red_wine_quality

September 2, 2020

This datasets is related to red variants of the Portuguese "Vinho Verde" wine. For more details, consult the reference (Cortez et al., 2009). Due to privacy and logistic issues, only physicochemical (inputs) and sensory (the output) variables are available (e.g. there is no data about grape types, wine brand, wine selling price, etc.).

P. Cortez, A. Cerdeira, F. Almeida, T. Matos and J. Reis. Modeling wine preferences by data mining from physicochemical properties. In Decision Support Systems, Elsevier, 47(4):547-553, 2009.

1 Import Libraries

First, we import necessary libraries, such as:

[18]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set()
```

2 Import The Data

[19]:
```
red_wine = pd.read_csv('/kaggle/input/red-wine-quality-cortez-et-al-2009/
↪winequality-red.csv')
```

3 Quick Look at The Data

[20]:
```
red_wine.head()
```

[20]:
```
   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
```

- Dataset's info

[21]:
```
red_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
```

- Dataset's descriptive statistics

[22]:
```
red_wine.describe(include='all')
```

[22]:
```
       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

- Check for missing data

[23]:
```
red_wine.isnull().sum()
```

[23]:
```
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
```

4 Exploratory Data Analysis

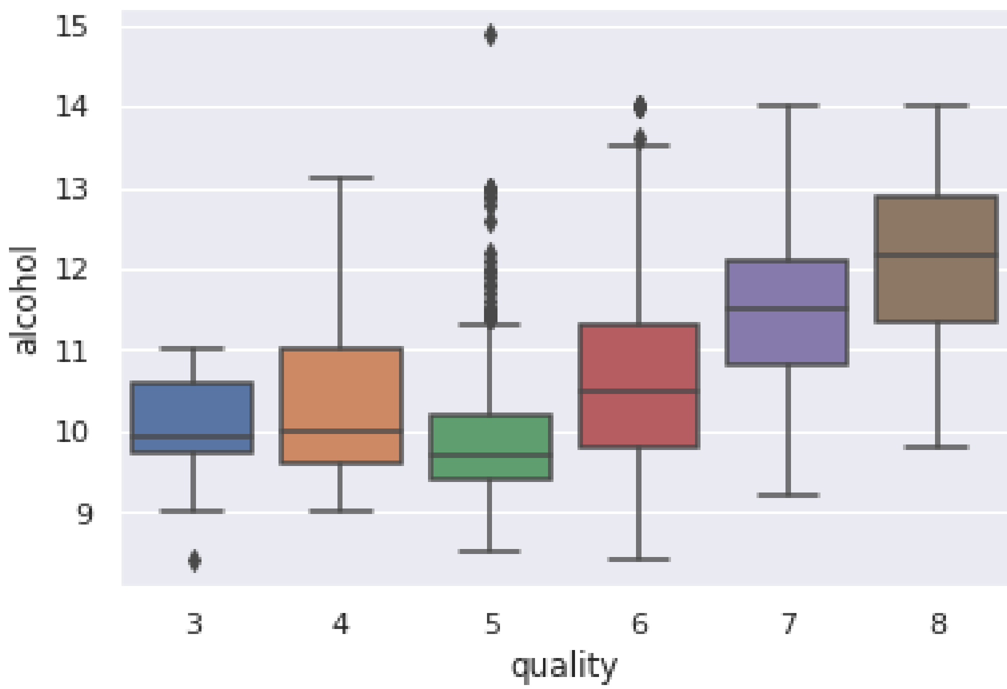
- Correlation of all the train features with target variable

[24]:
```
(red_wine.corr()**2)['quality'].sort_values(ascending = False)[1:]
```

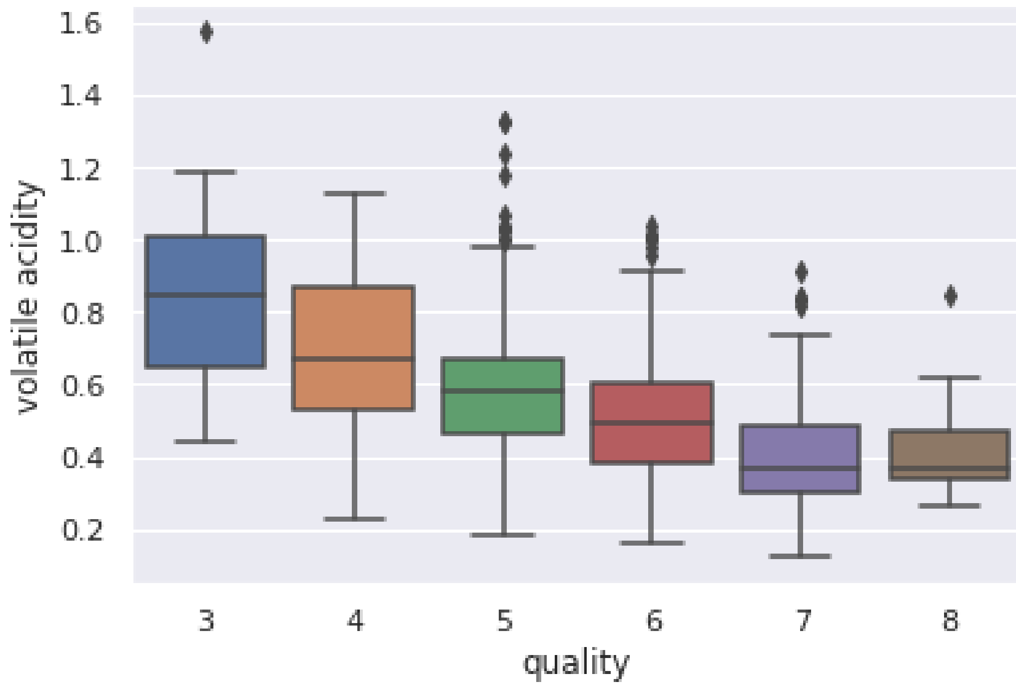
[24]:
```
alcohol                 0.226734
volatile acidity        0.152535
sulphates               0.063200
citric acid             0.051245
total sulfur dioxide    0.034262
density                 0.030597
chlorides               0.016617
fixed acidity           0.015389
pH                      0.003333
free sulfur dioxide     0.002566
residual sugar          0.000189
Name: quality, dtype: float64
```

Plot some top of the most correlated one.

[25]:
```
sns.boxplot(red_wine['quality'], red_wine['alcohol']);
```

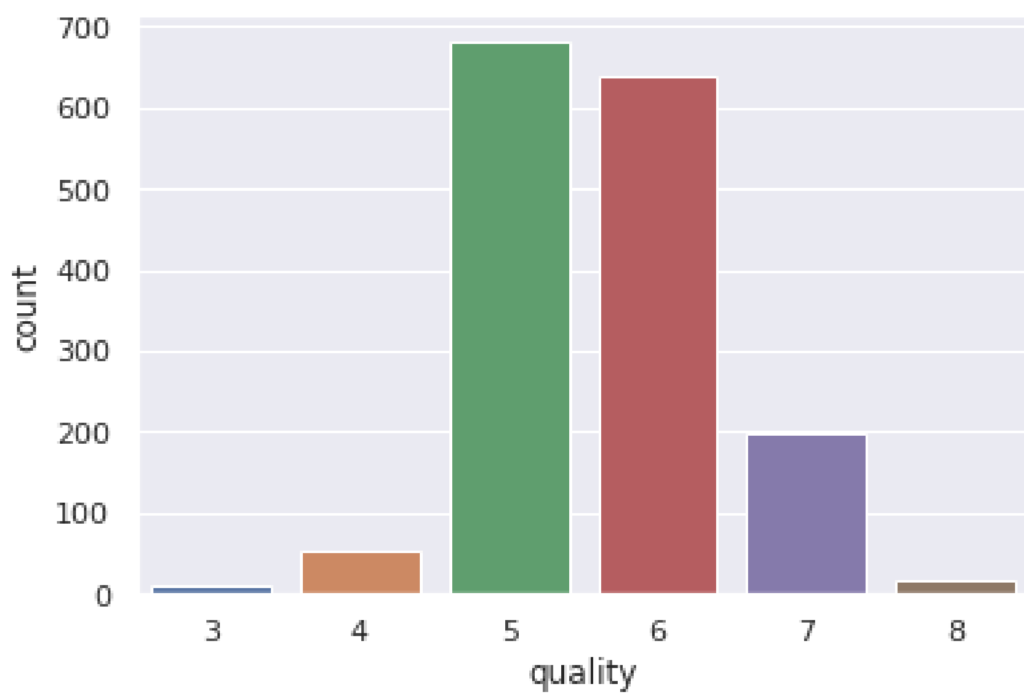


[26]:
```
sns.boxplot(red_wine['quality'], red_wine['volatile acidity']);
```



Let's see the distribution of quality feature by plotting it.

[27]:
```
sns.countplot(red_wine['quality'], data=red_wine);
```



In the real world, people often 'take it simple' by just classified red wine into 2 qualities, good and bad. I will try the same approach by transforming it to binary labels. Let's say wine with quality > 6 is good and the remainder is bad.

[28]:
```python
labels = ['bad', 'good']
bins = [2, 6, 8]
red_wine['quality'] = pd.cut(red_wine['quality'], bins=bins, labels=labels)
```

[29]:
```python
red_wine = pd.get_dummies(red_wine, drop_first=True)
red_wine
```

[29]:
```
      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  quality_good
0         9.4             0
1         9.8             0
2         9.8             0
3         9.8             0
4         9.4             0
…         …            …
1594     10.5             0
```

```
1595      11.2              0
1596      11.0              0
1597      10.2              0
1598      11.0              0

[1599 rows x 12 columns]
```

5 Creating A Model

We begin by splitting data into two subsets: for training data and for testing data.

[30]:
```python
from sklearn.model_selection import train_test_split

y = red_wine['quality_good']
X = red_wine.drop(['quality_good'], axis = 1)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.1)
```

Then, we standarize the train and the test datasets

[31]:
```python
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

scaler.fit(X_train)

X_train = scaler.transform(X_train)
print('X_train_scaled mean : ', X_train.mean(axis=0))
print('X_train_scaled std  : ', X_train.std(axis=0))

X_test = scaler.transform(X_test)
print('')
print('X_test_scaled mean : ', X_test.mean(axis=0))
print('X_test_scaled std  : ', X_test.std(axis=0))
```

```
X_train_scaled mean :  [-2.81451952e-16 -1.92572388e-16 -4.93775355e-17
2.65404253e-16
  2.33308855e-16  0.00000000e+00 -9.87550710e-18 -1.13605365e-14
  3.50580502e-16  3.35150022e-16  7.82633938e-16]
X_train_scaled std  :  [1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]

X_test_scaled mean :  [-0.06993313 -0.09650474  0.02502415 -0.06890154
0.08349466  0.02378321
  0.00024572 -0.03097825  0.00461156  0.11650666 -0.03174487]
X_test_scaled std  :  [0.93033989 1.02021541 0.9678853  0.97971602 1.41152659
1.08058636
```

```
 1.08590763 0.96012391 1.05688527 1.1821606  0.94855688]
```

Model training : Random Forest Classifier

[32]:
```
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier()
```

[33]:
```
#search grid for optimal parameters
from sklearn.model_selection import GridSearchCV

param_grid = {'n_estimators' : [100,1000],
              'max_depth': [None,10,100],
              'max_features': ['auto','sqrt','log2']}

grid = GridSearchCV(model, param_grid, cv=5)

grid.fit(X_train, y_train)

print(grid.best_params_)
print(grid.best_score_)
```

```
{'max_depth': 100, 'max_features': 'auto', 'n_estimators': 1000}
0.905485385210995
```

[34]:
```
from sklearn.metrics import mean_squared_error, classification_report

#use the best model
model = grid.best_estimator_

#make a prediction
y_predict = model.predict(X_test)

#calculate Mean Squared Error and classification report
print('MSE : ', mean_squared_error(y_test, y_predict))
print(classification_report(y_test,y_predict))
```

```
MSE :  0.0625
              precision    recall  f1-score   support

           0       0.94      0.99      0.96       139
           1       0.87      0.62      0.72        21

    accuracy                           0.94       160
   macro avg       0.91      0.80      0.84       160
weighted avg       0.93      0.94      0.93       160
```

```
[ ]:
```