In [208]:

```
import pandas as pd
import matplotlib.pyplot as plt
from IPython.display import display
import seaborn as sns
```

In [20]:

```
pd_city = pd.read_csv("./city_data.csv")
pd_city.head(5)
```

Out[20]:

	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

In [21]:

```
pd_city.dtypes
```

Out[21]:

```
city             object
driver_count      int64
type             object
dtype: object
```

In [22]:

```
pd_ride = pd.read_csv("./ride_data.csv")
pd_ride.head(5)
```

Out[22]:

	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

In [23]:

```
pd_ride.dtypes
```

Out[23]:

```
city          object
date          object
fare         float64
ride_id        int64
dtype: object
```

In [119]:

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

Out[119]:

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

In [37]:

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

...

In [111]:

```
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
```

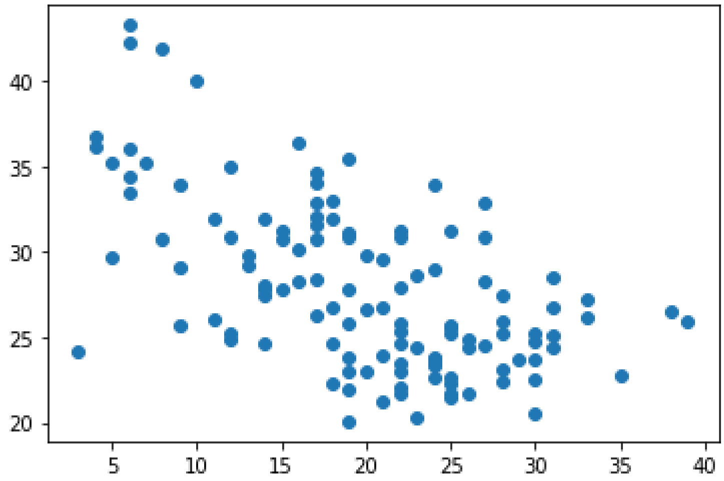
...

In [126]:

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

Out[126]:

```
<matplotlib.collections.PathCollection at 0x203f8839470>
```



In [127]:

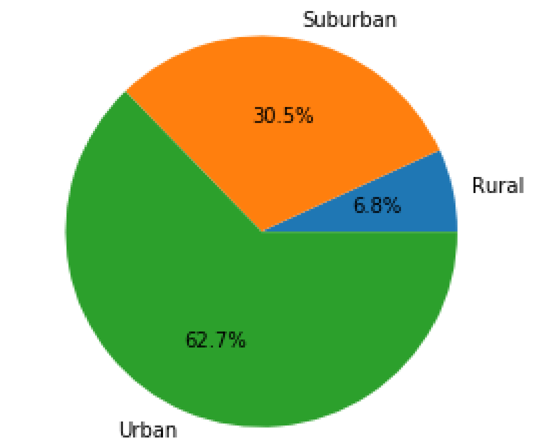
```
pd_join.groupby(by='type').sum()
```

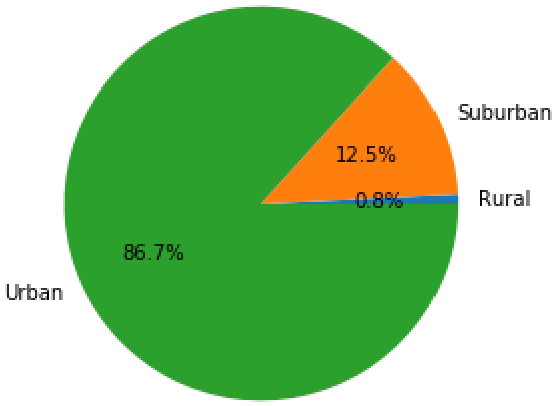
Out[127]:

	driver_count	fare	ride_id
type			
Rural	537	4327.93	580968240341287
Suburban	8570	19356.33	3106884522576766
Urban	59602	39854.38	7919412664056093

In [132]:

```
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()
```





In [170]:

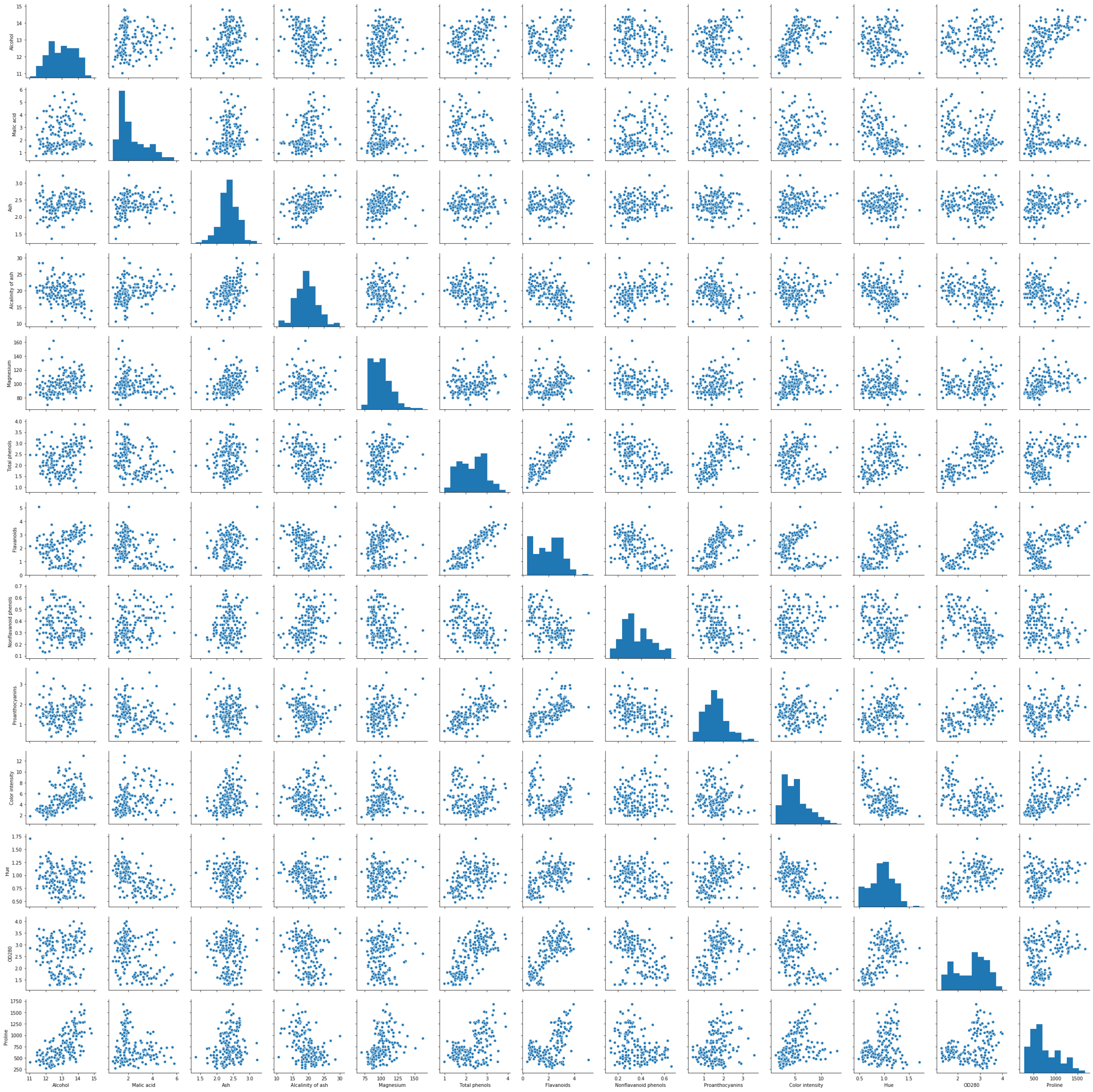
```
wine_pd = pd.read_csv("./wine_data.csv")
#wine_pd.head()
wine_pd['Label'].unique()
labels = wine_pd['Label']
labels
wine_pd = wine_pd.drop(axis=1,columns='Label')
wine_pd.head(5)
```

Out[170]:

	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocya
0	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	
1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	
2	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	
3	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	
4	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	

In [224]:

```
sns_plot = sns.pairplot(wine_pd,diag_kind="hist")
```

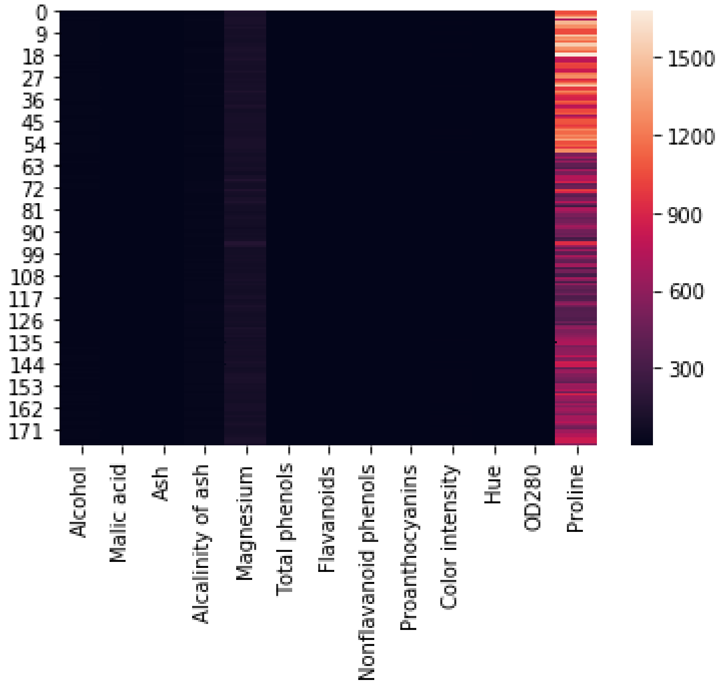


In [220]:

```
#plt.subplots(figsize=(100,100))
sns.heatmap(wine_pd)
```

Out[220]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x203942f9c88>
```



In [195]:

```
from sklearn import preprocessing
from sklearn.cluster import KMeans
```

In [227]:

```
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)
```

Out[227]:

```
array([[ 1.51861254, -0.5622498 ,  0.23205254, ...,  0.36217728,
         1.84791957,  1.01300893],
       [ 0.24628963, -0.49941338, -0.82799632, ...,  0.40605066,
         1.1134493 ,  0.96524152],
       [ 0.19687903,  0.02123125,  1.10933436, ...,  0.31830389,
         0.78858745,  1.39514818],
       ...,
       [ 0.33275817,  1.74474449, -0.38935541, ..., -1.61212515,
        -1.48544548,  0.28057537],
       [ 0.20923168,  0.22769377,  0.01273209, ..., -1.56825176,
        -1.40069891,  0.29649784],
       [ 1.39508604,  1.58316512,  1.36520822, ..., -1.52437837,
        -1.42894777, -0.59516041]])
```

In [203]:

```
kMeansClustering = KMeans(n_clusters = 3)
res = kMeansClustering.fit_predict(normalizedData)
res
```

Out[203]:

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

In [206]:

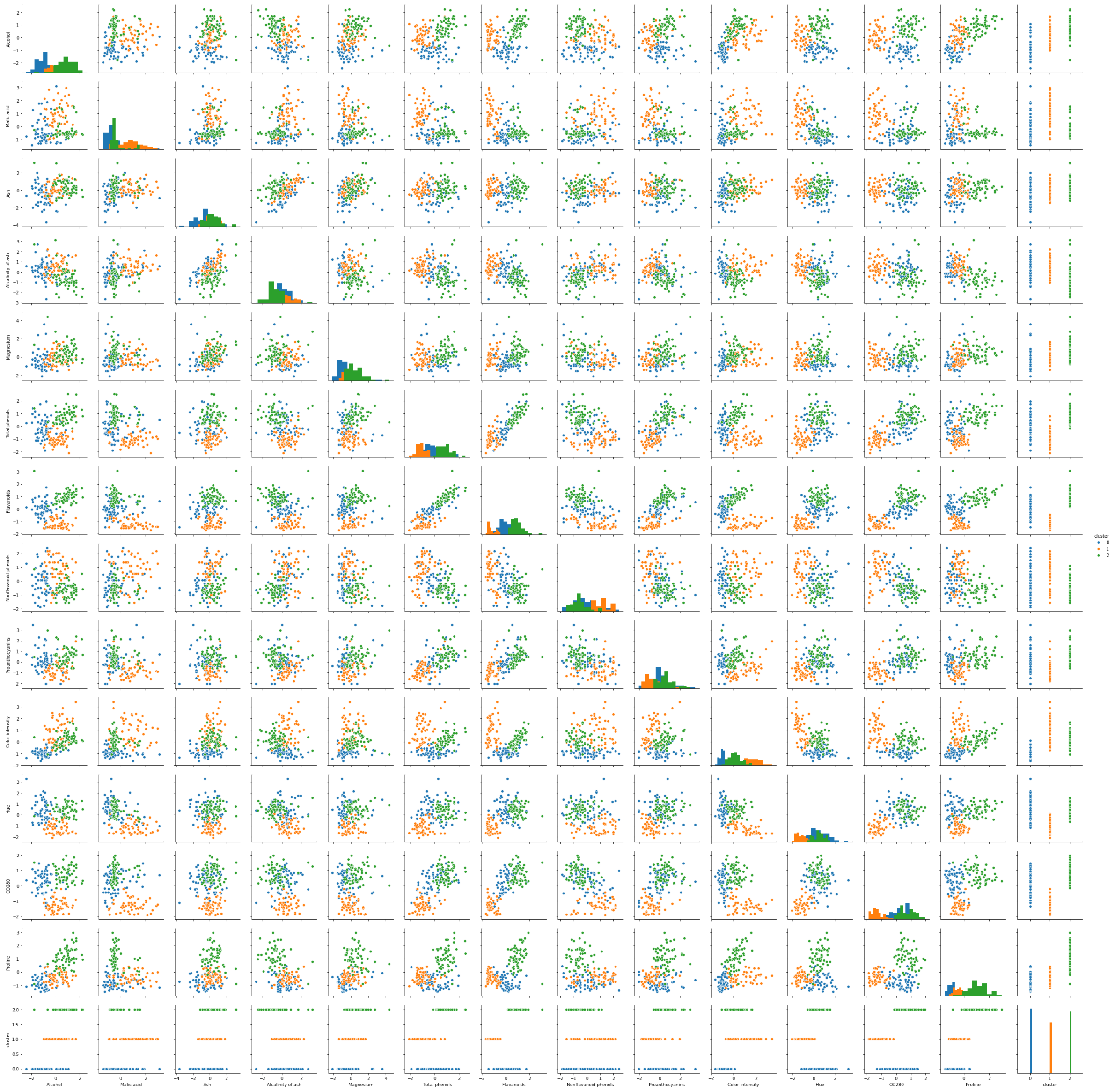
```
normalizedData['cluster'] = res
normalizedData.head(3)
```

Out[206]:

	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols
0	1.518613	-0.562250	0.232053	-1.169593	1.913905	0.808997	1.034819	-0.659563
1	0.246290	-0.499413	-0.827996	-2.490847	0.018145	0.568648	0.733629	-0.820719
2	0.196879	0.021231	1.109334	-0.268738	0.088358	0.808997	1.215533	-0.498407

In [209]:

```
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