

# red-wine-quality-predictiton

February 3, 2024

```
[3]: !pip install pandas  
!pip install numpy  
!pip install seaborn  
!pip install matplotlib
```

```
Requirement already satisfied: pandas in d:\python 3.8\lib\site-packages (2.0.3)  
Requirement already satisfied: python-dateutil>=2.8.2 in d:\python 3.8\lib\site-  
packages (from pandas) (2.8.2)  
Requirement already satisfied: pytz>=2020.1 in d:\python 3.8\lib\site-packages  
(from pandas) (2024.1)  
Requirement already satisfied: tzdata>=2022.1 in d:\python 3.8\lib\site-packages  
(from pandas) (2023.4)  
Requirement already satisfied: numpy>=1.20.3 in d:\python 3.8\lib\site-packages  
(from pandas) (1.24.4)  
Requirement already satisfied: six>=1.5 in d:\python 3.8\lib\site-packages (from  
python-dateutil>=2.8.2->pandas) (1.16.0)  
Requirement already satisfied: numpy in d:\python 3.8\lib\site-packages (1.24.4)  
Collecting seaborn  
  Using cached seaborn-0.13.2-py3-none-any.whl.metadata (5.4 kB)  
Requirement already satisfied: numpy!=1.24.0,>=1.20 in d:\python 3.8\lib\site-  
packages (from seaborn) (1.24.4)  
Requirement already satisfied: pandas>=1.2 in d:\python 3.8\lib\site-packages  
(from seaborn) (2.0.3)  
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in d:\python  
3.8\lib\site-packages (from seaborn) (3.7.4)  
Requirement already satisfied: contourpy>=1.0.1 in d:\python 3.8\lib\site-  
packages (from matplotlib!=3.6.1,>=3.4->seaborn) (1.1.1)  
Requirement already satisfied: cycler>=0.10 in d:\python 3.8\lib\site-packages  
(from matplotlib!=3.6.1,>=3.4->seaborn) (0.12.1)  
Requirement already satisfied: fonttools>=4.22.0 in d:\python 3.8\lib\site-  
packages (from matplotlib!=3.6.1,>=3.4->seaborn) (4.47.2)  
Requirement already satisfied: kiwisolver>=1.0.1 in d:\python 3.8\lib\site-  
packages (from matplotlib!=3.6.1,>=3.4->seaborn) (1.4.5)  
Requirement already satisfied: packaging>=20.0 in d:\python 3.8\lib\site-  
packages (from matplotlib!=3.6.1,>=3.4->seaborn) (23.2)  
Requirement already satisfied: pillow>=6.2.0 in d:\python 3.8\lib\site-packages  
(from matplotlib!=3.6.1,>=3.4->seaborn) (10.2.0)  
Requirement already satisfied: pyparsing>=2.3.1 in d:\python 3.8\lib\site-
```

```
packages (from matplotlib!=3.6.1,>=3.4->seaborn) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in d:\python 3.8\lib\site-
packages (from matplotlib!=3.6.1,>=3.4->seaborn) (2.8.2)
Requirement already satisfied: importlib-resources>=3.2.0 in d:\python
3.8\lib\site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (6.1.1)
Requirement already satisfied: pytz>=2020.1 in d:\python 3.8\lib\site-packages
(from pandas>=1.2->seaborn) (2024.1)
Requirement already satisfied: tzdata>=2022.1 in d:\python 3.8\lib\site-packages
(from pandas>=1.2->seaborn) (2023.4)
Requirement already satisfied: zipp>=3.1.0 in c:\users\hitesh
karthik\appdata\roaming\python\python38\site-packages (from importlib-
resources>=3.2.0->matplotlib!=3.6.1,>=3.4->seaborn) (3.17.0)
Requirement already satisfied: six>=1.5 in d:\python 3.8\lib\site-packages (from
python-dateutil>=2.7->matplotlib!=3.6.1,>=3.4->seaborn) (1.16.0)
Using cached seaborn-0.13.2-py3-none-any.whl (294 kB)
Installing collected packages: seaborn
Successfully installed seaborn-0.13.2
Requirement already satisfied: matplotlib in d:\python 3.8\lib\site-packages
(3.7.4)
Requirement already satisfied: contourpy>=1.0.1 in d:\python 3.8\lib\site-
packages (from matplotlib) (1.1.1)
Requirement already satisfied: cycler>=0.10 in d:\python 3.8\lib\site-packages
(from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in d:\python 3.8\lib\site-
packages (from matplotlib) (4.47.2)
Requirement already satisfied: kiwisolver>=1.0.1 in d:\python 3.8\lib\site-
packages (from matplotlib) (1.4.5)
Requirement already satisfied: numpy<2,>=1.20 in d:\python 3.8\lib\site-packages
(from matplotlib) (1.24.4)
Requirement already satisfied: packaging>=20.0 in d:\python 3.8\lib\site-
packages (from matplotlib) (23.2)
Requirement already satisfied: pillow>=6.2.0 in d:\python 3.8\lib\site-packages
(from matplotlib) (10.2.0)
Requirement already satisfied: pyparsing>=2.3.1 in d:\python 3.8\lib\site-
packages (from matplotlib) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in d:\python 3.8\lib\site-
packages (from matplotlib) (2.8.2)
Requirement already satisfied: importlib-resources>=3.2.0 in d:\python
3.8\lib\site-packages (from matplotlib) (6.1.1)
Requirement already satisfied: zipp>=3.1.0 in c:\users\hitesh
karthik\appdata\roaming\python\python38\site-packages (from importlib-
resources>=3.2.0->matplotlib) (3.17.0)
Requirement already satisfied: six>=1.5 in d:\python 3.8\lib\site-packages (from
python-dateutil>=2.7->matplotlib) (1.16.0)
```

```
[4]: import numpy as np
      import matplotlib.pyplot as plt
```

```

import pandas as pd
import seaborn as sns
from warnings import filterwarnings
filterwarnings(action='ignore')

```

C:\Users\Hitesh Karthik\AppData\Local\Temp\ipykernel\_27364\2861500716.py:3:  
DeprecationWarning:  
Pyarrow will become a required dependency of pandas in the next major release of  
pandas (pandas 3.0),  
(to allow more performant data types, such as the Arrow string type, and better  
interoperability with other libraries)  
but was not found to be installed on your system.  
If this would cause problems for you,  
please provide us feedback at <https://github.com/pandas-dev/pandas/issues/54466>

```

import pandas as pd
****Loading Dataset****

```

[5]: wine = pd.read\_csv(r"C:\Users\Hitesh Karthik\OneDrive\Desktop\machine learning\u
↪projects\Red Wine Quality Prediciton\winequality-red.csv")
wine.sample(25)

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides \
197	11.5	0.300	0.60	2.00	0.067
619	11.3	0.370	0.41	2.30	0.088
1022	7.0	0.510	0.09	2.10	0.062
525	10.4	0.640	0.24	2.80	0.105
599	12.7	0.590	0.45	2.30	0.082
80	6.2	0.450	0.20	1.60	0.069
344	11.9	0.570	0.50	2.60	0.082
860	7.2	0.620	0.06	2.70	0.077
717	7.6	0.460	0.11	2.60	0.079
116	8.3	0.540	0.28	1.90	0.077
1276	8.5	0.400	0.40	6.30	0.050
1596	6.3	0.510	0.13	2.30	0.076
978	7.0	0.400	0.32	3.60	0.061
46	7.7	0.935	0.43	2.20	0.114
1443	6.9	0.580	0.20	1.75	0.058
1466	7.3	0.480	0.32	2.10	0.062
196	7.3	0.580	0.30	2.40	0.074
659	7.1	0.840	0.02	4.40	0.096
1406	8.2	0.240	0.34	5.10	0.062
1431	7.6	0.430	0.31	2.10	0.069
452	6.8	0.560	0.03	1.70	0.084
542	9.3	0.715	0.24	2.10	0.070
244	15.0	0.210	0.44	2.20	0.075
1349	6.9	0.570	0.00	2.80	0.081

56 10.2 0.420 0.57 3.40 0.070

	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	\
197	12.0	27.0	0.99810	3.11	0.97	
619	6.0	16.0	0.99880	3.09	0.80	
1022	4.0	9.0	0.99584	3.35	0.54	
525	29.0	53.0	0.99980	3.24	0.67	
599	11.0	22.0	1.00000	3.00	0.70	
80	3.0	15.0	0.99580	3.41	0.56	
344	6.0	32.0	1.00060	3.12	0.78	
860	15.0	85.0	0.99746	3.51	0.54	
717	12.0	49.0	0.99680	3.21	0.57	
116	11.0	40.0	0.99780	3.39	0.61	
1276	3.0	10.0	0.99566	3.28	0.56	
1596	29.0	40.0	0.99574	3.42	0.75	
978	9.0	29.0	0.99416	3.28	0.49	
46	22.0	114.0	0.99700	3.25	0.73	
1443	8.0	22.0	0.99322	3.38	0.49	
1466	31.0	54.0	0.99728	3.30	0.65	
196	15.0	55.0	0.99680	3.46	0.59	
659	5.0	13.0	0.99700	3.41	0.57	
1406	8.0	22.0	0.99740	3.22	0.94	
1431	13.0	74.0	0.99580	3.26	0.54	
452	18.0	35.0	0.99680	3.44	0.63	
542	5.0	20.0	0.99660	3.12	0.59	
244	10.0	24.0	1.00005	3.07	0.84	
1349	21.0	41.0	0.99518	3.41	0.52	
56	4.0	10.0	0.99710	3.04	0.63	

alcohol quality

197	10.1	6
619	9.3	5
1022	10.5	5
525	9.9	5
599	9.3	6
80	9.2	5
344	10.7	6
860	9.5	5
717	10.0	5
116	10.0	6
1276	12.0	4
1596	11.0	6
978	11.3	7
46	9.2	5
1443	11.7	5
1466	10.0	7
196	10.2	5

```
659      11.0      4
1406     10.9      6
1431      9.9      6
452      10.0      6
542      9.9      5
244      9.2      7
1349     10.8      5
56       9.6      5
```

```
[6]: wine.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   fixed acidity    1599 non-null   float64
 1   volatile acidity 1599 non-null   float64
 2   citric acid     1599 non-null   float64
 3   residual sugar   1599 non-null   float64
 4   chlorides        1599 non-null   float64
 5   free sulfur dioxide 1599 non-null   float64
 6   total sulfur dioxide 1599 non-null   float64
 7   density          1599 non-null   float64
 8   pH               1599 non-null   float64
 9   sulphates        1599 non-null   float64
 10  alcohol          1599 non-null   float64
 11  quality          1599 non-null   int64  
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

## 1 Description

```
[7]: wine.describe()
```

```
fixed acidity  volatile acidity  citric acid  residual sugar \
count      1599.000000      1599.000000      1599.000000      1599.000000
mean       8.319637       0.527821       0.270976      2.538806
std        1.741096       0.179060       0.194801      1.409928
min        4.600000       0.120000       0.000000      0.900000
25%        7.100000       0.390000       0.090000      1.900000
50%        7.900000       0.520000       0.260000      2.200000
75%        9.200000       0.640000       0.420000      2.600000
max       15.900000      1.580000       1.000000     15.500000
```

```
chlorides  free sulfur dioxide  total sulfur dioxide      density \

```

```

count    1599.000000          1599.000000          1599.000000  1599.000000
mean      0.087467          15.874922          46.467792  0.996747
std       0.047065          10.460157          32.895324  0.001887
min       0.012000          1.000000          6.000000  0.990070
25%      0.070000          7.000000          22.000000  0.995600
50%      0.079000          14.000000          38.000000  0.996750
75%      0.090000          21.000000          62.000000  0.997835
max      0.611000          72.000000          289.000000 1.003690

```

	pH	sulphates	alcohol	quality
count	1599.000000	1599.000000	1599.000000	1599.000000
mean	3.311113	0.658149	10.422983	5.636023
std	0.154386	0.169507	1.065668	0.807569
min	2.740000	0.330000	8.400000	3.000000
25%	3.210000	0.550000	9.500000	5.000000
50%	3.310000	0.620000	10.200000	6.000000
75%	3.400000	0.730000	11.100000	6.000000
max	4.010000	2.000000	14.900000	8.000000

## 2 Finding Null Values

```
[8]: wine.isnull().sum()
```

```

[8]: fixed acidity      0
      volatile acidity   0
      citric acid        0
      residual sugar     0
      chlorides           0
      free sulfur dioxide 0
      total sulfur dioxide 0
      density              0
      pH                  0
      sulphates            0
      alcohol               0
      quality                0
      dtype: int64

```

```
[9]: wine.groupby('quality').mean()
```

```

[9]:      fixed acidity  volatile acidity  citric acid  residual sugar \
quality
3          8.360000      0.884500      0.171000      2.635000
4         7.779245      0.693962      0.174151      2.694340
5         8.167254      0.577041      0.243686      2.528855
6         8.347179      0.497484      0.273824      2.477194
7         8.872362      0.403920      0.375176      2.720603

```

```

8           8.566667      0.423333     0.391111      2.577778

      chlorides  free sulfur dioxide  total sulfur dioxide  density \
quality
3          0.122500        11.000000       24.900000   0.997464
4          0.090679        12.264151       36.245283   0.996542
5          0.092736        16.983847       56.513950   0.997104
6          0.084956        15.711599       40.869906   0.996615
7          0.076588        14.045226       35.020101   0.996104
8          0.068444        13.277778       33.444444   0.995212

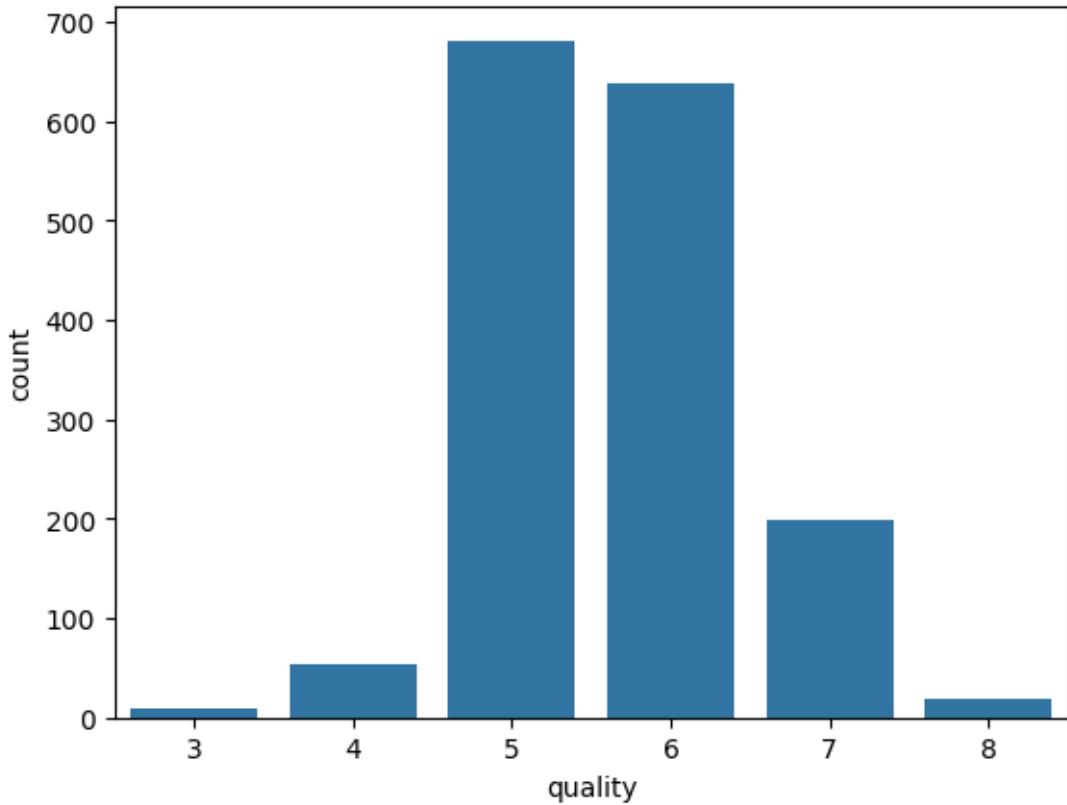
      pH  sulphates    alcohol
quality
3      3.398000  0.570000  9.955000
4      3.381509  0.596415 10.265094
5      3.304949  0.620969  9.899706
6      3.318072  0.675329 10.629519
7      3.290754  0.741256 11.465913
8      3.267222  0.767778 12.094444

```

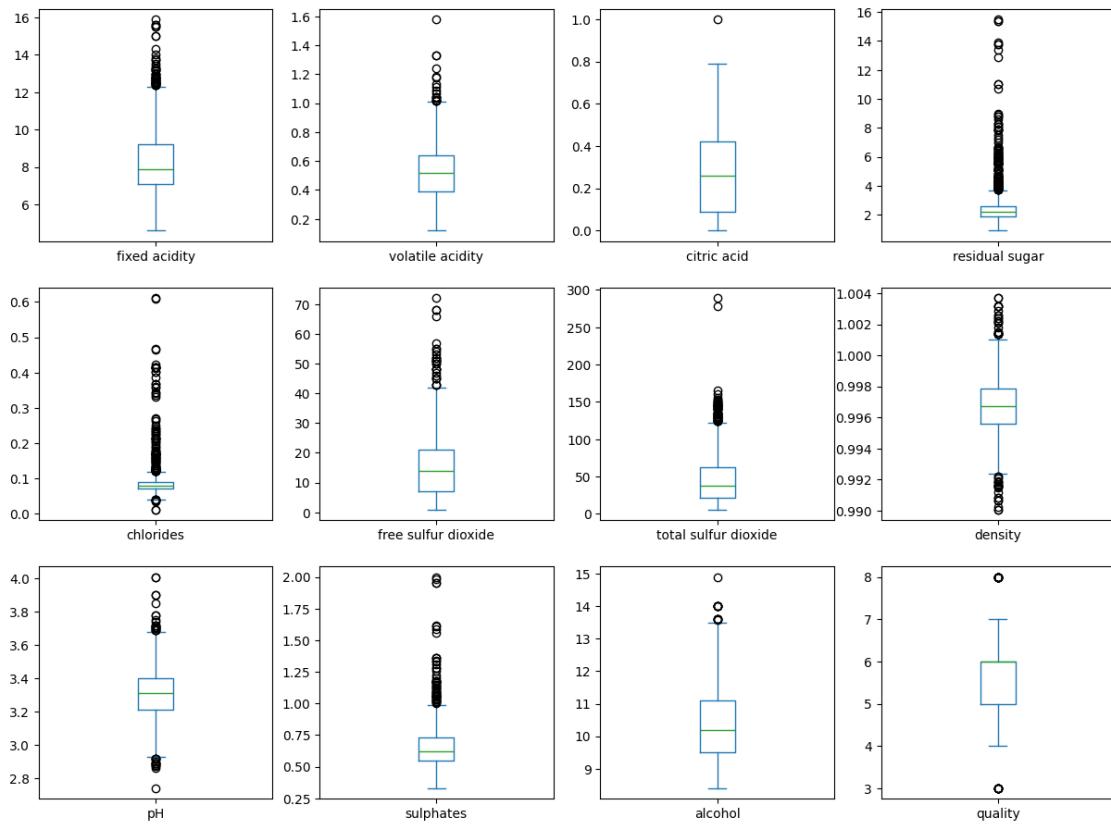
### 3 Data Analysis

#### 4 Countplot:

```
[10]: # Assuming 'wine' is your DataFrame
sns.countplot(data=wine, x='quality')
plt.show()
```

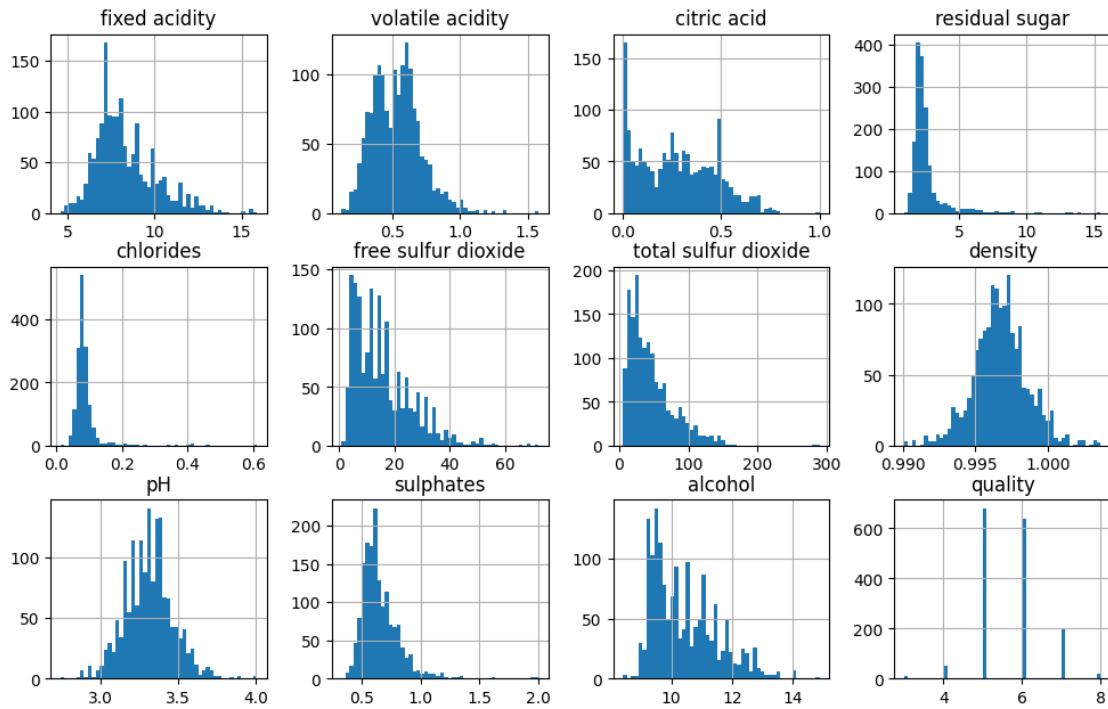


```
[11]: # Assuming 'wine' is your DataFrame
wine.plot(kind='box', subplots=True, layout=(4, 4), sharex=False, figsize=(15, 15))
plt.show()
```



## 5 Histogram

```
[12]: wine.hist(figsize=(12, 10), bins=50, layout=(4, 4))
plt.show()
```



## 6 Histplot

```
[13]: fig, axes = plt.subplots(3, 4, figsize=(60, 40))

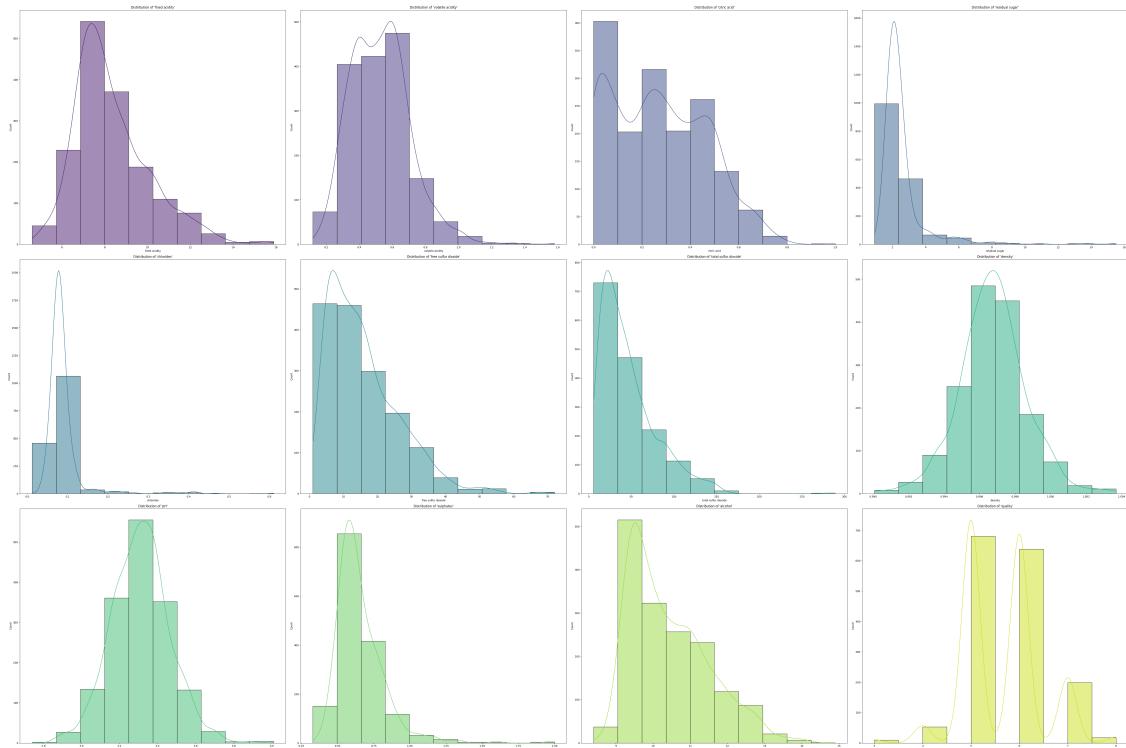
# List of features for iteration
features = ["fixed acidity", "volatile acidity", "citric acid", "residual sugar",
            "chlorides", "free sulfur dioxide", "total sulfur dioxide", "density",
            "pH", "sulphates", "alcohol", "quality"]

# Iterate over features and corresponding axes
for i, feature in enumerate(features):
    row, col = divmod(i, 4)

    # Set color dynamically based on the feature
    color = sns.color_palette("viridis", n_colors=len(features))[i]

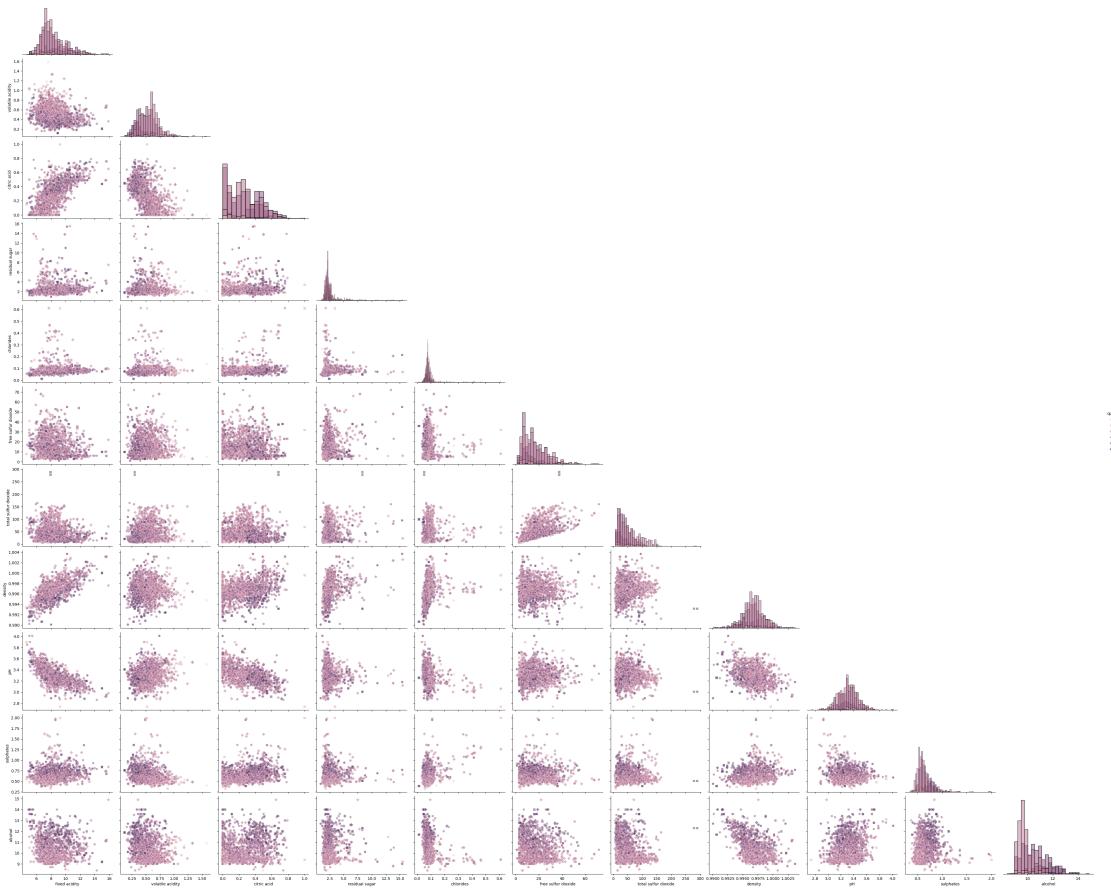
    # Create histograms
    sns.histplot(ax=axes[row, col], x=wine[feature], bins=10, kde=True, cbar=True, color=color)
    axes[row, col].set(title=f"Distribution of '{feature}'")
```

```
plt.tight_layout()
plt.show()
```



## 7 Pairplot

```
[14]: sns.pairplot(wine,
                  diag_kind="hist",
                  hue="quality",
                  height=3,
                  aspect=1.2,
                  corner=True,
                  markers=["o", "s", "D"], # Specify markers for each quality level
                  plot_kws={"alpha": 0.5} # Adjust transparency for better visibility
                 );
```



## 8 Scatterplot

```
[15]: fig, axes = plt.subplots(2, 3, figsize=(15, 10))
axes = axes.flatten()

# Relationship between 'residual_sugar' and 'quality'
sns.scatterplot(x="residual sugar", y="quality", hue="quality", data=wine, ax=axes[0])
axes[0].set_title("Relationship: 'Residual Sugar' vs 'Quality'")

# Relationship between 'alcohol' and 'quality'
sns.scatterplot(x="alcohol", y="quality", hue="quality", data=wine, ax=axes[1])
axes[1].set_title("Relationship: 'Alcohol' vs 'Quality'")

# Relationship between 'pH' and 'quality'
sns.scatterplot(x="pH", y="quality", hue="quality", data=wine, ax=axes[2])
axes[2].set_title("Relationship: 'pH' vs 'Quality'")
```

```

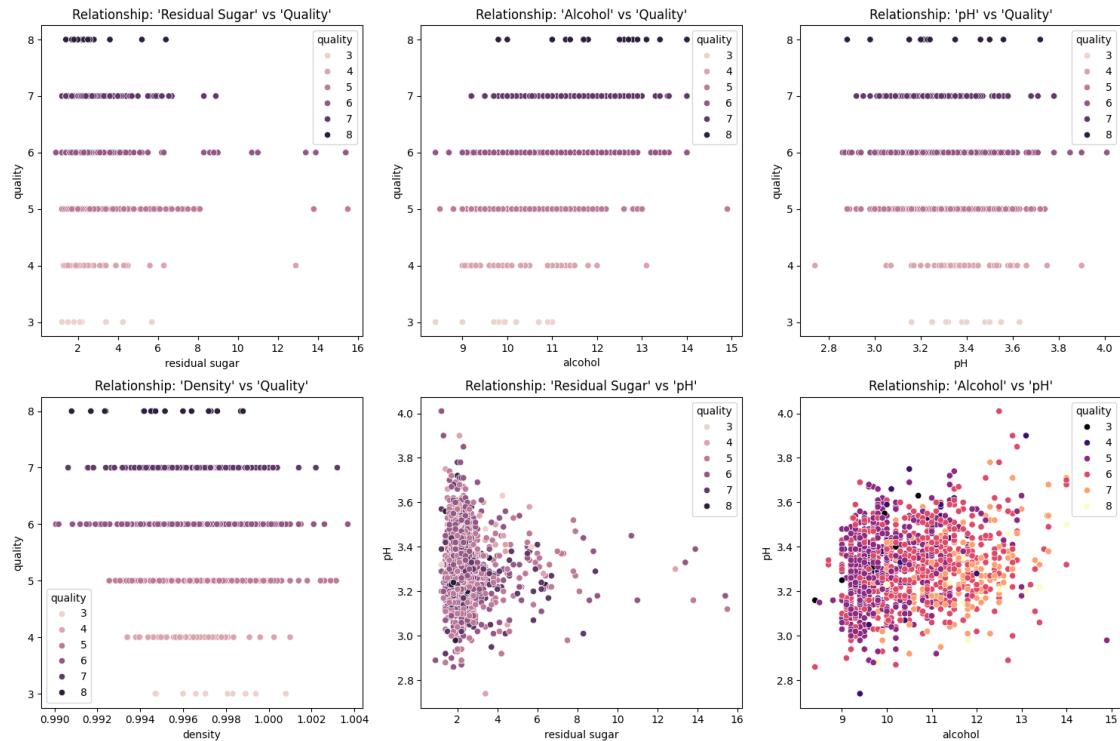
# Relationship between 'density' and 'quality'
sns.scatterplot(x="density", y="quality", hue="quality", data=wine, ax=axes[3])
axes[3].set_title("Relationship: 'Density' vs 'Quality'")

# Relationship between 'residual_sugar' and 'pH'
sns.scatterplot(x="residual sugar", y="pH", hue="quality", data=wine, ax=axes[4])
axes[4].set_title("Relationship: 'Residual Sugar' vs 'pH'")

# Relationship between 'alcohol' and 'pH'
sns.scatterplot(x="alcohol", y="pH", hue="quality", palette="magma", data=wine, ax=axes[5])
axes[5].set_title("Relationship: 'Alcohol' vs 'pH'")

plt.tight_layout()
plt.show()

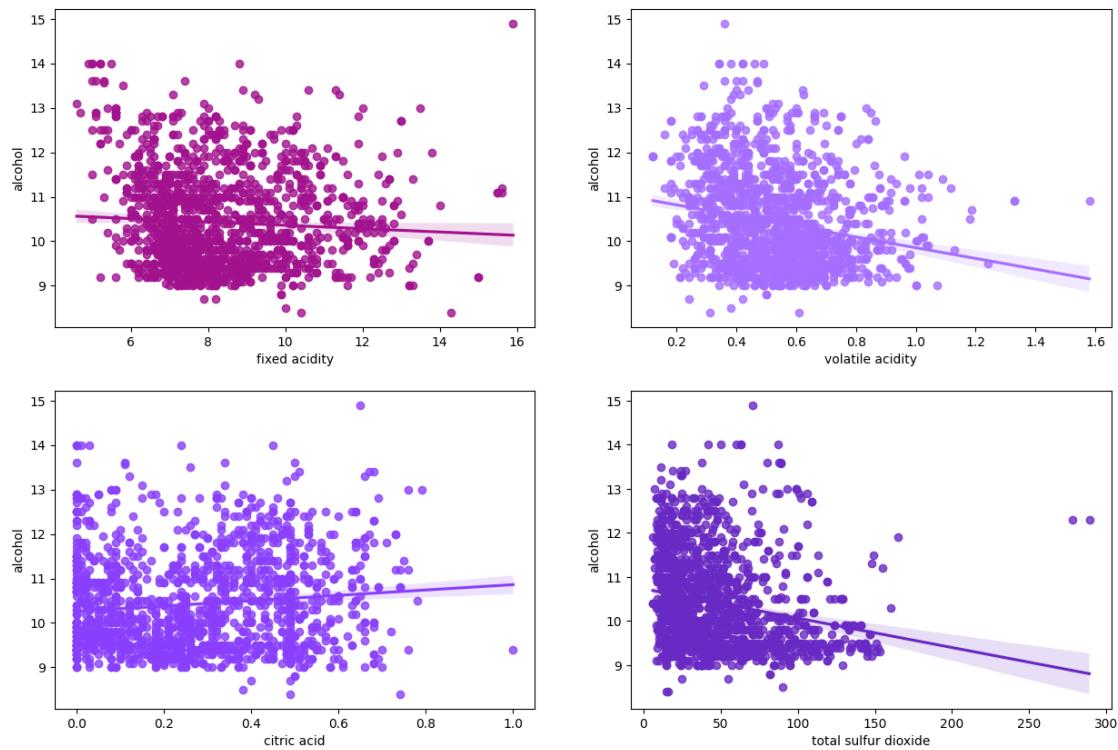
```



## 9 Regplot

```
[16]: fig, axes = plt.subplots(2, 2, figsize = (15, 10))
axes = axes.flatten()

sns.regplot(ax = axes[0], x = "fixed acidity", y = "alcohol", data = wine, color = "#A2128E");
sns.regplot(ax = axes[1], x = "volatile acidity", y = "alcohol", data = wine, color = "#A56EFF");
sns.regplot(ax = axes[2], x = "citric acid", y = "alcohol", data = wine, color = "#8A3FFC");
sns.regplot(ax = axes[3], x = "total sulfur dioxide", y = "alcohol", data = wine, color = "#6929C4");
```



## 10 Hexagonal Binned Plot

```
[17]: fig, ([ax0, ax1], [ax2, ax3]) = plt.subplots(nrows = 2, ncols = 2, figsize = (17, 10))

hb = ax0.hexbin(wine["sulphates"], wine["quality"], gridsize = 30, cmap = 'Purples_r')
ax0.set_title("Hexagon binning")
```

```

cb = fig.colorbar(hb, ax = ax0, label = 'counts')

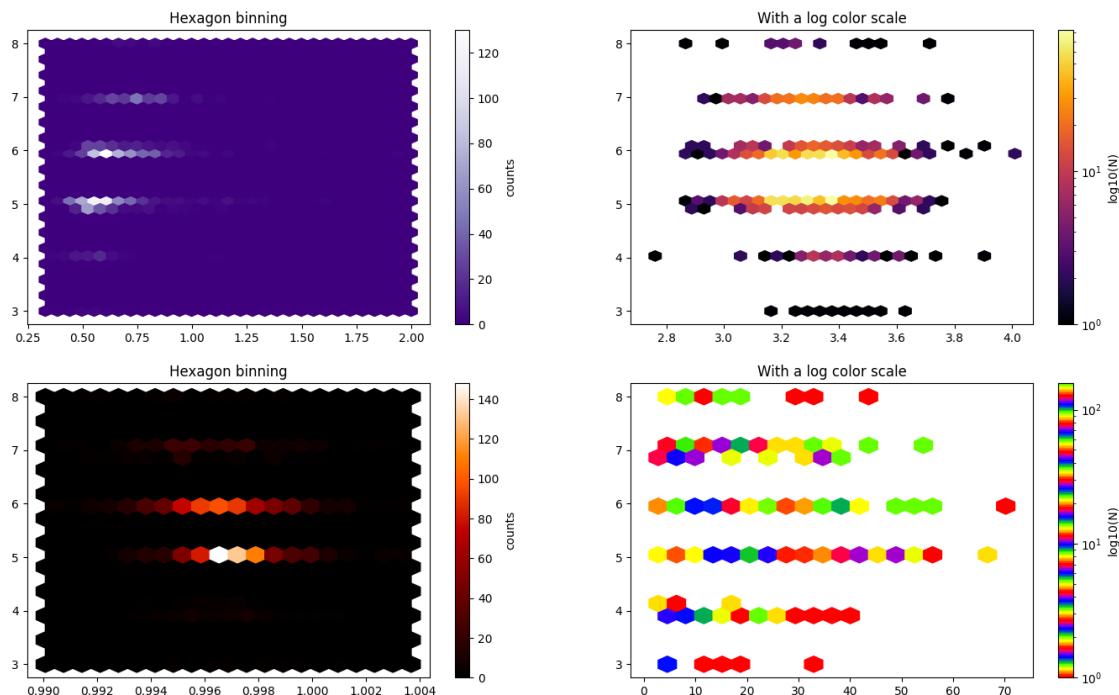
hb = ax1.hexbin(wine["pH"], wine["quality"], gridsize = 30, bins = 'log', cmap= 'inferno')
ax1.set_title("With a log color scale")
cb = fig.colorbar(hb, ax = ax1, label = 'log10(N)')

hb = ax2.hexbin(wine["density"], wine["quality"], gridsize = 20, cmap = 'gist_heat')
ax2.set_title("Hexagon binning")
cb = fig.colorbar(hb, ax = ax2, label = 'counts')

hb = ax3.hexbin(wine["free sulfur dioxide"], wine["quality"], gridsize = 20,bins = 'log',
                 cmap = 'prism')
ax3.set_title("With a log color scale")
cb = fig.colorbar(hb, ax = ax3, label = 'log10(N)')

plt.show()

```



# 11 Visualization with Plotly Express

## 11.0.1 Overview

Reference: <https://plotly.com/python/plotly-express/>

The `plotly.express` module contains functions that can create entire figures at once, and is referred to as Plotly Express or PX. Plotly Express is a built-in part of the `plotly` library, and is the recommended starting point for creating most common figures. Every Plotly Express function uses graph objects internally and returns a `plotly.graph_objects.Figure` instance. Throughout the `plotly` documentation, you will find the Plotly Express way of building figures at the top of any applicable page, followed by a section on how to use graph objects to build similar figures. Any figure created in a single function call with Plotly Express could be created using graph objects alone, but with between 5 and 100 times more code.

Plotly Express provides more than 30 functions for creating different types of figures. The API for these functions was carefully designed to be as consistent and easy to learn as possible, making it easy to switch from a scatter plot to a bar chart to a histogram to a sunburst chart throughout a data exploration session.

```
[18]: purple = ['#491D8B', '#6929C4', '#8A3FFC', '#A56EFF',
               '#BE95FF', '#CA96EC', '#A163CF', '#29066B',
               '#7D3AC1', '#AF4BCE', '#DB4CB2', '#EB548C',
               '#EC96E0', '#A2128E', '#E8D9F3', '#641811']

sns.palplot(purple, size = 2)
```



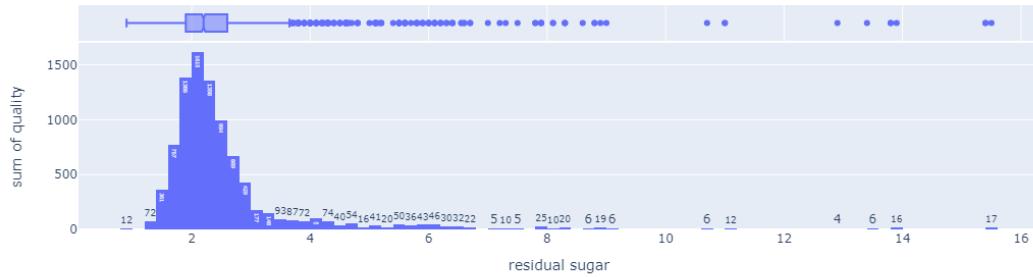
```
[19]: !pip install plotly pandas
```

```
Requirement already satisfied: plotly in d:\python 3.8\lib\site-packages
(5.18.0)
Requirement already satisfied: pandas in d:\python 3.8\lib\site-packages (2.0.3)
Requirement already satisfied: tenacity>=6.2.0 in d:\python 3.8\lib\site-
packages (from plotly) (8.2.3)
Requirement already satisfied: packaging in d:\python 3.8\lib\site-packages
(from plotly) (23.2)
Requirement already satisfied: python-dateutil>=2.8.2 in d:\python 3.8\lib\site-
packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in d:\python 3.8\lib\site-packages
(from pandas) (2024.1)
Requirement already satisfied: tzdata>=2022.1 in d:\python 3.8\lib\site-packages
(from pandas) (2023.4)
Requirement already satisfied: numpy>=1.20.3 in d:\python 3.8\lib\site-packages
(from pandas) (1.24.4)
```

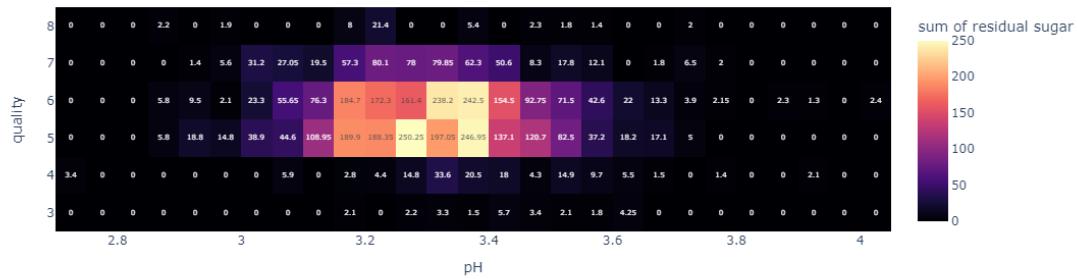
Requirement already satisfied: six>=1.5 in d:\python 3.8\lib\site-packages (from python-dateutil>=2.8.2->pandas) (1.16.0)

```
[20]: import plotly.express as px  
import pandas as pd
```

```
[21]: fig = px.histogram(wine, x = "residual sugar", y = "quality", marginal = "box",  
                      color = None, text_auto = True, hover_data = wine.columns)  
fig.show()
```



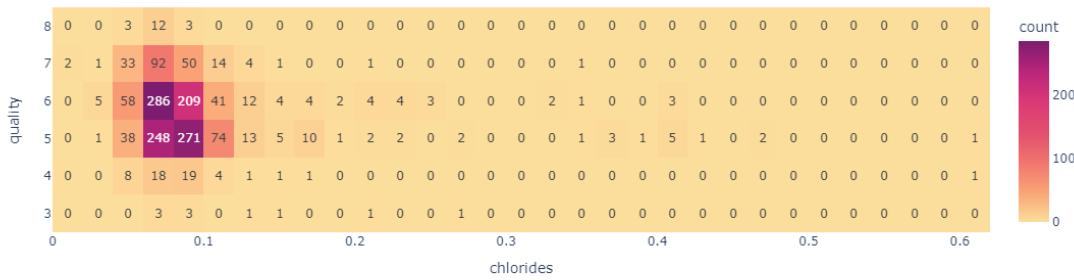
```
[22]: fig = px.density_heatmap(wine, x = "pH", y = "quality", z = "residual sugar",  
                           color_continuous_scale = "magma", text_auto = True)  
fig.show()
```



```
[23]: fig = px.density_heatmap(wine, x = "density", y = "quality", z = "chlorides",  
                           color_continuous_scale = "Viridis", text_auto = True)  
fig.show()
```



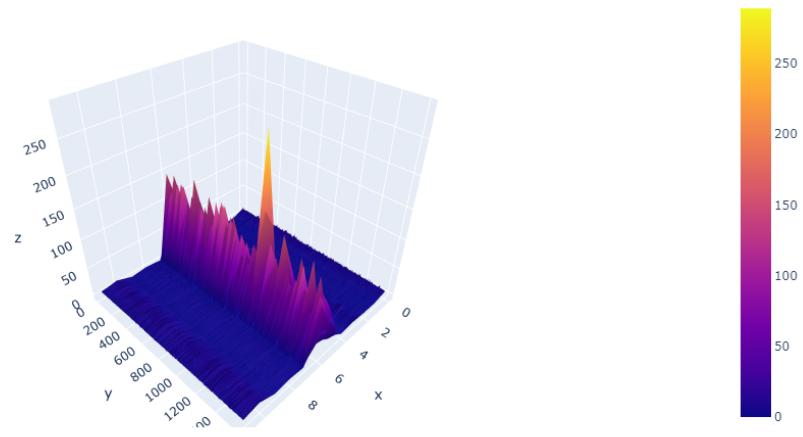
```
[24]: fig = px.density_heatmap(wine, x = "chlorides", y = "quality", text_auto = True,
                               color_continuous_scale = "sunsetdark")
      fig.show()
```



```
[25]: import plotly.graph_objects as go
```

```
[26]: data = wine
fig = go.Figure(data = [go.Surface(z = data.values)])
fig.update_layout(autosize = True, width = 600, height = 600)

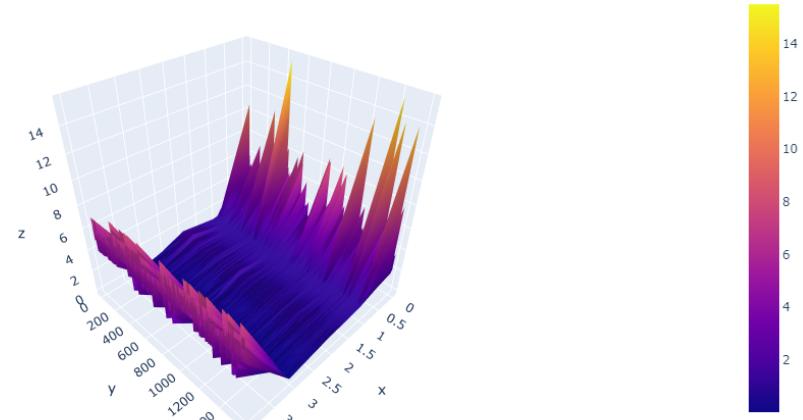
fig.show()
```



```
[27]: data = wine[["residual sugar", "density", "sulphates", "chlorides", "quality"]]

fig = go.Figure(data = [go.Surface(z = data.values)])
fig.update_layout(autosize = True, width = 600, height = 600)

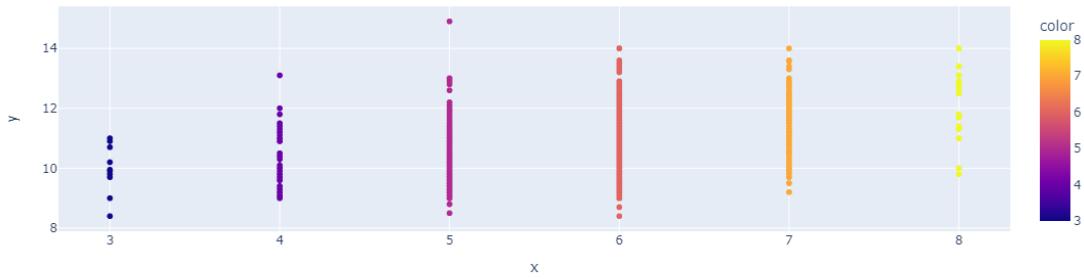
fig.show()
```



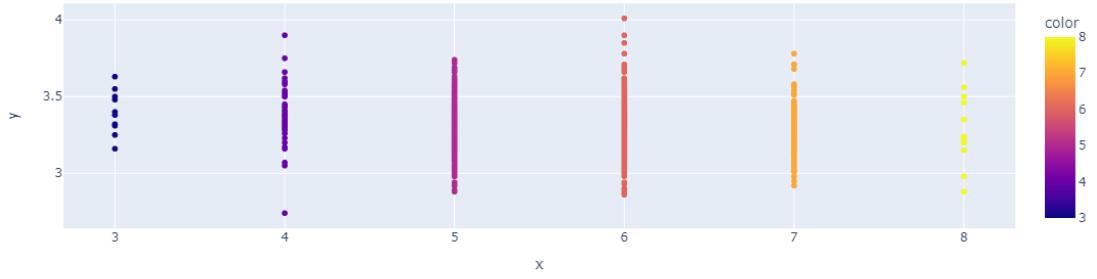
```
[39]: !pip install plotly  
import plotly.io as pio
```

Requirement already satisfied: plotly in d:\python 3.8\lib\site-packages (5.18.0)  
Requirement already satisfied: tenacity>=6.2.0 in d:\python 3.8\lib\site-packages (from plotly) (8.2.3)  
Requirement already satisfied: packaging in d:\python 3.8\lib\site-packages (from plotly) (23.2)

```
[42]: import plotly.express as px  
  
subject = wine["quality"]  
score = wine["alcohol"]  
  
fig = px.scatter(x=subject, y=score, color=subject)  
fig.show()
```



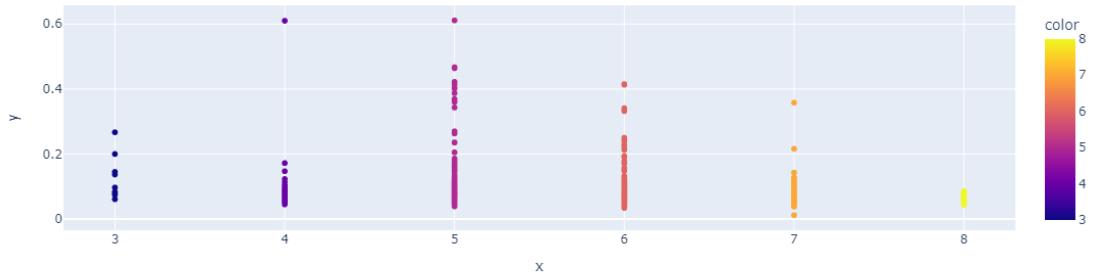
```
[43]: import plotly.express as px  
  
subject = wine["quality"]  
score = wine["pH"]  
  
fig = px.scatter(x=subject, y=score, color=subject)  
fig.show()
```



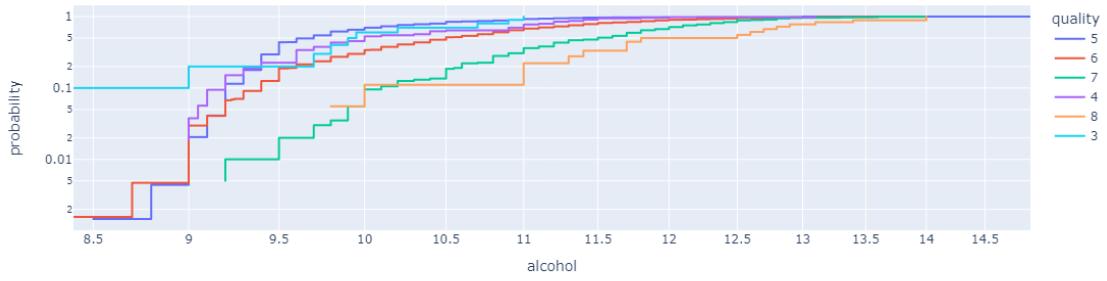
```
[44]: import plotly.express as px

subject = wine["quality"]
score = wine["chlorides"]

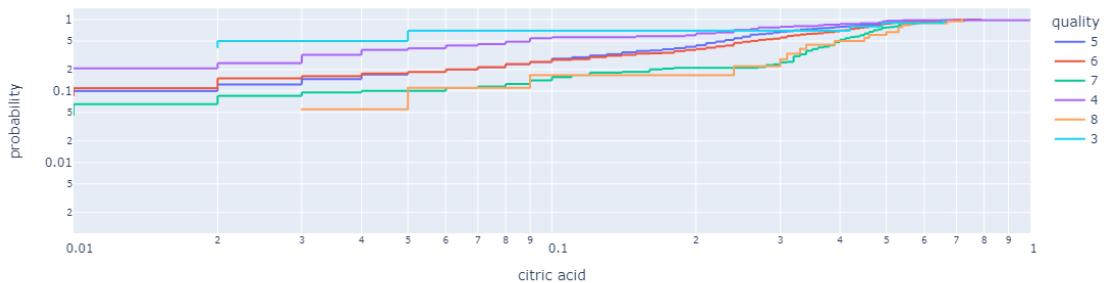
fig = px.scatter(x=subject, y=score, color=subject)
fig.show()
```



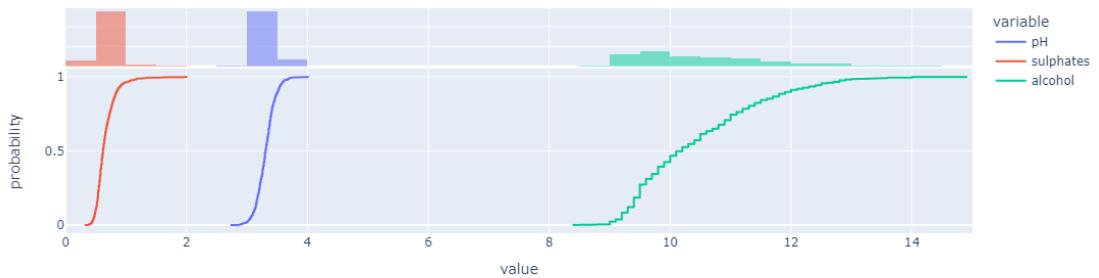
```
[36]: fig = px.ecdf(wine, x = "alcohol", log_x = True, log_y = True, color = wine["quality"])
fig.show()
```



```
[37]: fig = px.ecdf(wine, x = "citric acid", log_x = True, log_y = True, color = "quality")
fig.show()
```



```
[38]: fig = px.ecdf(wine, x = ["pH", "sulphates", "alcohol"],
                    marginal = "histogram", markers = False)
fig.show()
```



## 5.8 |Heatmap and Correlation

### 11.0.2 Correlation and Causation

Reference: <https://www.abs.gov.au/websitedbs/D3310114.nsf/home/statistical+language+-+correlation+and+causation>

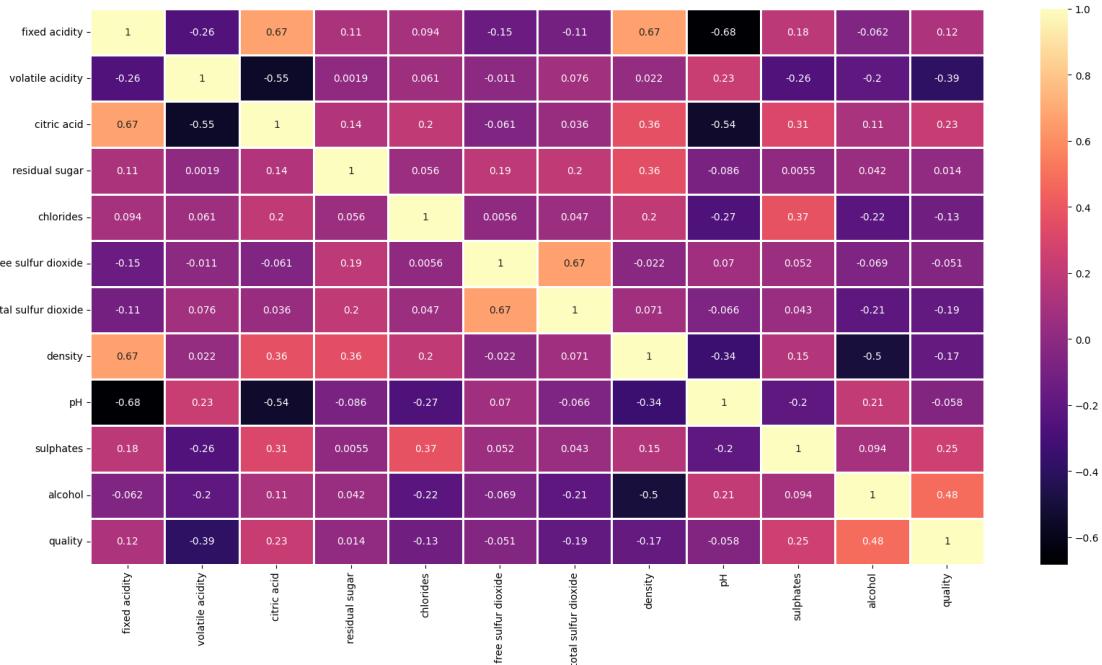
Two or more variables considered to be related, in a statistical context, if their values change so that as the value of one variable increases or decreases so does the value of the other variable (although it may be in the opposite direction). For example, for the two variables “hours worked” and “income earned” there is a relationship between the two if the increase in hours worked is associated with an increase in income earned. If we consider the two variables “price” and “purchasing power”, as the price of goods increases a person’s ability to buy these goods decreases (assuming a constant income).

Correlation is a statistical measure (expressed as a number) that describes the size and direction of a relationship between two or more variables. A correlation between variables, however, does not automatically mean that the change in one variable is the cause of the change in the values of the other variable.

Causation indicates that one event is the result of the occurrence of the other event; i.e. there is a causal relationship between the two events. This is also referred to as cause and effect.

Theoretically, the difference between the two types of relationships are easy to identify — an action or occurrence can cause another (e.g. smoking causes an increase in the risk of developing lung cancer), or it can correlate with another (e.g. smoking is correlated with alcoholism, but it does not cause alcoholism). In practice, however, it remains difficult to clearly establish cause and effect, compared with establishing correlation.

```
[46]: plt.figure(figsize = [20, 10], facecolor = 'white')
sns.heatmap(wine.corr(), annot = True, linewidths = 2, cmap = "magma");
```



## Correlation

**IMPORTANT NOTE!** There is ‘multicollinearity’ problem

Here we see that there is relatively high (0.67, positive) correlation between ‘free sulfur dioxide’ and ‘total\_sulfur\_dioxide’ variables. There is relatively high (-0.68, negative) correlation between “pH” and “fixed\_acidity” variables. And there is about 0.5 correlation between some of other variables. That’s why we must consider when build Machine Learning models.

```
[48]: list = (wine[["alcohol","density"]].corr(), wine[["fixed acidity","pH"]].corr(),
             wine[["citric acid","pH"]].corr(), wine[["fixed acidity","density"]].
             corr(),
             wine[["free sulfur dioxide","total sulfur dioxide"]].corr())
for corr in list:
    print(corr, "\n\n")
```

	alcohol	density
alcohol	1.00000	-0.49618
density	-0.49618	1.00000

	fixed acidity	pH
fixed acidity	1.000000	-0.682978
pH	-0.682978	1.000000

	citric acid	pH
citric acid	1.000000	-0.541904
pH	-0.541904	1.000000

	fixed acidity	density
fixed acidity	1.000000	0.668047
density	0.668047	1.000000

	free sulfur dioxide	total sulfur dioxide
free sulfur dioxide	1.000000	0.667666
total sulfur dioxide	0.667666	1.000000

In the code blocks below we will look at the Pearson correlation coefficient between some variables

```
[49]: !pip install scipy pandas
```

Requirement already satisfied: scipy in d:\python 3.8\lib\site-packages (1.10.1)

```
Requirement already satisfied: pandas in d:\python 3.8\lib\site-packages (2.0.3)
Requirement already satisfied: numpy<1.27.0,>=1.19.5 in d:\python 3.8\lib\site-
packages (from scipy) (1.24.4)
Requirement already satisfied: python-dateutil>=2.8.2 in d:\python 3.8\lib\site-
packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in d:\python 3.8\lib\site-packages
(from pandas) (2024.1)
Requirement already satisfied: tzdata>=2022.1 in d:\python 3.8\lib\site-packages
(from pandas) (2023.4)
Requirement already satisfied: six>=1.5 in d:\python 3.8\lib\site-packages (from
python-dateutil>=2.8.2->pandas) (1.16.0)
```

```
[50]: import scipy.stats as st
```

```
[51]: print("Pearson correlation coefficient:", st.pearsonr(wine["alcohol"], wine["density"]))
```

Pearson correlation coefficient: PearsonRResult(statistic=-0.4961797702417019, pvalue=3.9388353399870764e-100)

```
[52]: print("Pearson correlation coefficient:", st.pearsonr(wine["free sulfur dioxide"], wine["total sulfur dioxide"]))
```

Pearson correlation coefficient: PearsonRResult(statistic=0.6676664504810215, pvalue=6.404722954681174e-207)

Pearson correlation coefficient: PearsonRResult(statistic=-0.6829781945685319, pvalue=4.063034039841015e-220)

```
[54]: print("Pearson correlation coefficient:", st.pearsonr(wine["citric acid"], wine["pH"]))
```

Pearson correlation coefficient: PearsonRResult(statistic=-0.5419041447395099, pvalue=1.007201325911255e-122)

```
[55]: print("Pearson correlation coefficient:", st.pearsonr(wine["fixed acidity"], wine["density"]))
```

Pearson correlation coefficient: PearsonRResult(statistic=0.6680472921189741, pvalue=3.0747470608584777e-207)

## 12 Feature Selection

```
[56]: wine.sample(5)
```

```
[56]:    fixed acidity  volatile acidity  citric acid  residual sugar  chlorides \
500           7.8          0.52          0.25           1.9       0.081
1099          8.6          0.52          0.38           1.5       0.096
24            6.9          0.40          0.14           2.4       0.085
365           10.0          0.42          0.50           3.4       0.107
18             7.4          0.59          0.08           4.4       0.086

      free sulfur dioxide  total sulfur dioxide  density     pH  sulphates \
500                  14.0          38.0  0.99840  3.43       0.65
1099                 5.0          18.0  0.99666  3.20       0.52
24                   21.0          40.0  0.99680  3.43       0.63
365                  7.0          21.0  0.99790  3.26       0.93
18                   6.0          29.0  0.99740  3.38       0.50

      alcohol   quality
500        9.0       6
1099       9.4       5
24          9.7       6
365       11.8       6
18          9.0       4
```

```
[57]: wine['quality'].unique()
```

```
[57]: array([5, 6, 7, 4, 8, 3], dtype=int64)
```

```
[58]: # If wine quality is 7 or above then will consider as good quality wine
wine['goodquality'] = [1 if x >= 7 else 0 for x in wine['quality']]
wine.sample(5)
```

```
[58]:    fixed acidity  volatile acidity  citric acid  residual sugar  chlorides \
1198           7.7          0.260          0.26           2.0       0.052
109            8.1          0.785          0.52           2.0       0.122
487            10.2          0.645          0.36           1.8       0.053
1565           6.7          0.670          0.02           1.9       0.061
625             6.8          0.690          0.00           5.6       0.124

      free sulfur dioxide  total sulfur dioxide  density     pH  sulphates \
1198                  19.0          77.0  0.99510  3.15       0.79
109                   37.0          153.0  0.99690  3.21       0.69
487                   5.0          14.0  0.99820  3.17       0.42
1565                  26.0          42.0  0.99489  3.39       0.82
625                   21.0          58.0  0.99970  3.46       0.72
```

```

alcohol    quality   goodquality
1198      10.9       6           0
109       9.3        5           0
487       10.0       6           0
1565      10.9       6           0
625       10.2       5           0

```

[59]: # See total number of good vs bad wines samples  
`wine['goodquality'].value_counts()`

[59]: goodquality  
0 1382  
1 217  
Name: count, dtype: int64

[60]: # Separate dependent and independent variables  
`X = wine.drop(['quality', 'goodquality'], axis = 1)`  
`Y = wine['goodquality']`

[61]: X

[61]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	\
0	7.4	0.700	0.00	1.9	0.076	
1	7.8	0.880	0.00	2.6	0.098	
2	7.8	0.760	0.04	2.3	0.092	
3	11.2	0.280	0.56	1.9	0.075	
4	7.4	0.700	0.00	1.9	0.076	
...	...	...	...	...	...	
1594	6.2	0.600	0.08	2.0	0.090	
1595	5.9	0.550	0.10	2.2	0.062	
1596	6.3	0.510	0.13	2.3	0.076	
1597	5.9	0.645	0.12	2.0	0.075	
1598	6.0	0.310	0.47	3.6	0.067	
	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	\
0	11.0	34.0	0.99780	3.51	0.56	
1	25.0	67.0	0.99680	3.20	0.68	
2	15.0	54.0	0.99700	3.26	0.65	
3	17.0	60.0	0.99800	3.16	0.58	
4	11.0	34.0	0.99780	3.51	0.56	
...	...	...	...	...	...	
1594	32.0	44.0	0.99490	3.45	0.58	
1595	39.0	51.0	0.99512	3.52	0.76	
1596	29.0	40.0	0.99574	3.42	0.75	
1597	32.0	44.0	0.99547	3.57	0.71	
1598	18.0	42.0	0.99549	3.39	0.66	

```
alcohol
0      9.4
1      9.8
2      9.8
3      9.8
4      9.4
...
1594    10.5
1595    11.2
1596    11.0
1597    10.2
1598    11.0
```

[1599 rows x 11 columns]

```
[62]: print(Y)
```

```
0      0
1      0
2      0
3      0
4      0
...
1594    0
1595    0
1596    0
1597    0
1598    0
Name: goodquality, Length: 1599, dtype: int64
```

## 13 Feature Importance

```
[63]: from sklearn.ensemble import ExtraTreesClassifier
classifiern = ExtraTreesClassifier()
classifiern.fit(X,Y)
score = classifiern.feature_importances_
print(score)
```

```
[0.07504659 0.10451426 0.09082463 0.07550917 0.06635143 0.06800035
 0.08268497 0.08175961 0.0680887 0.10957794 0.17764234]
```

## 14 Splitting Dataset

```
[64]: from sklearn.model_selection import train_test_split  
X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size=0.  
         ↪3,random_state=7)
```

## 15 Result

```
[65]: model_res=pd.DataFrame(columns=['Model', 'Score'])
```

## 16 LogisticRegression:

```
[66]: from sklearn.linear_model import LogisticRegression  
model = LogisticRegression()  
model.fit(X_train,Y_train)  
y_pred = model.predict(X_test)  
  
from sklearn.metrics import accuracy_score,confusion_matrix  
# accuracy_score(Y_test,Y_pred)  
model_res.loc[len(model_res)] = ['LogisticRegression',  
         ↪accuracy_score(Y_test,y_pred)]  
model_res
```

```
[66]:
```

	Model	Score
0	LogisticRegression	0.872917

## 17 Using KNN:

```
[67]: from sklearn.neighbors import KNeighborsClassifier  
model = KNeighborsClassifier(n_neighbors=3)  
model.fit(X_train,Y_train)  
y_pred = model.predict(X_test)  
  
from sklearn.metrics import accuracy_score  
model_res.loc[len(model_res)] = ['KNeighborsClassifier',  
         ↪accuracy_score(Y_test,y_pred)]  
model_res
```

```
[67]:
```

	Model	Score
0	LogisticRegression	0.872917
1	KNeighborsClassifier	0.872917

## Using SVC:

```
[68]: from sklearn.svm import SVC
model = SVC()
model.fit(X_train,Y_train)
y_pred = model.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred))
model_res.loc[len(model_res)] = ['SVC', accuracy_score(Y_test,y_pred)]
model_res
```

Accuracy Score: 0.86875

```
[68]:          Model      Score
0    LogisticRegression  0.872917
1   KNeighborsClassifier  0.872917
2                 SVC  0.868750
```

## 18 Using Decision Tree:

```
[69]: from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier(criterion='entropy',random_state=7)
model.fit(X_train,Y_train)
y_pred = model.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred))
model_res.loc[len(model_res)] = ['DecisionTreeClassifier',accuracy_score(Y_test,y_pred)]
model_res
```

Accuracy Score: 0.8645833333333334

```
[69]:          Model      Score
0    LogisticRegression  0.872917
1   KNeighborsClassifier  0.872917
2                 SVC  0.868750
3  DecisionTreeClassifier  0.864583
```

## 19 Using GaussianNB:

```
[70]: from sklearn.naive_bayes import GaussianNB
model3 = GaussianNB()
model3.fit(X_train,Y_train)
y_pred = model3.predict(X_test)
```

```

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred))
model_res.loc[len(model_res)] = ['GaussianNB', accuracy_score(Y_test,y_pred)]
model_res

```

Accuracy Score: 0.833333333333334

```
[70]:      Model      Score
0    LogisticRegression  0.872917
1   KNeighborsClassifier  0.872917
2             SVC  0.868750
3  DecisionTreeClassifier  0.864583
4        GaussianNB  0.833333
```

## 20 Using Random Forest:

```

[71]: from sklearn.ensemble import RandomForestClassifier
model2 = RandomForestClassifier(random_state=1)
model2.fit(X_train, Y_train)
y_pred = model2.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred))
model_res.loc[len(model_res)] = ['RandomForestClassifier',accuracy_score(Y_test,y_pred)]
model_res

```

Accuracy Score: 0.89375

```
[71]:      Model      Score
0    LogisticRegression  0.872917
1   KNeighborsClassifier  0.872917
2             SVC  0.868750
3  DecisionTreeClassifier  0.864583
4        GaussianNB  0.833333
5  RandomForestClassifier  0.893750
```

## 21 Using Xgboost:

```

[72]: import xgboost as xgb
model5 = xgb.XGBClassifier(random_state=1)
model5.fit(X_train, Y_train)
y_pred = model5.predict(X_test)

from sklearn.metrics import accuracy_score

```

```
print("Accuracy Score:",accuracy_score(Y_test,y_pred))
model_res.loc[len(model_res)] = ['XGBClassifier', accuracy_score(Y_test,y_pred)]
model_res
```

Accuracy Score: 0.8895833333333333

```
[72]:          Model      Score
0    LogisticRegression  0.872917
1   KNeighborsClassifier  0.872917
2            SVC  0.868750
3  DecisionTreeClassifier  0.864583
4       GaussianNB  0.833333
5 RandomForestClassifier  0.893750
6        XGBClassifier  0.889583
```

```
[73]: model_res = model_res.sort_values(by='Score', ascending=False)
model_res
```

```
[73]:          Model      Score
5  RandomForestClassifier  0.893750
6        XGBClassifier  0.889583
0    LogisticRegression  0.872917
1   KNeighborsClassifier  0.872917
2            SVC  0.868750
3  DecisionTreeClassifier  0.864583
4       GaussianNB  0.833333
```

```
[47]: subject = wine["quality"]
score = wine["alcohol"]

data = [dict(x = subject, y = score, mode = "markers", type = "scatter",
            transforms = [dict(type = "groupby", groups = subject)])]

fig_dict = dict(data = data)
pio.show(fig_dict, validate = False)
```

```
[48]: subject = wine["quality"]
score = wine["pH"]

data = [dict(x = subject, y = score, mode = "markers", type = "scatter",
            transforms = [dict(type = "groupby", groups = subject)])]

fig_dict = dict(data = data)
pio.show(fig_dict, validate = False)
```

```
[49]: subject = wine["quality"]
score = wine["chlorides"]
```

```

data = [dict(x = subject, y = score, mode = "markers", type = "scatter",
             transforms = [dict(type = "groupby", groups = subject)])]

fig_dict = dict(data = data)
pio.show(fig_dict, validate = False)

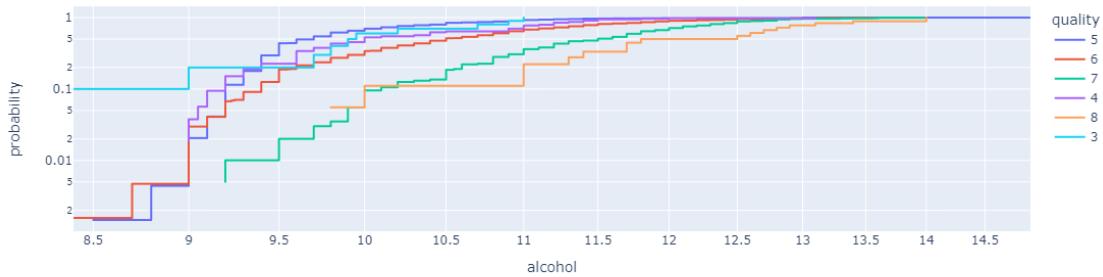
```

[51]:

```

fig = px.ecdf(wine, x = "alcohol", log_x = True, log_y = True, color = "quality")
fig.show()

```

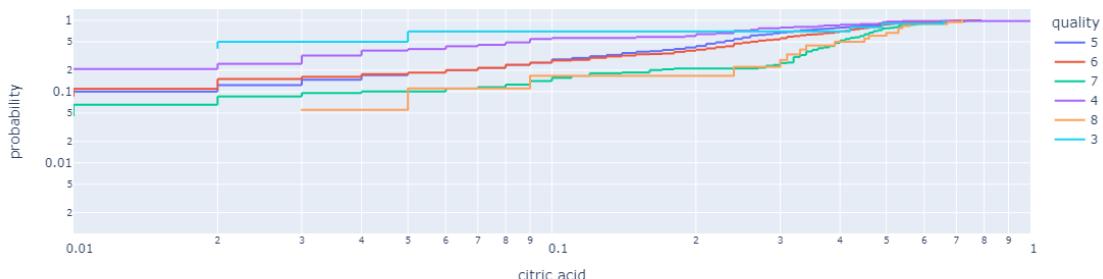


[52]:

```

fig = px.ecdf(wine, x = "citric acid", log_x = True, log_y = True, color = "quality")
fig.show()

```

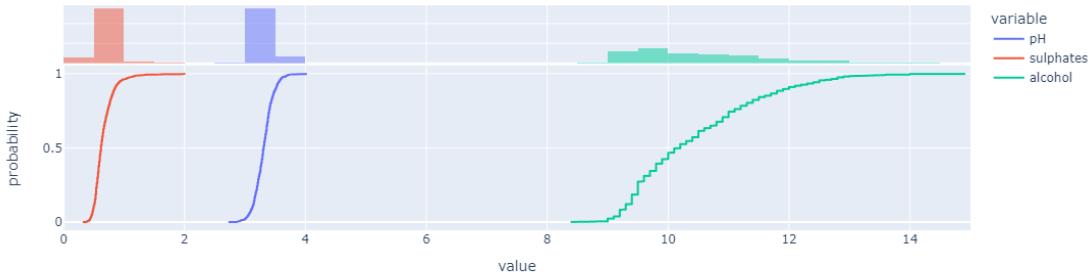


[53]:

```

fig = px.ecdf(wine, x = ["pH", "sulphates", "alcohol"],
               marginal = "histogram", markers = False)
fig.show()

```



## 22 Heatmap and Correlation

### 22.0.1 Correlation and Causation

Reference: <https://www.abs.gov.au/websitedbs/D3310114.nsf/home/statistical+language+-+correlation+and+causation>

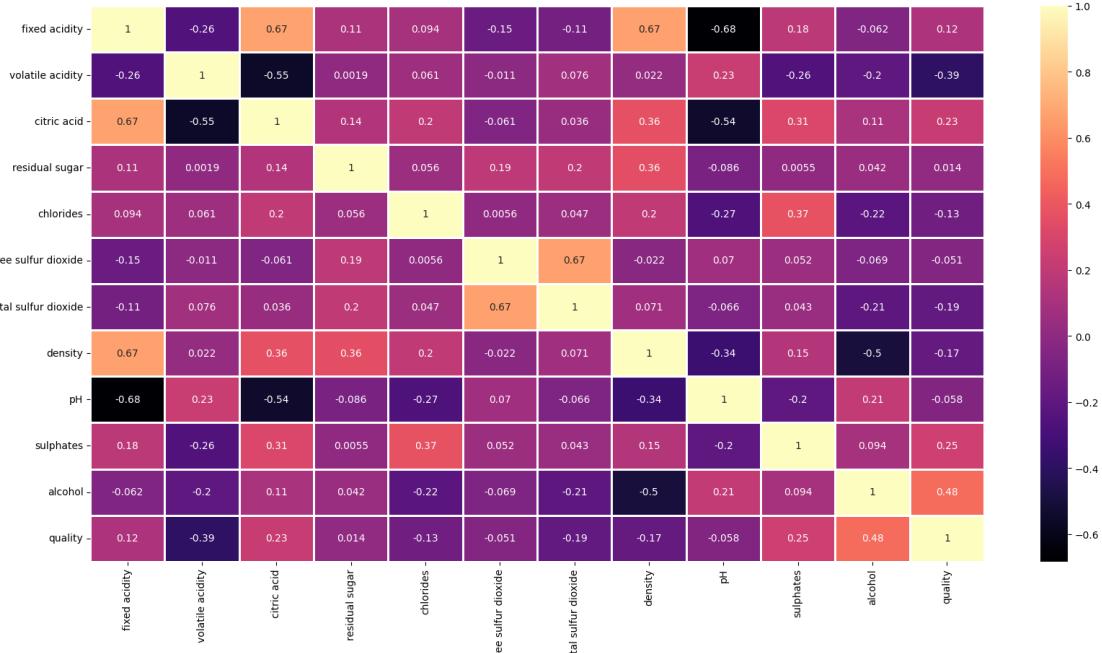
Two or more variables considered to be related, in a statistical context, if their values change so that as the value of one variable increases or decreases so does the value of the other variable (although it may be in the opposite direction). For example, for the two variables “hours worked” and “income earned” there is a relationship between the two if the increase in hours worked is associated with an increase in income earned. If we consider the two variables “price” and “purchasing power”, as the price of goods increases a person’s ability to buy these goods decreases (assuming a constant income).

Correlation is a statistical measure (expressed as a number) that describes the size and direction of a relationship between two or more variables. A correlation between variables, however, does not automatically mean that the change in one variable is the cause of the change in the values of the other variable.

Causation indicates that one event is the result of the occurrence of the other event; i.e. there is a causal relationship between the two events. This is also referred to as cause and effect.

Theoretically, the difference between the two types of relationships are easy to identify — an action or occurrence can cause another (e.g. smoking causes an increase in the risk of developing lung cancer), or it can correlate with another (e.g. smoking is correlated with alcoholism, but it does not cause alcoholism). In practice, however, it remains difficult to clearly establish cause and effect, compared with establishing correlation.

```
[55]: plt.figure(figsize = [20, 10], facecolor = 'white')
sns.heatmap(wine.corr(), annot = True, linewidths = 2, cmap = "magma");
```



## Correlation

**IMPORTANT NOTE!** There is ‘multicollinearity’ problem

Here we see that there is relatively high (0.67, positive) correlation between ‘free sulfur dioxide’ and ‘total\_sulfur\_dioxide’ variables. There is relatively high (-0.68, negative) correlation between “pH” and “fixed\_acidity” variables. And there is about 0.5 correlation between some of other variables. That’s why we must consider when build Machine Learning models.

```
[57]: list = (wine[["alcohol","density"]].corr(), wine[["fixed acidity","pH"]].corr(),
            wine[["citric acid","pH"]].corr(), wine[["fixed acidity","density"]].
            corr(),
            wine[["free sulfur dioxide","total sulfur dioxide"]].corr())
for corr in list:
    print(corr, "\n\n")

```

```

alcohol   density
alcohol  1.00000 -0.49618
density -0.49618  1.00000

```

```

fixed acidity      pH
fixed acidity      1.000000 -0.682978
pH                 -0.682978  1.000000

```

```
citric acid      pH
```

```

citric acid      1.000000 -0.541904
pH              -0.541904  1.000000

fixed acidity    density
fixed acidity     1.000000  0.668047
density          0.668047  1.000000

free sulfur dioxide total sulfur dioxide
free sulfur dioxide      1.000000      0.667666
total sulfur dioxide     0.667666      1.000000

```

In the code blocks below we will look at the Pearson correlation coefficient between some variables

[59]: `!pip install scipy pandas`

```

Requirement already satisfied: scipy in c:\python\lib\site-packages (1.12.0)
Requirement already satisfied: pandas in c:\python\lib\site-packages (2.2.0)
Requirement already satisfied: numpy<1.29.0,>=1.22.4 in c:\python\lib\site-
packages (from scipy) (1.26.3)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\python\lib\site-
packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in c:\python\lib\site-packages (from
pandas) (2023.4)
Requirement already satisfied: tzdata>=2022.7 in c:\python\lib\site-packages
(from pandas) (2023.4)
Requirement already satisfied: six>=1.5 in c:\python\lib\site-packages (from
python-dateutil>=2.8.2->pandas) (1.16.0)

```

[notice] A new release of pip is available: 23.2.1 -> 23.3.2  
[notice] To update, run: python.exe -m pip install --upgrade pip

[60]: `import scipy.stats as st`

[62]: `print("Pearson correlation coefficient:", st.pearsonr(wine["alcohol"],
wine["density"]))`

Pearson correlation coefficient: PearsonRResult(statistic=-0.4961797702417019,  
pvalue=3.9388353399870764e-100)

[64]: `print("Pearson correlation coefficient:", st.pearsonr(wine["free sulfur",
"density"]),
wine["total sulfur",
"density"]))`

```
Pearson correlation coefficient: PearsonRResult(statistic=0.6676664504810215,  
pvalue=6.404722954681174e-207)
```

```
[65]: print("Pearson correlation coefficient:", st.pearsonr(wine["fixed acidity"],  
wine["pH"]))
```

```
Pearson correlation coefficient: PearsonRResult(statistic=-0.6829781945685319,  
pvalue=4.063034039841015e-220)
```

```
[66]: print("Pearson correlation coefficient:", st.pearsonr(wine["citric acid"],  
wine["pH"]))
```

```
Pearson correlation coefficient: PearsonRResult(statistic=-0.5419041447395099,  
pvalue=1.007201325911255e-122)
```

```
[67]: print("Pearson correlation coefficient:", st.pearsonr(wine["fixed acidity"],  
wine["density"]))
```

```
Pearson correlation coefficient: PearsonRResult(statistic=0.6680472921189741,  
pvalue=3.0747470608584777e-207)
```

## 23 Feature Selection

```
[68]: wine.sample(5)
```

```
[68]:    fixed acidity  volatile acidity  citric acid  residual sugar  chlorides \
593           9.9            0.490       0.58          3.50      0.094
65            7.2            0.725       0.05          4.65      0.086
688           7.7            0.660       0.04          1.60      0.039
363          12.5            0.460       0.63          2.00      0.071
959           8.0            0.590       0.05          2.00      0.089

      free sulfur dioxide  total sulfur dioxide  density     pH  sulphates \
593                 9.0            43.0  1.00040   3.29      0.58
65                  4.0            11.0  0.99620   3.41      0.39
688                 4.0             9.0  0.99620   3.40      0.47
363                 6.0            15.0  0.99880   2.99      0.87
959                12.0            32.0  0.99735   3.36      0.61

      alcohol  quality
593      9.0      5
65      10.9      5
688      9.4      5
363      10.2      5
959     10.0      5
```

```
[69]: wine['quality'].unique()
```

```
[69]: array([5, 6, 7, 4, 8, 3], dtype=int64)
```

```
[70]: # If wine quality is 7 or above then will consider as good quality wine
wine['goodquality'] = [1 if x >= 7 else 0 for x in wine['quality']]
wine.sample(5)
```

```
[70]:    fixed acidity  volatile acidity  citric acid  residual sugar  chlorides \
773           7.9            0.400       0.29          1.80      0.157
588           5.0            0.420       0.24          2.00      0.060
554          15.5            0.645       0.49          4.20      0.095
462          11.0            0.260       0.68          2.55      0.085
269          11.5            0.180       0.51          4.00      0.104

      free sulfur dioxide  total sulfur dioxide  density  pH  sulphates \
773                  1.0            44.0   0.99730  3.30      0.92
588                 19.0            50.0   0.99170  3.72      0.74
554                 10.0            23.0   1.00315  2.92      0.74
462                 10.0            25.0   0.99700  3.18      0.61
269                  4.0            23.0   0.99960  3.28      0.97

      alcohol  quality  goodquality
773      9.5      6          0
588     14.0      8          1
554     11.1      5          0
462     11.8      5          0
269     10.1      6          0
```

```
[71]: # See total number of good vs bad wines samples
wine['goodquality'].value_counts()
```

```
[71]: goodquality
0    1382
1    217
Name: count, dtype: int64
```

```
[72]: # Separate dependent and independent variables
X = wine.drop(['quality', 'goodquality'], axis = 1)
Y = wine['goodquality']
```

```
[73]: X
```

```
[73]:    fixed acidity  volatile acidity  citric acid  residual sugar  chlorides \
0           7.4            0.700       0.00          1.9      0.076
1           7.8            0.880       0.00          2.6      0.098
2           7.8            0.760       0.04          2.3      0.092
3          11.2            0.280       0.56          1.9      0.075
4           7.4            0.700       0.00          1.9      0.076
```

...	...	...	...	...	...	...	...
1594	6.2	0.600	0.08	2.0	0.090		
1595	5.9	0.550	0.10	2.2	0.062		
1596	6.3	0.510	0.13	2.3	0.076		
1597	5.9	0.645	0.12	2.0	0.075		
1598	6.0	0.310	0.47	3.6	0.067		
	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	\	
0	11.0	34.0	0.99780	3.51	0.56		
1	25.0	67.0	0.99680	3.20	0.68		
2	15.0	54.0	0.99700	3.26	0.65		
3	17.0	60.0	0.99800	3.16	0.58		
4	11.0	34.0	0.99780	3.51	0.56		
...	...	...	...	...	...		
1594	32.0	44.0	0.99490	3.45	0.58		
1595	39.0	51.0	0.99512	3.52	0.76		
1596	29.0	40.0	0.99574	3.42	0.75		
1597	32.0	44.0	0.99547	3.57	0.71		
1598	18.0	42.0	0.99549	3.39	0.66		
	alcohol						
0	9.4						
1	9.8						
2	9.8						
3	9.8						
4	9.4						
...	...						
1594	10.5						
1595	11.2						
1596	11.0						
1597	10.2						
1598	11.0						

[1599 rows x 11 columns]

[74]: `print(Y)`

0	0
1	0
2	0
3	0
4	0
..	..
1594	0
1595	0
1596	0
1597	0

```
1598      0  
Name: goodquality, Length: 1599, dtype: int64
```

## 24 Feature Importance

```
[75]: from sklearn.ensemble import ExtraTreesClassifier  
classifiern = ExtraTreesClassifier()  
classifiern.fit(X,Y)  
score = classifiern.feature_importances_  
print(score)
```

```
[0.07141731 0.09966626 0.09740041 0.07393926 0.07001599 0.0703833  
 0.08189362 0.08701146 0.06695778 0.10889258 0.17242203]
```

## 25 Splitting Dataset

```
[76]: from sklearn.model_selection import train_test_split  
X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size=0.  
         ↪3,random_state=7)
```

## 26 Result

```
[83]: model_res=pd.DataFrame(columns=['Model', 'Score'])
```

## 27 LogisticRegression:

```
[84]: from sklearn.linear_model import LogisticRegression  
model = LogisticRegression()  
model.fit(X_train,Y_train)  
y_pred = model.predict(X_test)  
  
from sklearn.metrics import accuracy_score,confusion_matrix  
# accuracy_score(Y_test,Y_pred)  
model_res.loc[len(model_res)] = ['LogisticRegression',  
         ↪accuracy_score(Y_test,y_pred)]  
model_res
```

```
[84]:          Model      Score  
0  LogisticRegression  0.872917
```

## 28 Using KNN:

```
[85]: from sklearn.neighbors import KNeighborsClassifier  
model = KNeighborsClassifier(n_neighbors=3)  
model.fit(X_train,Y_train)  
y_pred = model.predict(X_test)  
  
from sklearn.metrics import accuracy_score  
model_res.loc[len(model_res)] = ['KNeighborsClassifier',  
    accuracy_score(Y_test,y_pred)]  
model_res
```

```
[85]:          Model      Score  
0   LogisticRegression  0.872917  
1   KNeighborsClassifier  0.872917
```

## 29 Using SVC

```
[86]: from sklearn.svm import SVC  
model = SVC()  
model.fit(X_train,Y_train)  
y_pred = model.predict(X_test)  
  
from sklearn.metrics import accuracy_score  
print("Accuracy Score:",accuracy_score(Y_test,y_pred))  
model_res.loc[len(model_res)] = ['SVC', accuracy_score(Y_test,y_pred)]  
model_res
```

Accuracy Score: 0.86875

```
[86]:          Model      Score  
0   LogisticRegression  0.872917  
1   KNeighborsClassifier  0.872917  
2           SVC  0.868750
```

## 30 Using Decision Tree:

```
[87]: from sklearn.tree import DecisionTreeClassifier  
model = DecisionTreeClassifier(criterion='entropy',random_state=7)  
model.fit(X_train,Y_train)  
y_pred = model.predict(X_test)  
  
from sklearn.metrics import accuracy_score  
print("Accuracy Score:",accuracy_score(Y_test,y_pred))
```

```

model_res.loc[len(model_res)] = ['DecisionTreeClassifier', accuracy_score(Y_test,y_pred)]
model_res

```

Accuracy Score: 0.864583333333334

```
[87]:          Model      Score
0    LogisticRegression  0.872917
1   KNeighborsClassifier  0.872917
2           SVC  0.868750
3 DecisionTreeClassifier  0.864583
```

## 31 Using GaussianNB:

```

[88]: from sklearn.naive_bayes import GaussianNB
model3 = GaussianNB()
model3.fit(X_train,Y_train)
y_pred = model3.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred))
model_res.loc[len(model_res)] = ['GaussianNB', accuracy_score(Y_test,y_pred)]
model_res

```

Accuracy Score: 0.833333333333334

```
[88]:          Model      Score
0    LogisticRegression  0.872917
1   KNeighborsClassifier  0.872917
2           SVC  0.868750
3 DecisionTreeClassifier  0.864583
4       GaussianNB  0.833333
```

## 32 Using Random Forest:

```

[89]: from sklearn.ensemble import RandomForestClassifier
model2 = RandomForestClassifier(random_state=1)
model2.fit(X_train, Y_train)
y_pred = model2.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred))
model_res.loc[len(model_res)] = ['RandomForestClassifier', accuracy_score(Y_test,y_pred)]
model_res

```

Accuracy Score: 0.89375

[89]:

	Model	Score
0	LogisticRegression	0.872917
1	KNeighborsClassifier	0.872917
2	SVC	0.868750
3	DecisionTreeClassifier	0.864583
4	GaussianNB	0.833333
5	RandomForestClassifier	0.893750

[90]:

```
!pip install xgboost
```

```
Collecting xgboost
  Obtaining dependency information for xgboost from https://files.pythonhosted.org/packages/24/ec/ad387100fa3cc2b9b81af0829b5ecfe75ec5bb19dd7c19d4fea06fb81802/xgboost-2.0.3-py3-none-win_amd64.whl.metadata
    Downloading xgboost-2.0.3-py3-none-win_amd64.whl.metadata (2.0 kB)
Requirement already satisfied: numpy in c:\python\lib\site-packages (from xgboost) (1.26.3)
Requirement already satisfied: scipy in c:\python\lib\site-packages (from xgboost) (1.12.0)
Downloading xgboost-2.0.3-py3-none-win_amd64.whl (99.8 MB)
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```

```
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```



```
Installing collected packages: xgboost
Successfully installed xgboost-2.0.3
```

```
[notice] A new release of pip is available: 23.2.1 -> 23.3.2
[notice] To update, run: python.exe -m pip install --upgrade pip
```

### 33 Using Xgboost:

```
[91]: import xgboost as xgb
model5 = xgb.XGBClassifier(random_state=1)
model5.fit(X_train, Y_train)
y_pred = model5.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred))
model_res.loc[len(model_res)] = ['XGBClassifier', accuracy_score(Y_test,y_pred)]
model_res
```

```
Accuracy Score: 0.8895833333333333
```

```
[91]:          Model      Score
0    LogisticRegression  0.872917
1    KNeighborsClassifier  0.872917
2            SVC  0.868750
3  DecisionTreeClassifier  0.864583
4        GaussianNB  0.833333
5 RandomForestClassifier  0.893750
6      XGBClassifier  0.889583
```

```
[94]: model_res = model_res.sort_values(by='Score', ascending=False)
model_res
```

```
[94]:          Model      Score
5 RandomForestClassifier  0.893750
6      XGBClassifier  0.889583
0    LogisticRegression  0.872917
1    KNeighborsClassifier  0.872917
2            SVC  0.868750
3  DecisionTreeClassifier  0.864583
4        GaussianNB  0.833333
```