Exploratory_Data_Analysis-Wine_Quality_Dataset (/github/PBPatil/Exploratory_Data_Analysis-Wine_Quality_Dataset/tree/master) / winequality_white.ipynb (/github/PBPatil/Exploratory_Data_Analysis-Wine_Quality_Dataset/tree/master/winequality_white.ipynb)

Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

- " %matplotlib inline " makes life easy by returning output plots without needing to write plt.show() code everytime after each plot!

Loading dataset

In [2]:
```
df = pd.read_csv('winequality-white.csv',sep=';')
df.head()
```

Out[2]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.0010	3.00	0.45	8.8	6
1	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.9940	3.30	0.49	9.5	6
2	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.9951	3.26	0.44	10.1	6
3	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40	9.9	6
4	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40	9.9	6

- Original data is seperated by delimiter " ; " in given dataset
- " .head() " returns first five observations of the dataset

Data Insights

In [3]:
```
df.shape
```

Out[3]:
```
(4898, 12)
```

- dataset comprises of 4898 observations and 12 chracteriestics
- out of which one is dependent variable and rest 11 are independent variables - physicochemical characteristics

In [4]:
```
df.columns.values
```

Out[4]:
```
array(['fixed acidity', 'volatile acidity', 'citric acid',
       'residual sugar', 'chlorides', 'free sulfur dioxide',
       'total sulfur dioxide', 'density', 'pH', 'sulphates', 'alcohol',
       'quality'], dtype=object)
```

- Label of each column

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4898 entries, 0 to 4897
Data columns (total 12 columns):
fixed acidity           4898 non-null float64
volatile acidity        4898 non-null float64
citric acid             4898 non-null float64
residual sugar          4898 non-null float64
chlorides               4898 non-null float64
free sulfur dioxide     4898 non-null float64
total sulfur dioxide    4898 non-null float64
density                 4898 non-null float64
pH                      4898 non-null float64
sulphates               4898 non-null float64
alcohol                 4898 non-null float64
quality                 4898 non-null int64
dtypes: float64(11), int64(1)
memory usage: 459.3 KB
```

- Data has only float and integer values
- No variable column has null/missing values

Summary Statistics

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

Out[6]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	der
count	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.00(
mean	6.854788	0.278241	0.334192	6.391415	0.045772	35.308085	138.360657	0.994
std	0.843868	0.100795	0.121020	5.072058	0.021848	17.007137	42.498065	0.00
min	3.800000	0.080000	0.000000	0.600000	0.009000	2.000000	9.000000	0.98
25%	6.300000	0.210000	0.270000	1.700000	0.036000	23.000000	108.000000	0.99
50%	6.800000	0.260000	0.320000	5.200000	0.043000	34.000000	134.000000	0.99
75%	7.300000	0.320000	0.390000	9.900000	0.050000	46.000000	167.000000	0.99(
max	14.200000	1.100000	1.660000	65.800000	0.346000	289.000000	440.000000	1.03

Key Observations -

- Mean value is less than median value of each column represented by 50%(50th percentile) in index column.

- Natably large differnece in 75th %tile and max values of predictors "residual sugar","free sulfur dioxide","total sulfur dioxide"
- Thus observations 1 and 2 suggests that there are extreme values-Outliers in our dataset

Understanding Target variable

In [7]:
```
df.quality.unique()
```

Out[7]:
```
array([6, 5, 7, 8, 4, 3, 9], dtype=int64)
```

- Target variable/Dependent variable is discrete and categorical in nature.
- "quality" score scale ranges from 1 to 10;where 1 being poor and 10 being the best.
- 1,2 & 10 Quality ratings are not given by any obseravtion.Only scores obtained are between 3 to 9.

In [8]:
```
df.quality.value_counts()
```

Out[8]:
```
6    2198
5    1457
7     880
8     175
4     163
3      20
9       5
Name: quality, dtype: int64
```

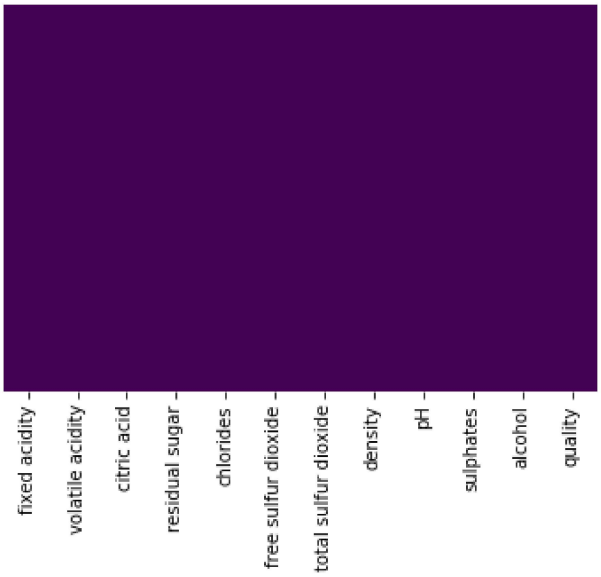
- This tells us vote count of each quality score in descending order.
- "quality" has most values concentrated in the categories 5, 6 and 7.
- Only a few observations made for the categories 3 & 9

Data Visualization

To check missing values

In [9]:
```
sns.heatmap(df.isnull(),cbar=False,yticklabels=False,cmap = 'viridis')
```

Out[9]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x85cec50>
```

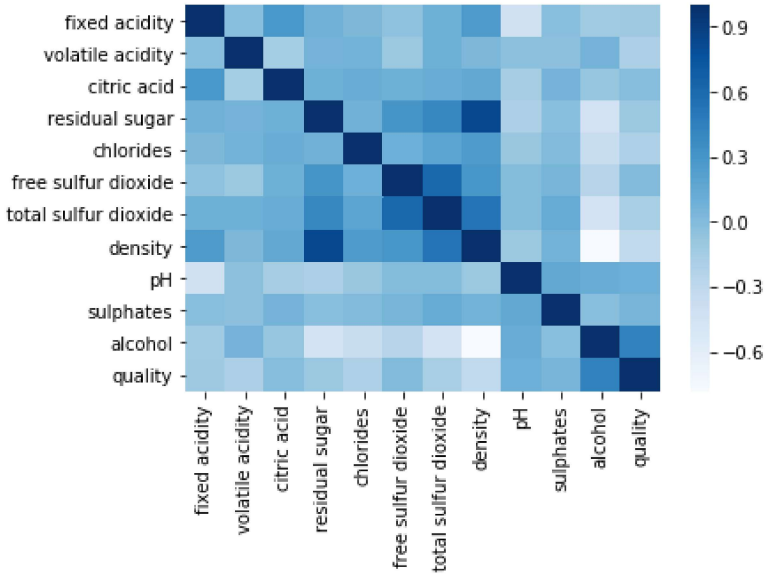


- Dataset has no missing values.
- If there were any, you would've noticed in figure represented by different colour shade on purple background.
- Do try it out with other dataset which has missing values,you'll see the difference.
- Ex.in titanic dataset,you will find "Age" and "Cabin" columns with differnt shades with this code.

To check correlation

In [10]:
```
plt.figure(figsize=(6,4))
sns.heatmap(df.corr(),cmap='Blues',annot=False)
```

Out[10]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xe793ac8>
```

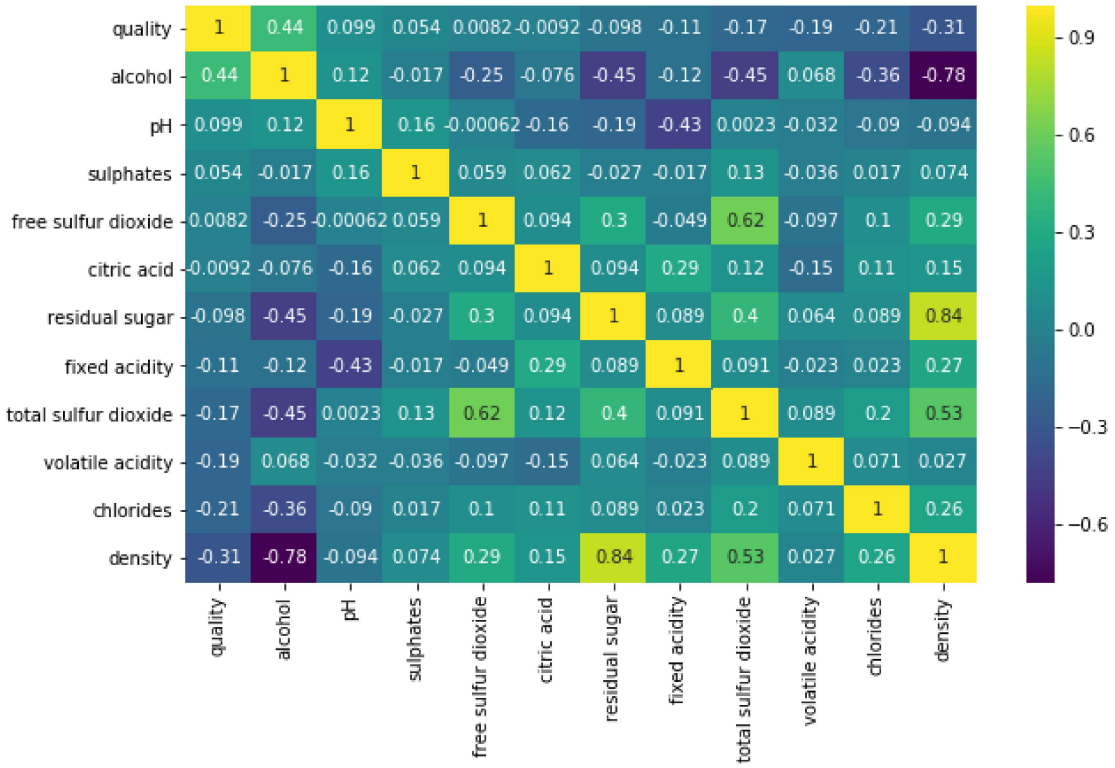


- Dark shades represents positive correlation while lighter shades represents negative correlation.

- If you set annot=True, you'll get values by which features are correlated to each other in grid-cells

In [11]:
```
#Quality correlation matrix
k = 12 #number of variables for heatmap
cols = df.corr().nlargest(k, 'quality')['quality'].index
cm = df[cols].corr()
plt.figure(figsize=(10,6))
sns.heatmap(cm, annot=True, cmap = 'viridis')
```

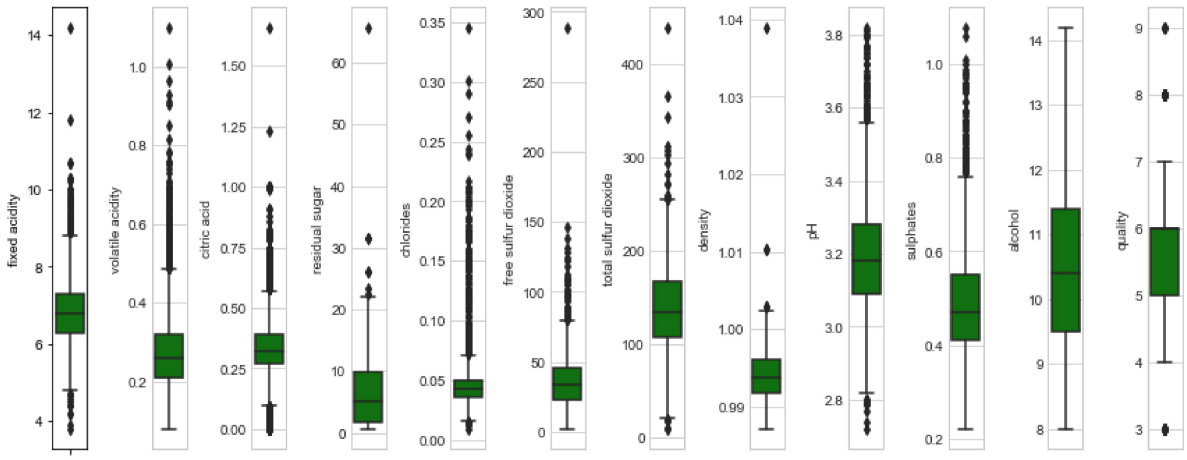
Out[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xe887f28>
```



- Here we can infer that "density" has strong positive correlation with "residual sugar" whereas it has strong negative correlation with "alcohol".
- "free sulphur dioxide" and "citric acid" has almost no correlation with "quality"
- Since correlation is zero we can infer there is no linear relationship between these two predictors.However it is safe to drop these features in case you're applying Linear Regression model to the dataset.

To check Outliers

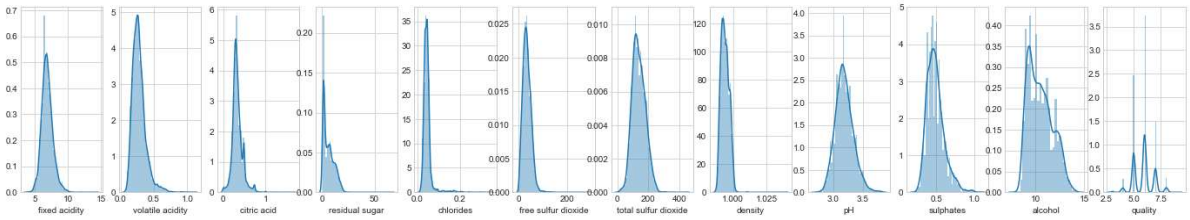
In [12]:
```
l = df.columns.values
number_of_columns=12
number_of_rows = len(l)-1/number_of_columns
plt.figure(figsize=(number_of_columns,5*number_of_rows))
for i in range(0,len(l)):
    plt.subplot(number_of_rows + 1,number_of_columns,i+1)
    sns.set_style('whitegrid')
    sns.boxplot(df[l[i]],color='green',orient='v')
    plt.tight_layout()
```



- Except "alcohol" all other features columns shows outliers. "'Color Codes : https://matplotlib.org/examples/color/colormaps_reference.html (https://matplotlib.org/examples/color/colormaps_reference.html)"'

To check distribution-Skewness

In [13]:
```
plt.figure(figsize=(2*number_of_columns,5*number_of_rows))
for i in range(0,len(l)):
    plt.subplot(number_of_rows + 1,number_of_columns,i+1)
    sns.distplot(df[l[i]],kde=True)
```



- "pH" column appears to be normally distributed
- remaining all independent variables are right skewed/positively skewed.