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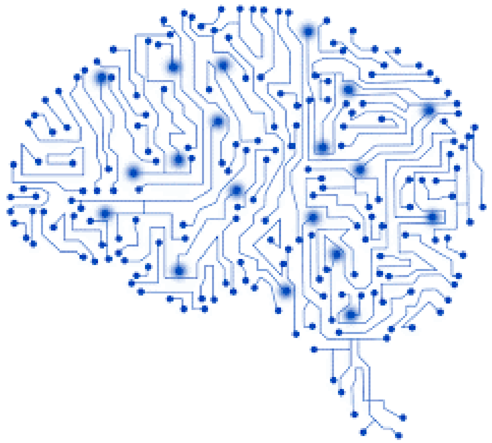

Dados e Aprendizagem Automática

Data Exploration and Preparation

DAA @ MEI-1º/MiEI-4º – 1º Semestre

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Part III

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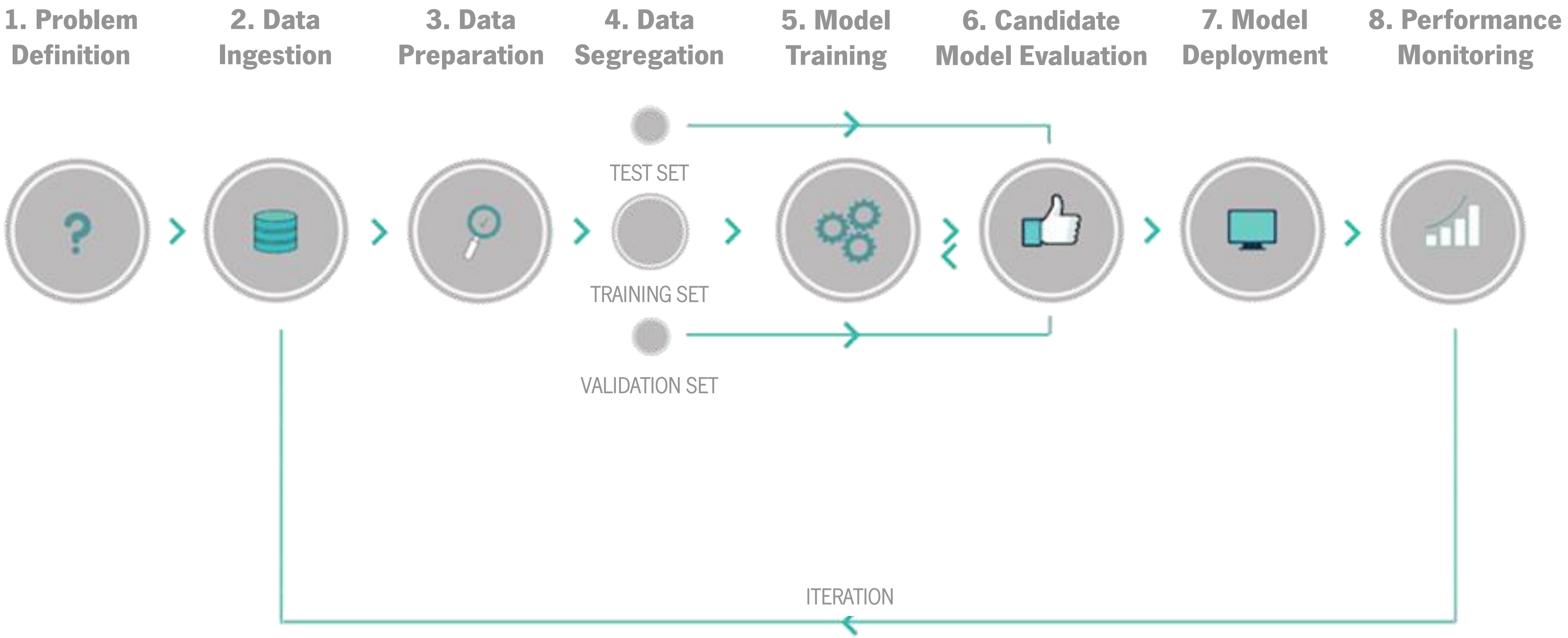
Understanding The Problem

Understanding The Problem

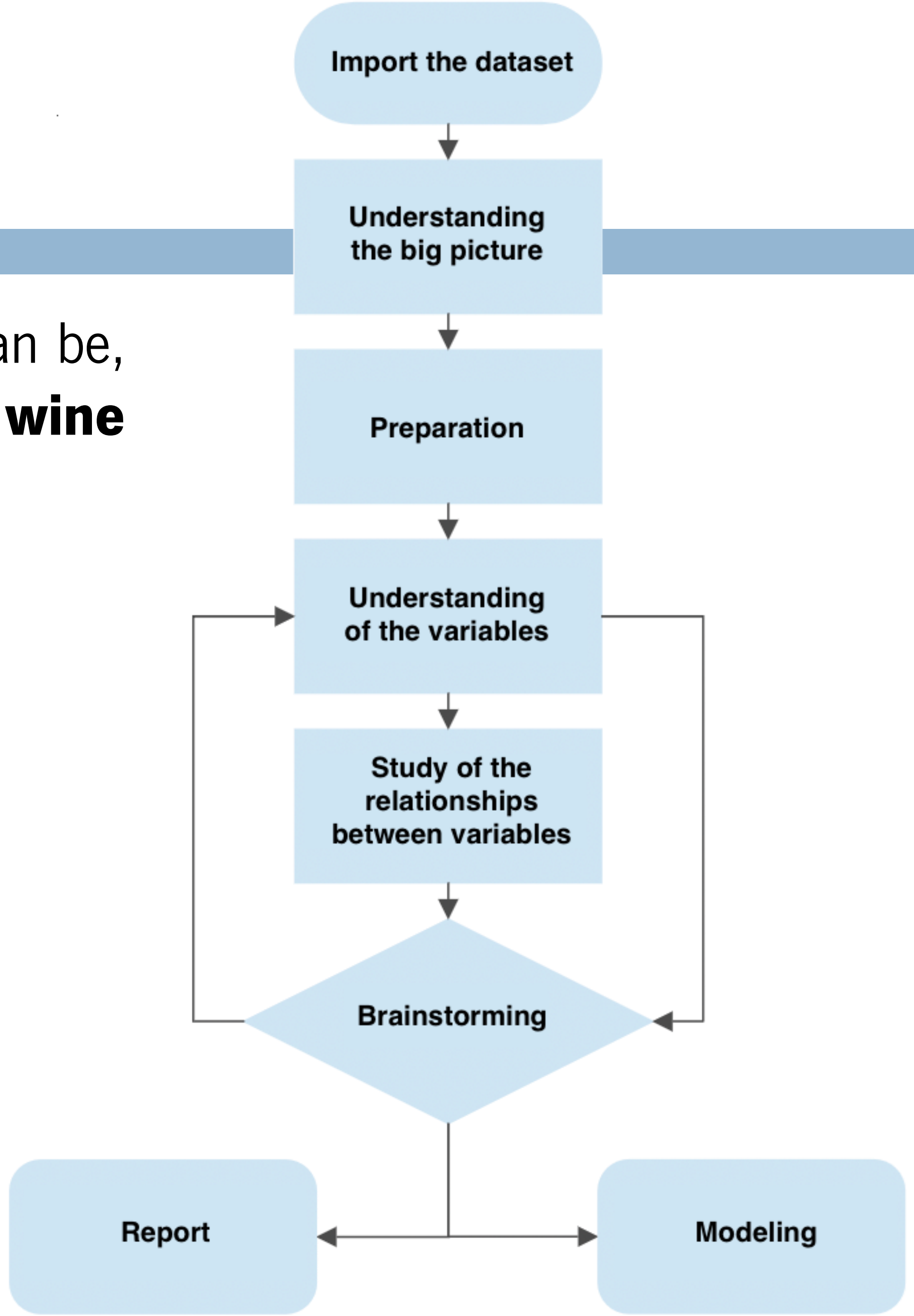


We need to look at our data and understand it.

Understanding the data is a huge step in the process and, as such, will take time. Nevertheless, it will give us a flavour of our dataset, each variable, its meaning and its relevance to this problem.

Understanding The Problem

Let's understand the type of features, how important it can be, if it is described in another feature, etc. Let's use the **wine dataset** available here: https://tinyurl.com/4cshpfac



https://medium.com/@theDrewDag

Imports

Let's import the necessary libraries:

```
import sklearn as skl
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
```

Load the dataset and inspect some meta-data:

```
df = pd.read_csv('wine.csv')
```

Data Exploration

Data Exploration

What about actual data? What can we **see**/**learn**/**understand** from this data?

```
print(df.columns)
```

```
Index(['Alcohol', 'Malic acid', 'Ash', 'Alcalinity of ash', 'Magnesium',
       'Total phenols', 'Flavanoids', 'Nonflavanoid phenols',
       'Proanthocyanins', 'Color intensity', 'Hue',
       'OD280/OD315 of diluted wines', 'Proline', 'Class'],
      dtype='object')
```

```
df.head()
```

	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocyanins	Color intensity	Hue	OD280/OD315 of diluted wines	Proline	Class
0	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	2.29	5.64	1.04	3.92	1065	one
1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	1.28	4.38	1.05	3.40	1050	one
2	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	2.81	5.68	1.03	3.17	1185	one
3	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	2.18	7.80	0.86	3.45	1480	one
4	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	1.82	4.32	1.04	2.93	735	one

Data Exploration


```
df.tail()
```

	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocyanins	Color intensity	Hue	OD280/OD315 of diluted wines	Proline	Class
173	13.71	5.65	2.45	20.5	95	1.68	0.61	0.52	1.06	7.7	0.64	1.74	740	three
174	13.40	3.91	2.48	23.0	102	1.80	0.75	0.43	1.41	7.3	0.70	1.56	750	three
175	13.27	4.28	2.26	20.0	120	1.59	0.69	0.43	1.35	10.2	0.59	1.56	835	three
176	13.17	2.59	2.37	20.0	120	1.65	0.68	0.53	1.46	9.3	0.60	1.62	840	three
177	14.13	4.10	2.74	24.5	96	2.05	0.76	0.56	1.35	9.2	0.61	1.60	560	three

```
df.shape
```

```
(178, 14)
```

We can see that we have 178 entries with 14 attributes each.
The Class has **3 classifications**: one, two and three, which refer to the type of wine.

Data Exploration

There are **no null values**, and the attributes are all numeric except for the Class.

```
df.dtypes
```

```
Alcohol                         float64
Malic acid                      float64
Ash                             float64
Alcalinity of ash               float64
Magnesium                         int64
Total phenols                   float64
Flavanoids                      float64
Nonflavanoid phenols            float64
Proanthocyanins                 float64
Color intensity                 float64
Hue                             float64
OD280/OD315 of diluted wines    float64
Proline                           int64
Class                            object
dtype: object
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178 entries, 0 to 177
Data columns (total 14 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Alcohol                       178 non-null    float64
 1   Malic acid                    178 non-null    float64
 2   Ash                           178 non-null    float64
 3   Alcalinity of ash             178 non-null    float64
 4   Magnesium                     178 non-null    int64  
 5   Total phenols                 178 non-null    float64
 6   Flavanoids                    178 non-null    float64
 7   Nonflavanoid phenols          178 non-null    float64
 8   Proanthocyanins               178 non-null    float64
 9   Color intensity               178 non-null    float64
 10  Hue                           178 non-null    float64
 11  OD280/OD315 of diluted wines  178 non-null    float64
 12  Proline                       178 non-null    int64  
 13  Class                         178 non-null    object 
dtypes: float64(11), int64(2), object(1)
memory usage: 19.6+ KB
```

Data Exploration

We can also get some descriptive statistics (for all numeric data or only desired):

```
df.describe()
```

	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocyanins	Color intensity	Hue	OD280/OD315 of diluted wines	Proline
count	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000
mean	13.000618	2.336348	2.366517	19.494944	99.741573	2.295112	2.029270	0.361854	1.590899	5.058090	0.957449	2.611685	746.893258
std	0.811827	1.117146	0.274344	3.339564	14.282484	0.625851	0.998859	0.124453	0.572359	2.318286	0.228572	0.709990	314.907474
min	11.030000	0.740000	1.360000	10.600000	70.000000	0.980000	0.340000	0.130000	0.410000	1.280000	0.480000	1.270000	278.000000
25%	12.362500	1.602500	2.210000	17.200000	88.000000	1.742500	1.205000	0.270000	1.250000	3.220000	0.782500	1.937500	500.500000
50%	13.050000	1.865000	2.360000	19.500000	98.000000	2.355000	2.135000	0.340000	1.555000	4.690000	0.965000	2.780000	673.500000
75%	13.677500	3.082500	2.557500	21.500000	107.000000	2.800000	2.875000	0.437500	1.950000	6.200000	1.120000	3.170000	985.000000
max	14.830000	5.800000	3.230000	30.000000	162.000000	3.880000	5.080000	0.660000	3.580000	13.000000	1.710000	4.000000	1680.000000

```
df['Color intensity'].describe()
```

```
count    178.000000
mean       5.058090
std        2.318286
min        1.280000
25%        3.220000
50%        4.690000
75%        6.200000
max       13.000000
Name: Color intensity, dtype: float64
```

Data Exploration

What about missing values?

```
df.isna().any()
```

```
Alcohol                         False
Malic acid                      False
Ash                             False
Alcalinity of ash               False
Magnesium                       False
Total phenols                   False
Flavanoids                      False
Nonflavanoid phenols            False
Proanthocyanins                 False
Color intensity                 False
Hue                             False
OD280/OD315 of diluted wines    False
Proline                         False
Class                           False
dtype: bool
```

```
print(df.isna().sum())
```

```
Alcohol                         0
Malic acid                      0
Ash                             0
Alcalinity of ash               0
Magnesium                       0
Total phenols                   0
Flavanoids                      0
Nonflavanoid phenols            0
Proanthocyanins                 0
Color intensity                 0
Hue                             0
OD280/OD315 of diluted wines    0
Proline                         0
Class                           0
dtype: int64
```

Data Exploration

Our analysis allows us to better characterize the dataset:

- It has **178 entries**
- **14 attributes** - 13 are physicochemical properties of the wine and 1 is the classification
- All **non-null values**
- There **are no missing values**

The **goal** of working with this dataset can be to **identify the type of wine by its properties** - the target is a numeric categorical variable that covers the values of one, two and three. When used for modelling, the characteristics of the wine can be used to **predict its type**.

Data Preparation

Data Preparation

It consists of several steps. Often (in fact, a lot of times), you will need to check the API of the library you are using.

Here are some links you can save for future reference:

- **Numpy** (https://numpy.org/doc/stable/)
- **Pandas** (https://pandas.pydata.org/docs/)
- **Matplotlib** (https://matplotlib.org/stable/users/index.html)
- **Seaborn** (https://seaborn.pydata.org/api.html)
- **Scikit Learn** (https://scikit-learn.org/stable/api/index.html)

Data Preparation

And here are some basic Pandas functions that you will need (sometime) in the future for data preparation:

```
pandas.DataFrame.drop
pandas.DataFrame.drop_duplicates
pandas.DataFrame.fillna
pandas.DataFrame.isna
pandas.DataFrame.interpolate
pandas.DataFrame.dropna
pandas.DataFrame.groupby
pandas.DataFrame.loc
pandas.DataFrame.iloc
```

Data Preparation

Some basic Sklearn functions/classes you will need as well:

```
sklearn.preprocessing.MinMaxScaler
sklearn.preprocessing.StandardScaler
sklearn.preprocessing.KBinsDiscretizer
sklearn.preprocessing.LabelEncoder
sklearn.feature_selection
sklearn.metrics
```

Data Preparation and Transformation

Remove duplicate values

```
print(df.duplicated().sum())
print(df.drop_duplicates(inplace=True))
print(df.info())
```

```
0
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178 entries, 0 to 177
Data columns (total 14 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Alcohol                       178 non-null    float64
 1   Malic acid                    178 non-null    float64
 2   Ash                           178 non-null    float64
 3   Alcalinity of ash             178 non-null    float64
 4   Magnesium                     178 non-null    int64  
 5   Total phenols                 178 non-null    float64
 6   Flavanoids                    178 non-null    float64
 7   Nonflavanoid phenols          178 non-null    float64
 8   Proanthocyanins               178 non-null    float64
 9   Color intensity               178 non-null    float64
 10  Hue                           178 non-null    float64
 11  OD280/OD315 of diluted wines  178 non-null    float64
 12  Proline                       178 non-null    int64  
 13  Class                         178 non-null    object 
dtypes: float64(11), int64(2), object(1)
memory usage: 19.6+ KB
None
```

Rename attributes

```
df.rename(columns={"OD280/OD315 of diluted wines": "Protein Concentration"}, inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178 entries, 0 to 177
Data columns (total 14 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   Alcohol                178 non-null    float64
 1   Malic acid             178 non-null    float64
 2   Ash                    178 non-null    float64
 3   Alcalinity of ash      178 non-null    float64
 4   Magnesium              178 non-null    int64  
 5   Total phenols          178 non-null    float64
 6   Flavanoids             178 non-null    float64
 7   Nonflavanoid phenols   178 non-null    float64
 8   Proanthocyanins        178 non-null    float64
 9   Color intensity        178 non-null    float64
 10  Hue                    178 non-null    float64
 11  Protein Concentration  178 non-null    float64
 12  Proline                178 non-null    int64  
 13  Class                  178 non-null    object 
dtypes: float64(11), int64(2), object(1)
memory usage: 19.6+ KB
```

Data Preparation and Transformation


```python
df_clean = df.drop(df.loc[(df['Ash']<2) & (df['Alcalinity of ash']>15)].index)
print(df_clean)
```

As all the variables appear to be physicochemical measures, they could all be useful and help to define the segmentation of the wine type. There is **no reason to remove columns**.

```
     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
..       ...         ...   ...                ...        ...            ...
173    13.71        5.65  2.45               20.5         95           1.68
174    13.40        3.91  2.48               23.0        102           1.80
175    13.27        4.28  2.26               20.0        120           1.59
176    13.17        2.59  2.37               20.0        120           1.65
177    14.13        4.10  2.74               24.5         96           2.05

     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
..          ...                   ...              ...              ...   ...
173        0.61                  0.52             1.06             7.70  0.64
174        0.75                  0.43             1.41             7.30  0.70
175        0.69                  0.43             1.35            10.20  0.59
176        0.68                  0.53             1.46             9.30  0.60
177        0.76                  0.56             1.35             9.20  0.61

     Protein Concentration  Proline  Class
0                     3.92     1065    one
1                     3.40     1050    one
2                     3.17     1185    one
3                     3.45     1480    one
4                     2.93      735    one
..                     ...      ...    ...
173                   1.74      740  three
174                   1.56      750  three
175                   1.56      835  three
176                   1.62      840  three
177                   1.60      560  three

[164 rows x 14 columns]
```

Univariate Analysis

Univariate Analysis

Get basic information by iterating through each relevant variable:

```
df['Alcohol'].value_counts()
```

```
Alcohol
13.05    6
12.37    6
12.08    5
12.29    4
12.42    3
        ..
13.72    1
13.29    1
13.74    1
13.77    1
14.13    1
Name: count, Length: 126, dtype: int64
```

```
df['Class'].value_counts(normalize=True)
```

```
Class
two      0.398876
one      0.331461
three    0.269663
Name: proportion, dtype: float64
```

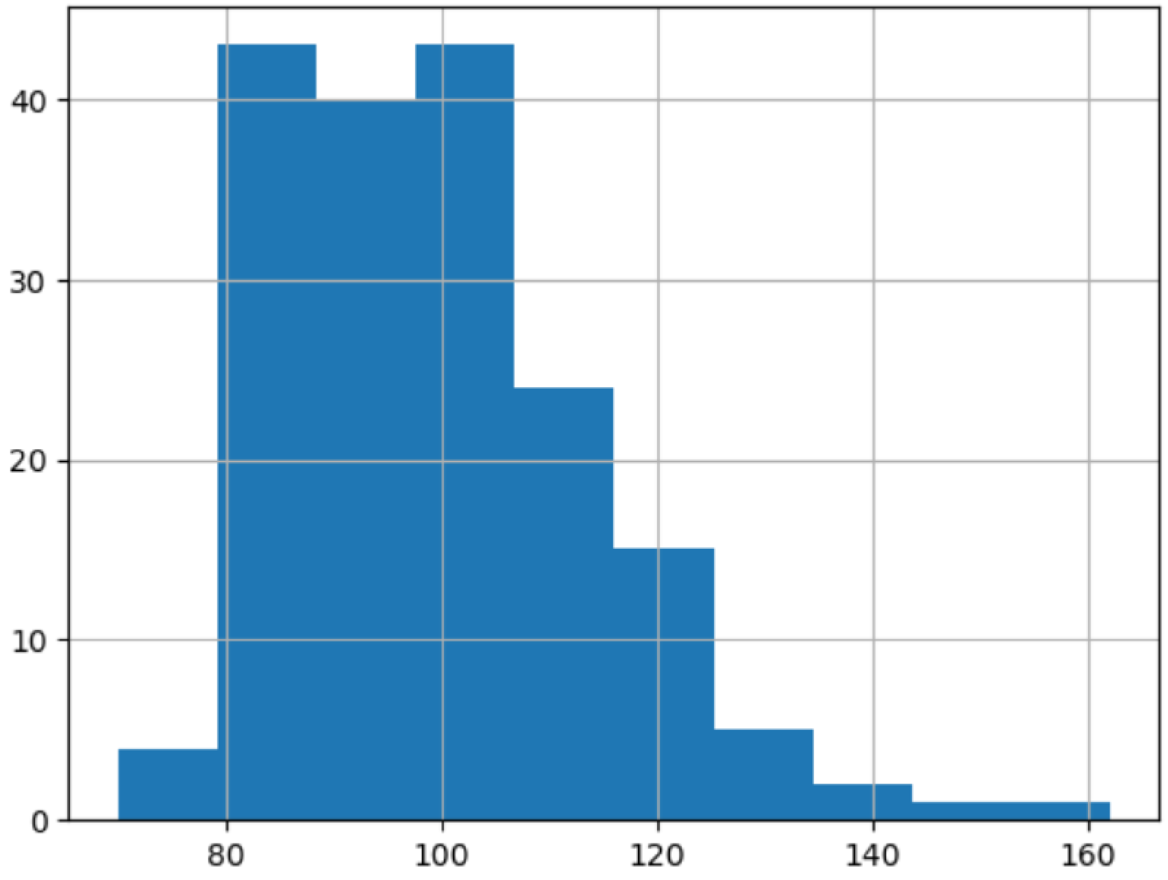
```
'''
Numeric variables
'''
df['Magnesium'].describe()
```

```
count    178.000000
mean      99.741573
std       14.282484
min       70.000000
25%       88.000000
50%       98.000000
75%      107.000000
max      162.000000
Name: Magnesium, dtype: float64
```

Univariate Analysis


```
print(f"Histogram: {df['Magnesium'].hist()}")
```

```
Histogram: Axes(0.125,0.11;0.775x0.77)
```



Does **not follow a normal curve** and **has spikes**.

Univariate Analysis

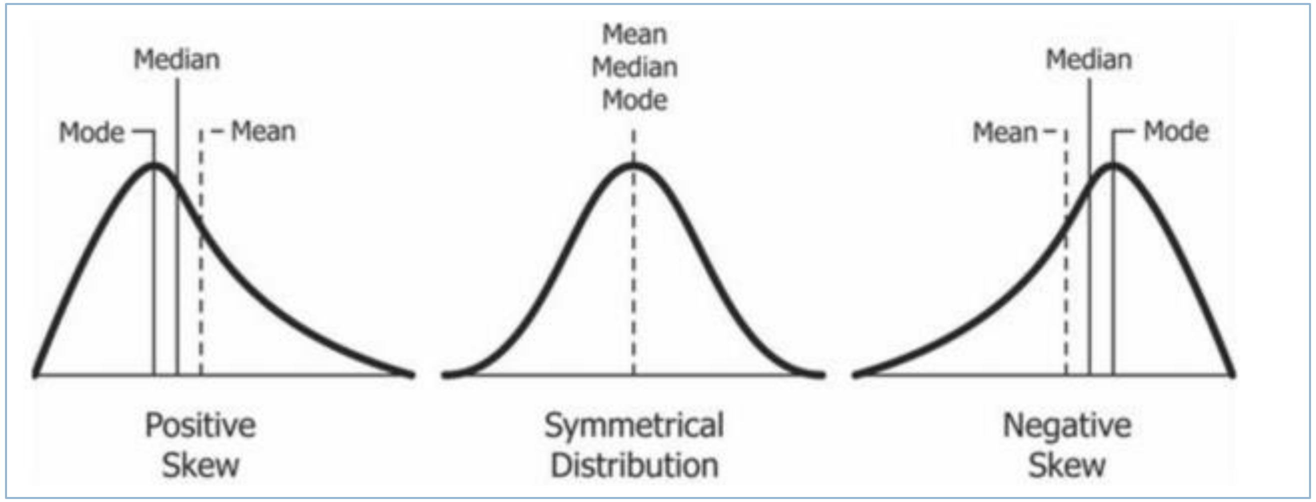

```python
print(f"Skewness: {df['Magnesium'].skew()}")
```

```
Skewness: 1.098191054755161
```

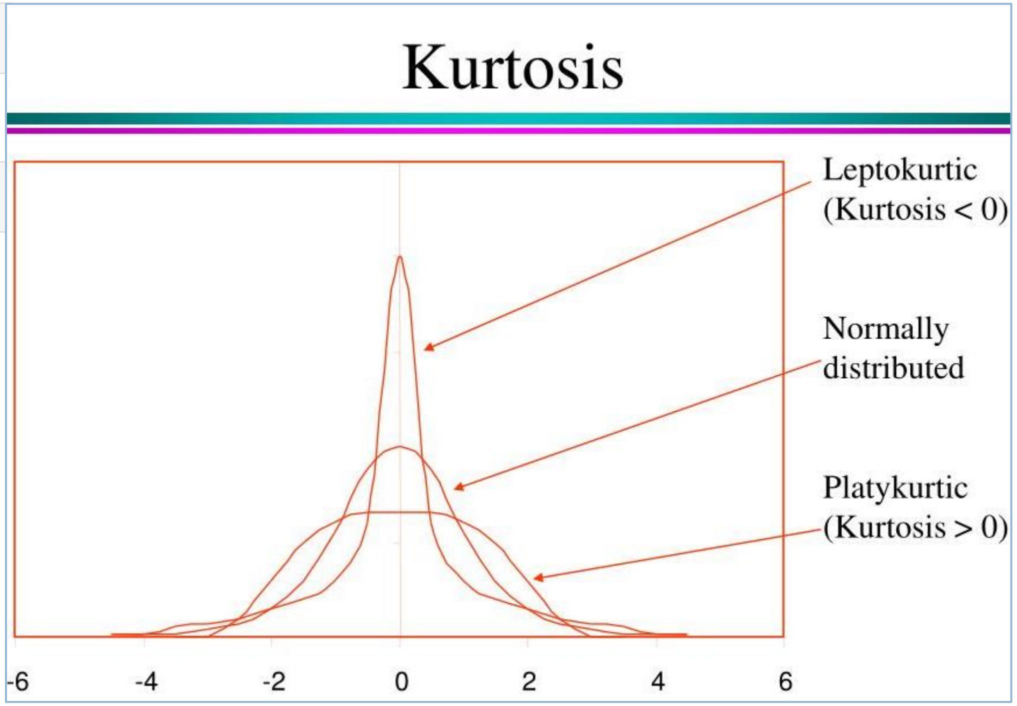
```python
print(f"Kurtosis: {df['Magnesium'].kurt()}")
```

```
Kurtosis: 2.1049913235905557
```

Kurtosis and asymmetry values are **greater than 1**.



https://t.ly/rISUJ



https://t.ly/us-2I

Univariate Analysis

Now we can summarize the dataset by creating a small document with detailed information:

- ***Variable***: the name of the variable
- ***Type***: the type or format of the variable. This can be categorical, numerical, Boolean, etc.
- ***Context***: useful information to understand the semantic space of the variable. In the case of our dataset, the context is always the physicochemical one
- ***Expectation***: how relevant is this variable for our task? We can use a scale "High, Medium, Low"
- ***Comments***: if we have any comments to make about the variable

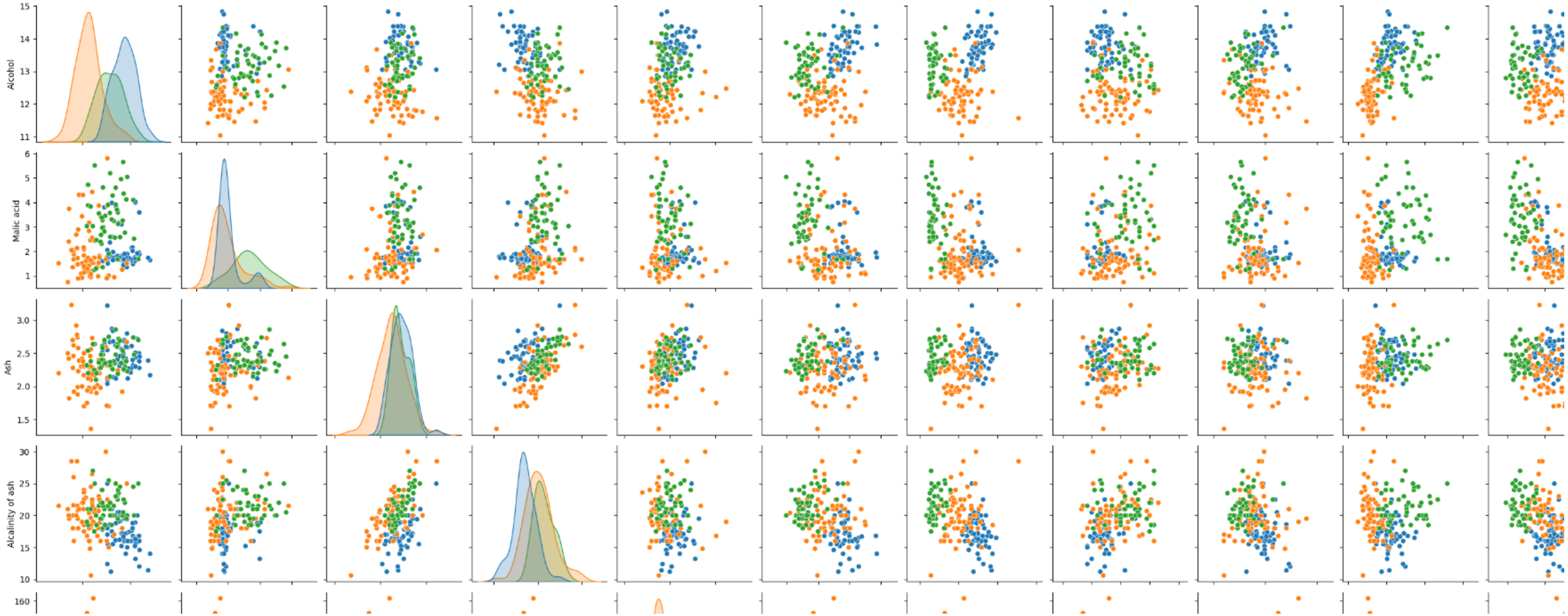
Multivariate Analysis

Multivariate Analysis

We can start by looking at the **relationship** between all the variables:

```
sns.pairplot(df, hue="Class")
```

```
<seaborn.axisgrid.PairGrid at 0x1e31c6eb620>
```



Multivariate Analysis

We can **group** by variables:

```
df.groupby(by=['Class']).mean(numeric_only=True)
```

Class	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocyanins	Color intensity	Hue	Protein Concentration	Proline
one	13.744746	2.010678	2.455593	17.037288	106.338983	2.840169	2.982373	0.290000	1.899322	5.528305	1.062034	3.157797	1115.711864
three	13.153750	3.333750	2.437083	21.416667	99.312500	1.678750	0.781458	0.447500	1.153542	7.396250	0.682708	1.683542	629.895833
two	12.278732	1.932676	2.244789	20.238028	94.549296	2.258873	2.080845	0.363662	1.630282	3.086620	1.056282	2.785352	519.507042

Multivariate Analysis


```
df.groupby(by=['Class', 'Proline']).mean(numeric_only=True)
```

Class	Proline	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocyanins	Color intensity	Hue	Protein Concentration
one	**680**	13.240	3.980	2.290	17.5	103.0	2.640	2.630	0.32	1.66	4.360	0.820	3.00
	735	13.240	2.590	2.870	21.0	118.0	2.800	2.690	0.39	1.82	4.320	1.040	2.93
	760	14.220	3.990	2.510	13.2	128.0	3.000	3.040	0.20	2.08	5.100	0.890	3.53
	770	12.930	3.800	2.650	18.6	102.0	2.410	2.410	0.25	1.98	4.500	1.030	3.52
	780	14.060	1.630	2.280	16.0	126.0	3.000	3.170	0.24	2.10	5.650	1.090	3.71
...	**...**	...	...	...	...	...	...	...	...	...	...	...	...
two	**750**	12.835	0.965	2.155	15.9	123.0	2.215	1.575	0.45	1.59	3.285	1.040	2.12
	870	12.290	1.610	2.210	20.4	103.0	1.100	1.020	0.37	1.46	3.050	0.906	1.82
	886	11.960	1.090	2.300	21.0	101.0	3.380	2.140	0.13	1.65	3.210	0.990	3.13
	937	12.470	1.520	2.200	19.0	162.0	2.500	2.270	0.32	3.28	2.600	1.160	2.63
	985	12.990	1.670	2.600	30.0	139.0	3.300	2.890	0.21	1.96	3.350	1.310	3.50

138 rows × 12 columns

Multivariate Analysis


```
print(df.groupby(by=['Alcohol']).agg([pd.Series.mode]))
```

```
          Malic acid           Ash Alcalinity of ash Magnesium Total phenols  \
                mode          mode              mode      mode          mode   
Alcohol                                                                        
11.03           1.51           2.2              21.5        85          2.46   
11.41           0.74           2.5              21.0        88          2.48   
11.45            2.4          2.42              20.0        96           2.9   
11.46           3.74          1.82              19.5       107          3.18   
11.56           2.05          3.23              28.5       119          3.18   
...              ...           ...               ...       ...           ...   
14.37           1.95           2.5              16.8       113          3.85   
14.38   [1.87, 3.59]  [2.28, 2.38]      [12.0, 16.0]       102   [3.25, 3.3]   
14.39           1.87          2.45              14.6        96           2.5   
14.75           1.73          2.39              11.4        91           3.1   
14.83           1.64          2.17              14.0        97           2.8   

          Flavanoids Nonflavanoid phenols Proanthocyanins Color intensity  \
                mode                 mode            mode            mode   
Alcohol                                                                     
11.03           2.17                 0.52            2.01             1.9   
11.41           2.01                 0.42            1.44            3.08   
11.45           2.79                 0.32            1.83            3.25   
11.46           2.58                 0.24            3.58             2.9   
11.56           5.08                 0.47            1.87             6.0   
...              ...                  ...             ...             ...   
14.37           3.49                 0.24            2.18             7.8   
14.38   [3.17, 3.64]         [0.27, 0.29]    [2.19, 2.96]      [4.9, 7.5]   
14.39           2.52                  0.3            1.98            5.25   
14.75           3.69                 0.43            2.81             5.4   
14.83           2.98                 0.29            1.98             5.2   
```

```
print(df.groupby(by=['Alcohol', 'Flavanoids']).mean(numeric_only=True))
```

```
                    Malic acid   Ash  Alcalinity of ash  Magnesium  \
Alcohol Flavanoids                                                   
11.03   2.17              1.51  2.20               21.5       85.0   
11.41   2.01              0.74  2.50               21.0       88.0   
11.45   2.79              2.40  2.42               20.0       96.0   
11.46   2.58              3.74  1.82               19.5      107.0   
11.56   5.08              2.05  3.23               28.5      119.0   
...                        ...   ...                ...        ...   
14.38   3.17              3.59  2.28               16.0      102.0   
        3.64              1.87  2.38               12.0      102.0   
14.39   2.52              1.87  2.45               14.6       96.0   
14.75   3.69              1.73  2.39               11.4       91.0   
14.83   2.98              1.64  2.17               14.0       97.0   

                    Total phenols  Nonflavanoid phenols  Proanthocyanins  \
Alcohol Flavanoids                                                         
11.03   2.17                 2.46                  0.52             2.01   
11.41   2.01                 2.48                  0.42             1.44   
11.45   2.79                 2.90                  0.32             1.83   
11.46   2.58                 3.18                  0.24             3.58   
11.56   5.08                 3.18                  0.47             1.87   
...                           ...                   ...              ...   
14.38   3.17                 3.25                  0.27             2.19   
        3.64                 3.30                  0.29             2.96   
14.39   2.52                 2.50                  0.30             1.98   
14.75   3.69                 3.10                  0.43             2.81   
14.83   2.98                 2.80                  0.29             1.98   
```

Multivariate Analysis

We can create **bins**.

Data binning (or bucketing) groups data into bins (or buckets) in the sense that it replaces values contained in a small interval with a single representative value for that interval. It is a **type of data pre-processing**, a mechanism that also includes missing value handling, formatting, normalization and standardization.

Binning is a **data smoothing technique**. Data smoothing is **used to remove noise from data**.

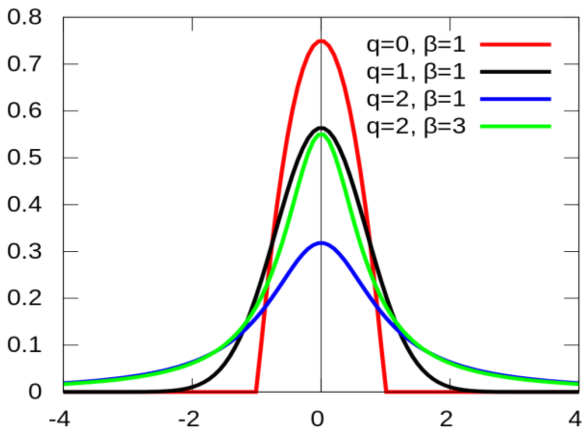
```python
estimator = preprocessing.KBinsDiscretizer(n_bins=3, encode='ordinal', strategy='quantile')
df['alcohol_binned'] = estimator.fit_transform(df[['Alcohol']])

print('Bin Edges')
print(estimator.bin_edges_[0])
print('Alcohol Groups')
print(df.groupby(by=['alcohol_binned']).count())
```

```
Bin Edges
[11.03 12.52 13.48 14.83]
Alcohol Groups
                Alcohol  Malic acid  Ash  Alcalinity of ash  Magnesium  \
alcohol_binned
0.0                  59          59   59                 59         59
1.0                  58          58   58                 58         58
2.0                  61          61   61                 61         61

                Total phenols  Flavanoids  Nonflavanoid phenols  \
alcohol_binned
0.0                        59          59                    59
1.0                        58          58                    58
2.0                        61          61                    61

                Proanthocyanins  Color intensity  Hue  Protein Concentration  \
alcohol_binned
0.0                          59               59   59                     59
1.0                          58               58   58                     58
2.0                          61               61   61                     61

                Proline  Class
alcohol_binned
0.0                  59     59
1.0                  58     58
2.0                  61     61
```

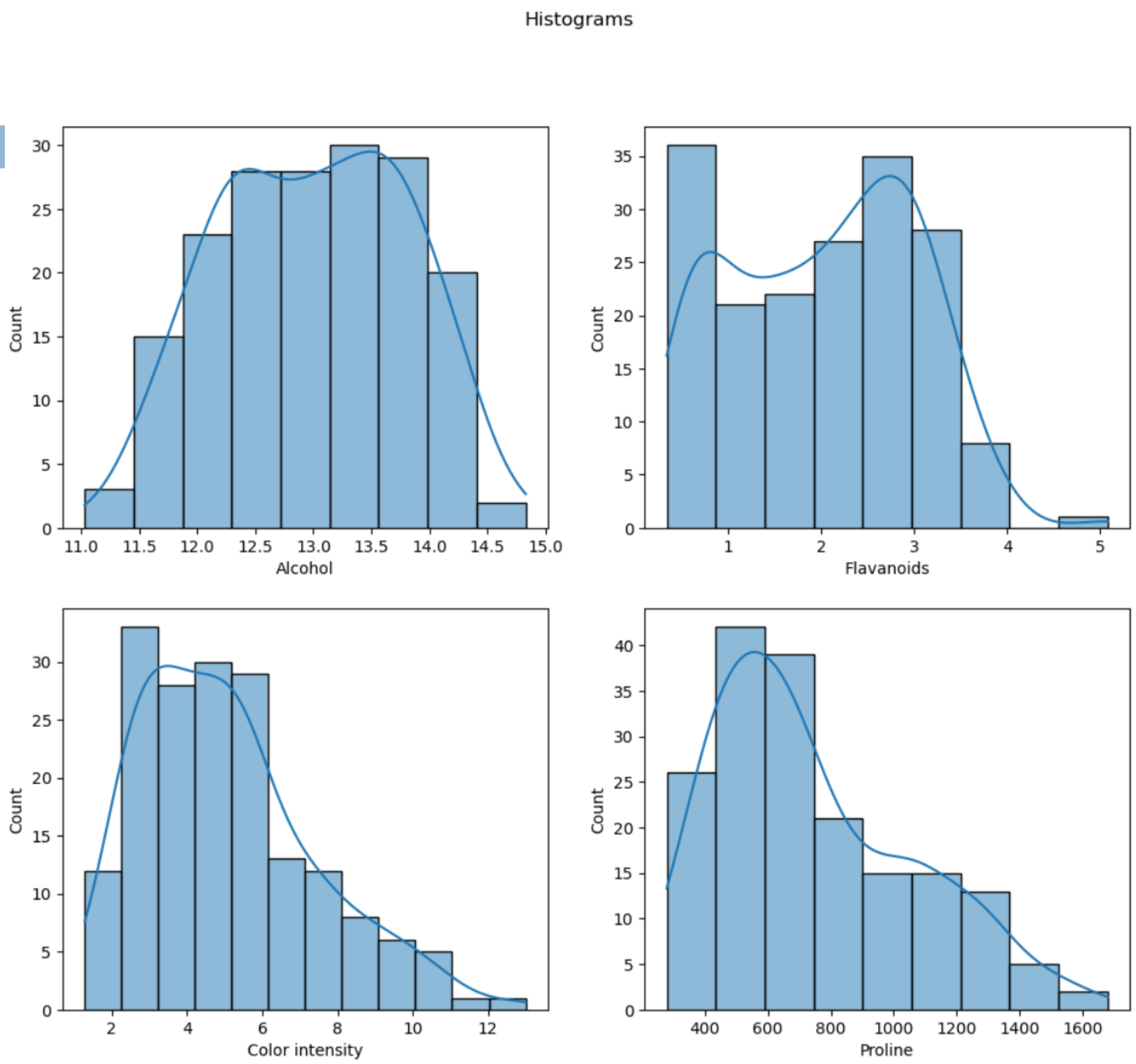
Multivariate Analysis

Dispersion: does it follow a Gaussian distribution?

```
fig, axs = plt.subplots(2, 2, figsize=(12, 10))
fig.suptitle('Histograms')

sns.histplot(df['Alcohol'], ax=axs[0, 0], kde=True)
sns.histplot(df['Flavanoids'], ax=axs[0, 1], kde=True)
sns.histplot(df['Color intensity'], ax=axs[1, 0], kde=True)
sns.histplot(df['Proline'], ax=axs[1, 1], kde=True)
```



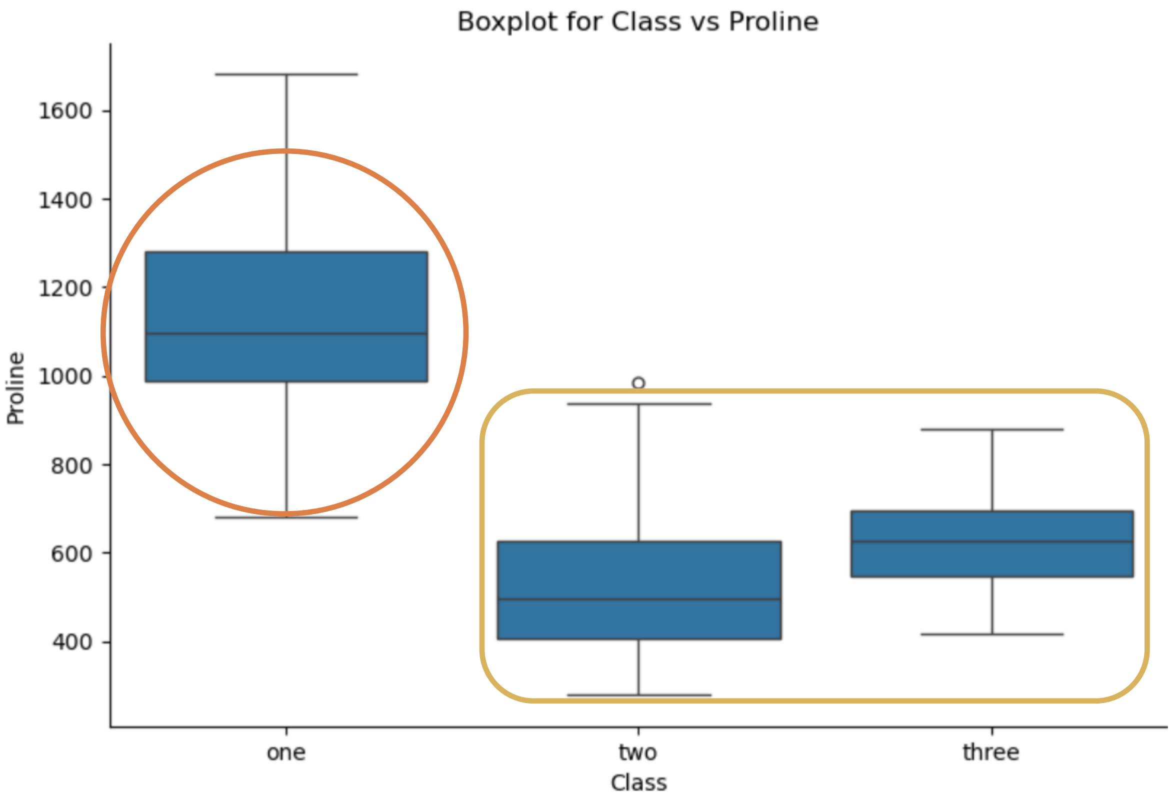
https://en.wikipedia.org/wiki/Q-Gaussian_distribution



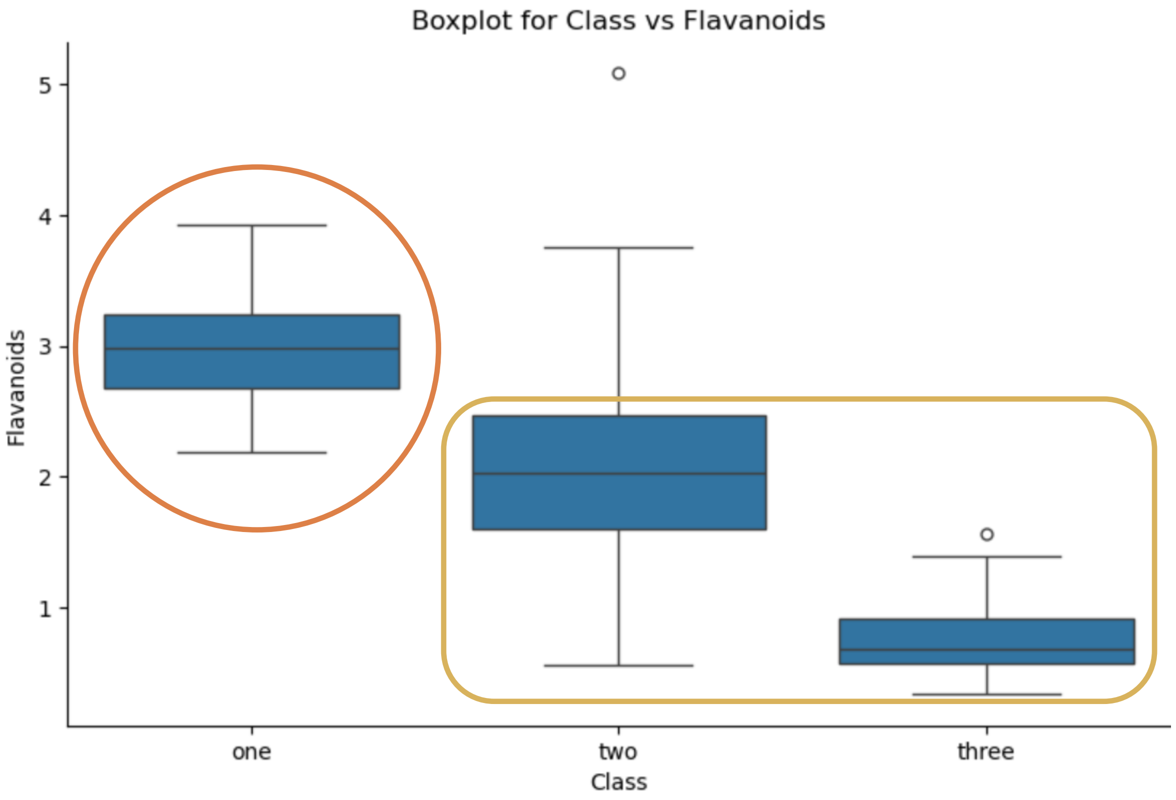
Multivariate Analysis

The best way to understand the relationship between a numeric variable and a categorical variable is through a boxplot:

```
sns.catplot(x="Class", y="Proline", data=df, kind="box", aspect=1.5)
plt.title("Boxplot for Class vs Proline")
plt.show()
```

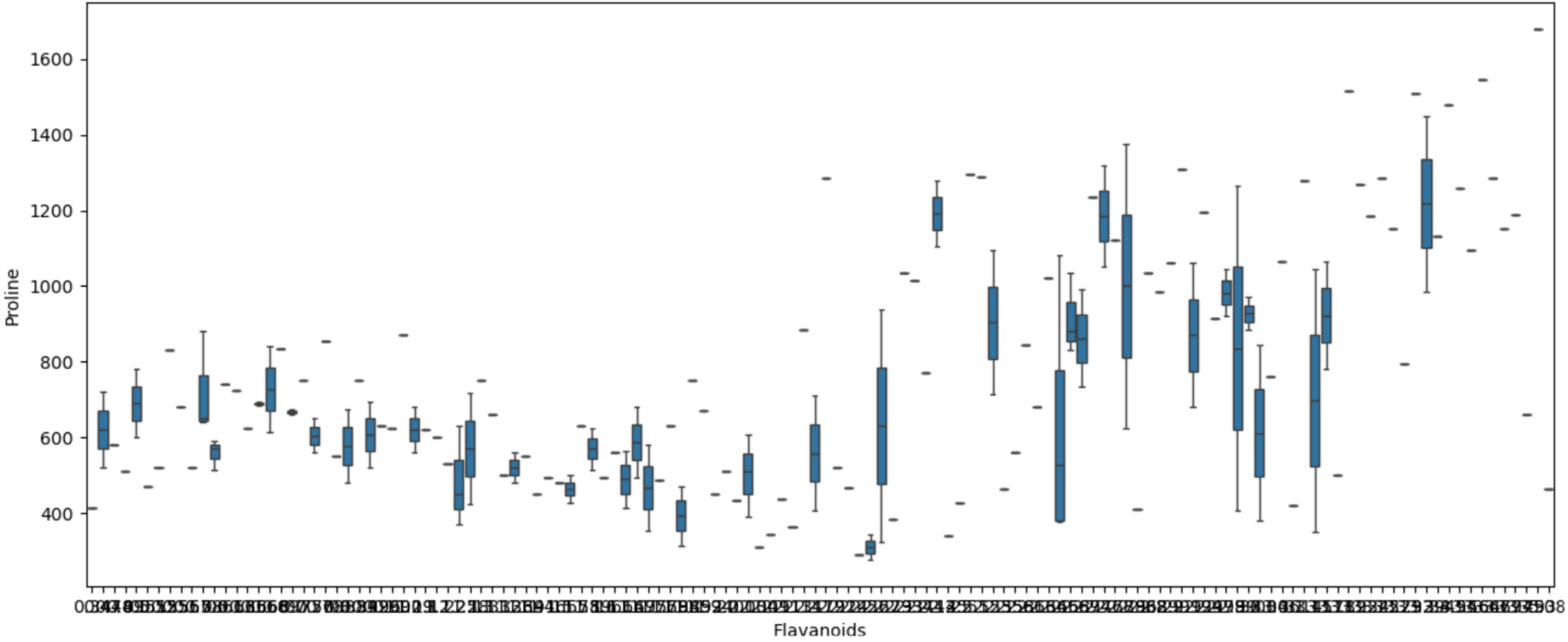



```
sns.catplot(x="Class", y="Flavanoids", data=df, kind="box", aspect=1.5)
plt.title("Boxplot for Class vs Flavanoids")
plt.show()
```



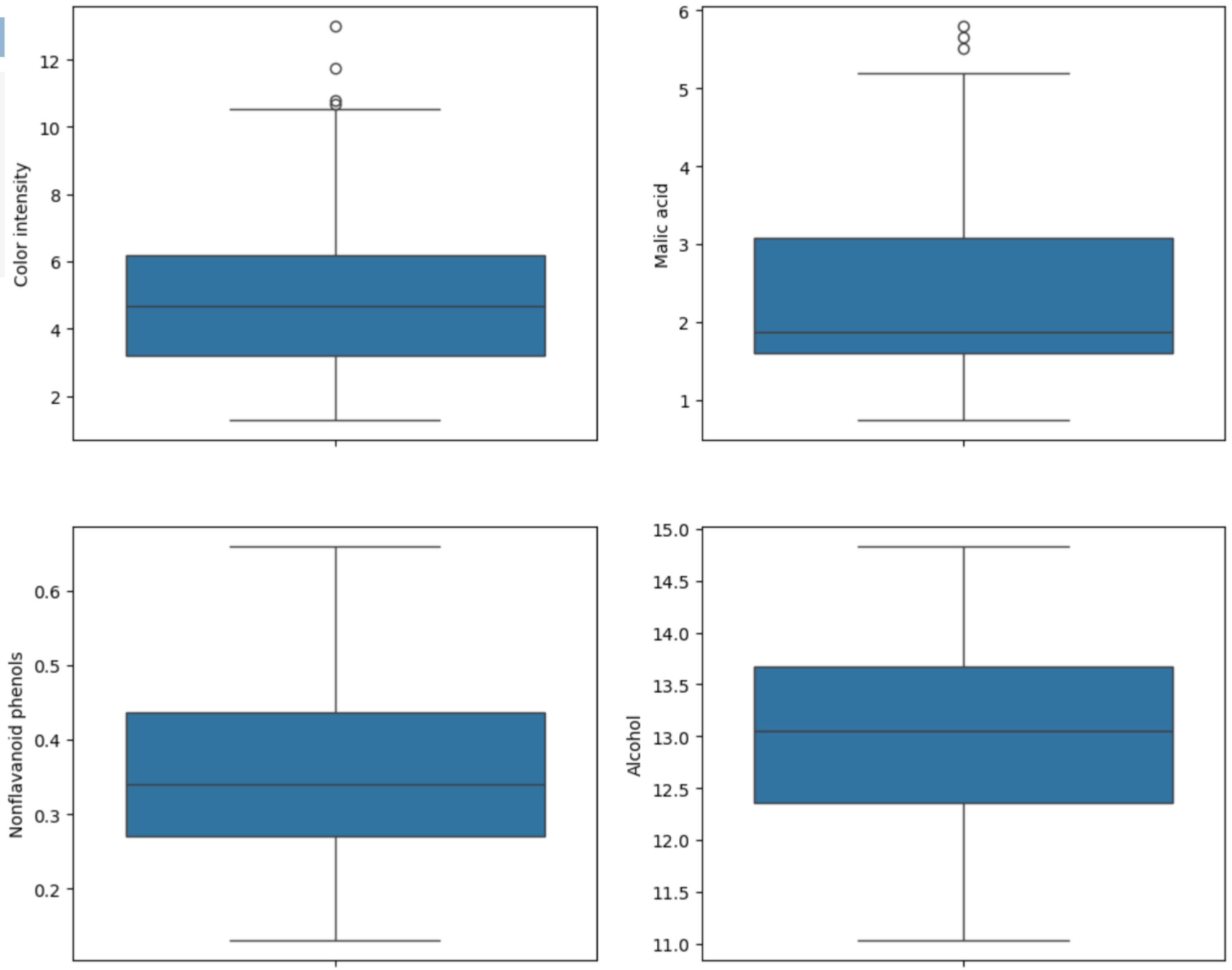
Multivariate Analysis


```
_, ax = plt.subplots(figsize=(15, 6))
fig.suptitle('Boxplot for Flavanoids vs Proline')
sns.boxplot(x=df["Flavanoids"], y=df["Proline"])
```



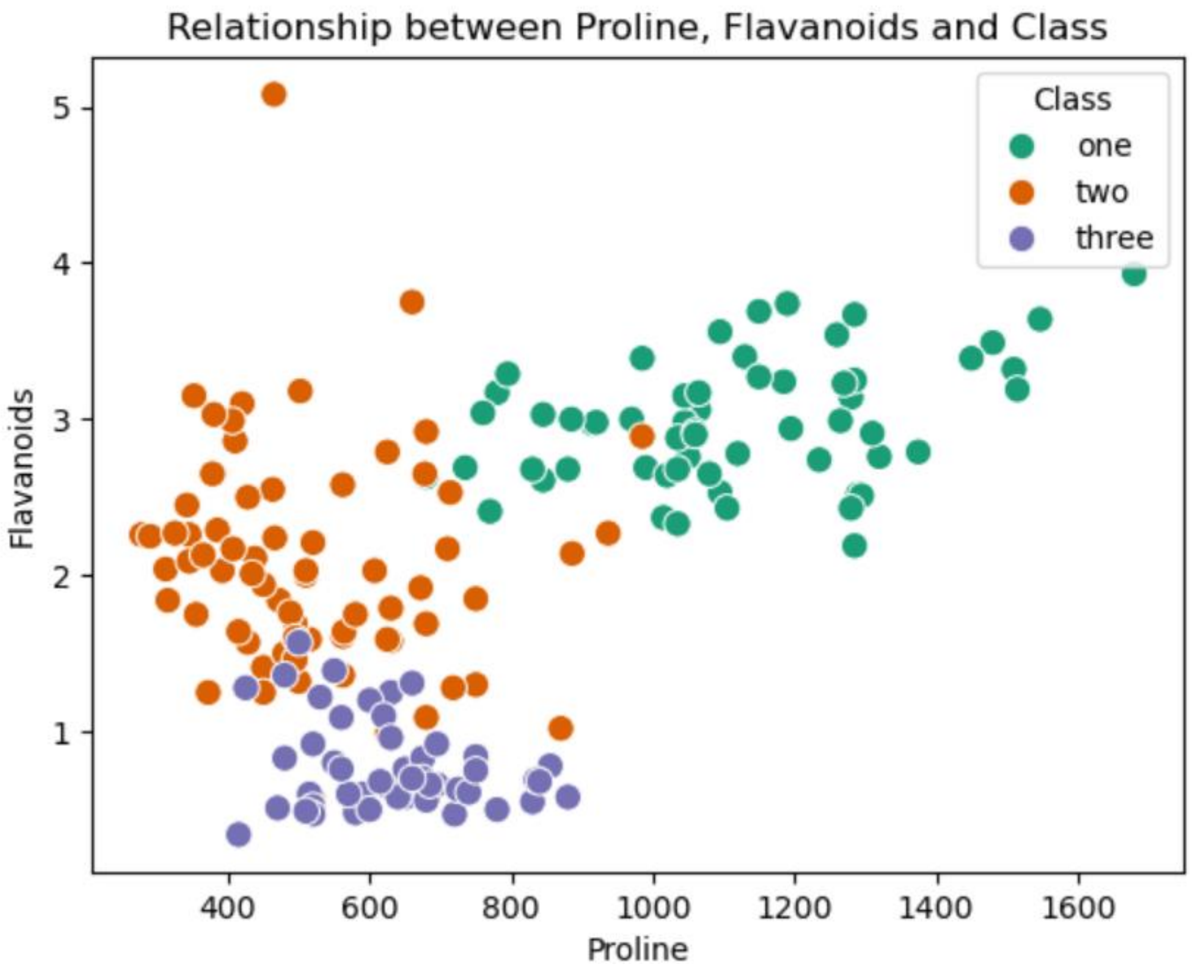
Multivariate Analysis


```
fig, axs = plt.subplots(2, 2, figsize=(12, 10))
fig.suptitle('Boxplots for 4 variables')
sns.boxplot(y=df['Color intensity'], ax=axs[0, 0])
sns.boxplot(y=df['Malic acid'], ax=axs[0, 1])
sns.boxplot(y=df['Nonflavanoid phenols'], ax=axs[1, 0])
sns.boxplot(y=df['Alcohol'], ax=axs[1, 1])
```



Multivariate Analysis

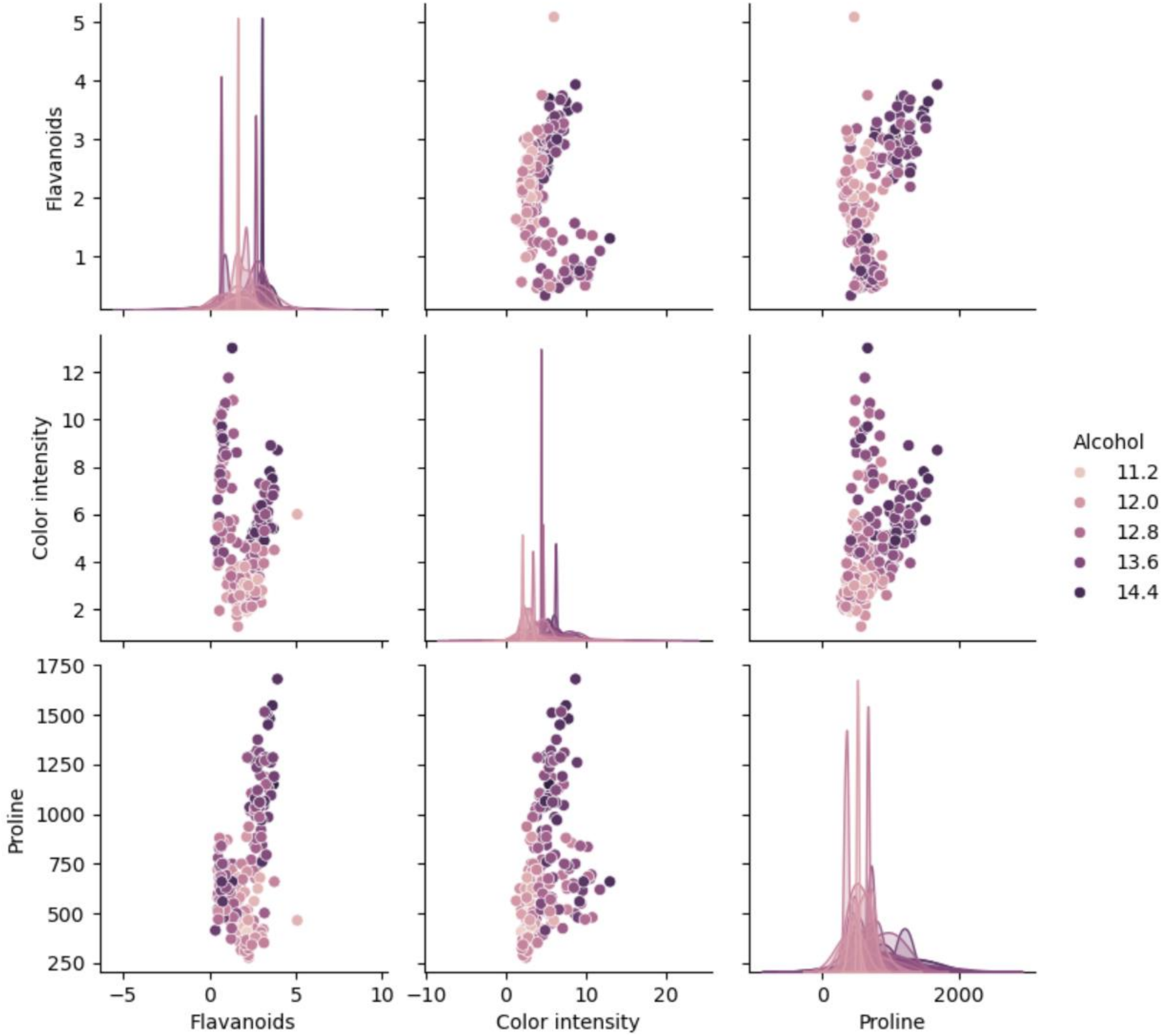

```
sns.scatterplot(x="Proline", y="Flavanoids", hue="Class", data=df, palette="Dark2", s=80)
plt.title("Relationship between Proline, Flavanoids and Class")
plt.show()
```



In Class one, Proline levels are much **higher**, while Flavanoids levels are **stable** around the value of 3.

Multivariate Analysis


```
cols = ['Alcohol', 'Flavanoids', 'Color intensity', 'Proline']
_ = sns.pairplot(df[cols], hue='Alcohol', height = 2.5)
```

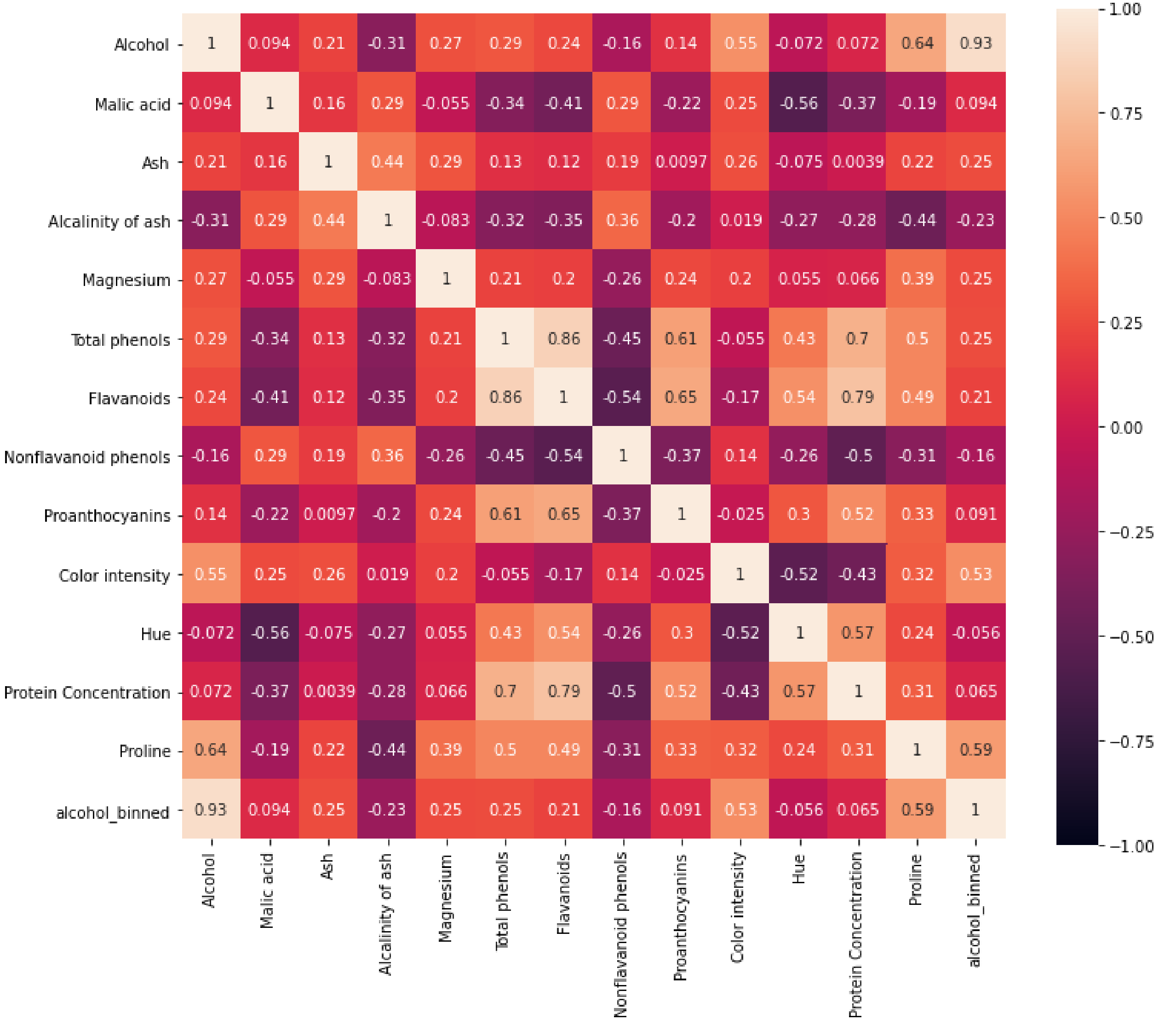


Multivariate Analysis


```
corr_matrix = df.corr(numeric_only=True)
f, ax = plt.subplots(figsize=(6,4))
sns.heatmap(corr_matrix, vmin=-1, vmax=1, square=True, annot=True)
```

When the Class variable **decreases** (tends to go to 0), Flavanoids, Total phenols, Proline and other proteins tend to **increase**. And vice versa.

There is a **very strong correlation between Alcohol and Proline**. High levels of Alcohol correspond to high levels of Proline.



Critical Analysis

- Which components characterize the different types of wine?
- Which component is the most important?

Hands On