lab3

November 29, 2019

[103]:
```
import pandas as pd
import matplotlib.pyplot as plt
from IPython.display import display
import seaborn as sns
```

[104]:
```
pd_city = pd.read_csv("./city_data.csv")
pd_city.head(5)
```

[104]:
```
           city  driver_count   type
0   Richardfort            38  Urban
1  Williamsstad            59  Urban
2   Port Angela            67  Urban
3    Rodneyfort            34  Urban
4   West Robert            39  Urban
```

[105]:
```
pd_city.dtypes
```

[105]:
```
city            object
driver_count     int64
type            object
dtype: object
```

[106]:
```
pd_ride = pd.read_csv("./ride_data.csv")
pd_ride.head(5)
```

[106]:
```
                 city                 date   fare        ride_id
0  Lake Jonathanshire  2018-01-14 10:14:22  13.83  5739410935873
1  South Michelleport  2018-03-04 18:24:09  30.24  2343912425577
2  Port Samanthamouth  2018-02-24 04:29:00  33.44  2005065760003
3          Rodneyfort  2018-02-10 23:22:03  23.44  5149245426178
4          South Jack  2018-03-06 04:28:35  34.58  3908451377344
```

[107]:
```
pd_ride.dtypes
```

[107]:
```
city        object
date        object
fare       float64
ride_id      int64
dtype: object
```

[108]:
```
pd_join = pd_city.join(pd_ride.set_index("city"),on="city")
pd_join['type'].unique()
```

[108]:
```
array(['Urban', 'Suburban', 'Rural'], dtype=object)
```

[109]:
```
pd_join[pd_join['city']=='Amandaburgh']
```

[109]:
```
           city  driver_count   type                 date   fare  \
61  Amandaburgh            12  Urban  2018-03-05 02:15:38  26.28
61  Amandaburgh            12  Urban  2018-02-24 23:10:49  43.66
61  Amandaburgh            12  Urban  2018-02-10 20:42:46  36.17
61  Amandaburgh            12  Urban  2018-01-11 02:22:07  29.24
61  Amandaburgh            12  Urban  2018-01-21 04:12:54   9.26
61  Amandaburgh            12  Urban  2018-04-19 16:30:12   6.27
61  Amandaburgh            12  Urban  2018-03-20 07:40:33  27.45
61  Amandaburgh            12  Urban  2018-04-01 09:24:21  24.29
61  Amandaburgh            12  Urban  2018-04-20 02:16:07  16.27
61  Amandaburgh            12  Urban  2018-03-13 12:52:31  13.88
61  Amandaburgh            12  Urban  2018-04-22 21:34:17  42.52
61  Amandaburgh            12  Urban  2018-02-06 10:02:30  11.93
61  Amandaburgh            12  Urban  2018-04-24 08:02:27  14.55
61  Amandaburgh            12  Urban  2018-04-05 10:22:33  25.55
61  Amandaburgh            12  Urban  2018-03-07 02:26:33  18.76
61  Amandaburgh            12  Urban  2018-01-02 09:57:04  33.06
61  Amandaburgh            12  Urban  2018-01-13 16:04:10  23.35
61  Amandaburgh            12  Urban  2018-01-29 23:28:12  41.06

          ride_id
61   906850928986
61  6573820412437
61  6455620849753
61  7279902884763
61  5528427024492
61  4400632718421
61  3701008274871
61  1995462170530
61  3513123734716
61  6222134922674
61  1901157522591
61  7550325158038
61  7836117055007
61  8581415267582
61  3419454549176
61  6330658179518
61  9975084532253
61  4296858665195
```

[110]:
```
pd_group = pd.DataFrame(data=list(pd_join.groupby(by='city').
 ↪mean()['fare']),columns=['Average Fare'])

type(pd_join.groupby(by='city').mean()['fare'])
```

```
pd_group['city'] = pd_join.groupby(by='city').indices
a = pd_join.groupby(by='city').count()['driver_count']
pd_group['Number of Drivers'] = list(pd_join.groupby(by='city').
 ↪count()['driver_count'])
pd_group['Number of Rides'] =pd_group['Number of Drivers']
pd_group.set_index('city')
#pd_group.set_index('city')
#pd_group() why re set_index in other cell
```

[110]:

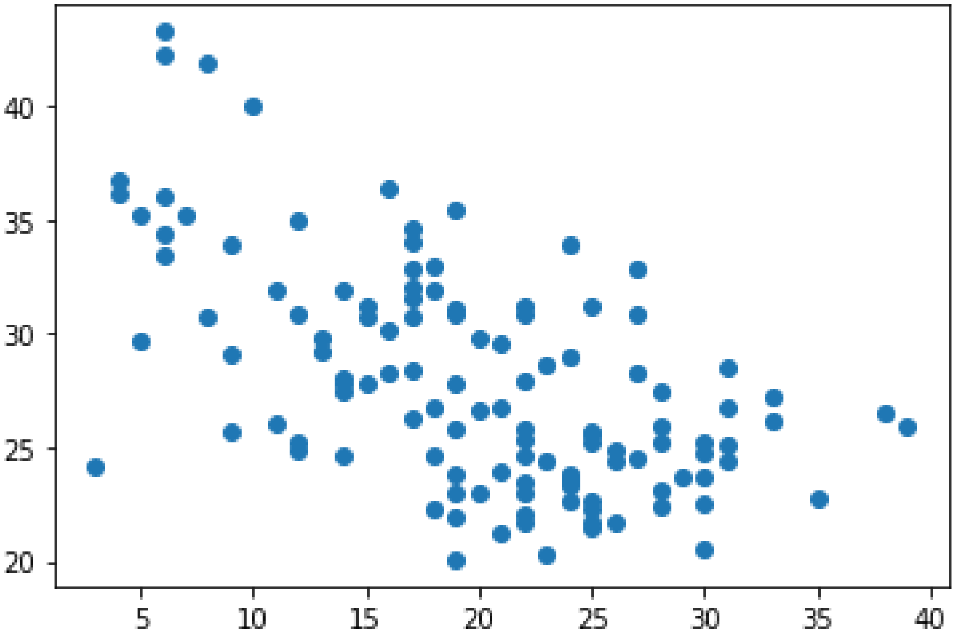
```
                       Average Fare  Number of Drivers  Number of Rides
city
Amandaburgh               24.641667                 18               18
Barajasview               25.332273                 22               22
Barronchester             36.422500                 16               16
Bethanyland               32.956111                 18               18
Bradshawfurt              40.064000                 10               10
Brandonfort               35.437368                 19               19
Carriemouth               28.314444                 27               27
Christopherfurt           24.501852                 27               27
Colemanland               30.894545                 22               22
Davidfurt                 31.995882                 17               17
Deanville                 25.842632                 19               19
East Aaronbury            25.661111                  9                9
East Danielview           31.560588                 17               17
East Kaylahaven           23.757931                 29               29
East Kentstad             29.823077                 13               13
East Marymouth            30.835185                 27               27
Erikaland                 24.906667                 12               12
Garzaport                 24.123333                  3                3
Grahamburgh               25.221200                 25               25
Grayville                 27.763333                 15               15
Harringtonfort            33.470000                  6                6
Huntermouth               28.993750                 24               24
Hurleymouth               25.891429                 28               28
Jerryton                  25.649200                 25               25
Jessicaport               36.013333                  6                6
Johnton                   26.785714                 21               21
Joneschester              22.289600                 25               25
Josephside                32.858148                 27               27
Justinberg                23.694333                 30               30
Karenberg                 26.340000                 17               17
...                             ...                ...              ...
South Evanton             26.726129                 31               31
South Jack                22.965263                 19               19
South Jennifer            35.264286                  7                7
South Karenland           26.535526                 38               38
South Latoya              20.093158                 19               19
South Marychester        41.870000                  8                8
South Michelleport       24.451613                 31               31
South Phillip            28.571290                 31               31
South Saramouth          36.160000                  4                4
South Teresa             31.220455                 22               22
Taylorhaven              42.263333                  6                6
Valentineton             24.636364                 22               22
Veronicaberg             32.828235                 17               17
Victoriaport             27.780000                 14               14
West Angela              25.990000                 39               39
West Anthony             24.736667                 30               30
West Christopherberg     24.421154                 26               26
West Ericstad            22.347222                 18               18
West Gabriel             20.346087                 23               23
West Hannah              29.547619                 21               21
West Heather             33.890000                  9                9
West Heidi               23.133929                 28               28
West Josephberg          21.720385                 26               26
West Kimmouth            29.871500                 20               20
West Patrickchester      28.233125                 16               16
West Robert              25.123871                 31               31
West Samuelburgh         21.767600                 25               25
Williamsonville          31.875000                 14               14
Williamsstad             24.362174                 23               23
Williamsview             26.599000                 20               20

[120 rows x 3 columns]
```

[111]:

```
plt.scatter(list(pd_group['Number of Drivers']),list(pd_group['Average Fare']))
```

[111]:

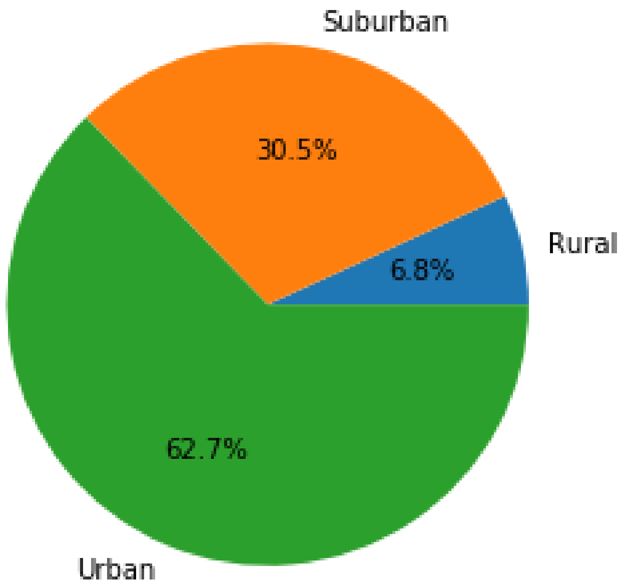
```
<matplotlib.collections.PathCollection at 0x268f0cbc0b8>
```

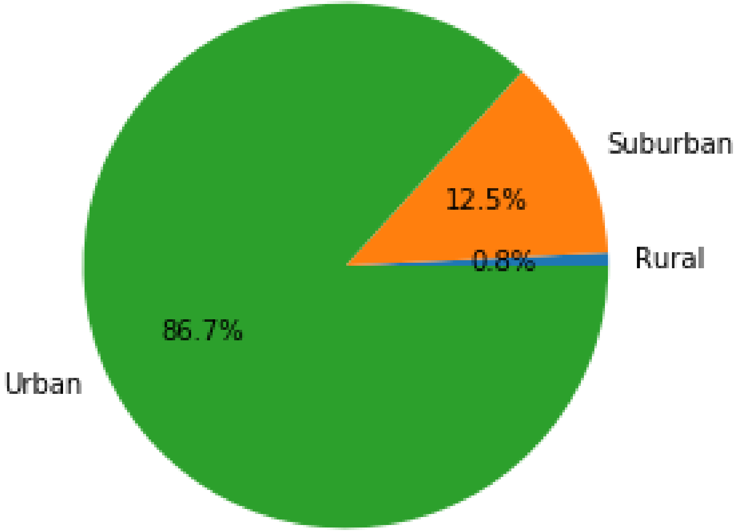


[112]:
```
pd_join.groupby(by='type').sum()
```

[112]:
```
          driver_count       fare            ride_id
type
Rural              537    4327.93    580968240341287
Suburban          8570   19356.33   3106884522576766
Urban            59602   39854.38   7919412664056093
```

[113]:
```
fig,axe1 = plt.subplots()
total_fare_index = pd_join.groupby(by='type').sum()['fare'].index
total_fare_value = list(pd_join.groupby(by='type').sum()['fare'])
axe1.pie(total_fare_value,labels=total_fare_index,autopct='%1.1f%%')
axe1.axis('equal')
total_ride_index = pd_join.groupby(by='type').sum()['driver_count'].index
total_ride_value = list(pd_join.groupby(by='type').sum()['driver_count'])
fig,axe2 = plt.subplots()
axe2.pie(total_ride_value,labels=total_ride_index,autopct='%1.1f%%')
axe2.axis('equal')
plt.show()
```





[114]:

```
#t = sns.load_dataset("titanic") why "" not working
t = sns.load_dataset('titanic')
#len(t.index)
t.head(10)
```

[114]:

```
   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
```

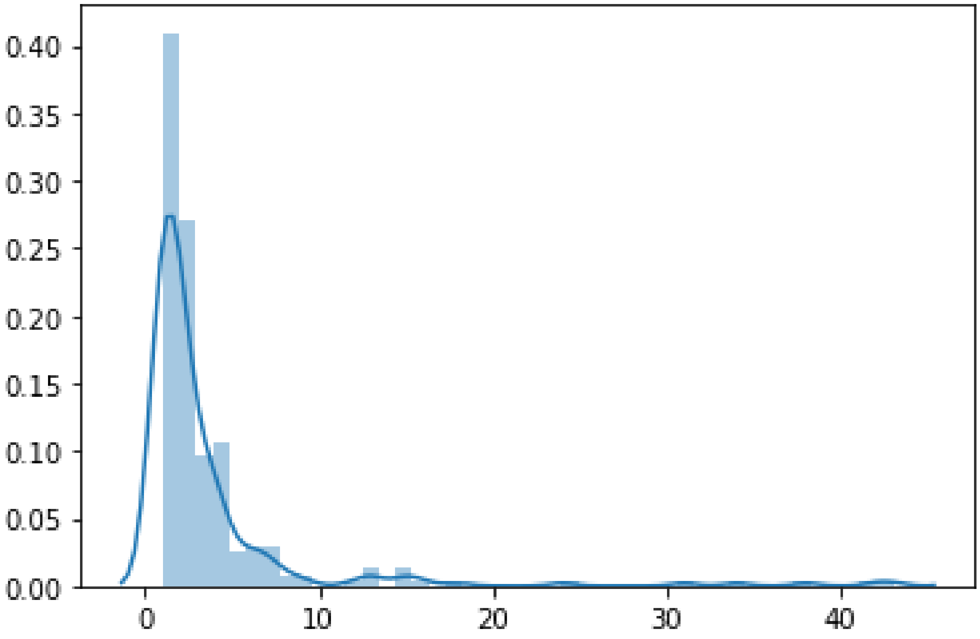
```
2         1       3  female  26.0      0      0   7.9250       S   Third
3         1       1  female  35.0      1      0  53.1000       S   First
4         0       3    male  35.0      0      0   8.0500       S   Third
5         0       3    male   NaN      0      0   8.4583       Q   Third
6         0       1    male  54.0      0      0  51.8625       S   First
7         0       3    male   2.0      3      1  21.0750       S   Third
8         1       3  female  27.0      0      2  11.1333       S   Third
9         1       2  female  14.0      1      0  30.0708       C  Second

     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
5    man        True  NaN   Queenstown    no   True
6    man        True    E  Southampton    no   True
7  child       False  NaN  Southampton    no  False
8  woman       False  NaN  Southampton   yes  False
9  child       False  NaN    Cherbourg   yes  False
```

[115]:

```
fare_pd = pd.DataFrame()
fare_pd['fare']= t.groupby('fare').indices
fare_pd['count']= t.groupby('fare').count()['sex']
fare_pd.set_index('fare',inplace=True,drop=True)
#type(fare_pd)
#fare_pd
#t.groupby('fare').count().head(3)
sns.distplot(fare_pd)
```

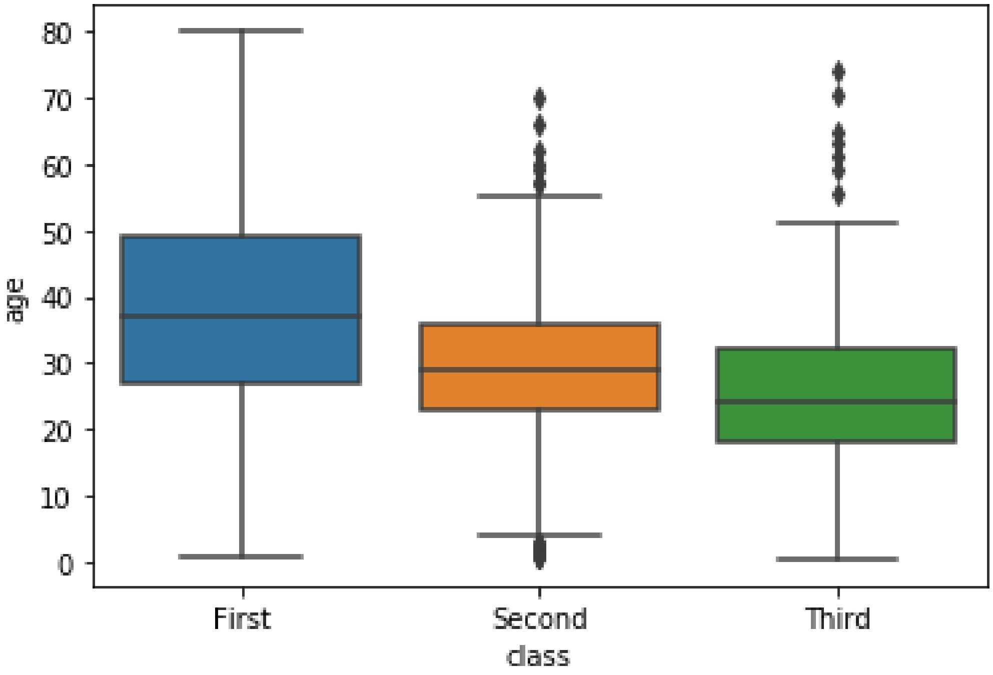
[115]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x268f0d2b198>
```



[116]:
```
sns.boxplot(x='class',y='age',data=t)
```

[116]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x268ef495358>
```



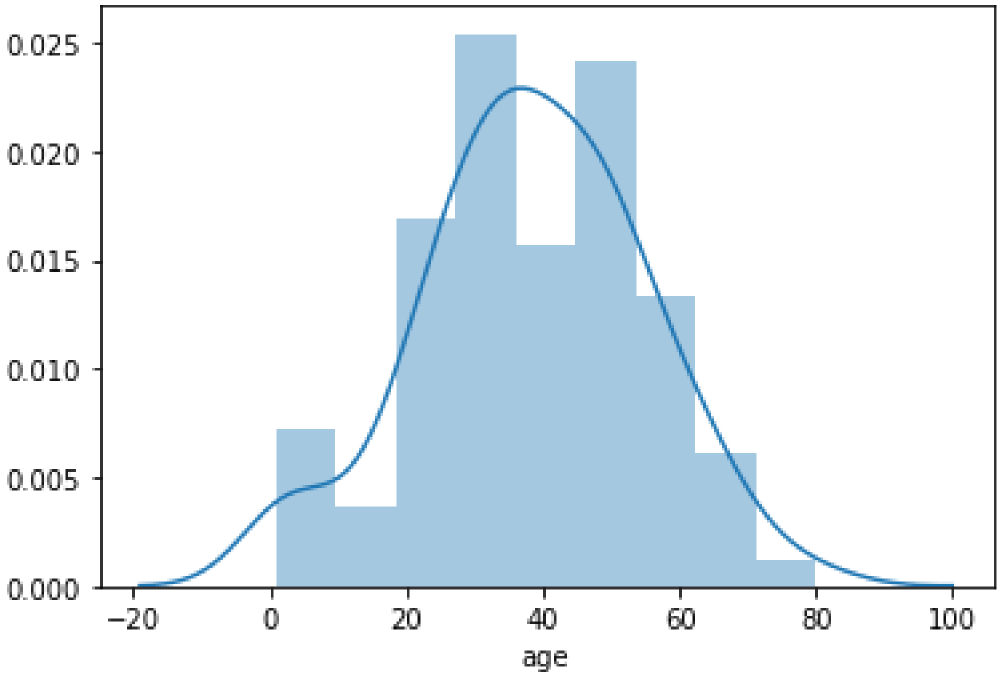
[117]:

```
male_pd = t[t['sex']=='male']
male_pd.head(5)
male_pd.dropna(inplace=True)
male_pd['age']
#male_pd.groupby('age').count()
#male_pd['age']<=80
sns.distplot(male_pd['age'])
```

```
E:\software\anaconda\lib\site-packages\ipykernel_launcher.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports
until
```

[117]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x268f0cfe6a0>
```

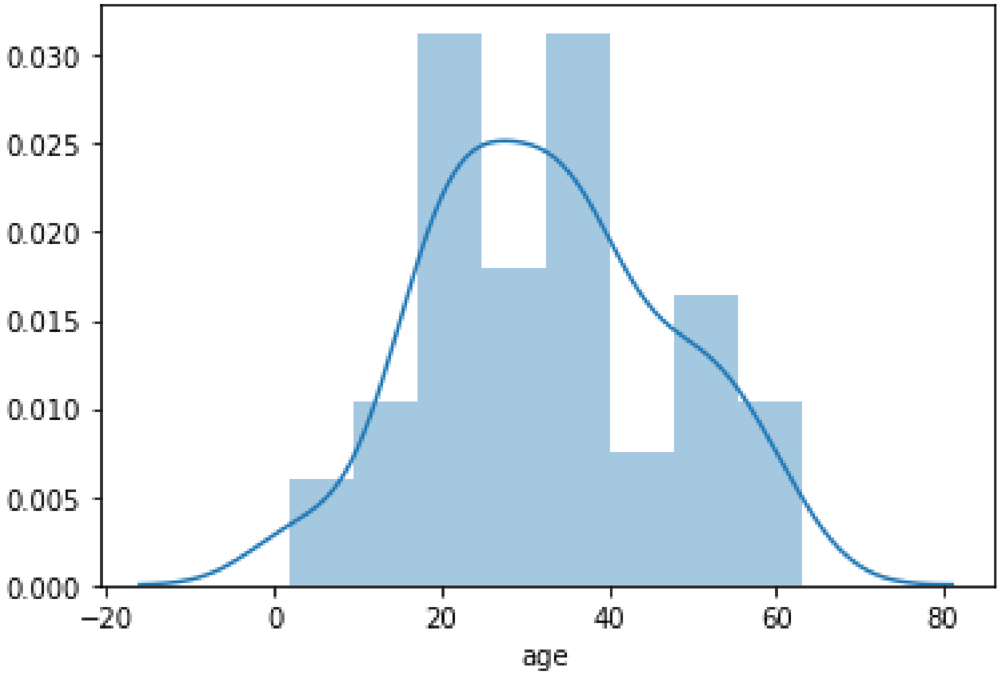


[118]:

```
female_pd = t[t['sex']=='female']
female_pd.dropna(inplace=True)
#female_pd['age']
#male_pd.groupby('age').count()
#male_pd['age']<=80
sns.distplot(female_pd['age'])
```

```
E:\software\anaconda\lib\site-packages\ipykernel_launcher.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
```

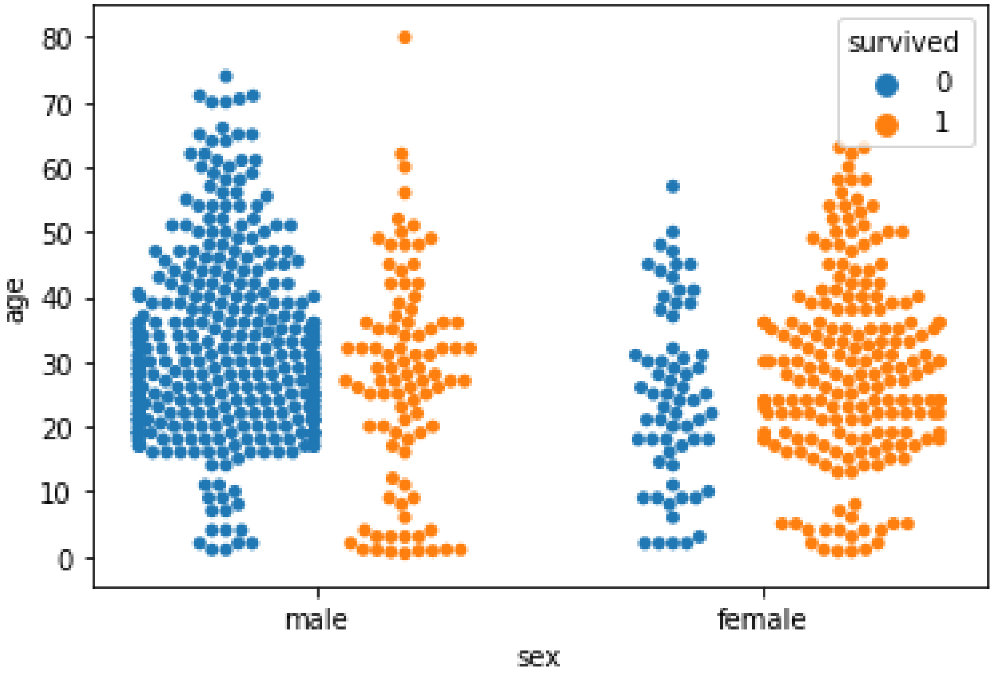
[118]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x268ec1d7940>
```



[119]:
```
sns.swarmplot(x='sex',y='age',hue='survived',dodge=True,data=t)
```

```
E:\software\anaconda\lib\site-packages\seaborn\categorical.py:1324:
RuntimeWarning: invalid value encountered in less
  off_low = points < low_gutter
E:\software\anaconda\lib\site-packages\seaborn\categorical.py:1328:
RuntimeWarning: invalid value encountered in greater
  off_high = points > high_gutter
```

[119]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x268ef2884a8>
```

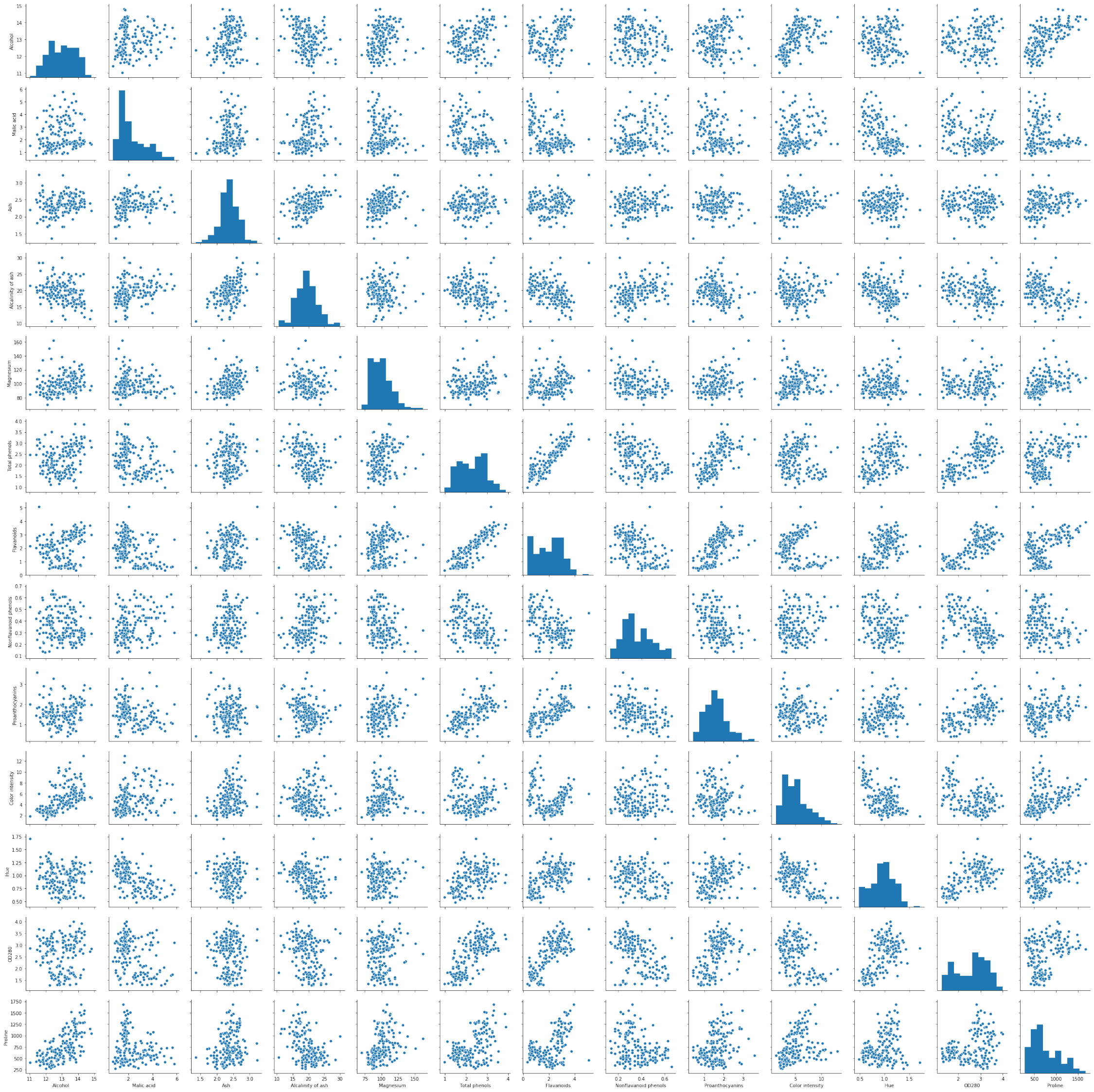


[120]:
```
wine_pd = pd.read_csv("./wine_data.csv")
#wine_pd.head()
wine_pd['Label'].unique()
labels = wine_pd['Label']
labels
wine_pd = wine_pd.drop(axis=1,columns='Label')
wine_pd.head(5)
```

[120]:
```
   Alcohol  Malic acid   Ash  Alcalinity of ash  Magnesium  Total phenols  \
0    14.23        1.71  2.43               15.6        127           2.80
1    13.20        1.78  2.14               11.2        100           2.65
2    13.16        2.36  2.67               18.6        101           2.80
3    14.37        1.95  2.50               16.8        113           3.85
4    13.24        2.59  2.87               21.0        118           2.80

   Flavanoids  Nonflavanoid phenols  Proanthocyanins  Color intensity   Hue  \
0        3.06                  0.28             2.29             5.64  1.04
1        2.76                  0.26             1.28             4.38  1.05
2        3.24                  0.30             2.81             5.68  1.03
3        3.49                  0.24             2.18             7.80  0.86
4        2.69                  0.39             1.82             4.32  1.04

   OD280  Proline
0   3.92     1065
1   3.40     1050
2   3.17     1185
```

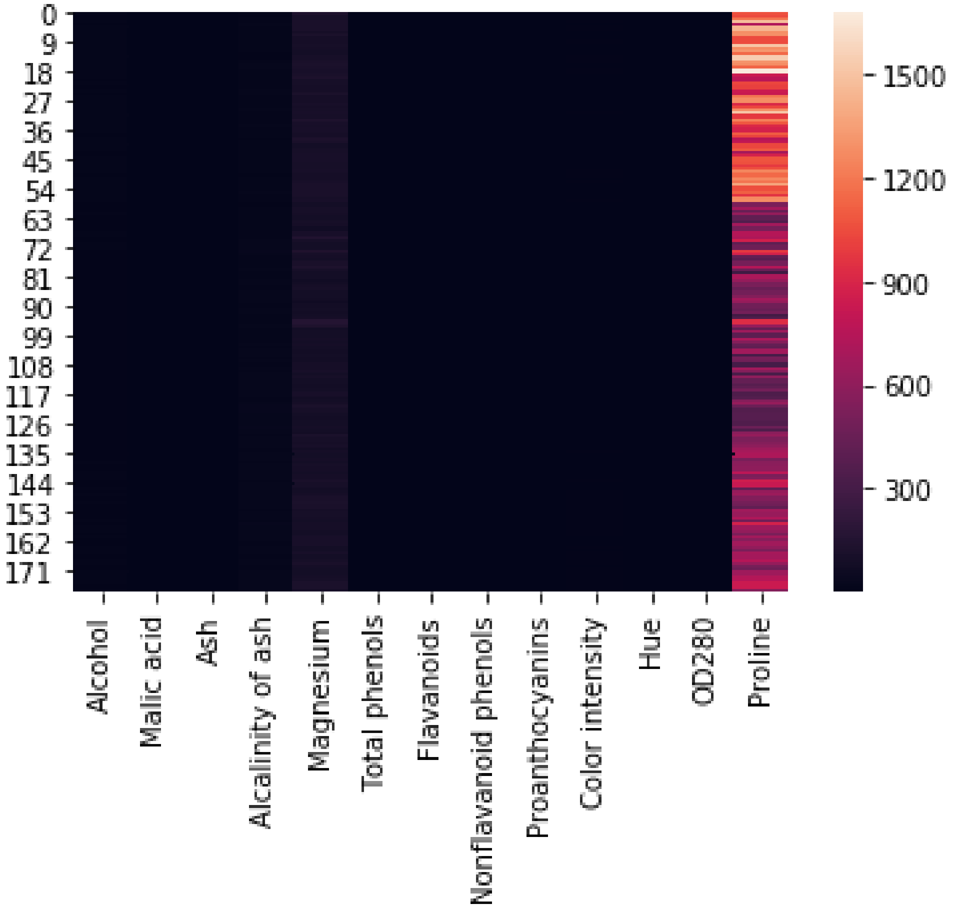
```
3   3.45      1480
4   2.93       735
```

[121]:
```
sns_plot = sns.pairplot(wine_pd,diag_kind="hist")
```



[122]:
```
#plt.subplots(figsize=(100,100))
sns.heatmap(wine_pd)
```

[122]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x268e20205f8>
```



[123]:
```
from sklearn import preprocessing
from sklearn.cluster import KMeans
```

[124]:
```
standardScaler = preprocessing.StandardScaler()
standardScaler.fit(wine_pd)
X_scaled_array = standardScaler.transform(wine_pd)
#X_scaled_array
normalizedData = pd.DataFrame(X_scaled_array, columns = wine_pd.columns)
normalizedData.head(5)
len(normalizedData.index)
```

[124]:
```
178
```

[125]:
```
kMeansClustering = KMeans(n_clusters = 3)
res = kMeansClustering.fit_predict(normalizedData)
res
```

[125]:
```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 0, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 0, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0])
```

[126]:

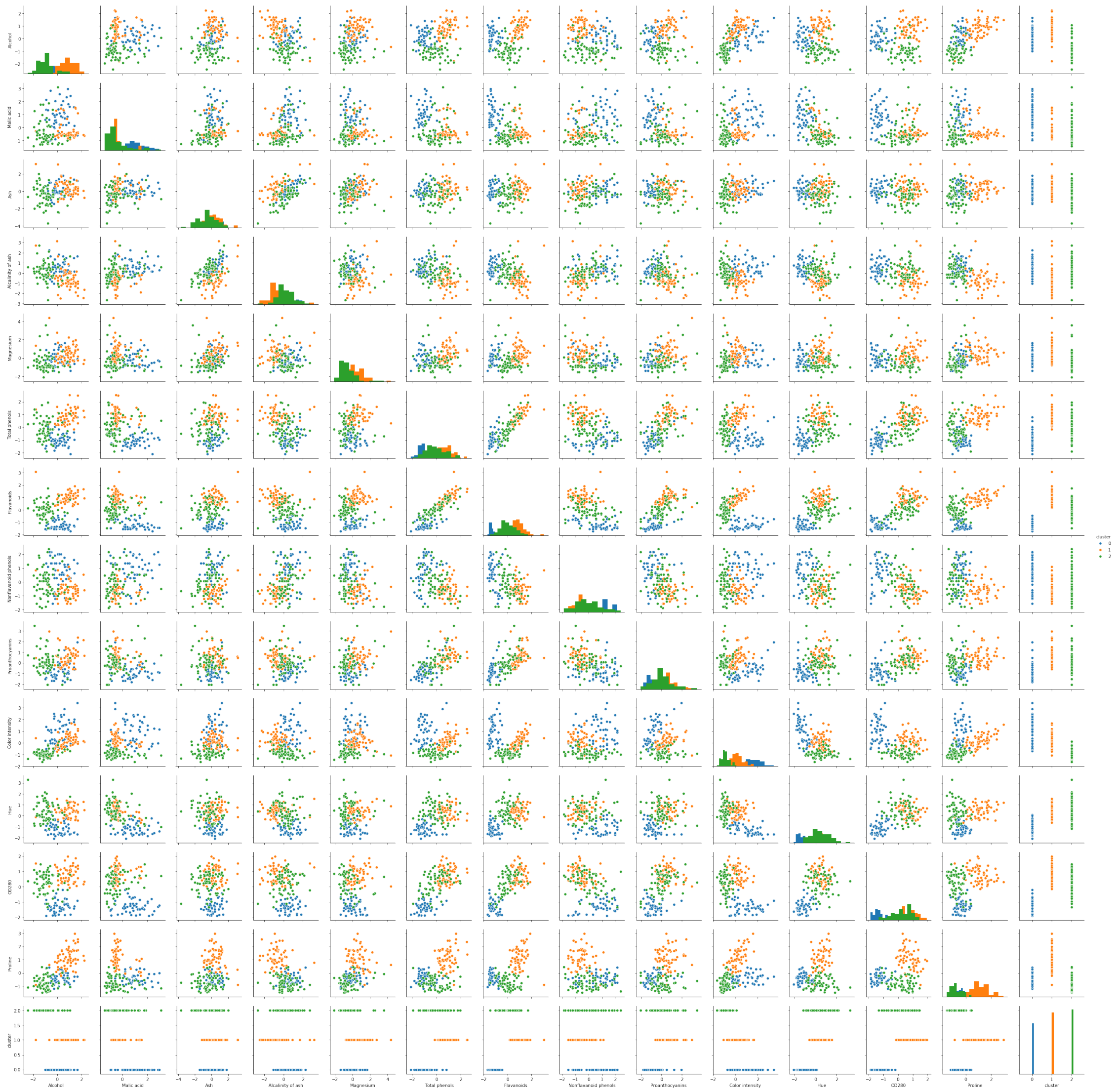
```
normalizedData['cluster'] = res
normalizedData.head(3)
```

[126]:

```
    Alcohol  Malic acid       Ash  Alcalinity of ash  Magnesium  \
0  1.518613   -0.562250  0.232053          -1.169593   1.913905
1  0.246290   -0.499413 -0.827996          -2.490847   0.018145
2  0.196879    0.021231  1.109334          -0.268738   0.088358

   Total phenols  Flavanoids  Nonflavanoid phenols  Proanthocyanins  \
0       0.808997    1.034819             -0.659563         1.224884
1       0.568648    0.733629             -0.820719        -0.544721
2       0.808997    1.215533             -0.498407         2.135968

   Color intensity       Hue     OD280   Proline  cluster
0         0.251717  0.362177  1.847920  1.013009        1
1        -0.293321  0.406051  1.113449  0.965242        1
2         0.269020  0.318304  0.788587  1.395148        1
```

[127]:

```
sns_plot = sns.pairplot(normalizedData, hue = "cluster",diag_kind="hist")
```


Alcohol
Malic acid
Ash
Alcalinity of ash
Magnesium
Total phenols
Flavanoids
Nonflavanoid phenols
Proanthocyanins
Color intensity
Hue
OD280
Proline
cluster
cluster
0
1
2