Data Preprocessing

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1 Lab Assignment 1

1.1 Data Preprocessing

1.1.1 Submitted to : Prof. Sweetlin Hemlatha

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```
In [3]: import numpy as np
        import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt

        %matplotlib inline
```

```
In [3]: data = pd.read_csv("iris-data.csv")
        data.head()
```

```
Out[3]:    sepal_length_cm  sepal_width_cm  petal_length_cm  petal_width_cm  \
        0              5.1             3.5              1.4             0.2
        1              4.9             3.0              1.4             0.2
        2              4.7             3.2              1.3             0.2
        3              4.6             3.1              1.5             0.2
        4              5.0             3.6              1.4             0.2

                 class
        0  Iris-setosa
        1  Iris-setosa
        2  Iris-setosa
        3  Iris-setosa
        4  Iris-setosa
```

```
In [4]: data.dtypes
```

```
Out[4]: sepal_length_cm    float64
        sepal_width_cm     float64
        petal_length_cm    float64
        petal_width_cm     float64
        class               object
        dtype: object
```

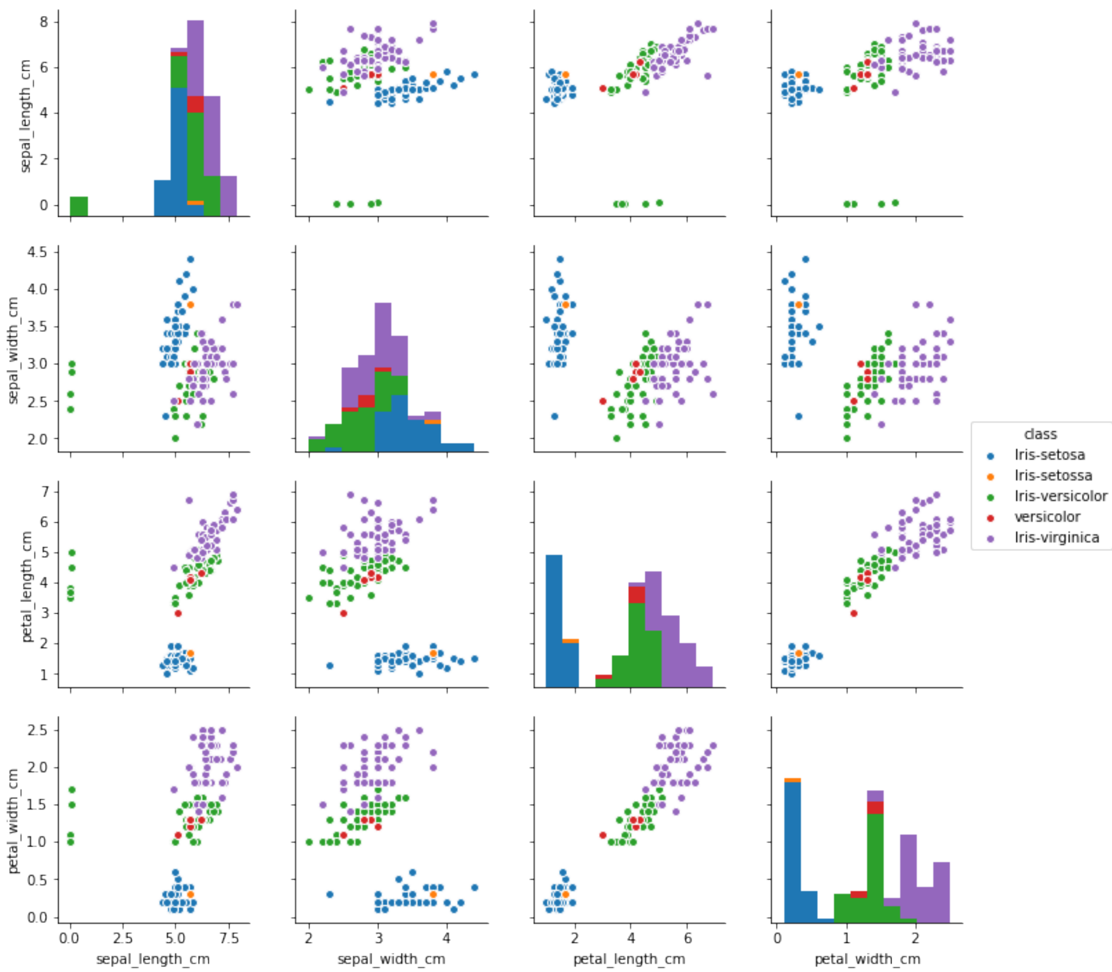
In [5]:
```
data.describe()
```

Out[5]:

	sepal_length_cm	sepal_width_cm	petal_length_cm	petal_width_cm
count	150.000000	150.000000	150.000000	145.000000
mean	5.644627	3.054667	3.758667	1.236552
std	1.312781	0.433123	1.764420	0.755058
min	0.055000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.400000
50%	5.700000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

In [6]:
```
sns.pairplot(data=data.dropna(),hue='class')
```

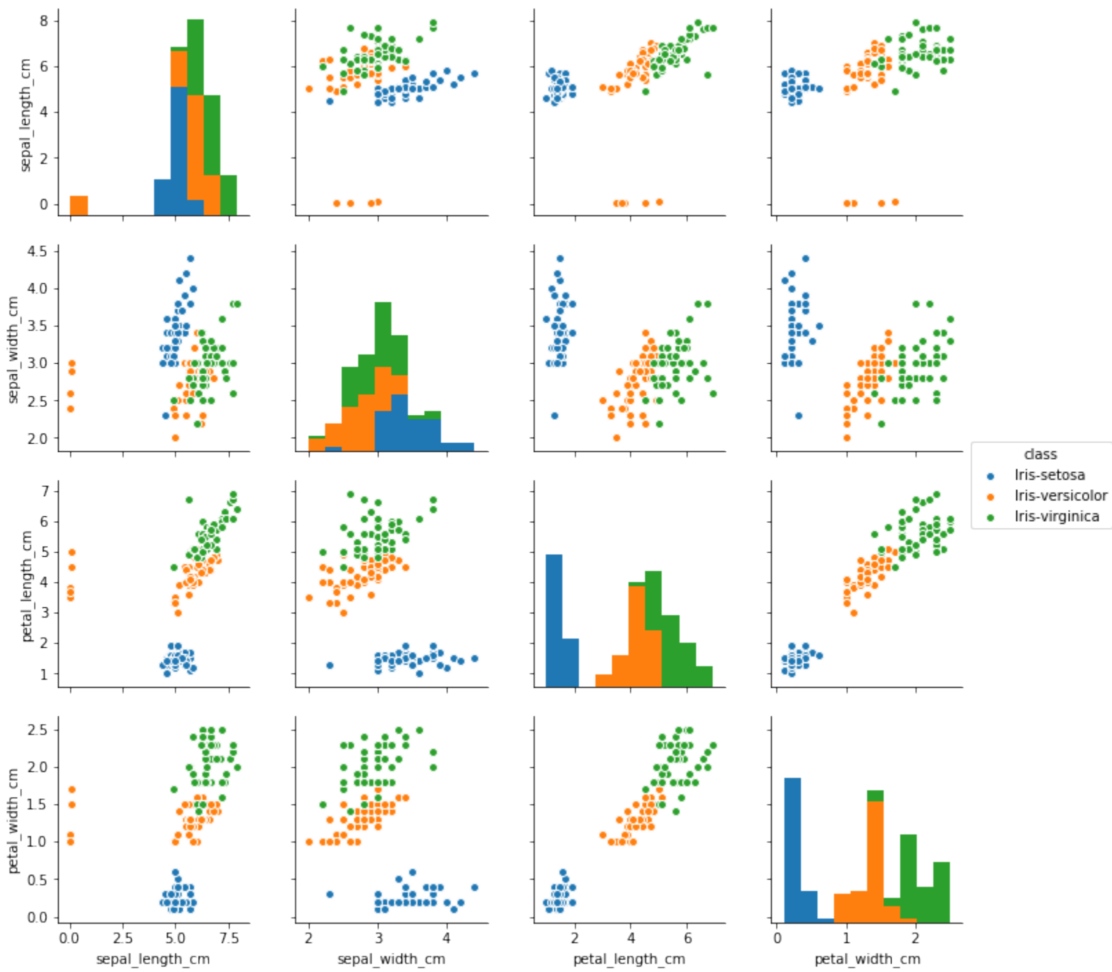
Out[6]:
```
<seaborn.axisgrid.PairGrid at 0x7fddb39ba400>
```



In [7]:
```
# Inference from previous cell missmatching class label (versicolor and setosa)
data.loc[data["class"] == "versicolor","class"] = "Iris-versicolor"
data.loc[data["class"] == "Iris-setossa","class"] = "Iris-setosa"
```

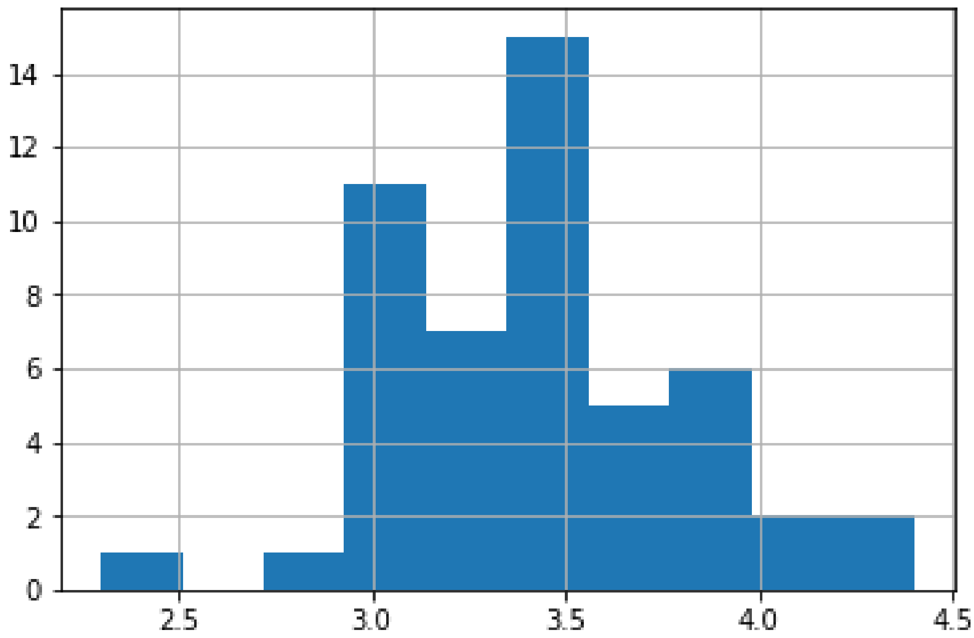
```
In [8]: sns.pairplot(data=data.dropna(),hue='class') #Plot after fixing class labels
```

```
Out[8]: <seaborn.axisgrid.PairGrid at 0x7fddb0fed080>
```




```
In [9]: data.loc[data["class"]=="Iris-setosa","sepal_width_cm"].hist()
```

```
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7fddaabda7b8>
```



In [10]:
```
data.loc[data["petal_width_cm"].isnull()]
```

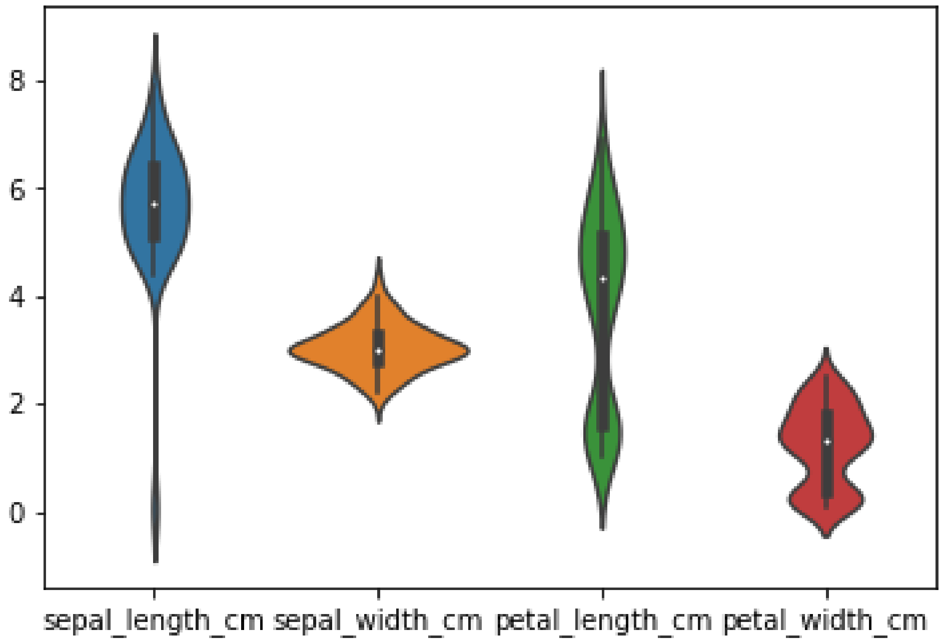
Out[10]:
```
    sepal_length_cm  sepal_width_cm  petal_length_cm  petal_width_cm  \
7               5.0             3.4              1.5             NaN
8               4.4             2.9              1.4             NaN
9               4.9             3.1              1.5             NaN
10              5.4             3.7              1.5             NaN
11              4.8             3.4              1.6             NaN

          class
7   Iris-setosa
8   Iris-setosa
9   Iris-setosa
10  Iris-setosa
11  Iris-setosa
```

In [11]:
```
#Fixing missing values of petal_width_cm from data.describe() mean
data.loc[data["petal_width_cm"].isnull(),"petal_width_cm"] = 1.236552
data.loc[data["petal_width_cm"].isnull()]
```

Out[11]:
```
Empty DataFrame
Columns: [sepal_length_cm, sepal_width_cm, petal_length_cm, petal_width_cm, class]
Index: []
```

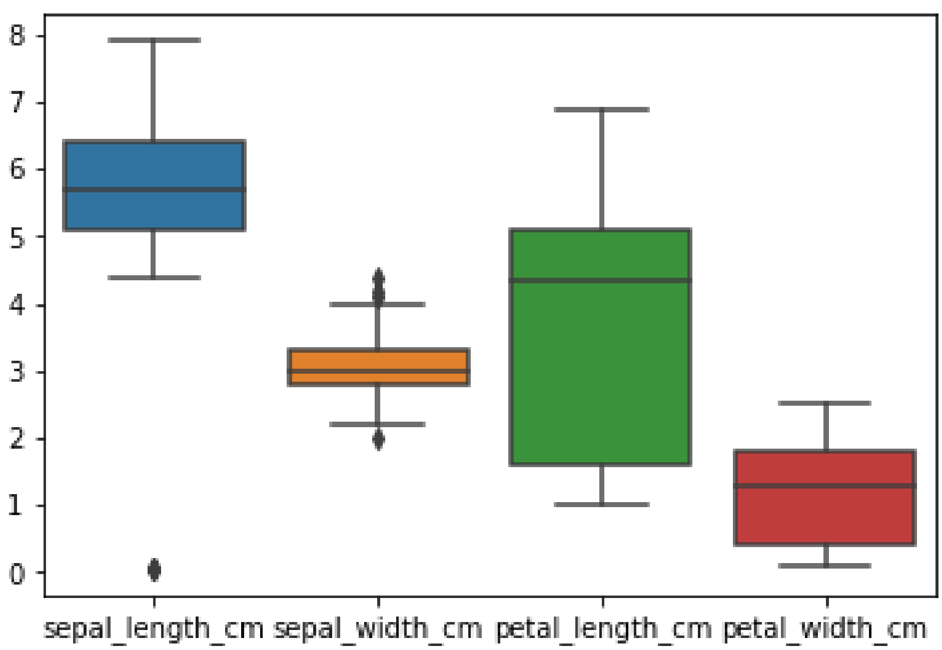
In [12]:
```
sns.violinplot(data=data) # Violin Plot// They represent probability density also whe
```

Out[12]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fddaa45af60>
```




```
In [13]: sns.boxplot(data=data) #Box plot representing mean and quantiles
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7fddaa3e5ac8>
```



Applying the above functions to my own dataset

In [4]:
```
wine_data = pd.read_csv('../Dataset/winequality-white.csv', sep=';')
red_wine = pd.read_csv('../Dataset/winequality-red.csv', sep=';')
sns.set(style='whitegrid', context='notebook', font_scale=1)
```

In [5]:
```
    wine_data.append(red_wine)
wine_data["quality"] = wine_data["quality"].astype(str)
wine_data.head(10)
```

Out[5]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.0              0.27         0.36            20.7      0.045
1            6.3              0.30         0.34             1.6      0.049
2            8.1              0.28         0.40             6.9      0.050
3            7.2              0.23         0.32             8.5      0.058
4            7.2              0.23         0.32             8.5      0.058
5            8.1              0.28         0.40             6.9      0.050
6            6.2              0.32         0.16             7.0      0.045
7            7.0              0.27         0.36            20.7      0.045
8            6.3              0.30         0.34             1.6      0.049
9            8.1              0.22         0.43             1.5      0.044

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 45.0                 170.0   1.0010  3.00       0.45
1                 14.0                 132.0   0.9940  3.30       0.49
2                 30.0                  97.0   0.9951  3.26       0.44
3                 47.0                 186.0   0.9956  3.19       0.40
4                 47.0                 186.0   0.9956  3.19       0.40
5                 30.0                  97.0   0.9951  3.26       0.44
6                 30.0                 136.0   0.9949  3.18       0.47
7                 45.0                 170.0   1.0010  3.00       0.45
8                 14.0                 132.0   0.9940  3.30       0.49
9                 28.0                 129.0   0.9938  3.22       0.45

   alcohol quality
0      8.8       6
1      9.5       6
2     10.1       6
3      9.9       6
4      9.9       6
5     10.1       6
6      9.6       6
7      8.8       6
8      9.5       6
9     11.0       6
```

In [6]:
```
wine_data.describe()
```

Out[6]:
```
       fixed acidity  volatile acidity  citric acid  residual sugar  \
count    4898.000000       4898.000000  4898.000000     4898.000000
```

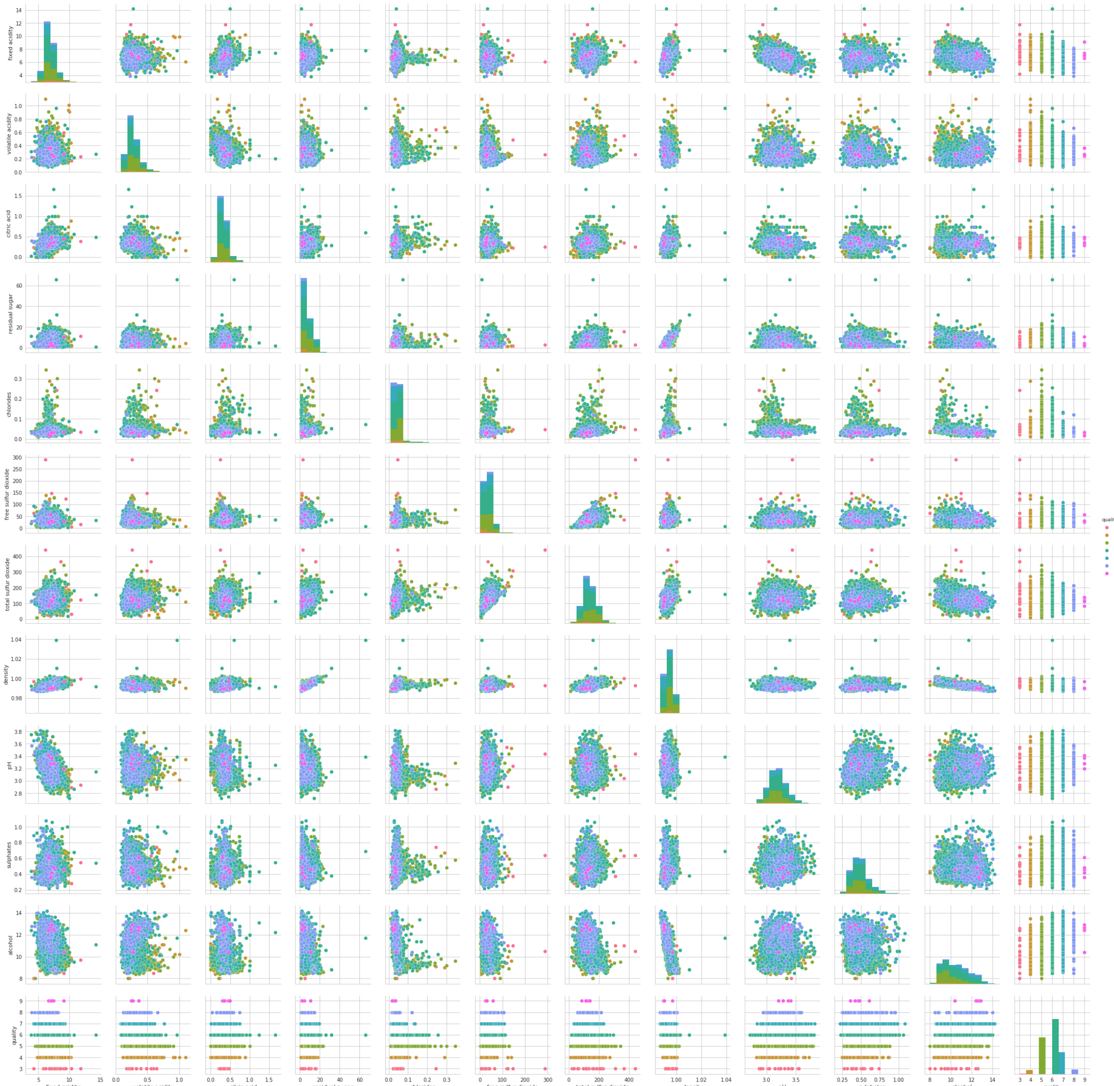
```
mean        6.854788         0.278241     0.334192        6.391415
std         0.843868         0.100795     0.121020        5.072058
min         3.800000         0.080000     0.000000        0.600000
25%         6.300000         0.210000     0.270000        1.700000
50%         6.800000         0.260000     0.320000        5.200000
75%         7.300000         0.320000     0.390000        9.900000
max        14.200000         1.100000     1.660000       65.800000

         chlorides  free sulfur dioxide  total sulfur dioxide      density  \
count  4898.000000          4898.000000           4898.000000  4898.000000
mean      0.045772            35.308085            138.360657     0.994027
std       0.021848            17.007137             42.498065     0.002991
min       0.009000             2.000000              9.000000     0.987110
25%       0.036000            23.000000            108.000000     0.991723
50%       0.043000            34.000000            134.000000     0.993740
75%       0.050000            46.000000            167.000000     0.996100
max       0.346000           289.000000            440.000000     1.038980

                pH    sulphates      alcohol
count  4898.000000  4898.000000  4898.000000
mean      3.188267     0.489847    10.514267
std       0.151001     0.114126     1.230621
min       2.720000     0.220000     8.000000
25%       3.090000     0.410000     9.500000
50%       3.180000     0.470000    10.400000
75%       3.280000     0.550000    11.400000
max       3.820000     1.080000    14.200000
```

In [7]:
```
wine_data.dtypes
```

Out[7]:
```
fixed acidity           float64
volatile acidity        float64
citric acid             float64
residual sugar          float64
chlorides               float64
free sulfur dioxide     float64
total sulfur dioxide    float64
density                 float64
pH                      float64
sulphates               float64
alcohol                 float64
quality                  object
dtype: object
```

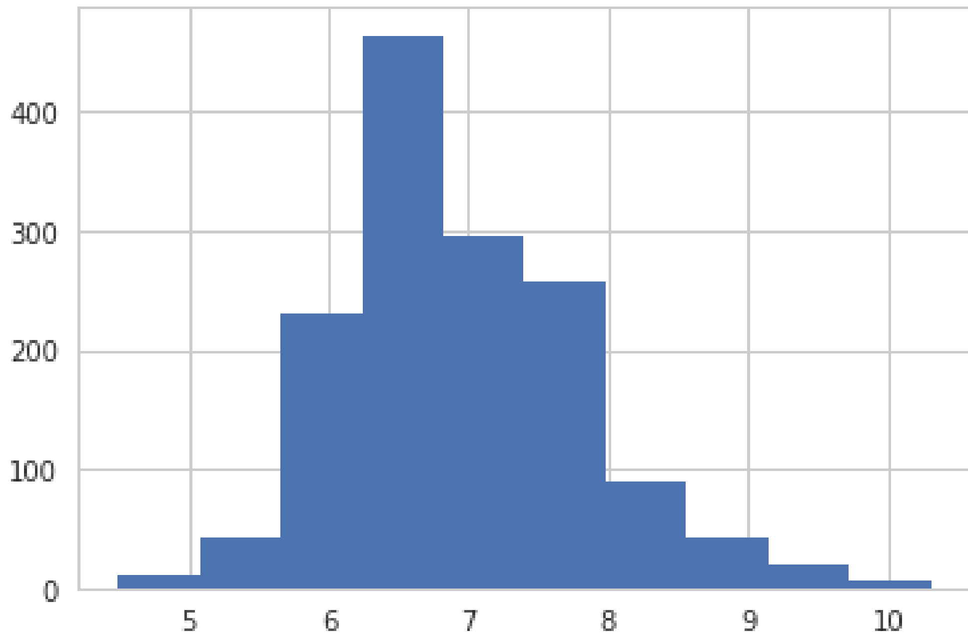
In [8]:
```
sns.pairplot(wine_data.dropna(), size=2.5, hue="quality")
```

Out[8]:
```
<seaborn.axisgrid.PairGrid at 0x7fe2f539cdd8>
```



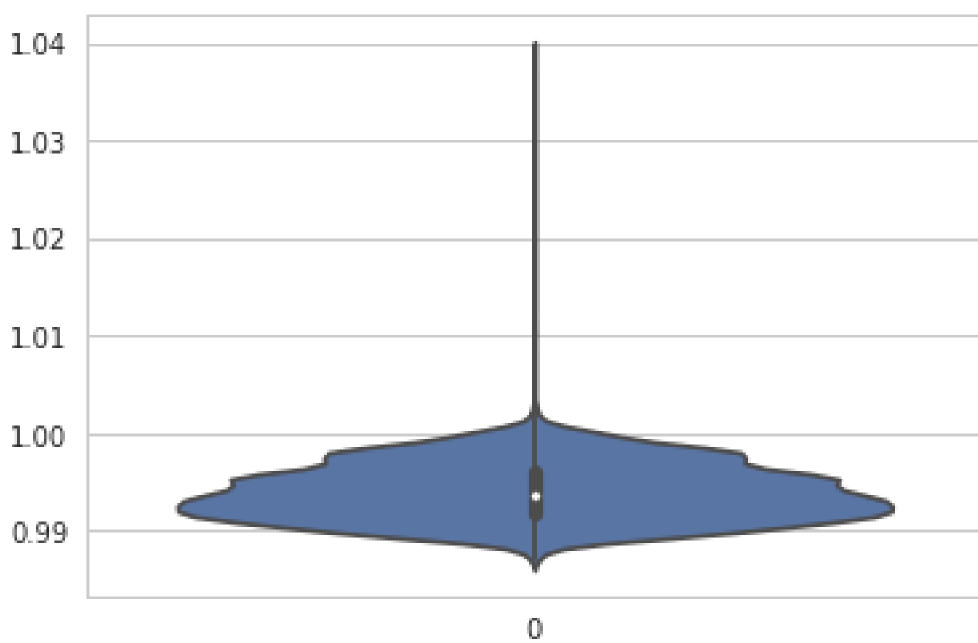
```
In [9]: wine_data.loc[wine_data["quality"]=='5',"fixed acidity"].hist()
```

```
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe2eb803b38>
```



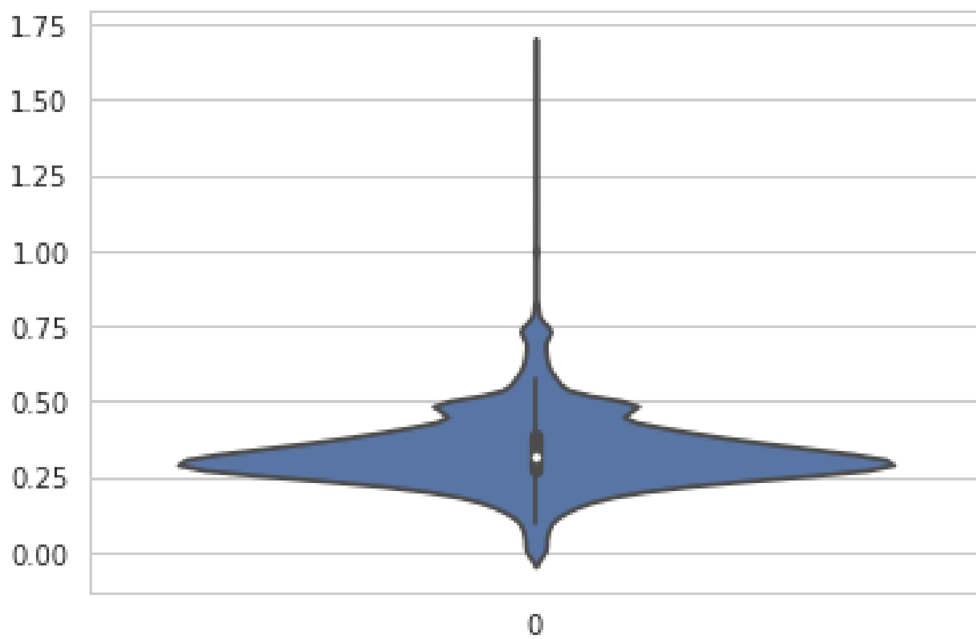
In [57]: `sns.violinplot(data=wine_data["density"], size=10)`

Out[57]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6474553b70>



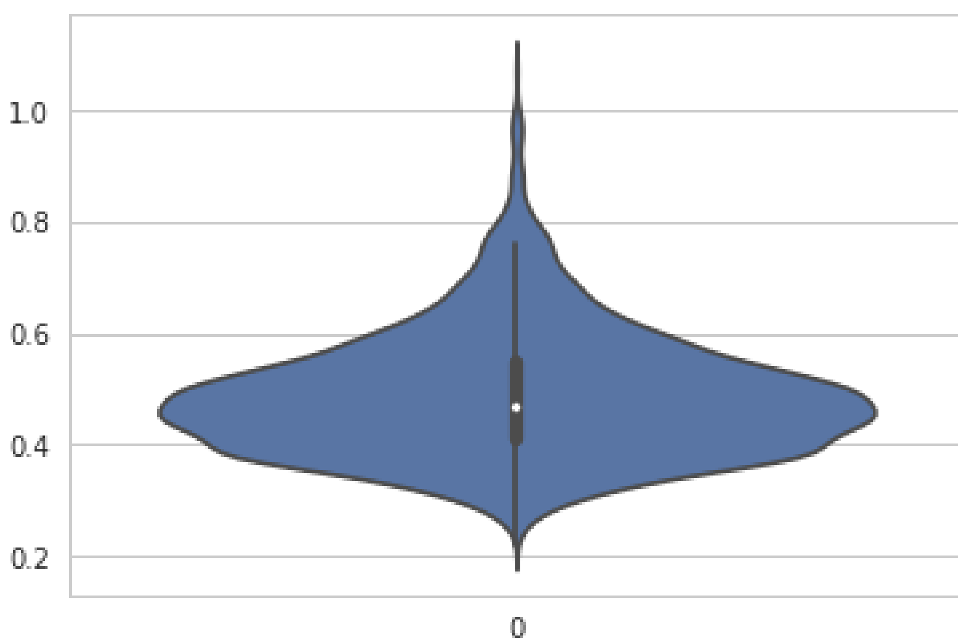
```
In [44]: sns.violinplot(data=wine_data["citric acid"], size=10)
```

```
Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x7f647c0660f0>
```

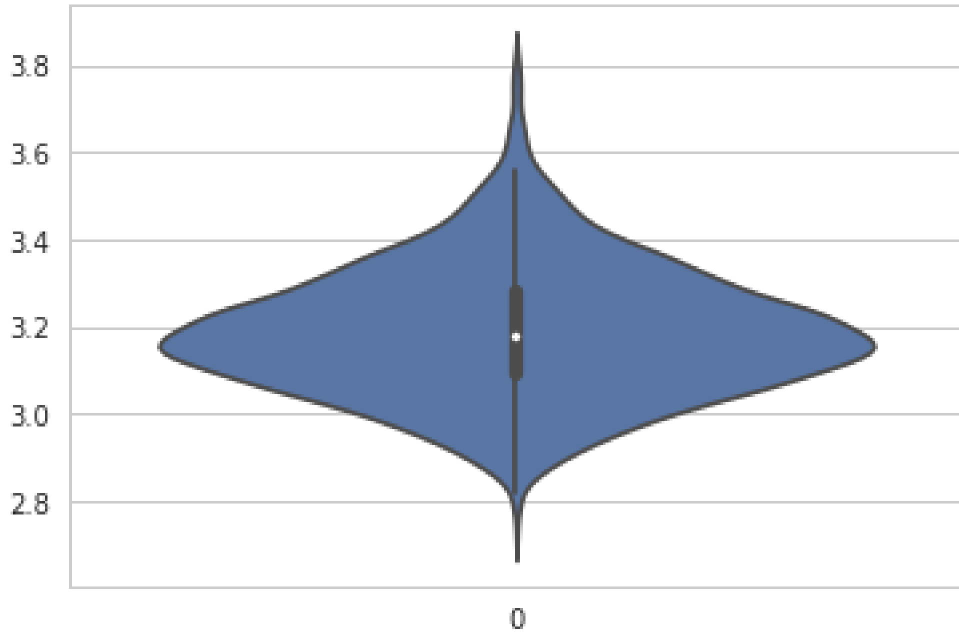



```
In [45]: sns.violinplot(data=wine_data["sulphates"], size=10)
```

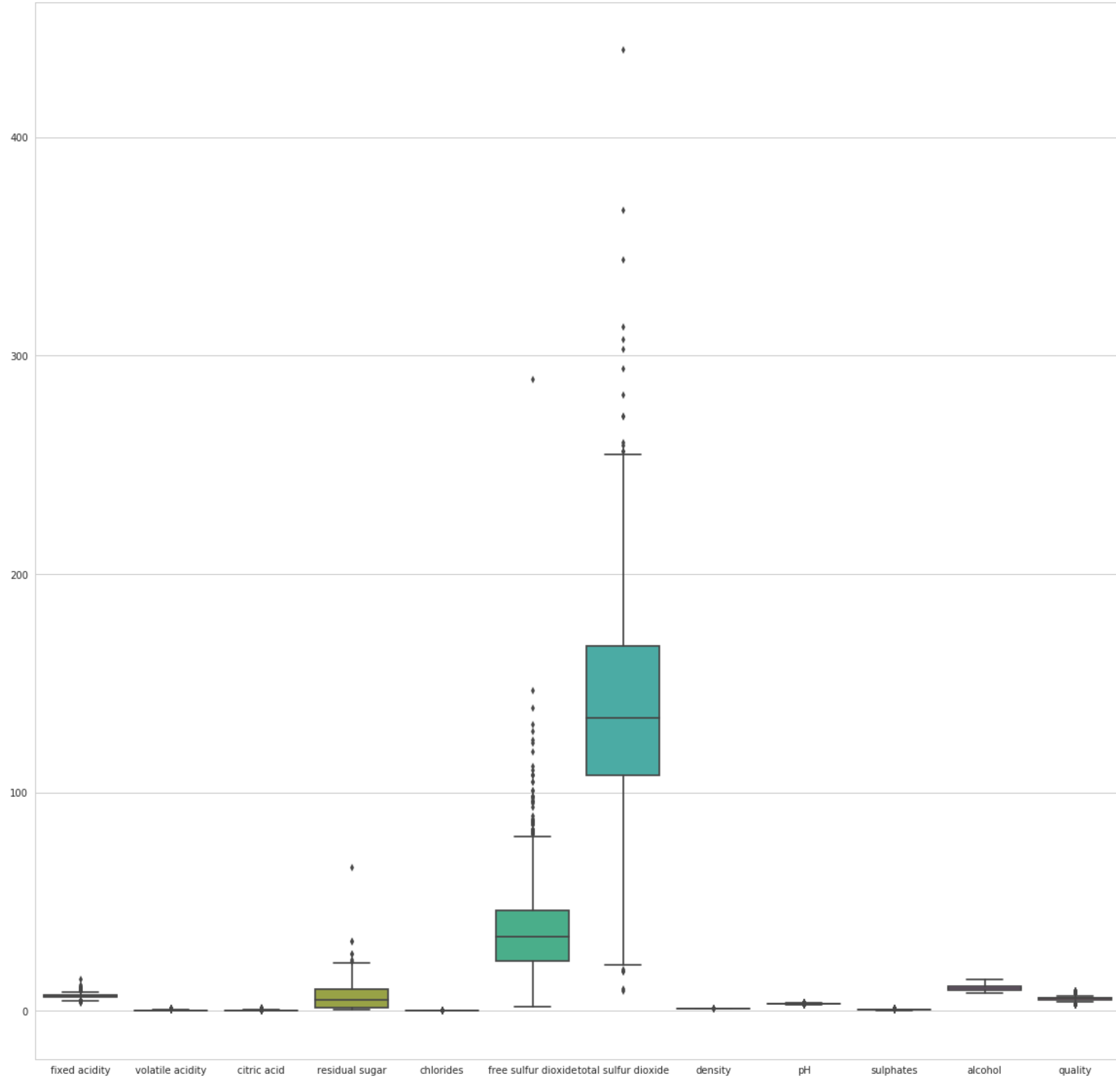
```
Out[45]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6476e25e10>
```



```
In [46]: sns.violinplot(data=wine_data["pH"], size=10)

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6476d8f630>
```




```
In [55]: fig, ax = plt.subplots(figsize=(20, 20))
         # seaborn.violinplot(ax=ax, data=df, **violin_options)
         sns.boxplot(ax=ax, data=wine_data)

Out[55]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6476575ef0>
```



400
300
200
100
0
fixed acidity
volatile acidity
citric acid
residual sugar
chlorides
free sulfur dioxide
total sulfur dioxide
density
pH
sulphates
alcohol
quality