wine-quality

March 22, 2021

[1]:
```
import numpy as np
import pandas as pd
import matplotlib as plt
import seaborn as sns
import plotly.express as px
%matplotlib inline
```

[2]:
```
red= pd.read_csv('E:\\JOB\\winequality\\winequality-red.csv', sep=';')
white= pd.read_csv('E:\\JOB\\winequality\\winequality-white.csv', sep=';')
```

[3]:
```
print("rows, columns: "+ str(red.shape))
```

```
rows, columns: (1599, 12)
```

[4]:
```
red.head()
```

[4]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

[5]:
```
print("rows, columns: "+ str(white.shape))
```

```
rows, columns: (4898, 12)
```

[6]:
```
white.head()
```

[6]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.0              0.27         0.36            20.7      0.045
1            6.3              0.30         0.34             1.6      0.049
2            8.1              0.28         0.40             6.9      0.050
3            7.2              0.23         0.32             8.5      0.058
4            7.2              0.23         0.32             8.5      0.058

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 45.0                 170.0   1.0010  3.00       0.45
1                 14.0                 132.0   0.9940  3.30       0.49
2                 30.0                  97.0   0.9951  3.26       0.44
3                 47.0                 186.0   0.9956  3.19       0.40
4                 47.0                 186.0   0.9956  3.19       0.40

   alcohol  quality
0      8.8        6
1      9.5        6
2     10.1        6
3      9.9        6
4      9.9        6
```

[7]:
```
#missing values of red
print(red.isna().sum())
```

```
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
```

[8]:
```
#missing values of white
print(white.isna().sum())
```

```
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
```

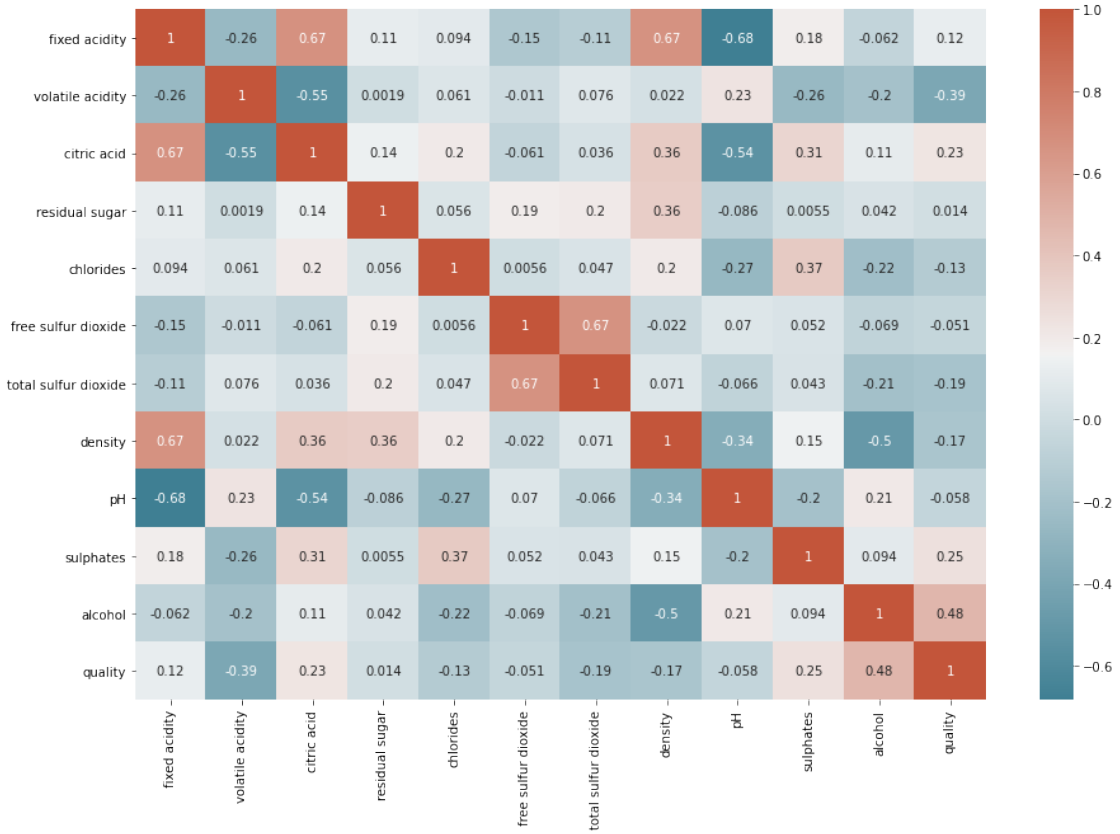
```
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

[17]:
```
#histogram of quality variable of red
px.histogram(red, x='quality')
```

[16]:
```
#histogram of quality variable of white
px.histogram(white, x='quality')
```

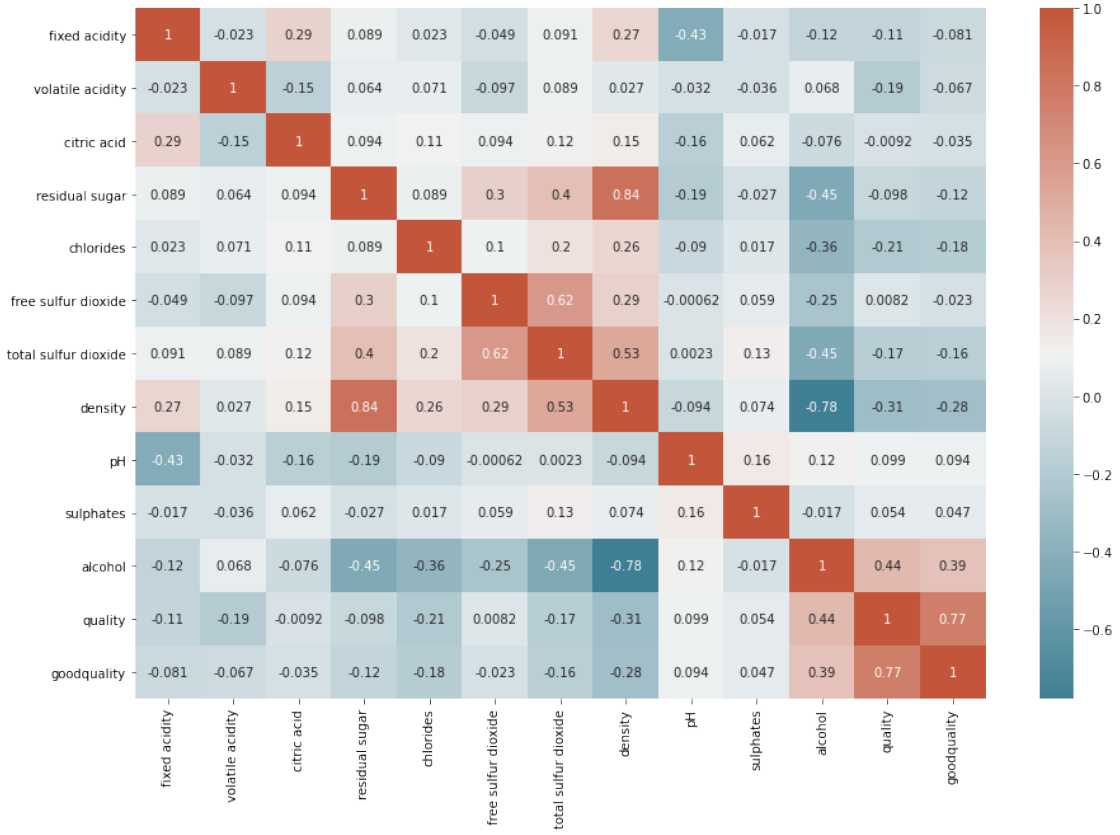
[8]:
```
#correlation matrix of red
rcorr= red.corr()
plt.pyplot.subplots(figsize=(15,10))
sns.heatmap(rcorr, xticklabels= rcorr.columns, yticklabels= rcorr.columns,␣
 ↪annot=True, cmap= sns.diverging_palette(220,20,as_cmap=True))
```

[8]: <AxesSubplot:>



[36]:
```
#correlation matrix of white
wcorr= white.corr()
plt.pyplot.subplots(figsize=(15,10))
sns.heatmap(wcorr, xticklabels= wcorr.columns, yticklabels= wcorr.columns,␣
↪annot=True, cmap= sns.diverging_palette(220,20,as_cmap=True))
```

[36]: <AxesSubplot:>



[22]:
```
#converting the quality of red wine variable to classification variable
red['goodquality']= [1 if x>=7 else 0 for x in red['quality']]
#separating featue and target variables
Xr= red.drop(['quality', 'goodquality'], axis=1)
Yr= red['goodquality']
```

[23]:
```
#converting the quality of white wine variable to classification variable
white['goodquality']= [1 if x>=7 else 0 for x in white['quality']]
#separating featue and target variables
Xw= white.drop(['quality', 'goodquality'], axis=1)
```

```
Yw= white['goodquality']
```

[24]:
```
#propotions of good vs bad wine in red
red['goodquality'].value_counts()
```

[24]:
```
0    1382
1     217
Name: goodquality, dtype: int64
```

[25]:
```
#propotions of good vs bad wine in white
white['goodquality'].value_counts()
```

[25]:
```
0    3838
1    1060
Name: goodquality, dtype: int64
```

[26]:
```
#normalizing feature variables in red
from sklearn.preprocessing import StandardScaler
Xr_feautres = Xr
Xr = StandardScaler().fit_transform(Xr)
#normalizing feature variables in whhite
Xw_feautres = Xw
Xw = StandardScaler().fit_transform(Xw)
```

[27]:
```
#splitting data into train and test sets
from sklearn.model_selection import train_test_split
Xr_train, Xr_test, Yr_train, Yr_test = train_test_split(Xr, Yr, test_size=.25,␣
 ↪random_state=0)
Xw_train, Xw_test, Yw_train, Yw_test = train_test_split(Xw, Yw, test_size=.25,␣
 ↪random_state=0)
```

[28]:
```
#model: Decision Trees
#red
from sklearn.metrics import classification_report
from sklearn.tree import DecisionTreeClassifier

modelr= DecisionTreeClassifier(random_state=1)
modelr.fit(Xr_train, Yr_train)
Y_predr = modelr.predict(Xr_test)

print(classification_report(Yr_test, Y_predr))
```

```
              precision    recall  f1-score   support

           0       0.96      0.92      0.94       355
           1       0.53      0.73      0.62        45

    accuracy                           0.90       400
```

```
   macro avg       0.75      0.83      0.78       400
weighted avg       0.92      0.90      0.90       400
```

[29]:
```
#model: Decision Trees
#white

modelw= DecisionTreeClassifier(random_state=1)
modelw.fit(Xw_train, Yw_train)
Y_predw = modelw.predict(Xw_test)

print(classification_report(Yw_test, Y_predw))
```

```
              precision    recall  f1-score   support

           0       0.88      0.89      0.89       963
           1       0.58      0.57      0.58       262

    accuracy                           0.82      1225
   macro avg       0.73      0.73      0.73      1225
weighted avg       0.82      0.82      0.82      1225
```

Decision Trees is a popular machine Learning model. The model for red wine is predicted with 90% accuracy and white wine model is predicted with 82% accuracy.

[30]:
```
#Random Trees
#red
from sklearn.ensemble import RandomForestClassifier
model2r = RandomForestClassifier(random_state=1)
model2r.fit(Xr_train, Yr_train)
Yr_pred2 = model2r.predict(Xr_test)
print(classification_report(Yr_test, Yr_pred2))
```

```
              precision    recall  f1-score   support

           0       0.95      0.97      0.96       355
           1       0.68      0.58      0.63        45

    accuracy                           0.92       400
   macro avg       0.82      0.77      0.79       400
weighted avg       0.92      0.92      0.92       400
```

[31]:
```
#Random Trees
#white

model2w = RandomForestClassifier(random_state=1)
model2w.fit(Xw_train, Yw_train)
```

```
Yw_pred2 = model2w.predict(Xw_test)
print(classification_report(Yw_test, Yw_pred2))
```

```
              precision    recall  f1-score   support

           0       0.88      0.95      0.92       963
           1       0.76      0.53      0.63       262

    accuracy                           0.86      1225
   macro avg       0.82      0.74      0.77      1225
weighted avg       0.86      0.86      0.85      1225
```

Random Forest is another popular ML model that build off of Decision Trees. it is more accurate than Decision Trees.The model selects the mode of all of the predictions of each decision tree. It relies on a majority-wins model, it reduces the risk of error from an individual tree.