].mode()[0])
```

[11]:
```
df.isnull().sum()* 100/len(df)
```

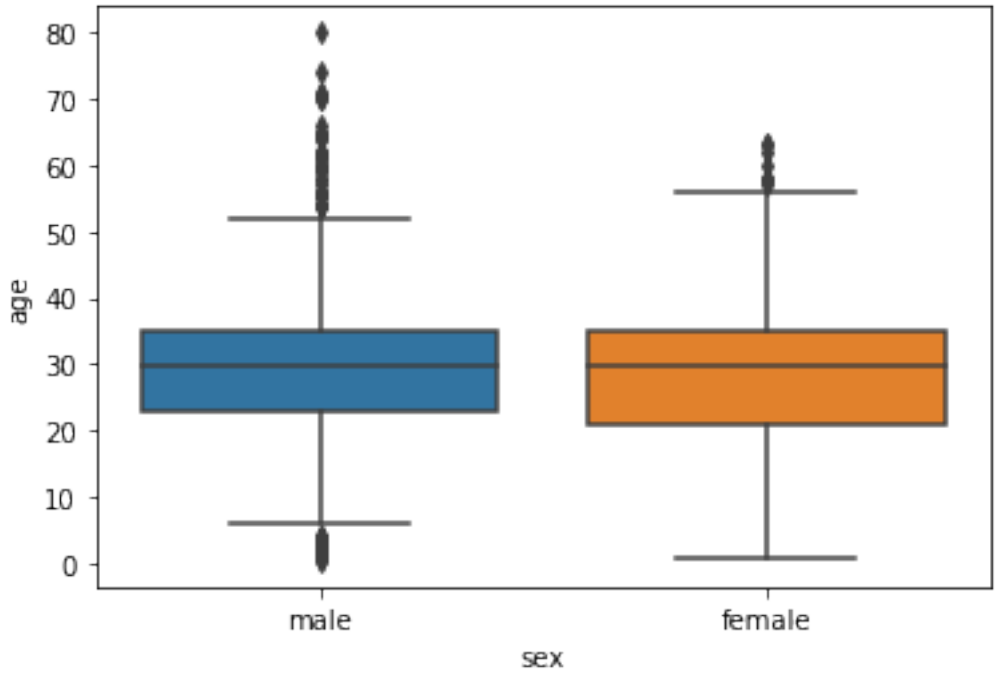
[11]:
```
survived       0.0
pclass         0.0
sex            0.0
age            0.0
sibsp          0.0
parch          0.0
fare           0.0
embarked       0.0
class          0.0
who            0.0
adult_male     0.0
embark_town    0.0
alive          0.0
alone          0.0
dtype: float64
```

1 Outlier Removal

1.1 Visualization Method

[12]:
```
import seaborn as sns
sns.boxplot(data=df, y='age', x='sex')
```

[12]:
```
<AxesSubplot:xlabel='sex', ylabel='age'>
```



[13]:
```
df.shape
```

[13]: (891, 14)

2 IQR Method

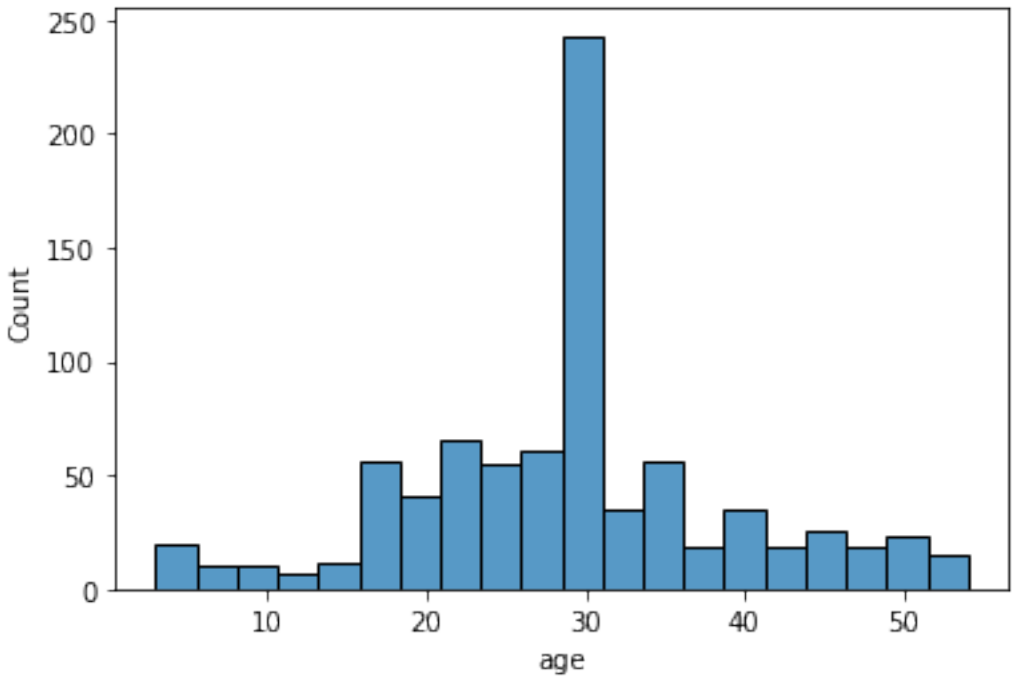
[14]:
```
Q1 = df['age'].quantile(0.25)
Q3 = df['age'].quantile(0.75)
IQR =Q3-Q1
IQR
lower_bound = Q1-1.5*IQR
upper_bound = Q3+1.5*IQR
df = df[(df['age'] > lower_bound) & (df['age'] < upper_bound)]
```

[15]:
```
df.shape
```

[15]: (825, 14)

[16]:
```
sns.histplot(df['age'])
```

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



[17]:
```
df.shape
```

[17]: (825, 14)

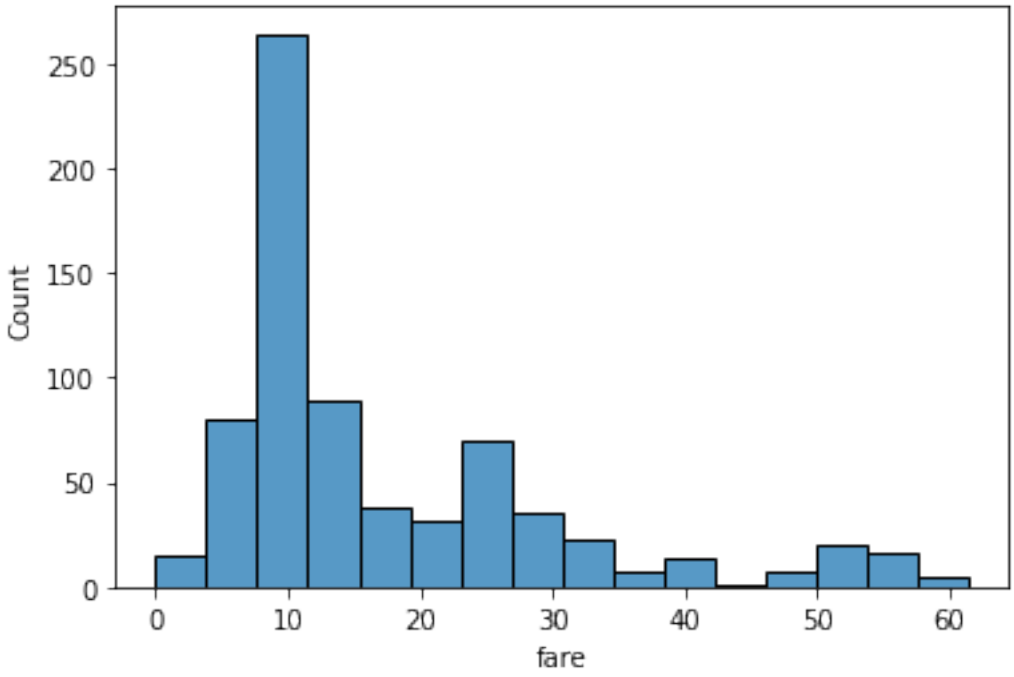
[18]:
```
Q1 = df['fare'].quantile(0.25)
Q3 = df['fare'].quantile(0.75)
IQR =Q3-Q1
IQR
lower_bound = Q1-1.5*IQR
upper_bound = Q3+1.5*IQR
df = df[(df['fare'] > lower_bound) & (df['fare'] < upper_bound)]
```

[19]:
```
df.shape
```

[19]: (718, 14)

[20]:
```
sns.histplot(df['fare'])
```

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



[21]:
```
# ZScore
```

[22]:
```
# pip install scipy
```

[23]:
```
df.dtypes
```

[23]:
```
survived          int64
pclass            int64
sex              object
age             float64
sibsp             int64
parch             int64
fare            float64
embarked         object
class          category
who              object
adult_male         bool
embark_town      object
alive            object
alone              bool
dtype: object
```

[24]:
```
import numpy as np
from scipy import stats
```

```
zscore = np.abs(stats.zscore(df['age']))
threshold = 3
df = df[(zscore < threshold)]
```

[25]:
```
df.shape
```

[25]: (718, 14)

3 Finding Duplicates

[26]:
```
df.duplicated().sum()
```

[26]: 103

[27]:
```
df_duplicates = df[df.duplicated()]
df_duplicates.head()
```

[27]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	\
47	1	3	female	29.699118	0	0	7.7500	Q	Third	
76	0	3	male	29.699118	0	0	7.8958	S	Third	
77	0	3	male	29.699118	0	0	8.0500	S	Third	
87	0	3	male	29.699118	0	0	8.0500	S	Third	
95	0	3	male	29.699118	0	0	8.0500	S	Third	

	who	adult_male	embark_town	alive	alone
47	woman	False	Queenstown	yes	True
76	man	True	Southampton	no	True
77	man	True	Southampton	no	True
87	man	True	Southampton	no	True
95	man	True	Southampton	no	True

[28]:
```
df_duplicates.shape
```

[28]: (103, 14)

4 Droping Duplicates

[29]:
```
df.drop_duplicates(inplace=True)
```

[30]:
```
df.shape
```

[30]: (615, 14)

[31]:
```
# pip install scikit-learn
# 1. Import libraries
```

```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler

# 2. Data
df

# 3. select column to normalize
cols_to_normalize = ['age', 'fare']

# 4. create the scaler function / tool
scaler =MinMaxScaler()

# 5. fit and transform the dataon scaler or vise versa
df[cols_to_normalize] = scaler.fit_transform(df[cols_to_normalize])

# 6. Check the data
df
```

[31]:

```
     survived  pclass     sex       age  sibsp  parch      fare embarked  \
0           0       3    male  0.372549      1      0  0.118118        S
2           1       3  female  0.450980      0      0  0.129115        S
3           1       1  female  0.627451      1      0  0.865114        S
4           0       3    male  0.627451      0      0  0.131152        S
5           0       3    male  0.523512      0      0  0.137804        Q
..        …     …      …        …    …    …        …       …
885         0       3  female  0.705882      0      5  0.474509        Q
887         1       1  female  0.313725      0      0  0.488765        S
888         0       3  female  0.523512      1      2  0.382051        S
889         1       1    male  0.450980      0      0  0.488765        C
890         0       3    male  0.568627      0      0  0.126264        Q

     class    who  adult_male  embark_town alive  alone
0    Third    man        True  Southampton    no  False
2    Third  woman       False  Southampton   yes   True
3    First  woman       False  Southampton   yes  False
4    Third    man        True  Southampton    no   True
5    Third    man        True   Queenstown    no   True
..     …    …          …           …   …    …
885  Third  woman       False   Queenstown    no  False
887  First  woman       False  Southampton   yes   True
888  Third  woman       False  Southampton    no  False
889  First    man        True    Cherbourg   yes   True
890  Third    man        True   Queenstown    no   True

[615 rows x 14 columns]
```

[32]:

```
df.describe()
```

[32]:

	survived	pclass	age	sibsp	parch	fare
count	615.000000	615.000000	615.000000	615.000000	615.000000	615.000000
mean	0.360976	2.469919	0.497584	0.460163	0.365854	0.298831
std	0.480674	0.741063	0.209485	0.894039	0.835572	0.221334
min	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	0.372549	0.000000	0.000000	0.128640
50%	0.000000	3.000000	0.523512	0.000000	0.000000	0.211798
75%	1.000000	3.000000	0.607843	1.000000	0.000000	0.423596
max	1.000000	3.000000	1.000000	5.000000	6.000000	1.000000

[33]:

```
# 1. Import libraries

import pandas as pd
from sklearn.preprocessing import StandardScaler

# 2. Data
df

# 3. select column to normalize
cols_to_normalize = ['age', 'fare']

# 4. create the scaler function / tool
scaler =StandardScaler()

# 5. fit and transform the dataon scaler or vise versa
df[cols_to_normalize] = scaler.fit_transform(df[cols_to_normalize])

# 6. Check the data
df
```

[33]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	embark_town	alive	alone
0	0	3	male	-0.597354	1	0	-0.817136	S	Third	man	True	Southampton	no	False
2	1	3	female	-0.222648	0	0	-0.767410	S	Third	woman	False	Southampton	yes	True
3	1	1	female	0.620441	1	0	2.560585	S	First	woman	False	Southampton	yes	False
4	0	3	male	0.620441	0	0	-0.758201	S						
5	0	3	male	0.123872	0	0	-0.728122	Q						
..	…	…	…	…	…	…	…	…						
885	0	3	female	0.995147	0	5	0.794372	Q						
887	1	1	female	-0.878384	0	0	0.858832	S						
888	0	3	female	0.123872	1	2	0.376301	S						
889	1	1	male	-0.222648	0	0	0.858832	C						
890	0	3	male	0.339411	0	0	-0.780302	Q						

```
4    Third    man        True  Southampton    no   True
5    Third    man        True   Queenstown    no   True
..     …    …          …           …   …    …
885  Third  woman       False   Queenstown    no  False
887  First  woman       False  Southampton   yes   True
888  Third  woman       False  Southampton    no  False
889  First    man        True    Cherbourg   yes   True
890  Third    man        True   Queenstown    no   True

[615 rows x 14 columns]
```

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

[34]:
```
         survived      pclass           age       sibsp       parch  \
count  615.000000  615.000000  6.150000e+02  615.000000  615.000000
mean     0.360976    2.469919  3.061688e-16    0.460163    0.365854
std      0.480674    0.741063  1.000814e+00    0.894039    0.835572
min      0.000000    1.000000 -2.377209e+00    0.000000    0.000000
25%      0.000000    2.000000 -5.973545e-01    0.000000    0.000000
50%      0.000000    3.000000  1.238725e-01    0.000000    0.000000
75%      1.000000    3.000000  5.267644e-01    1.000000    0.000000
max      1.000000    3.000000  2.400296e+00    5.000000    6.000000

               fare
count  6.150000e+02
mean  -1.213122e-16
std    1.000814e+00
min   -1.351236e+00
25%   -7.695610e-01
50%   -3.935399e-01
75%    5.641565e-01
max    3.170505e+00
```

5 Log Transmition

[35]:
```
kashti = sns.load_dataset('titanic')
kashti.head()
```

[35]:
```
   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
```

[36]:
```
# Log Transmition
kashti['age'] = kashti['age'].fillna(kashti['age'].median())
kashti['fare'] = kashti['fare'].fillna(kashti['fare'].median())
```

[37]:
```
kashti['age'] = np.log(kashti['age'])
kashti['fare']= np.log(kashti['fare'])
kashti.head()
```

```
c:\Users\Al HAfiz Enterprises\AppData\Local\Programs\Python\Python39\lib\site-
packages\pandas\core\arraylike.py:397: RuntimeWarning: divide by zero
encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

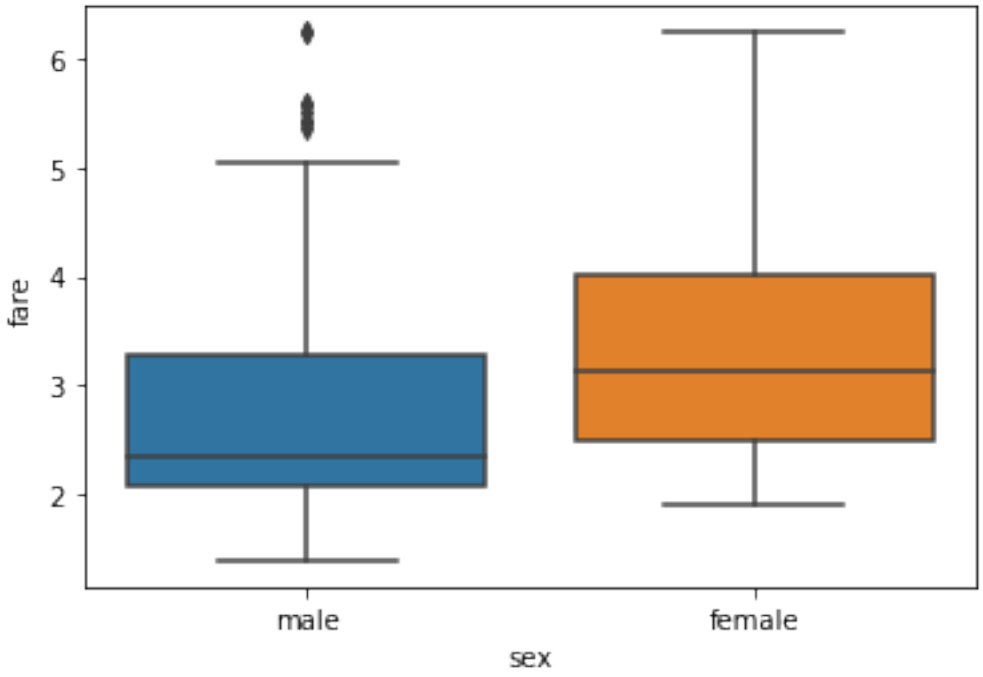
[37]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	\
0	0	3	male	3.091042	1	0	1.981001	S	Third	
1	1	1	female	3.637586	1	0	4.266662	C	First	
2	1	3	female	3.258097	0	0	2.070022	S	Third	
3	1	1	female	3.555348	1	0	3.972177	S	First	
4	0	3	male	3.555348	0	0	2.085672	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

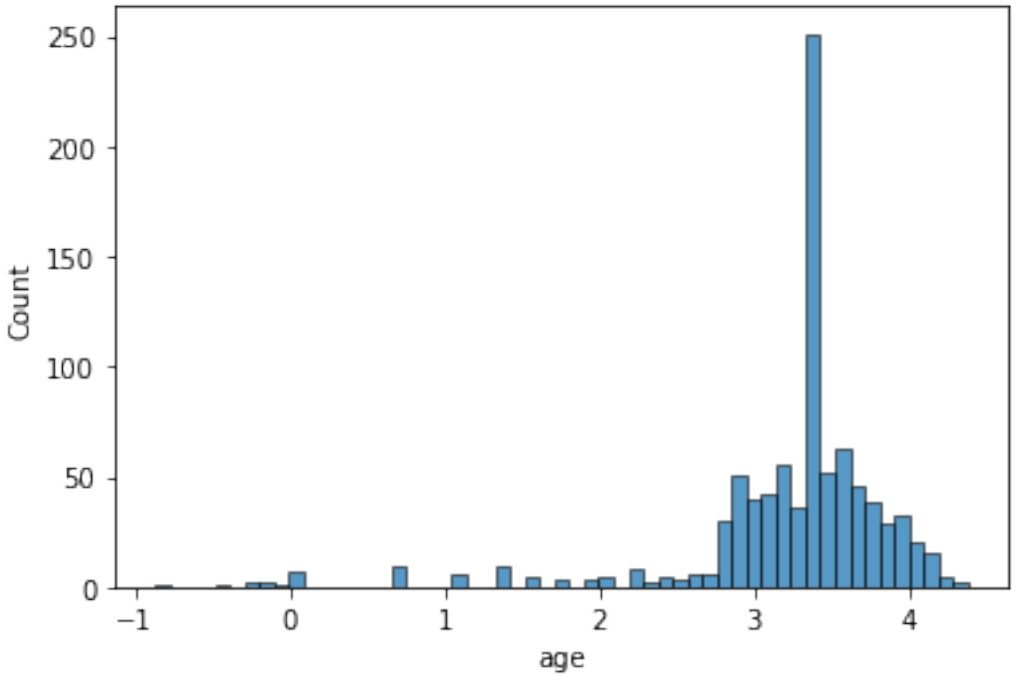
[38]:
```
sns.boxplot(data=kashti, x="sex", y='fare')
```

[38]:
```
<AxesSubplot:xlabel='sex', ylabel='fare'>
```



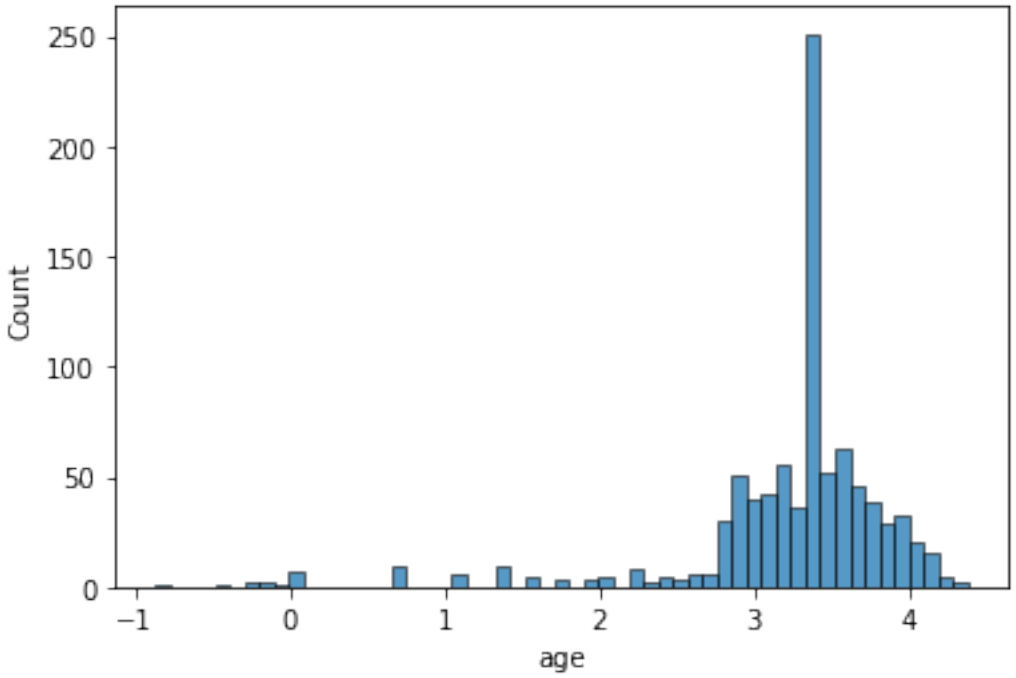
[39]:
```
sns.histplot(kashti['age'])
```

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



[40]:
```
sns.histplot(kashti['age'])
```

[40]:
```
<AxesSubplot:xlabel='age', ylabel='Count'>
```



[41]:
```
df.columns
```

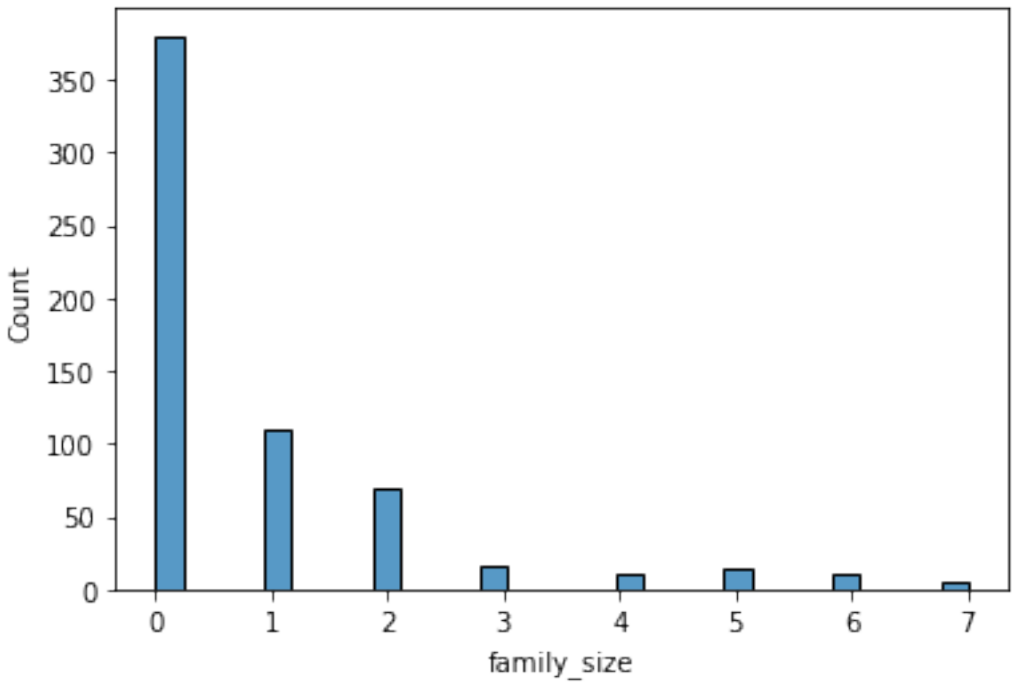
[41]:
```
Index(['survived', 'pclass', 'sex', 'age', 'sibsp', 'parch', 'fare',
       'embarked', 'class', 'who', 'adult_male', 'embark_town', 'alive',
       'alone'],
      dtype='object')
```

6 Organizing the Data

[42]:
```
df['family_size'] = df['sibsp']+df['parch']
```

[43]:
```
sns.histplot(df['family_size'])
```

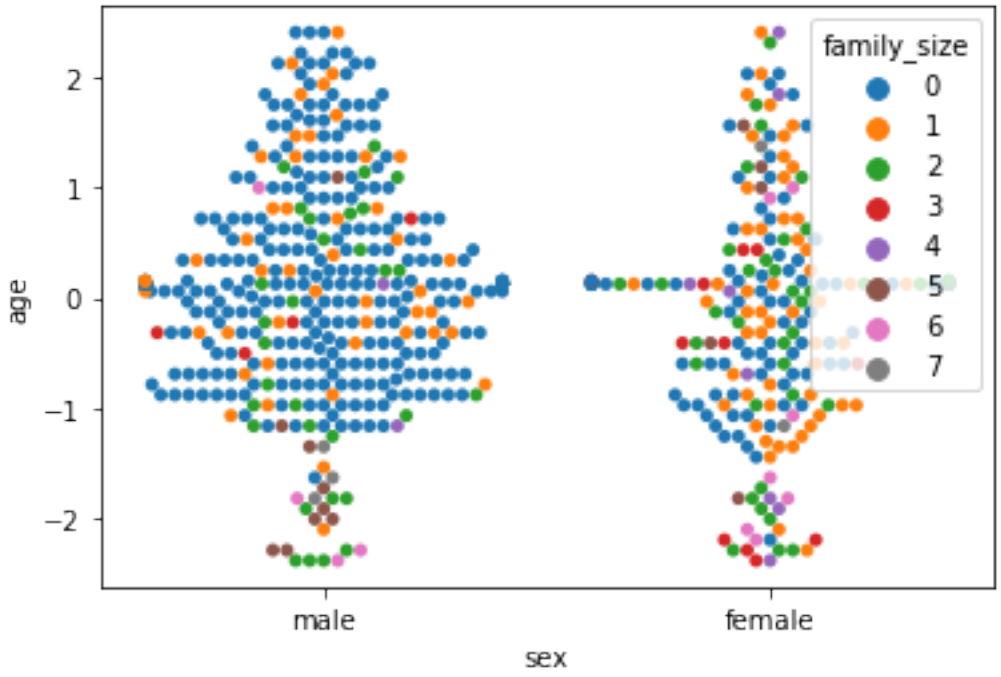
[43]:
```
<AxesSubplot:xlabel='family_size', ylabel='Count'>
```



[44]:
```
sns.swarmplot(data=df, x="sex", y="age", hue="family_size")
```

```
c:\Users\Al HAfiz Enterprises\AppData\Local\Programs\Python\Python39\lib\site-
packages\seaborn\categorical.py:1296: UserWarning: 14.9% of the points cannot be
placed; you may want to decrease the size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
c:\Users\Al HAfiz Enterprises\AppData\Local\Programs\Python\Python39\lib\site-
packages\seaborn\categorical.py:1296: UserWarning: 7.1% of the points cannot be
placed; you may want to decrease the size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
```

[44]:
```
<AxesSubplot:xlabel='sex', ylabel='age'>
```



[45]:
```
df = df.rename(columns={'survived': 'survival'})
df.columns
```

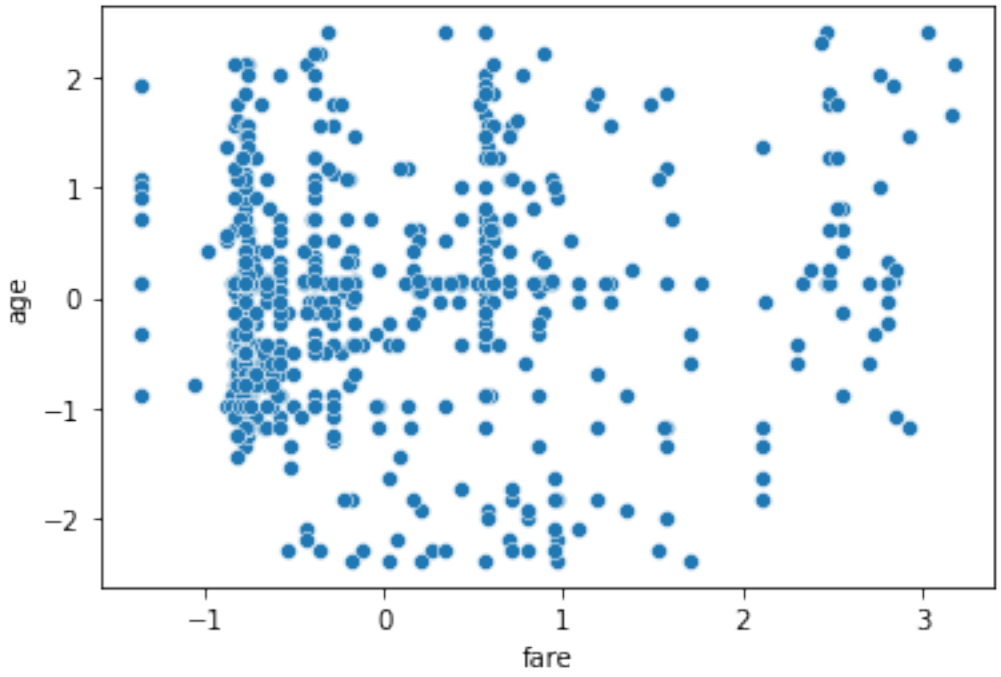
[45]:
```
Index(['survival', 'pclass', 'sex', 'age', 'sibsp', 'parch', 'fare',
       'embarked', 'class', 'who', 'adult_male', 'embark_town', 'alive',
       'alone', 'family_size'],
      dtype='object')
```

[46]:
```
table = pd.pivot_table(df, values='fare', index='pclass',
                       columns="survival", aggfunc=np.sum)
table
```

[46]:
```
survival           0          1
pclass
1          47.098956  86.811732
2          -1.053066  13.921025
3        -109.690971 -37.087677
```

[47]:
```
sns.scatterplot(data=df, x="fare", y="age")
```

[47]:
```
<AxesSubplot:xlabel='fare', ylabel='age'>
```



[48]:
```
df['family_size'] = df['sibsp']+df['parch']
```

[49]:
```
df.head()
```

[49]:

	survival	pclass	sex	age	sibsp	parch	fare	embarked	class	\
0	0	3	male	-0.597354	1	0	-0.817136	S	Third	
2	1	3	female	-0.222648	0	0	-0.767410	S	Third	
3	1	1	female	0.620441	1	0	2.560585	S	First	
4	0	3	male	0.620441	0	0	-0.758201	S	Third	
5	0	3	male	0.123872	0	0	-0.728122	Q	Third	

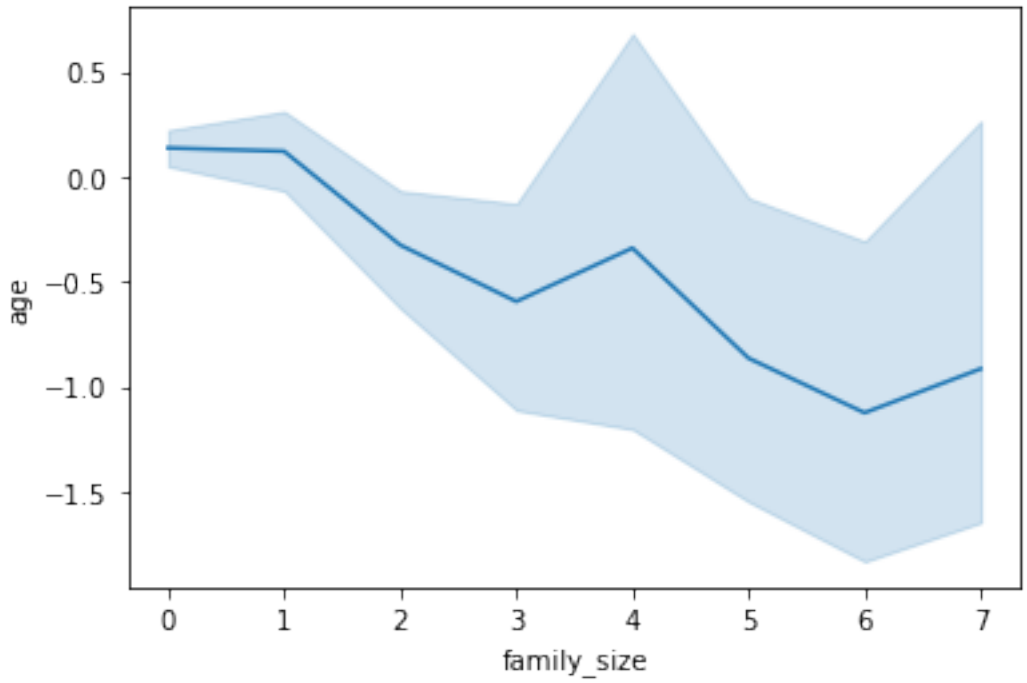
	who	adult_male	embark_town	alive	alone	family_size
0	man	True	Southampton	no	False	1
2	woman	False	Southampton	yes	True	0
3	woman	False	Southampton	yes	False	1
4	man	True	Southampton	no	True	0
5	man	True	Queenstown	no	True	0

7 Saving the wrangleed data

[50]:
```
df.to_csv("pre-rocess_data.csv")
```

[51]:
```
sns.lineplot(data=df, x='family_size', y="age")
```

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



[55]:
```
!jupyter nbconvert --to pdf Data_Wrangling.ipynb
```

[ ]:
```

```