assignment-4

September 21, 2023

#Grapes to Greatness: Machine Learning in Wine Quality Prediction

0.0.1 Task 1 : Load the Dataset

[1]:
```
# import required libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
df = pd.read_csv('/content/winequality-red.csv')
df.head()
```

[2]:
```
   fixed_acidity  volatile_acidity  citric_acid  residual_sugar  chlorides  \
0            7.4              0.70         0.00             1.9      0.076
1            7.8              0.88         0.00             2.6      0.098
2            7.8              0.76         0.04             2.3      0.092
3           11.2              0.28         0.56             1.9      0.075
4            7.4              0.70         0.00             1.9      0.076

   free_sulfur_dioxide  total_sulfur_dioxide  density    pH  sulphates  \
0                 11.0                  34.0   0.9978  3.51       0.56
1                 25.0                  67.0   0.9968  3.20       0.68
2                 15.0                  54.0   0.9970  3.26       0.65
3                 17.0                  60.0   0.9980  3.16       0.58
4                 11.0                  34.0   0.9978  3.51       0.56

   alcohol  quality
0      9.4        5
1      9.8        5
2      9.8        5
3      9.8        6
4      9.4        5
```

0.0.2 Task 2 : Data preprocessing including visualization

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

[3]:
```
(1599, 12)
```

[4]:
```
df.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
```

[5]:
```
df.isnull().sum() # There are no null values in the dataset.
```

[5]:
```
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
```

[6]:
```
df.describe() # Descriptive Statistics
```

[6]:

	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

[7]:
```
df.corr()
```

[7]:

	fixed_acidity	volatile_acidity	citric_acid	\
fixed_acidity	1.000000	-0.256131	0.671703	
volatile_acidity	-0.256131	1.000000	-0.552496	
citric_acid	0.671703	-0.552496	1.000000	
residual_sugar	0.114777	0.001918	0.143577	
chlorides	0.093705	0.061298	0.203823	
free_sulfur_dioxide	-0.153794	-0.010504	-0.060978	
total_sulfur_dioxide	-0.113181	0.076470	0.035533	
density	0.668047	0.022026	0.364947	
pH	-0.682978	0.234937	-0.541904	
sulphates	0.183006	-0.260987	0.312770	
alcohol	-0.061668	-0.202288	0.109903	
quality	0.124052	-0.390558	0.226373	

	residual_sugar	chlorides	free_sulfur_dioxide	\

```
fixed_acidity              0.114777   0.093705            -0.153794
volatile_acidity           0.001918   0.061298            -0.010504
citric_acid                0.143577   0.203823            -0.060978
residual_sugar             1.000000   0.055610             0.187049
chlorides                  0.055610   1.000000             0.005562
free_sulfur_dioxide        0.187049   0.005562             1.000000
total_sulfur_dioxide       0.203028   0.047400             0.667666
density                    0.355283   0.200632            -0.021946
pH                        -0.085652  -0.265026             0.070377
sulphates                  0.005527   0.371260             0.051658
alcohol                    0.042075  -0.221141            -0.069408
quality                    0.013732  -0.128907            -0.050656

                      total_sulfur_dioxide   density        pH  sulphates  \
fixed_acidity                    -0.113181  0.668047 -0.682978   0.183006
volatile_acidity                  0.076470  0.022026  0.234937  -0.260987
citric_acid                       0.035533  0.364947 -0.541904   0.312770
residual_sugar                    0.203028  0.355283 -0.085652   0.005527
chlorides                         0.047400  0.200632 -0.265026   0.371260
free_sulfur_dioxide               0.667666 -0.021946  0.070377   0.051658
total_sulfur_dioxide              1.000000  0.071269 -0.066495   0.042947
density                           0.071269  1.000000 -0.341699   0.148506
pH                               -0.066495 -0.341699  1.000000  -0.196648
sulphates                         0.042947  0.148506 -0.196648   1.000000
alcohol                          -0.205654 -0.496180  0.205633   0.093595
quality                          -0.185100 -0.174919 -0.057731   0.251397

                       alcohol   quality
fixed_acidity        -0.061668  0.124052
volatile_acidity     -0.202288 -0.390558
citric_acid           0.109903  0.226373
residual_sugar        0.042075  0.013732
chlorides            -0.221141 -0.128907
free_sulfur_dioxide  -0.069408 -0.050656
total_sulfur_dioxide -0.205654 -0.185100
density              -0.496180 -0.174919
pH                    0.205633 -0.057731
sulphates             0.093595  0.251397
alcohol               1.000000  0.476166
quality               0.476166  1.000000
```

[8]:
```
# Correlation of dependent varriables with the target variable

df.corr().quality.sort_values(ascending = False)
```

[8]:
```
quality                 1.000000
alcohol                 0.476166
```

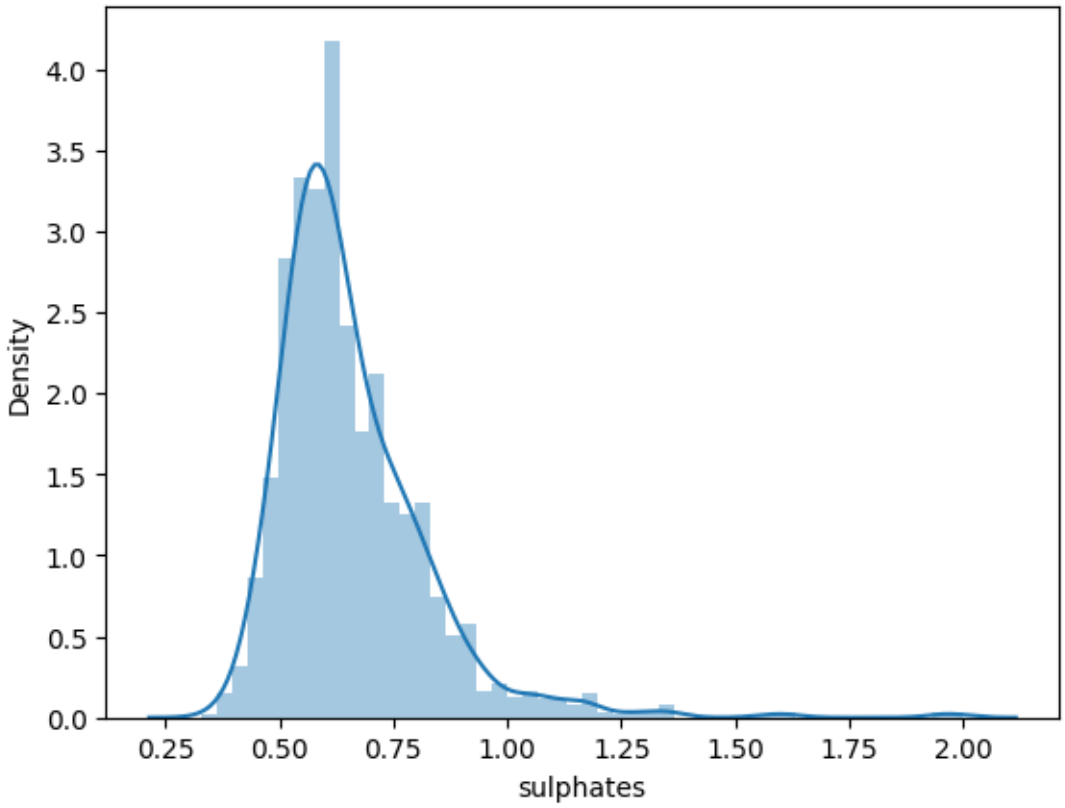
```
sulphates               0.251397
citric_acid             0.226373
fixed_acidity           0.124052
residual_sugar          0.013732
free_sulfur_dioxide    -0.050656
pH                     -0.057731
chlorides              -0.128907
density                -0.174919
total_sulfur_dioxide   -0.185100
volatile_acidity       -0.390558
Name: quality, dtype: float64
```

Univariate Analysis

[9]:
```
sns.distplot(df.sulphates)
```

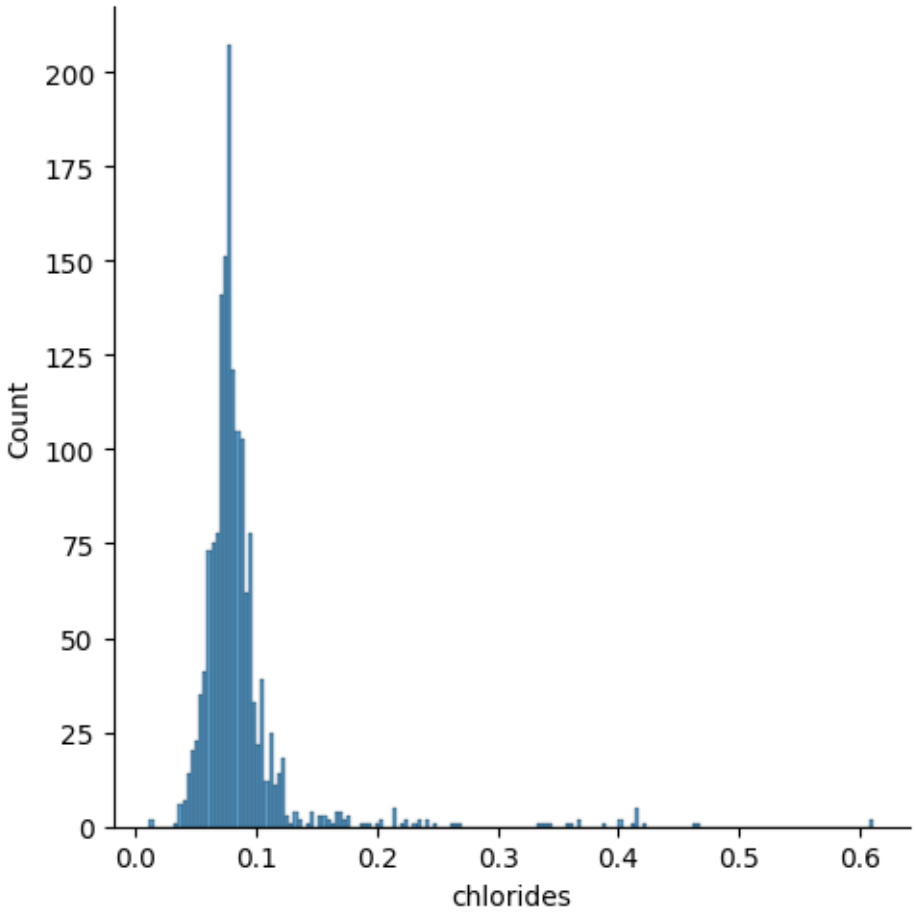
```
<ipython-input-9-8b271c44c149>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df.sulphates)
```

[9]:
```
<Axes: xlabel='sulphates', ylabel='Density'>
```



[10]:
```
sns.displot(df.chlorides)
```

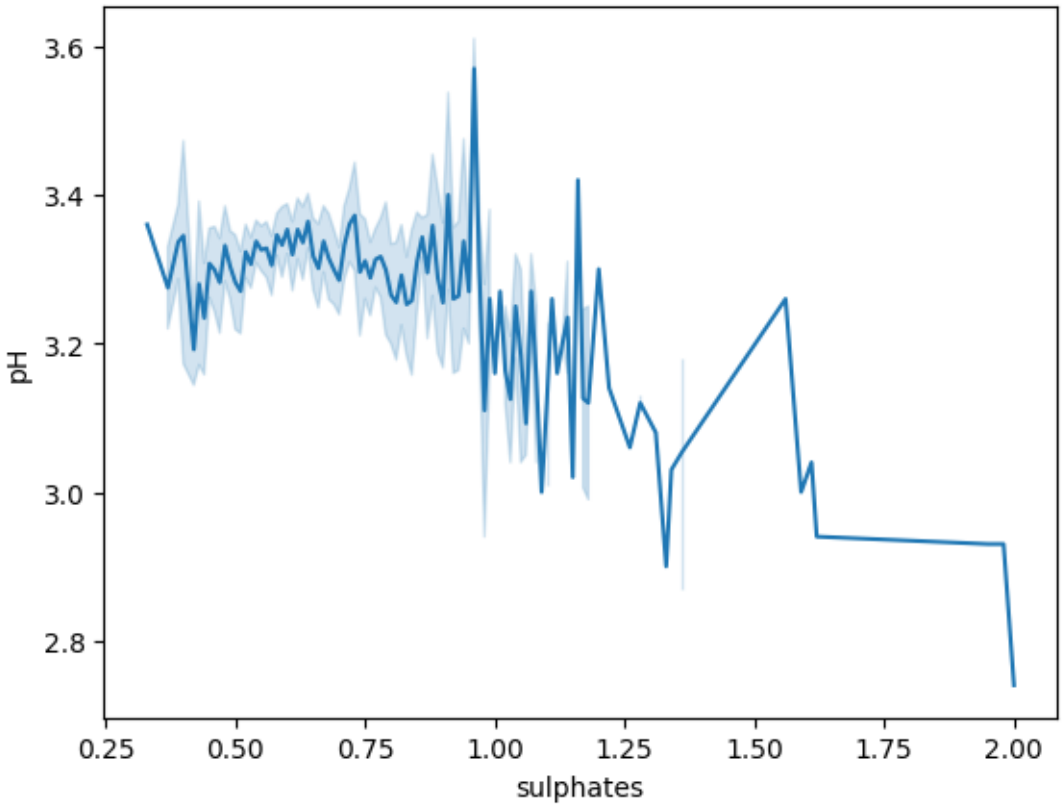
[10]: <seaborn.axisgrid.FacetGrid at 0x7ddd8a543160>



Bivariate Analysis

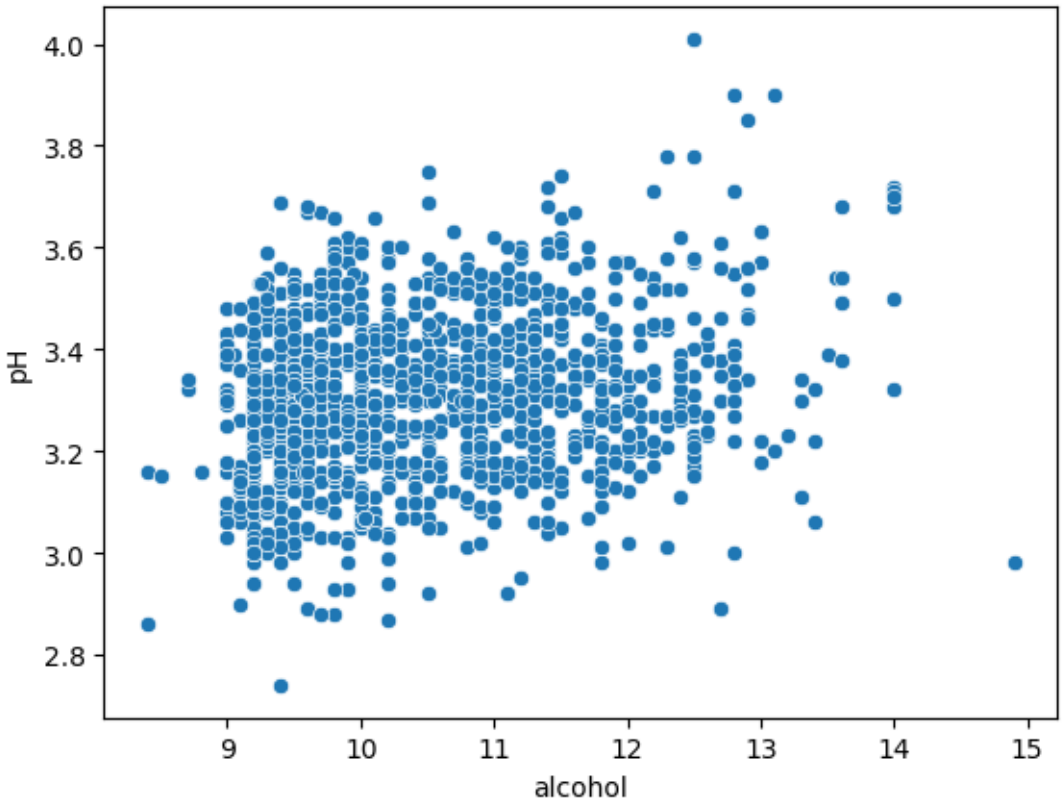
[11]:
```
sns.lineplot(x=df.sulphates, y=df.pH)
```

[11]:
```
<Axes: xlabel='sulphates', ylabel='pH'>
```



[12]:
```
sns.scatterplot(x=df.alcohol, y=df.pH)
```

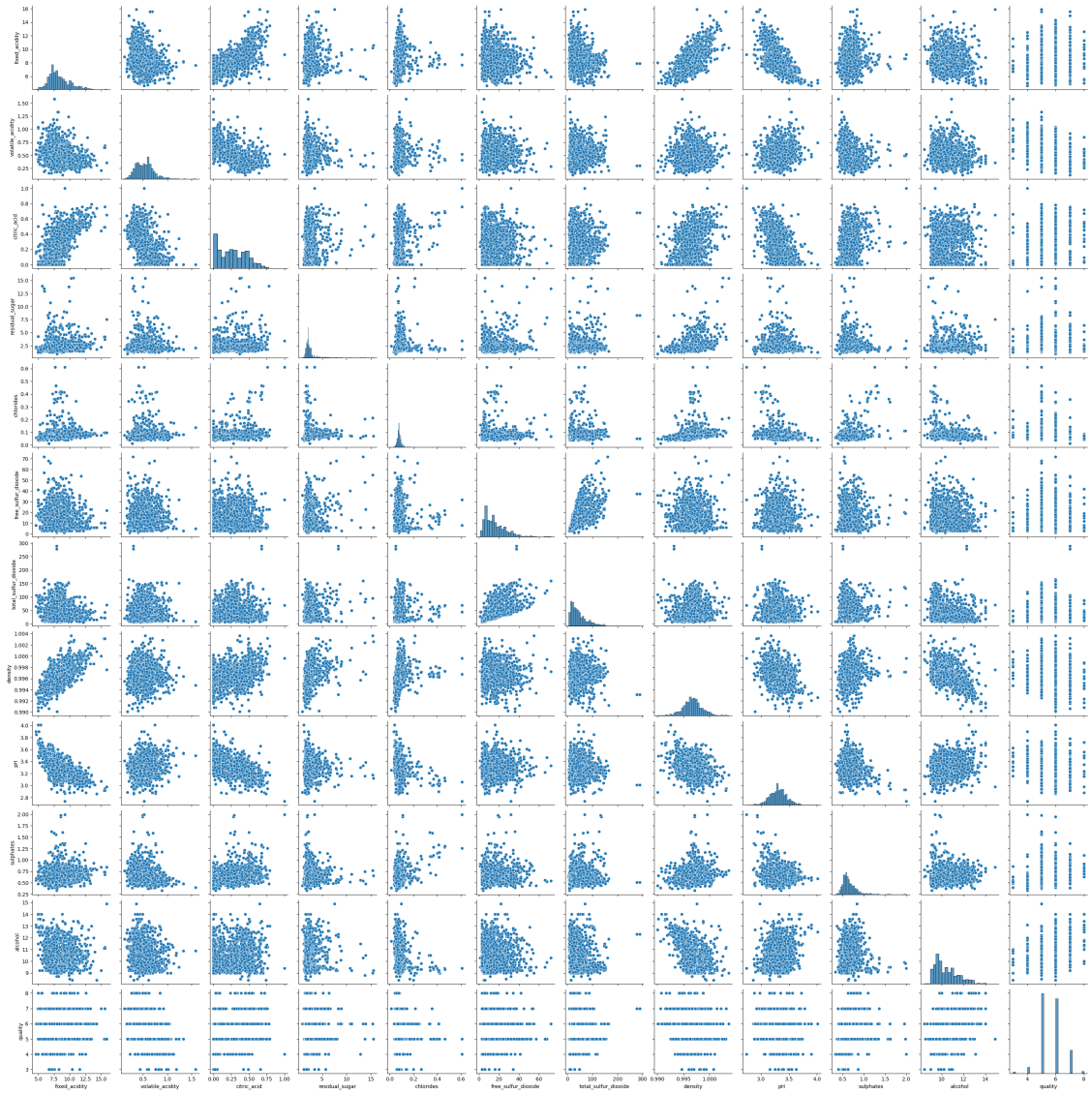
[12]:
```
<Axes: xlabel='alcohol', ylabel='pH'>
```



Multivariate Analysis

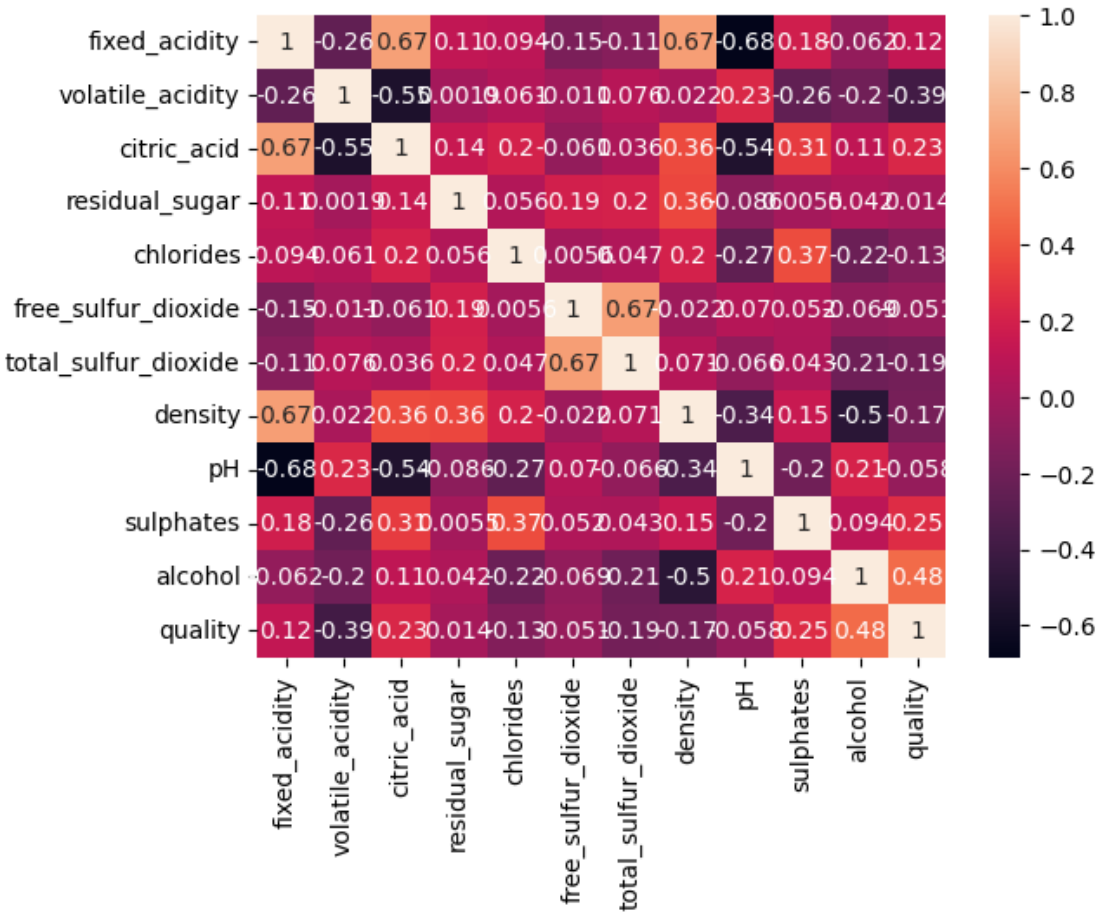
[13]:
```
sns.pairplot(df)
```

[13]:
```
<seaborn.axisgrid.PairGrid at 0x7ddd4f583280>
```



[14]:
```
# Correlation Heatmap

sns.heatmap(df.corr(),annot=True)
```

[14]: <Axes: >



Outlier Detection and removal by percentile method & IQR MEthod

[16]:
```
df.head()
```

[16]:

	fixed_acidity	volatile_acidity	citric_acid	residual_sugar	chlorides	\
0	7.4	0.70	0.00	1.9	0.076	
1	7.8	0.88	0.00	2.6	0.098	
2	7.8	0.76	0.04	2.3	0.092	
3	11.2	0.28	0.56	1.9	0.075	
4	7.4	0.70	0.00	1.9	0.076	

	free_sulfur_dioxide	total_sulfur_dioxide	density	pH	sulphates	\
0	11.0	34.0	0.9978	3.51	0.56	
1	25.0	67.0	0.9968	3.20	0.68	
2	15.0	54.0	0.9970	3.26	0.65	
3	17.0	60.0	0.9980	3.16	0.58	
4	11.0	34.0	0.9978	3.51	0.56	

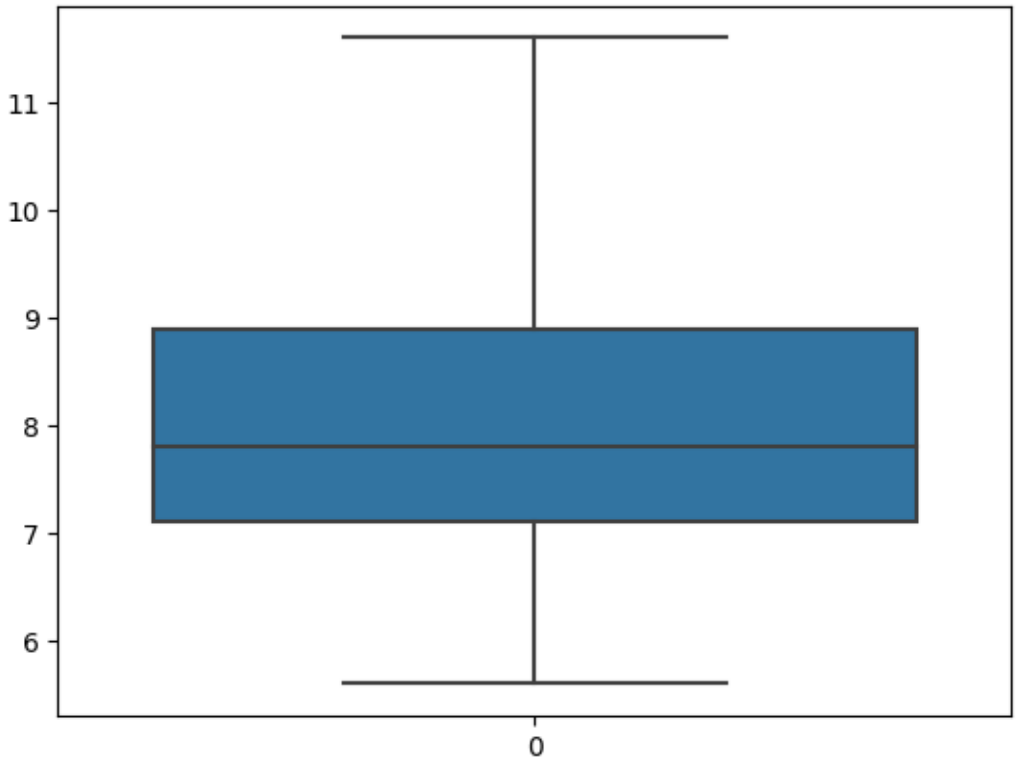
```
   alcohol  quality
0      9.4        5
1      9.8        5
2      9.8        5
3      9.8        6
4      9.4        5
```

[49]:
```
# Removing outliers from fixed_acidity column

f1 = df.fixed_acidity.quantile(0.25) #Q1
f3 = df.fixed_acidity.quantile(0.75) #Q3
IQR_f = f3 - f1
upper_limit_f = f3+(1.5)*(IQR_f)
lower_limit_f = f1-(1.5)*(IQR_f)
print(f1)
print(f3)
print(IQR_f)
print(upper_limit_f)
print(lower_limit_f)
```

```
7.1
8.9
1.8000000000000007
11.600000000000001
4.399999999999999
```

[51]:
```
df=df[(df.fixed_acidity<upper_limit_f) & (df.fixed_acidity>lower_limit_f)]
sns.boxplot(df.fixed_acidity)
```

[51]: <Axes: >

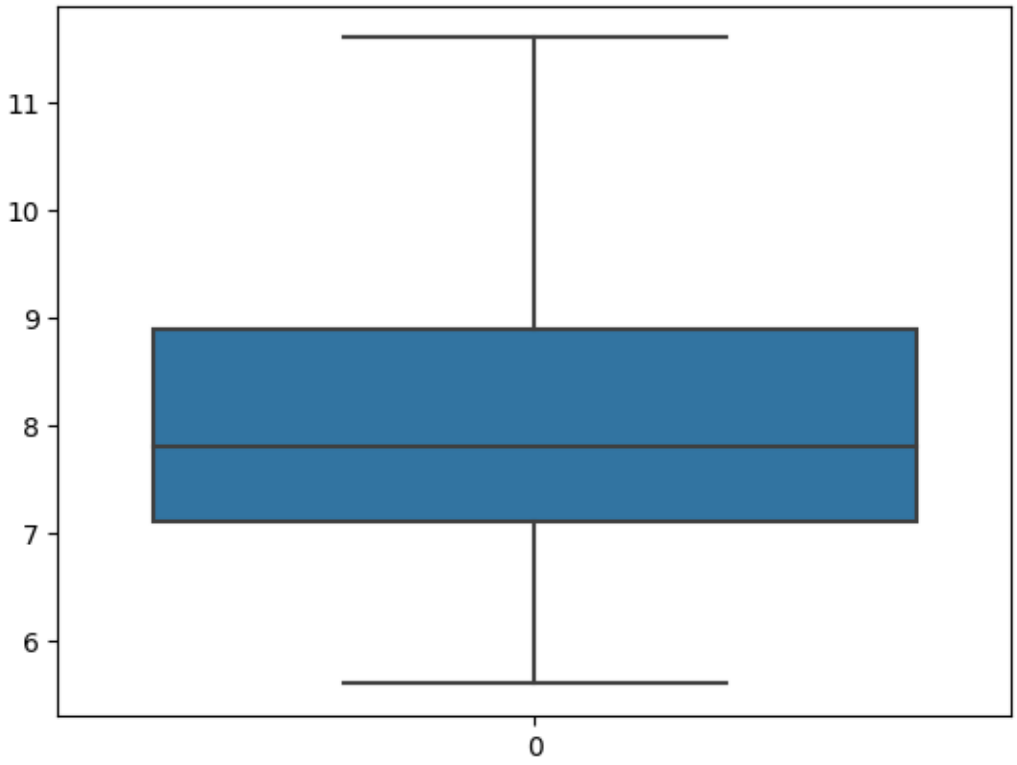


[47]:
```
fa_01=df.fixed_acidity.quantile(0.01)
fa_9=df.fixed_acidity.quantile(0.98)
print(fa_01)
print(fa_98)
```

```
5.6
11.6
```

[48]:
```
df=df[(df.fixed_acidity>=fa_01) & (df.fixed_acidity<=fa_98)]
sns.boxplot(df.fixed_acidity)
```

[48]: <Axes: >

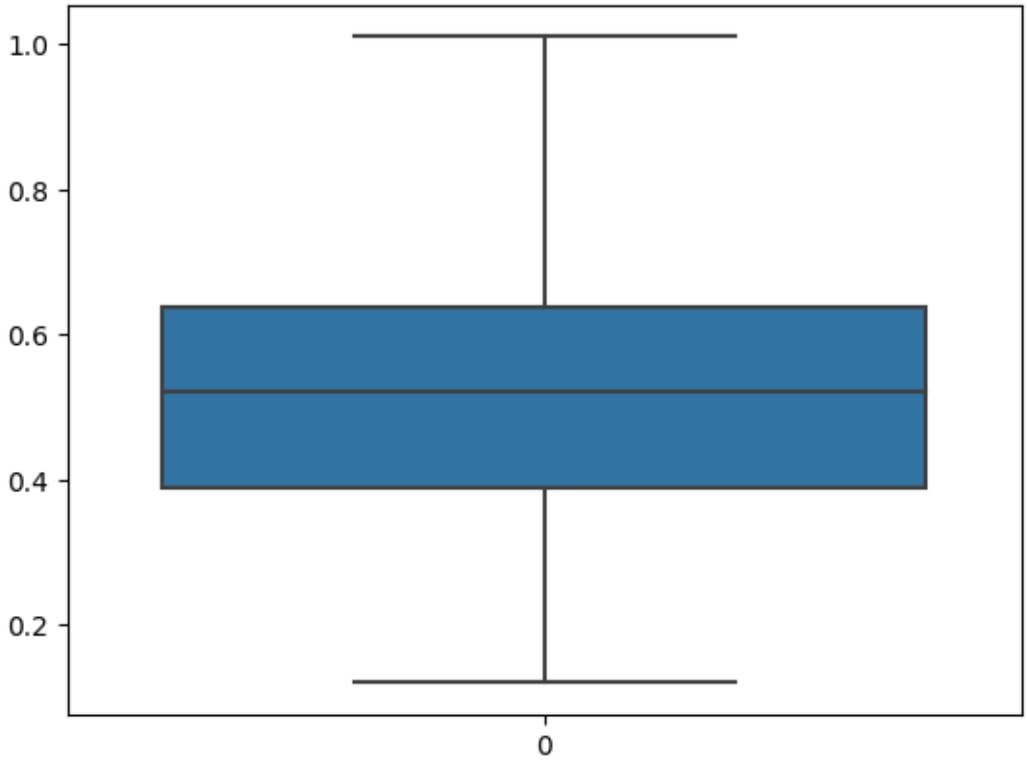


[22]:
```
# Removing outliers from volatile_acidity column

v1 = df.volatile_acidity.quantile(0.25) #Q1
v3 = df.volatile_acidity.quantile(0.75) #Q3
IQR_v = v3 - v1
upper_limit_v = v3+(1.5)*(IQR_v)
lower_limit_v = v1-(1.5)*(IQR_v)
print(v1)
print(v3)
print(IQR_v)
print(upper_limit_v)
print(lower_limit_v)
```

```
0.3925
0.64
0.2475
1.01125
0.021250000000000047
```

[23]:
```
df=df[(df.volatile_acidity<upper_limit_v) & (df.volatile_acidity>lower_limit_v)]
sns.boxplot(df.volatile_acidity)
```

[23]: <Axes: >

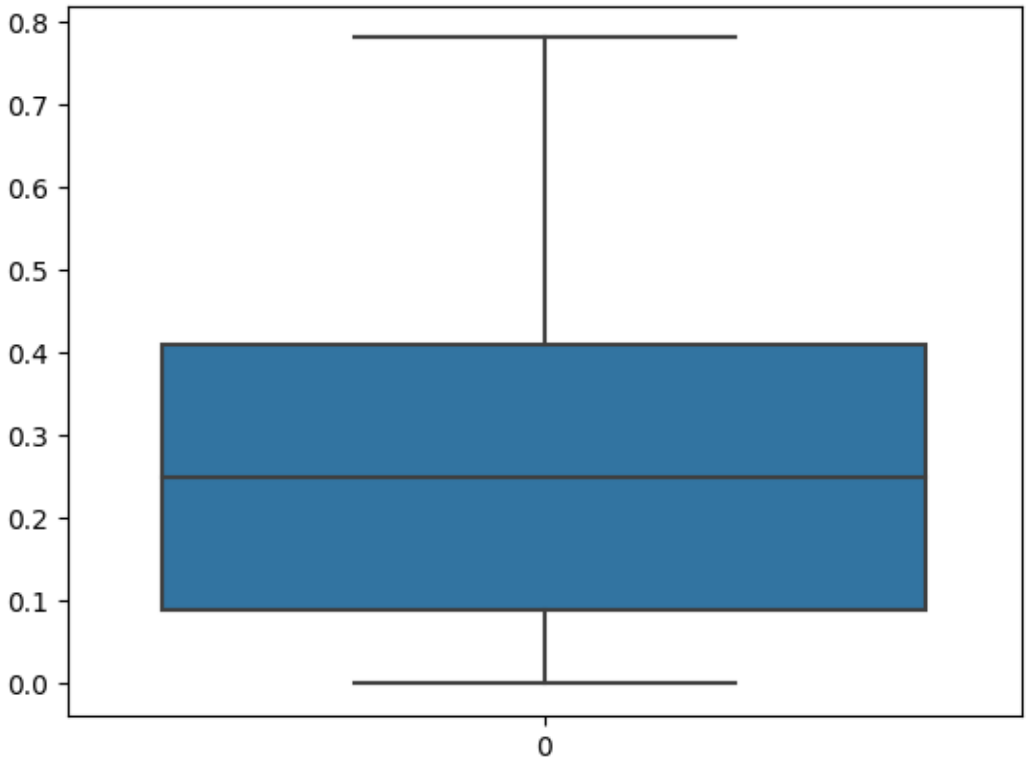


[24]:
```
# Removing outliers from citric_acid column

c1 = df.citric_acid.quantile(0.25) #Q1
c3 = df.citric_acid.quantile(0.75) #Q3
IQR_c = c3 - c1
upper_limit_c = c3+(1.5)*(IQR_c)
lower_limit_c = c1-(1.5)*(IQR_c)
print(c1)
print(c3)
print(IQR_c)
print(upper_limit_c)
print(lower_limit_c)
```

```
0.09
0.41
0.31999999999999995
0.8899999999999999
-0.3899999999999999
```

[25]:
```
df=df[(df.citric_acid<upper_limit_c) & (df.citric_acid>lower_limit_c)]
sns.boxplot(df.citric_acid)
```

[25]: <Axes: >



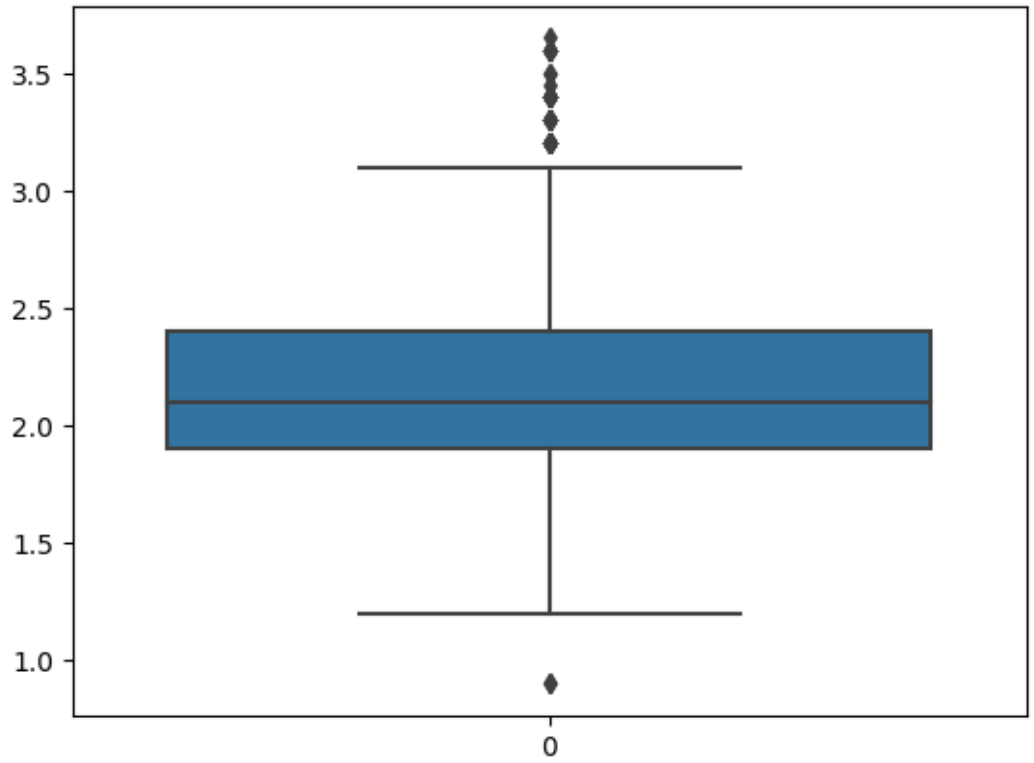
[26]:
```
# Removing outliers from residual_sugar column

r1 = df.residual_sugar.quantile(0.25) #Q1
r3 = df.residual_sugar.quantile(0.75) #Q3
IQR_r = r3 - r1
upper_limit_r = r3+(1.5)*(IQR_r)
lower_limit_r = r1-(1.5)*(IQR_r)
print(r1)
print(r3)
print(IQR_r)
print(upper_limit_r)
print(lower_limit_r)
```

```
1.9
2.6
0.7000000000000002
3.6500000000000004
```

0.8499999999999996

[27]:
```
df=df[(df.residual_sugar<upper_limit_r) & (df.residual_sugar>lower_limit_r)]
sns.boxplot(df.residual_sugar)
```

[27]: <Axes: >

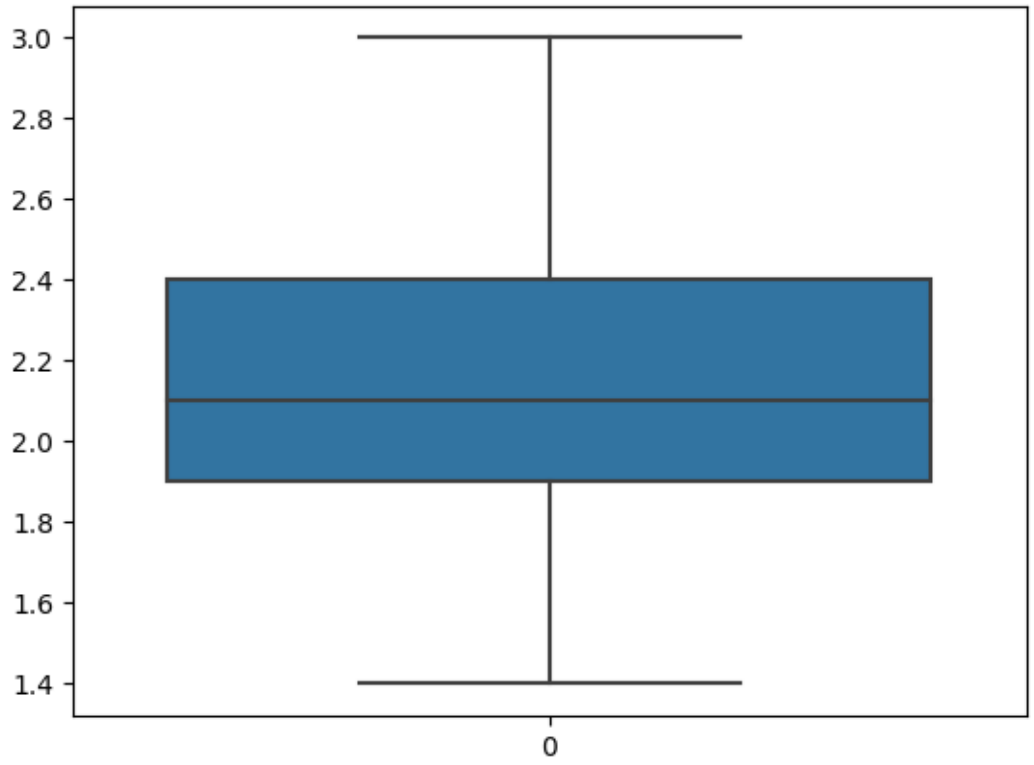


[34]:
```
rs_02=df.residual_sugar.quantile(0.02)
rs_96=df.residual_sugar.quantile(0.96)
print(rs_02)
print(rs_96)
```

1.4
3.0159999999999854

[35]:
```
df=df[(df.residual_sugar>=rs_02) & (df.residual_sugar<=rs_96)]
sns.boxplot(df.residual_sugar)
```

[35]: <Axes: >

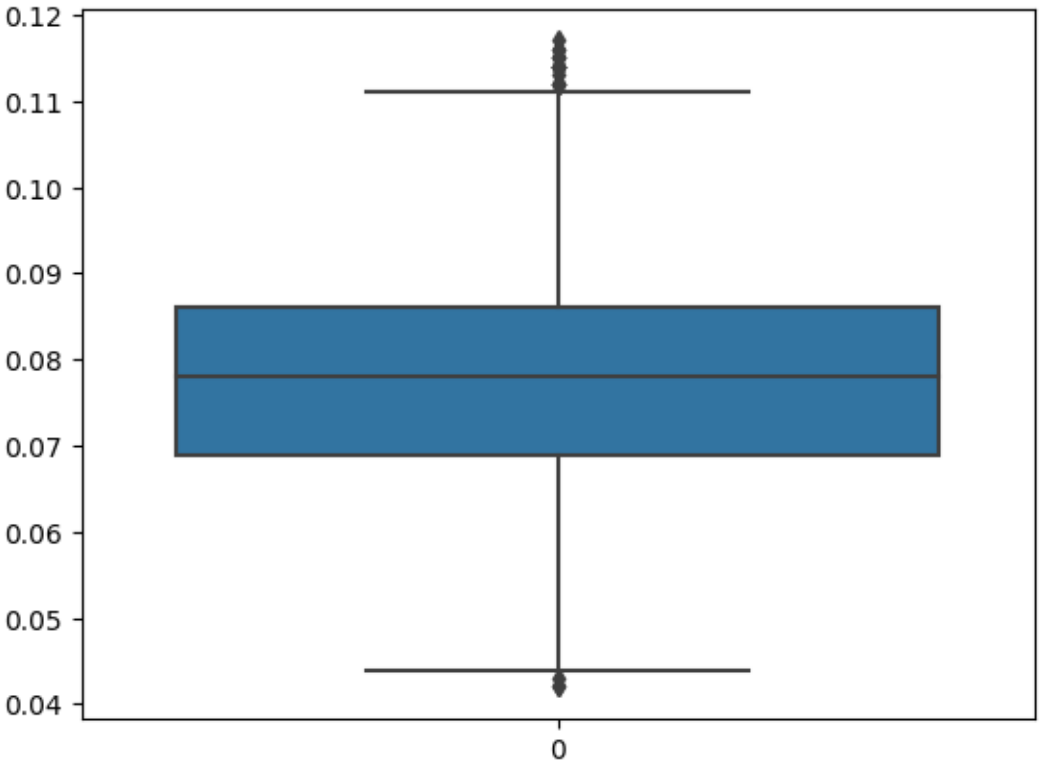


[36]:
```
# Removing outliers from chlorides column

ch1 = df.chlorides.quantile(0.25) #Q1
ch3 = df.chlorides.quantile(0.75) #Q3
IQR_ch = ch3 - ch1
upper_limit_ch = ch3+(1.5)*(IQR_ch)
lower_limit_ch = ch1-(1.5)*(IQR_ch)
print(ch1)
print(ch3)
print(IQR_ch)
print(upper_limit_ch)
print(lower_limit_ch)
```

```
0.07
0.089
0.01899999999999999
0.11749999999999998
0.04150000000000002
```

[37]:
```
df=df[(df.chlorides<upper_limit_ch) & (df.chlorides>lower_limit_ch)]
sns.boxplot(df.chlorides)
```

[37]: <Axes: >

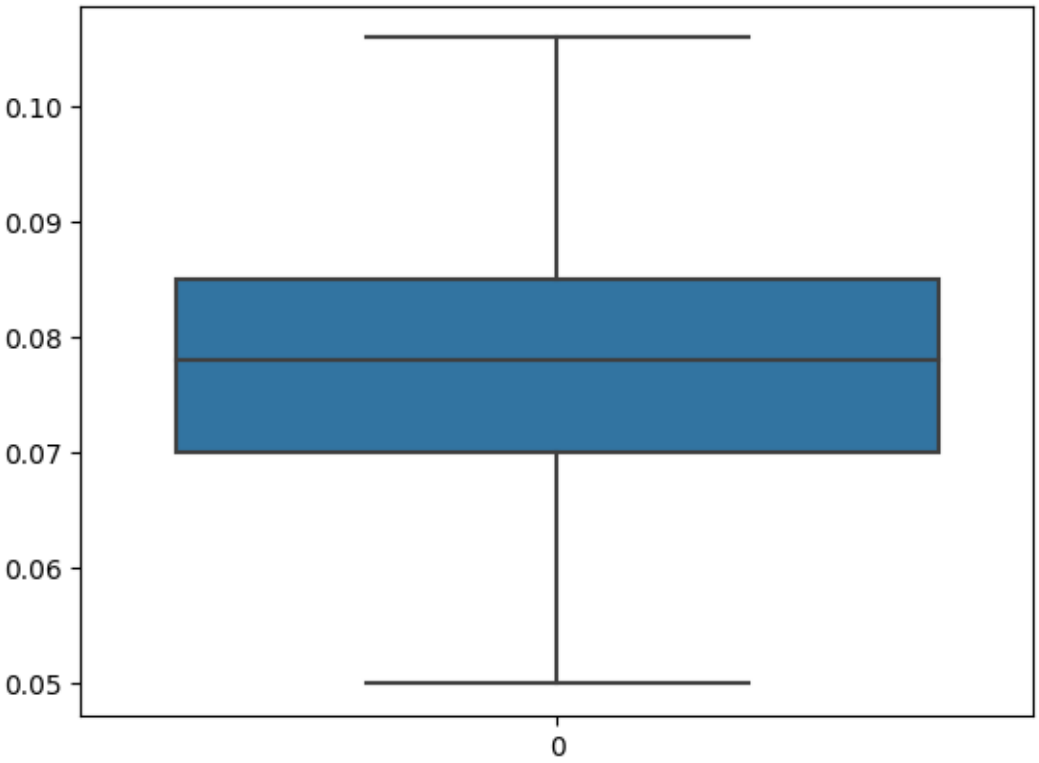


[44]:
```
ch_01=df.chlorides.quantile(0.01)
ch_97=df.chlorides.quantile(0.97)
print(ch_01)
print(ch_97)
```

```
0.049890000000000004
0.106
```

[45]:
```
df=df[(df.chlorides>=ch_01) & (df.chlorides<=ch_97)]
sns.boxplot(df.chlorides)
```

[45]: <Axes: >

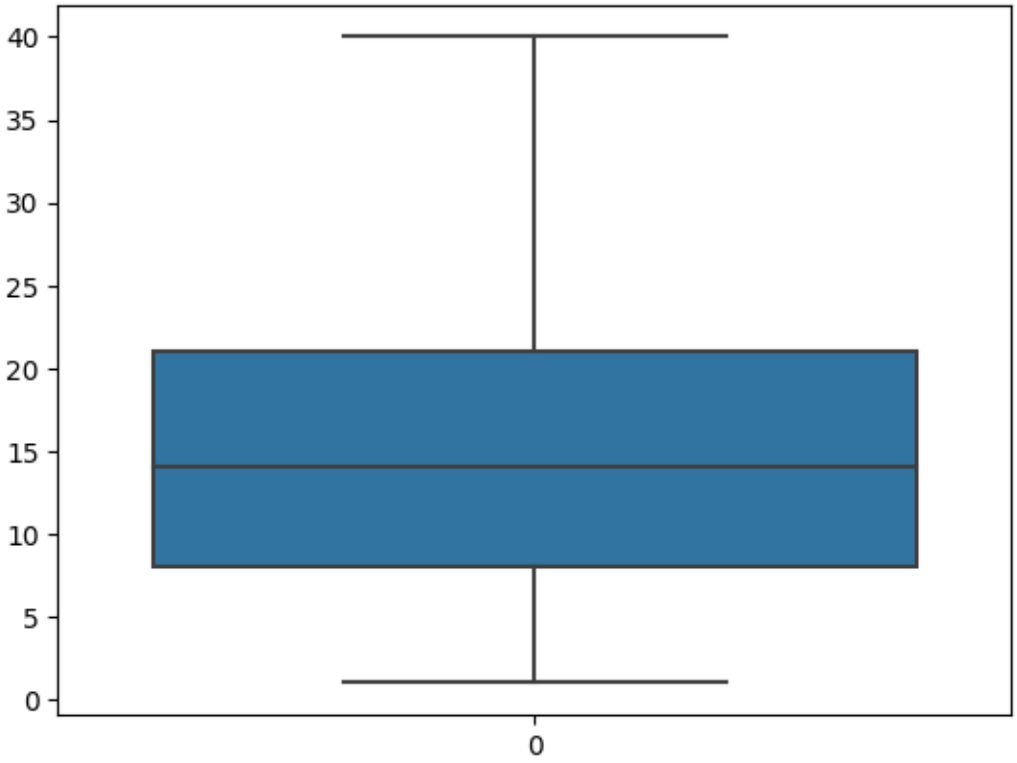


[52]:
```
# Removing outliers from free_sulfur_dioxide column

fs1 = df.free_sulfur_dioxide.quantile(0.25) #Q1
fs3 = df.free_sulfur_dioxide.quantile(0.75) #Q3
IQR_fs = fs3 - fs1
upper_limit_fs = fs3+(1.5)*(IQR_fs)
lower_limit_fs = fs1-(1.5)*(IQR_fs)
print(fs1)
print(fs3)
print(IQR_fs)
print(upper_limit_fs)
print(lower_limit_fs)
```

```
8.0
21.0
13.0
40.5
-11.5
```

[53]:
```
df=df[(df.free_sulfur_dioxide<upper_limit_fs) & (df.
  ↪free_sulfur_dioxide>lower_limit_fs)]
sns.boxplot(df.free_sulfur_dioxide)
```

[53]: <Axes: >

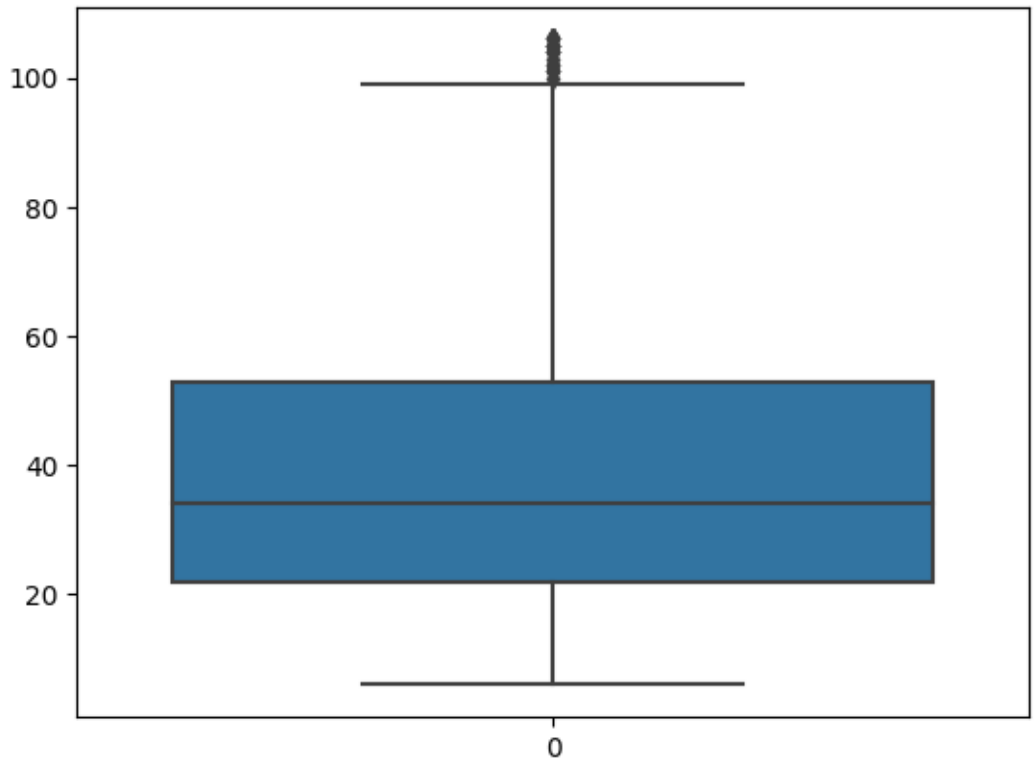


[54]:
```
# Removing outliers from total_sulfur_dioxide column

ts1 = df.total_sulfur_dioxide.quantile(0.25) #Q1
ts3 = df.total_sulfur_dioxide.quantile(0.75) #Q3
IQR_ts = ts3 - ts1
upper_limit_ts = ts3+(1.5)*(IQR_ts)
lower_limit_ts = ts1-(1.5)*(IQR_ts)
print(ts1)
print(ts3)
print(IQR_ts)
print(upper_limit_ts)
print(lower_limit_ts)
```

```
23.0
57.0
34.0
108.0
-28.0
```

[55]:
```
df=df[(df.total_sulfur_dioxide<upper_limit_ts) & (df.
  ↪total_sulfur_dioxide>lower_limit_ts)]
sns.boxplot(df.total_sulfur_dioxide)
```

[55]: <Axes: >

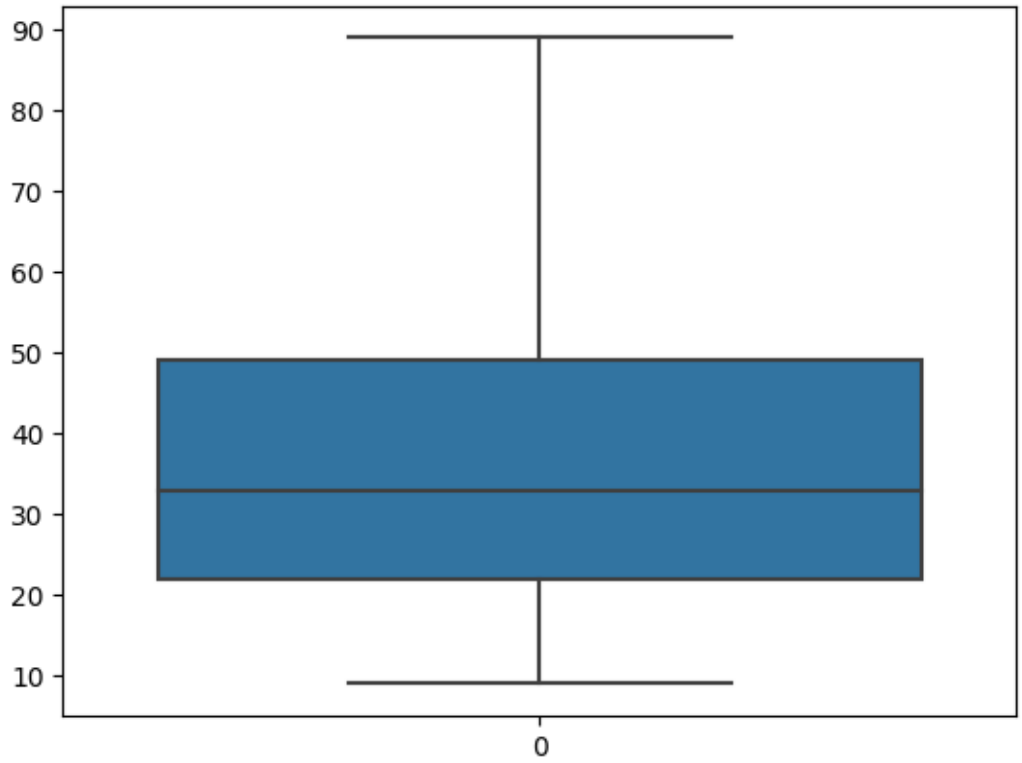


[60]:
```
ts_01=df.total_sulfur_dioxide.quantile(0.01)
ts_97=df.total_sulfur_dioxide.quantile(0.97)
print(ts_01)
print(ts_97)
```

```
9.0
89.0
```

[61]:
```
df=df[(df.total_sulfur_dioxide>=ts_01) & (df.total_sulfur_dioxide<=ts_97)]
sns.boxplot(df.total_sulfur_dioxide)
```

[61]: <Axes: >

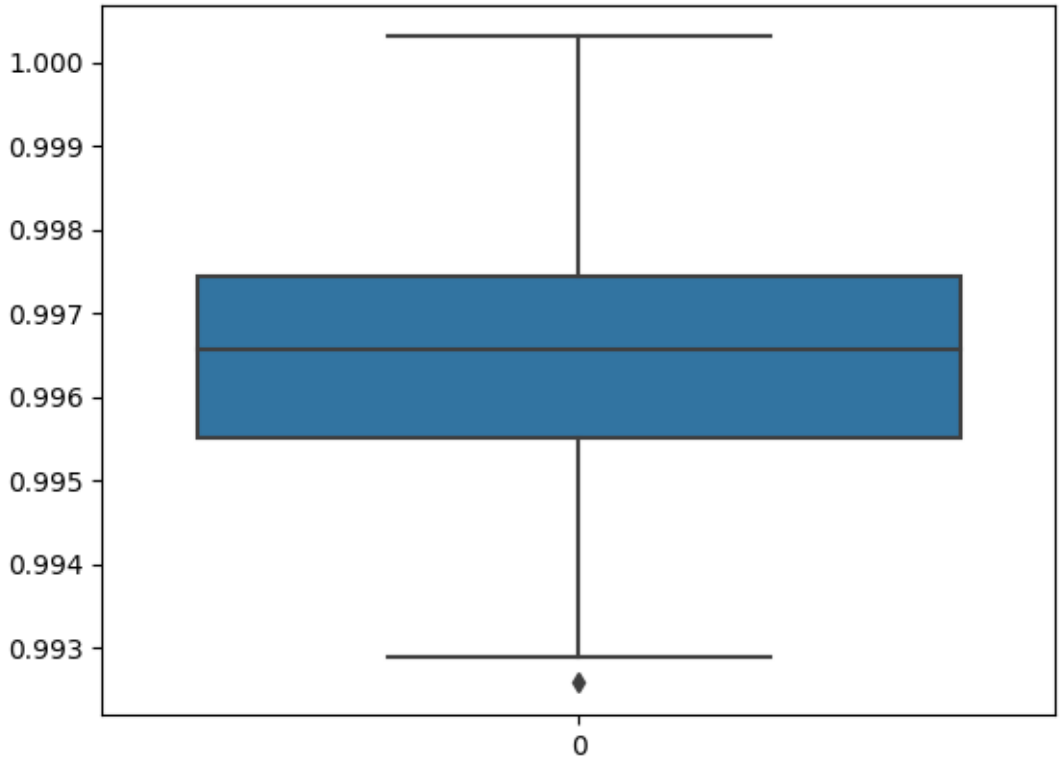


[62]:
```
# Removing outliers from density column

d1 = df.density.quantile(0.25) #Q1
d3 = df.density.quantile(0.75) #Q3
IQR_d = d3 - d1
upper_limit_d = d3+(1.5)*(IQR_d)
lower_limit_d = d1-(1.5)*(IQR_d)
print(d1)
print(d3)
print(IQR_d)
print(upper_limit_d)
print(lower_limit_d)
```

```
0.9955
0.99745
0.0019499999999998963
1.0003749999999998
0.9925750000000002
```

[63]:
```
df=df[(df.density<upper_limit_d) & (df.density>lower_limit_d)]
sns.boxplot(df.density)
```

[63]: <Axes: >

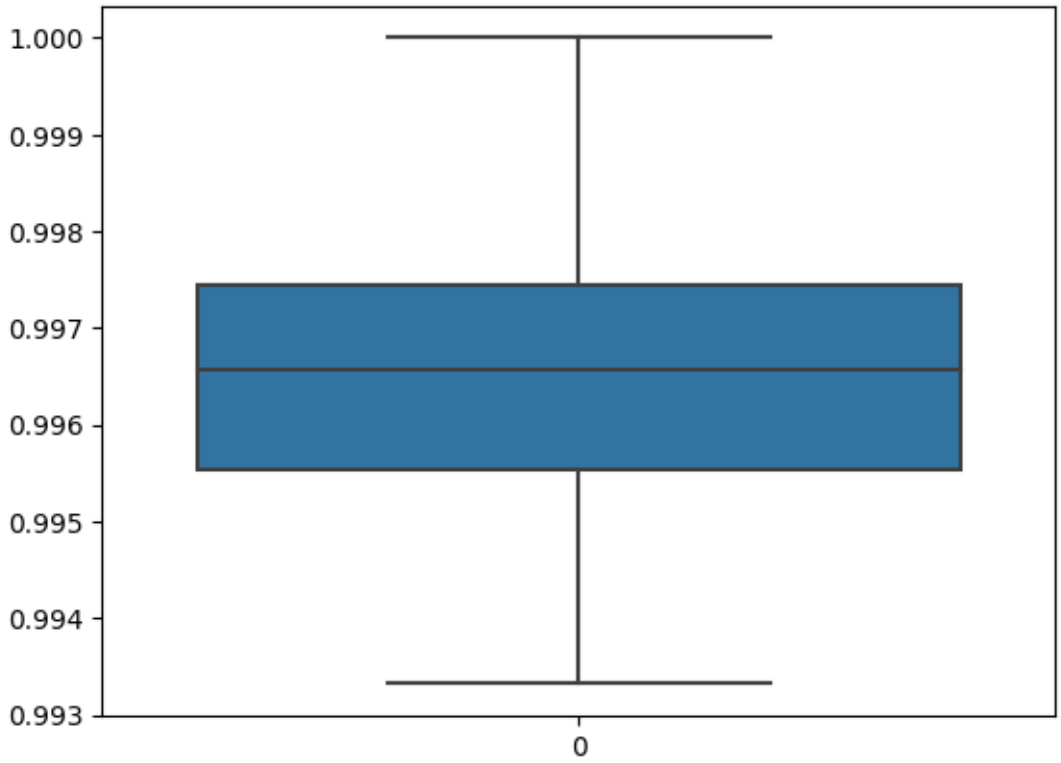


[64]:
```
d_01=df.density.quantile(0.01)
d_99=df.density.quantile(0.99)
print(d_01)
print(d_99)
```

```
0.9933132
1.0
```

[65]:
```
df=df[(df.density>=d_01) & (df.density<=d_99)]
sns.boxplot(df.density)
```

[65]: <Axes: >

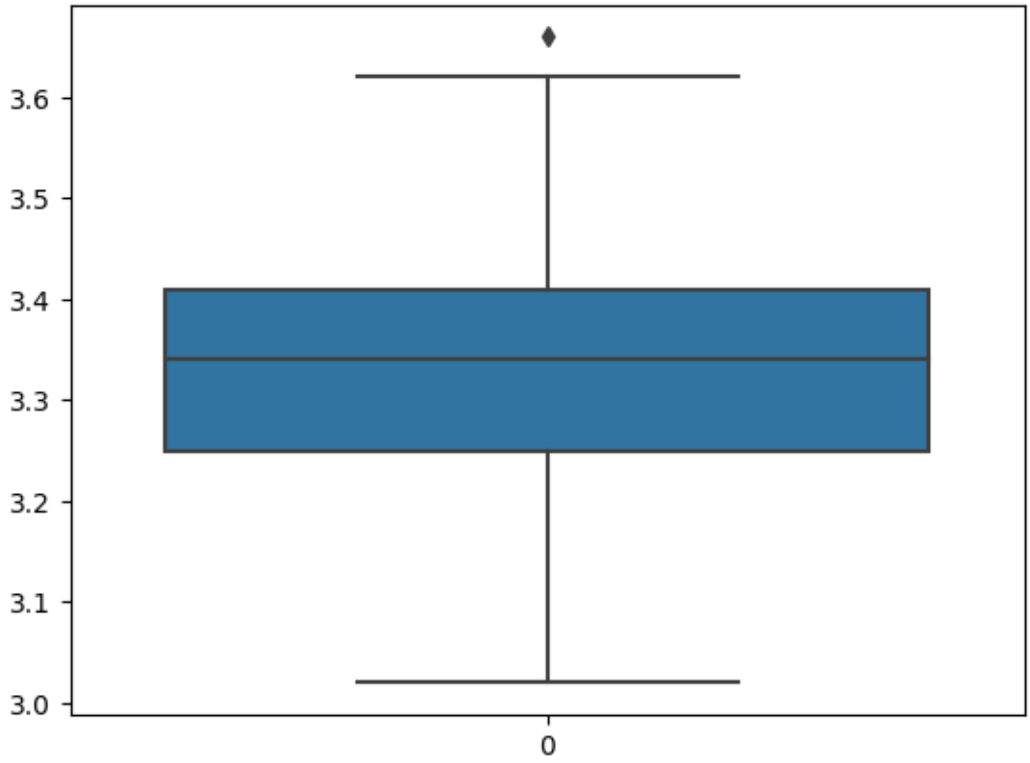


[66]:
```
# Removing outliers from pH column

pH1 = df.pH.quantile(0.25) #Q1
pH3 = df.pH.quantile(0.75) #Q3
IQR_pH = pH3 - pH1
upper_limit_pH = pH3+(1.5)*(IQR_pH)
lower_limit_pH = pH1-(1.5)*(IQR_pH)
print(pH1)
print(pH3)
print(IQR_pH)
print(upper_limit_pH)
print(lower_limit_pH)
```

```
3.2425
3.41
0.16749999999999998
3.66125
2.99125
```

[67]:
```
df=df[(df.pH<upper_limit_pH) & (df.pH>lower_limit_pH)]
sns.boxplot(df.pH)
```

[67]: <Axes: >

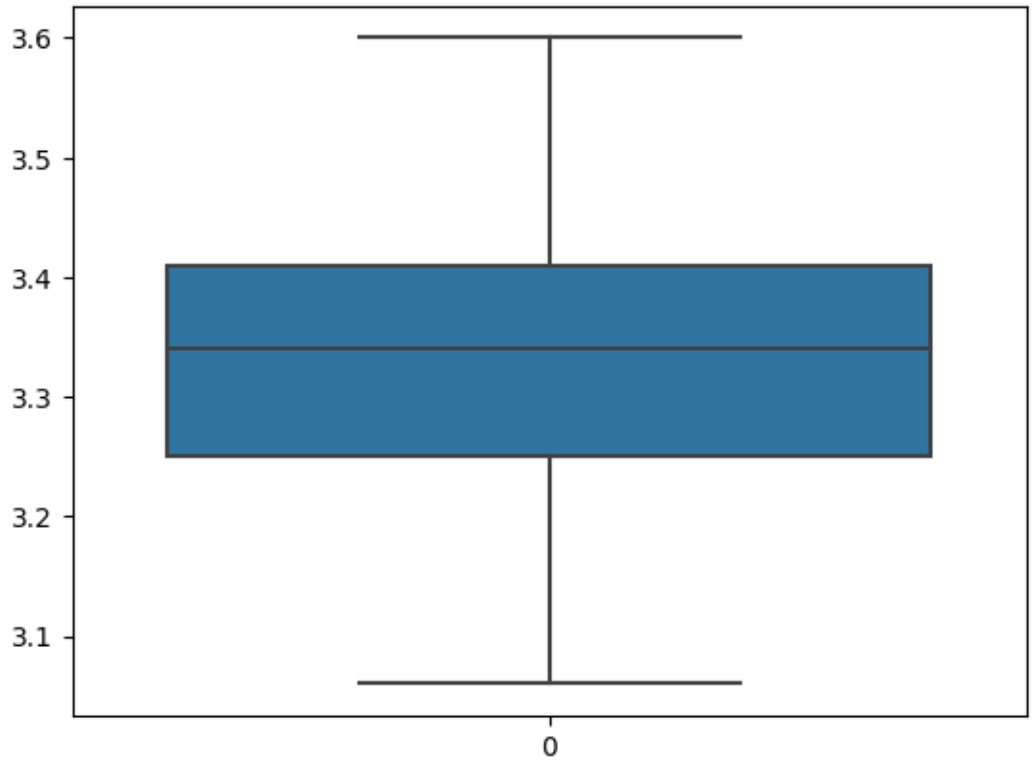


[68]:
```
pH_01=df.pH.quantile(0.01)
pH_99=df.pH.quantile(0.99)
print(pH_01)
print(pH_99)
```

```
3.06
3.6066
```

[69]:
```
df=df[(df.pH>=pH_01) & (df.pH<=pH_99)]
sns.boxplot(df.pH)
```

[69]: <Axes: >

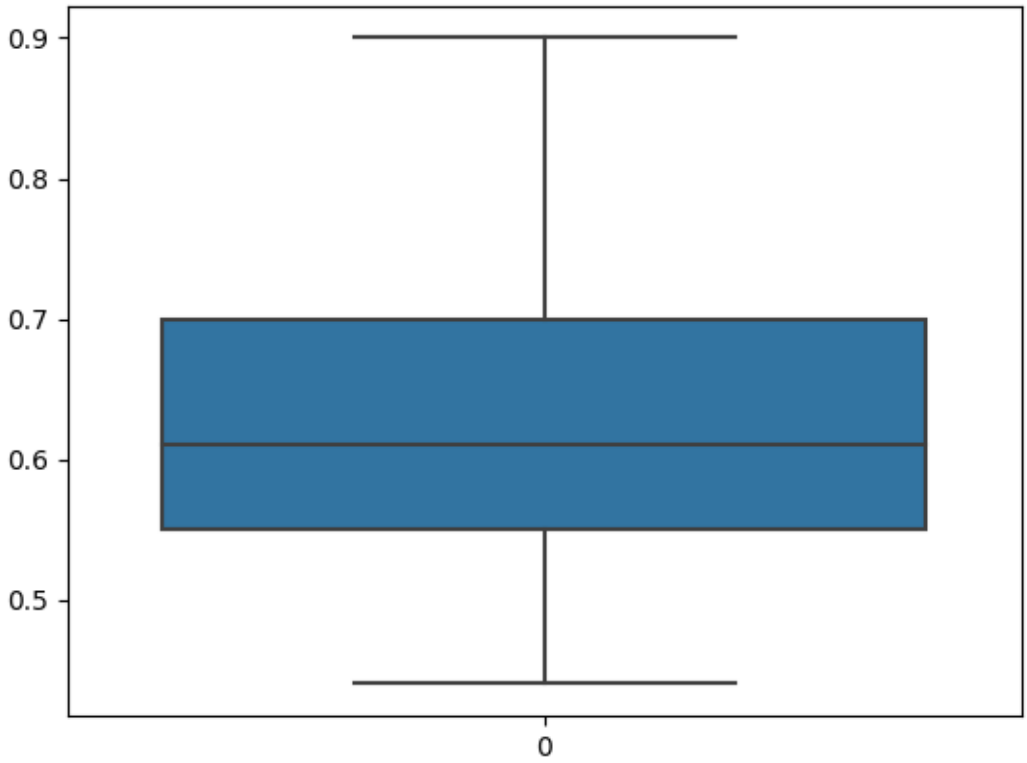


[74]:
```
# Removing outliers from fixed_acidity column

su_01=df.sulphates.quantile(0.01)
su_98=df.sulphates.quantile(0.98)
print(su_01)
print(su_98)
```

```
0.44
0.9
```

[75]:
```
df=df[(df.sulphates>=su_01) & (df.sulphates<=su_98)]
sns.boxplot(df.sulphates)
```

[75]: <Axes: >

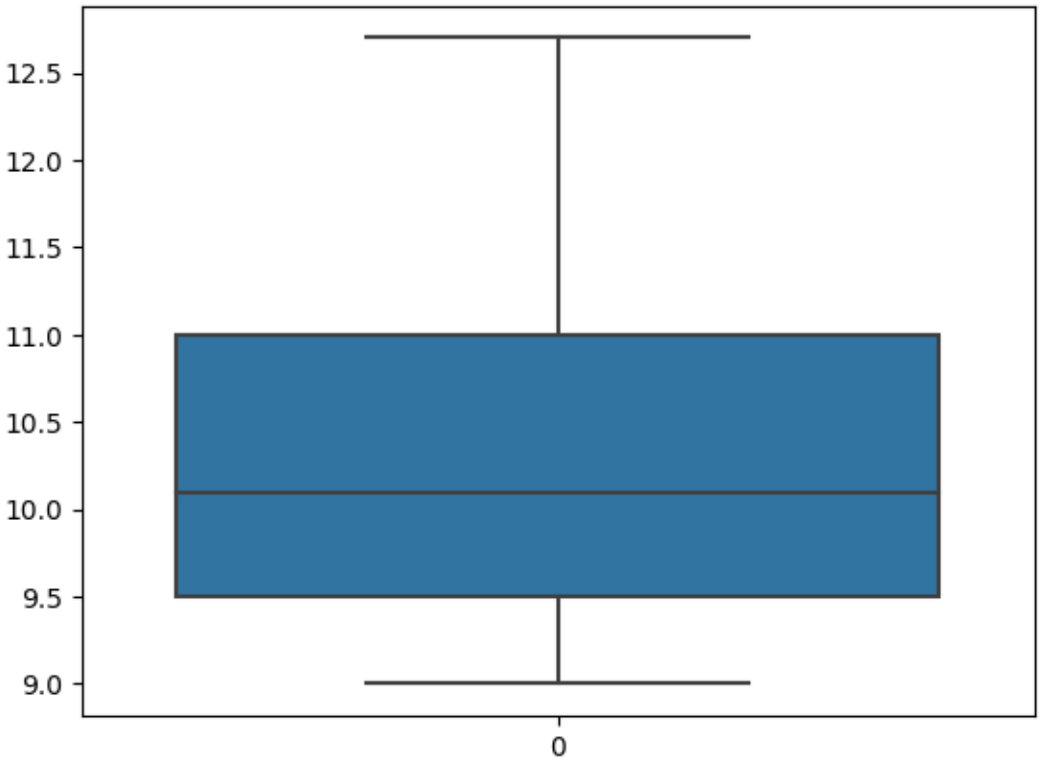


[76]:
```
# Removing outliers from alcohol column

a_01=df.alcohol.quantile(0.01)
a_99=df.alcohol.quantile(0.99)
print(a_01)
print(a_99)
```

```
9.0
12.724
```

[77]:
```
df=df[(df.alcohol>=a_01) & (df.alcohol<=a_99)]
sns.boxplot(df.alcohol)
```

[77]: <Axes: >



Therefore all the outliers are removed

0.0.3 Task - 3 : Machine Learning Model Building

[233]:
```
# split into X and y

X =df.iloc[:,:-1]
X.head()
```

[233]:

	fixed_acidity	volatile_acidity	citric_acid	residual_sugar	chlorides	\
0	7.4	0.70	0.00	1.9	0.076	
1	7.8	0.88	0.00	2.6	0.098	
2	7.8	0.76	0.04	2.3	0.092	
3	11.2	0.28	0.56	1.9	0.075	
4	7.4	0.70	0.00	1.9	0.076	

	free_sulfur_dioxide	total_sulfur_dioxide	density	pH	sulphates	\
0	11.0	34.0	0.9978	3.51	0.56	
1	25.0	67.0	0.9968	3.20	0.68	
2	15.0	54.0	0.9970	3.26	0.65	
3	17.0	60.0	0.9980	3.16	0.58	
4	11.0	34.0	0.9978	3.51	0.56	

```
   alcohol
0      9.4
1      9.8
2      9.8
3      9.8
4      9.4
```

[234]:
```
Y =df.quality
Y.head()
```

[234]:
```
0    5
1    5
2    5
3    6
4    5
Name: quality, dtype: int64
```

Label Binarisation (Conidering alcohol quality > 7 as good and assigning '1' to it else assigning '0')

[235]:
```
Y = df['quality'].apply(lambda y_value: 1 if y_value>=7 else 0)
```

[236]:
```
print(Y)
```

```
0       0
1       0
2       0
3       0
4       0
       ..
1593    0
1594    0
1595    0
1596    0
1597    0
Name: quality, Length: 866, dtype: int64
```

[237]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,␣
 ↪random_state=3)
```

[238]:
```
X_train.shape
```

[238]:
```
(692, 11)
```

[239]:
```
X_test.shape
```

[239]: (174, 11)

[240]:
```
print(Y.shape, Y_train.shape, Y_test.shape)
```

```
(866,) (692,) (174,)
```

0.0.4 Decision Tree Classifier

[242]:
```
from sklearn.tree import DecisionTreeClassifier
model1 = DecisionTreeClassifier(max_depth=2,splitter='best',criterion='entropy')
model1.fit(X_train,Y_train)
```

[242]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=2)
```

[243]:
```
d_y_predict = model1.predict(X_test)
d_y_predict
```

[243]:
```
array([1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0])
```

[245]:
```
d_y_predict_train = model1.predict(X_train)
```

0.0.5 Task - 4 : Evaluating the model (Decision tree classifier)

[246]:
```
from sklearn.metrics import␣
 ↪accuracy_score,classification_report,confusion_matrix
print('Testing Accuracy = ', accuracy_score(Y_test,d_y_predict))
print('Training Accuracy = ', accuracy_score(Y_train,d_y_predict_train))
```

```
Testing Accuracy =  0.8793103448275862
Training Accuracy =  0.8916184971098265
```

0.0.6 Random Forest Classifier

[247]:
```
from sklearn.ensemble import RandomForestClassifier
model2 =RandomForestClassifier(n_estimators=200,criterion='entropy')
model2.fit(X_train,Y_train)
```

[247]:
```
RandomForestClassifier(criterion='entropy', n_estimators=200)
```

[248]:
```
r_y_predict = model2.predict(X_test)
r_y_predict_train = model2.predict(X_train)
```

0.0.7 Task - 4 : Evaluating Random Forest Model

[249]:
```
print('Testing Accuracy = ', accuracy_score(Y_test,r_y_predict))
print('Training Accuracy = ', accuracy_score(Y_train,r_y_predict_train))
```

```
Testing Accuracy =  0.9425287356321839
Training Accuracy =  1.0
```

0.0.8 Naive Bayesian Classification Model

[251]:
```
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB()
gnb.fit(X_train,Y_train)
```

[251]:
```
GaussianNB()
```

[252]:
```
y_pred2 = gnb.predict(X_test)
y_pred2
```

[252]:
```
array([1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0])
```

0.0.9 Task - 4 : Evaluating Naive Bayesian Classification Model

[254]:
```
from sklearn.metrics import accuracy_score
gnb_acc=accuracy_score(Y_test,y_pred2)
gnb_acc
```

[254]:
```
0.8850574712643678
```

0.1 Accuracies of all the algorithms used in model nuilding phase :

Decision Tree Classification : 87.93 %

0.1.1 Random Forset Classification : 94.25 %

Naive Bayesian Classification : 88.50 %

0.1.2 Conclusion : Random Forest Classifier Model is best suited for the wine quality dataset.

0.1.3 Task - 5 : Test with random observation

[262]:
```
input_data = [7.9, 1.0, 0, 3.0, 0.08, 30, 100, 0.9562, 3.1, 0.74, 11.5]
prediction = model1.predict([input_data])
prediction
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does
not have valid feature names, but DecisionTreeClassifier was fitted with feature
names
  warnings.warn(
```

[262]:
```
array([0])
```

According to "decision tree classifier" model, the above random observation gives prediction "array([0])" i.e., bad quality alcohol

[263]:
```
input_data_2 = [7.9, 1.0, 0, 3.0, 0.08, 30, 100, 0.9562, 3.1, 0.74, 11.5]
prediction2 = model2.predict([input_data_2])
prediction2
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does
not have valid feature names, but RandomForestClassifier was fitted with feature
names
  warnings.warn(
```

[263]:
```
array([0])
```

According to "Random Forest classifier" model, the above random observation gives prediction "array([0])" i.e., bad quality alcohol

[264]:
```
input_data_3 = [7.9, 1.0, 0, 3.0, 0.08, 30, 100, 0.9562, 3.1, 0.74, 11.5]
prediction3 = gnb.predict([input_data_3])
prediction3
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does
not have valid feature names, but GaussianNB was fitted with feature names
  warnings.warn(
```

[264]:
```
array([0])
```

According to "Naive Bayesian classifier" model, the above random observation gives prediction "array([0])" i.e., bad quality alcohol

0.2 CONCLUSION : For the same random observation, all the three models gave the "alchohol quality is BAD"

1 The End !!!!