Machine Learning Lab 1

Data Preprocessing

Data preprocessing is a data mining technique that involves transforming raw data into an understandable format. Real world data is often incomplete, inconsistent, and/or lacking in certain behaviors or trends, and is likely to contain many errors. Data preprocessing is a proven method of resolving such issues. Data preprocessing prepares raw data for further processing. Data preprocessing steps include but are not limited to data cleaning, data integration, data transformation, data reduction and data discretization.

The dataset

The dataset used to perform this experiment is the wine quality dataset, it is a combination of data on two types of wine variants, namely red wine and white wine, of the portuguese "Vinho Verde" wine. The dataset contains information on the parameters for fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, free sulfur dioxide, total sulfur dioxide, density, pH, sulphates, alcohol.

Experiment

In this experiment, I have performed operations to clean the data, done statistical analysis of the data and then used various visualization tools to visualize the data in different ways which in turn reveals different information about the data which are otherwise not easily discernible.

Using the pandas library in I loaded the red wine and white wine datasets into the memory from their respective csv files and then merged the two datasets into one single pandas dataframe.

Using the pandas.Dataframe.describe() function in pandas I calculated the various statistical measures of each of the columns of the dataset.

- * The dataset has a total of 4898 rows.
- * The means for each of the columns are calculated as:

Fixed acidity -> 6.85

Volatile acidity -> 0.27

Citric acid -> 0.33

Residual sugar -> 6.39

Chlorides -> 0.045

Free sulphur dioxides -> 35.30

Total sulphur dioxides -> 138.36

Density -> 0.99

pH -> 3.18

Sulphates -> 0.48

Alcohol -> 10.51

Using the pandas. Dataframe. dtypes method gives the datatypes of all the columns in the dataframe.

The pairplot function in seaborn library in python I was able to plot each column vs every other column in the dataset in the form of a scatter plot. And for also look at the values of each column in the form of a histogram.

Using the violin plot function in seaborn I am able to plot a violin plot for a column is the dataset. Violin plots are similar to box plots except that they also show the probability density of the data at different values. Thy also include a marker for median of the data and a box indicating the inter quartile range.

Using the violin plots I was able to infer that the median for the density lies between 1.00 and 0.99, and that for citric acid lies between 0.25 and 0.5, and for sulphates it lies between 0.6 and 0.4.

Seaborn library also allows to plot box plot for a dataset with its boxplot function. A boxplot depicts groups through their quartiles. It has whiskers indicating variability outside the upper and lower quartiles. Outliers are plotted as individual points as can be seen in the diagram in the jupyter notebook.

The code and plots can be found in the accompanying jupyter notebook.

Data Preprocessing

October 25, 2018

1 Lab Assignment 1

1.1 Data Preprocessing

class

dtype: object

```
1.1.1 Submitted to: Prof. Sweetlin Hemlatha
```

1.1.2 Submitted by: Prateek Singh (15BCE1091)

```
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 \
                                       3.5
                                                         1.4
                                                                         0.2
        0
                       5.1
        1
                       4.9
                                       3.0
                                                                         0.2
                                                         1.4
        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
         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
```

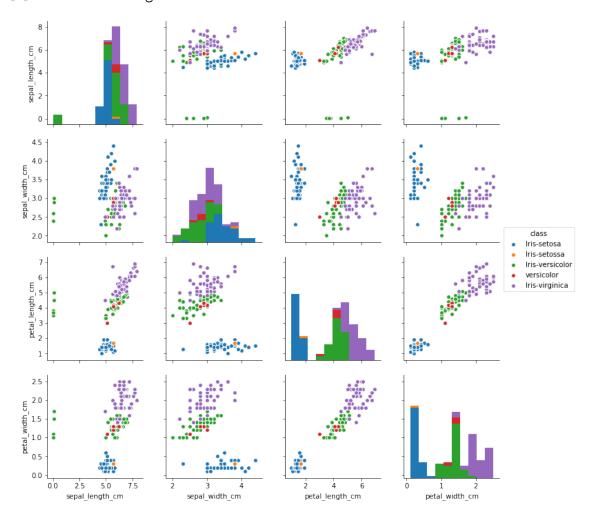
object

In [5]: data.describe()

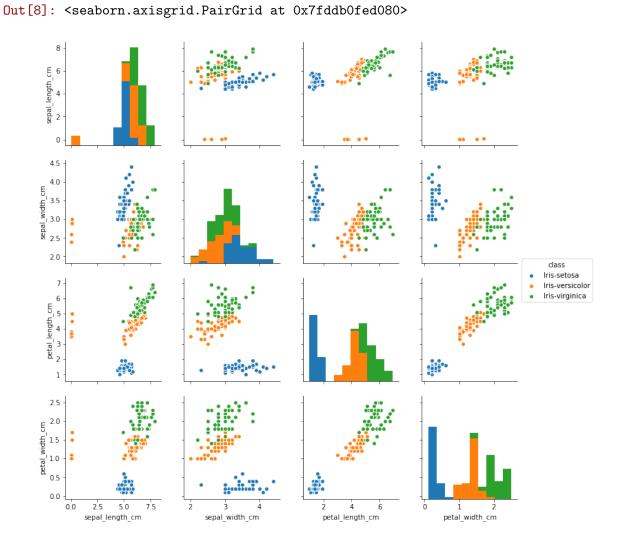
Out[5]:		sepal_length_cm	sepal_width_cm	petal_length_cm	petal_width_cm
	count	150.000000	150.000000	150.000000	145.000000
	mean	5.644627	3.054667	3.758667	1.236552
	std	1.312781	0.433123	1.764420	0.755058
	min	0.055000	2.000000	1.000000	0.100000
	25%	5.100000	2.800000	1.600000	0.400000
	50%	5.700000	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>

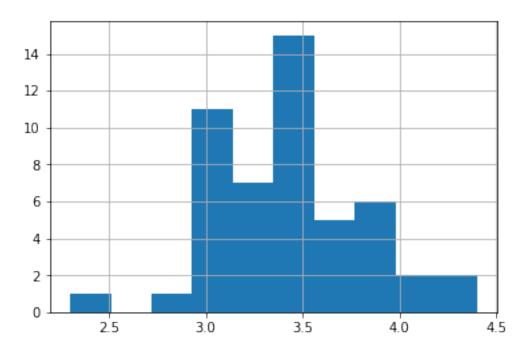


In [8]: sns.pairplot(data=data.dropna(),hue='class') #Plot after fixing class labels



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()]

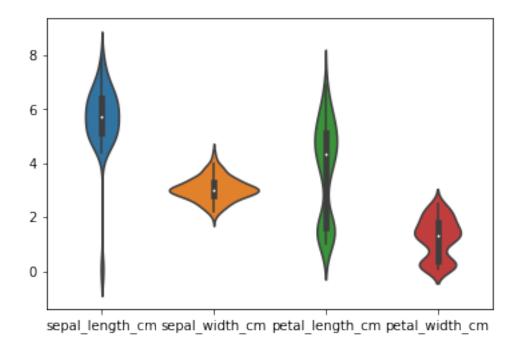
Out[10]:	sepal_length_cm	sepal_width_cm	petal_length_cm	<pre>petal_width_cm \</pre>	
7	5.0	3.4	1.5	NaN	
8	4.4	2.9	1.4	NaN	
9	4.9	3.1	1.5	NaN	
10	5.4	3.7	1.5	NaN	
11	4.8	3.4	1.6	NaN	

class

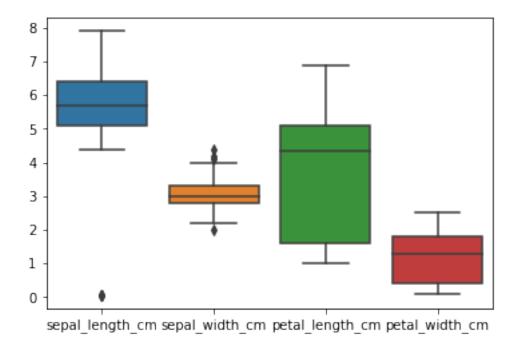
- 7 Iris-setosa
- 8 Iris-setosa
- 9 Iris-setosa
- 10 Iris-setosa
- 11 Iris-setosa

In [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
                                                                                 0.049
        8
                      6.3
                                        0.30
                                                      0.34
                                                                        1.6
        9
                      8.1
                                        0.22
                                                      0.43
                                                                        1.5
                                                                                 0.044
           free sulfur dioxide total sulfur dioxide
                                                         density
                                                                    рΗ
                                                                         sulphates \
        0
                           45.0
                                                                              0.45
                                                 170.0
                                                          1.0010
                                                                  3.00
                           14.0
        1
                                                          0.9940 3.30
                                                                              0.49
                                                 132.0
        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
                                                          0.9956 3.19
                                                                              0.40
                                                 186.0
        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
                           14.0
        8
                                                 132.0
                                                          0.9940 3.30
                                                                              0.49
        9
                                                 129.0
                                                                              0.45
                           28.0
                                                          0.9938 3.22
           alcohol quality
        0
               8.8
                          6
               9.5
        1
                          6
        2
              10.1
                          6
        3
               9.9
                          6
               9.9
        4
                          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
```

4898.000000 4898.000000

4898.000000

4898.000000

count

	mean	6.854788	3 0.	278241	0.334192	6.3	91415	
	std	0.843868	3 0.	100795	0.121020	5.0	72058	
	min	3.800000	0.	080000	0.000000	0.6	00000	
	25%	6.30000	0.	210000	0.270000	1.7	00000	
	50%	6.800000	0.	260000	0.320000	5.2	200000	
	75%	7.300000	0.	320000	0.390000	9.9	00000	
	max	14.200000	1.	100000	1.660000	65.8	800000	
		chlorides	free sulfur		total sulf		density	\
	count	4898.000000		.000000		898.000000	4898.000000	
	mean	0.045772		.308085		138.360657	0.994027	
	std	0.021848		.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	
			7 1 .	-	1 7			
		рН	sulphates		ohol			
	count	4898.000000	4898.000000	4898.00				
	mean	3.188267	0.489847	10.51				
	std	0.151001	0.114126	1.23				
	min	2.720000	0.220000	8.00				
	25%	3.090000	0.410000	9.50				
	50%	3.180000	0.470000	10.40	0000			
	75%	3.280000	0.550000	11.40	0000			
	max	3.820000	1.080000	14.20	0000			
In [7]:	wine_da	ata.dtypes						
Out[7]:	: fixed acidity volatile acidity citric acid residual sugar		float64					
			float64					
			float64					
			float64					
	chlori	-	float64					
		ulfur dioxide	float64					
		arrar aroniae	1100001					

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

float64

float64 float64

float64

float64

object

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

total sulfur dioxide

density

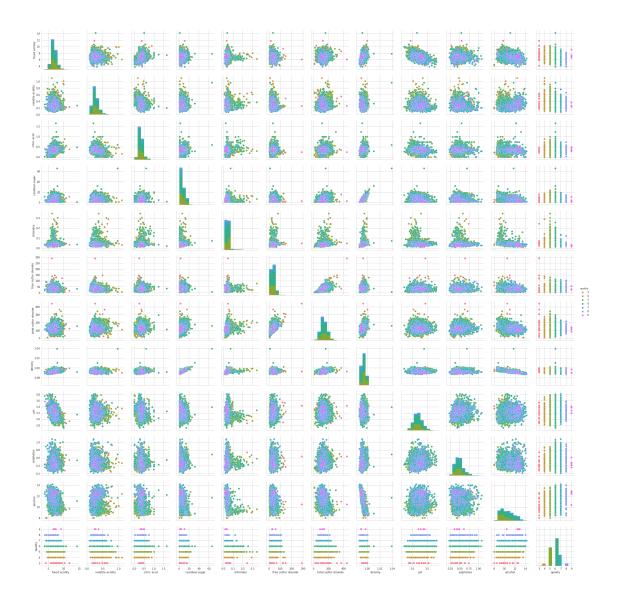
alcohol

quality

sulphates

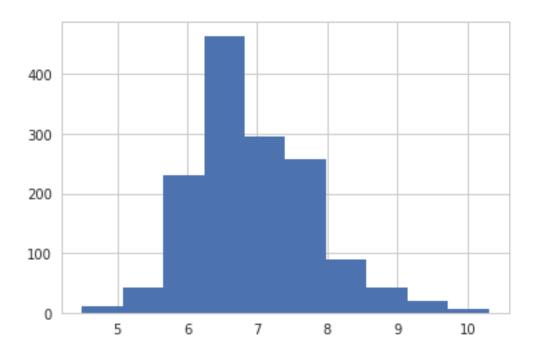
dtype: object

рΗ



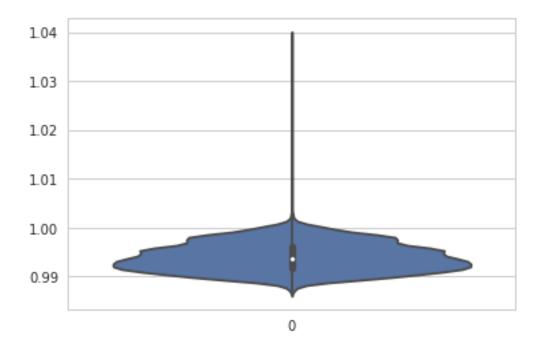
In [9]: wine_data.loc[wine_data["quality"] == '5', "fixed acidity"].hist()

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



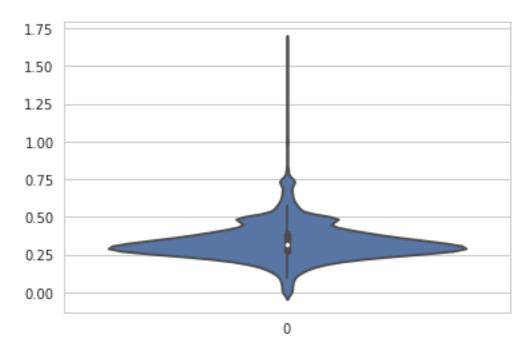
In [57]: sns.violinplot(data=wine_data["density"], size=10)

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



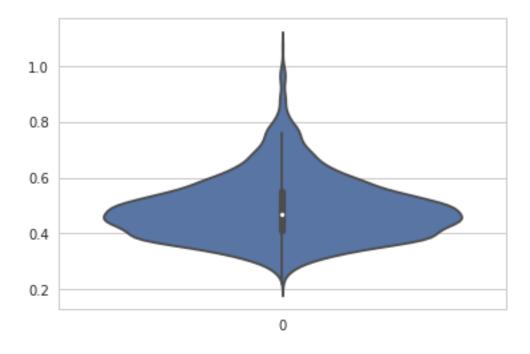
In [44]: sns.violinplot(data=wine_data["citric acid"], size=10)

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



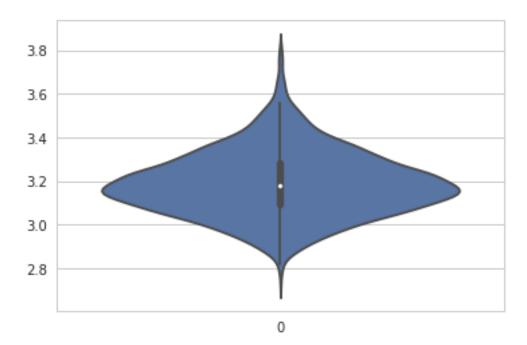
In [45]: sns.violinplot(data=wine_data["sulphates"], size=10)

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>

