Red Wine Quality Prediction Analysis

March 30, 2024

1 Wine Quality Prediction Analysis

The two datasets are related to red and white variants of the Portuguese "Vinho Verde" wine. These datasets can be viewed as **classification or regression** tasks. The classes are ordered and not balanced (e.g. there are munch more normal wines than excellent or poor ones).Outlier detection algorithms could be used to detect the few excellent or poor wines. Also, we are not sure if all input variables are relevant. So it could be interesting to test feature selection methods. Two datasets were combined and few values were randomly removed

1.1 Attribute Information:

Input variables (based on physicochemical tests):

1. **fixed acidity**
2. **volatile acidity**
3. **citric acid**
4. **residual sugar**
5. **chlorides**
6. **free sulfur dioxide**
7. **total sulfur dioxide**
8. **density**
9. **pH**
10. **sulphates**
11. **alcohol**

Output variable (based on sensory data):

12. **quality** (score between 0 and 10)

1.2 Import Modules

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
%matplotlib inline
warnings.filterwarnings('ignore')
```

1.3 Loading The Dataset

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

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

   chlorides  free sulfur dioxide  total sulfur dioxide  density    pH  \
0      0.045                 45.0                 170.0   1.0010  3.00
1      0.049                 14.0                 132.0   0.9940  3.30
2      0.050                 30.0                  97.0   0.9951  3.26
3      0.058                 47.0                 186.0   0.9956  3.19
4      0.058                 47.0                 186.0   0.9956  3.19

   sulphates  alcohol  quality
0       0.45      8.8        6
1       0.49      9.5        6
2       0.44     10.1        6
3       0.40      9.9        6
4       0.40      9.9        6
```

[3]:
```
# statistical information
df.describe()
```

[3]:
```
       fixed acidity  volatile acidity  citric acid  residual sugar  \
count    6487.000000       6489.000000  6494.000000     6495.000000
mean        7.216579          0.339691     0.318722        5.444326
std         1.296750          0.164649     0.145265        4.758125
min         3.800000          0.080000     0.000000        0.600000
25%         6.400000          0.230000     0.250000        1.800000
50%         7.000000          0.290000     0.310000        3.000000
75%         7.700000          0.400000     0.390000        8.100000
max        15.900000          1.580000     1.660000       65.800000

         chlorides  free sulfur dioxide  total sulfur dioxide      density  \
count  6495.000000          6497.000000           6497.000000  6497.000000
mean      0.056042            30.525319            115.744574     0.994697
std       0.035036            17.749400             56.521855     0.002999
min       0.009000             1.000000              6.000000     0.987110
25%       0.038000            17.000000             77.000000     0.992340
50%       0.047000            29.000000            118.000000     0.994890
75%       0.065000            41.000000            156.000000     0.996990
max       0.611000           289.000000            440.000000     1.038980
```

```
                 pH    sulphates      alcohol      quality
count  6488.000000  6493.000000  6497.000000  6497.000000
mean      3.218395     0.531215    10.491801     5.818378
std       0.160748     0.148814     1.192712     0.873255
min       2.720000     0.220000     8.000000     3.000000
25%       3.110000     0.430000     9.500000     5.000000
50%       3.210000     0.510000    10.300000     6.000000
75%       3.320000     0.600000    11.300000     6.000000
max       4.010000     2.000000    14.900000     9.000000
```

[4]:
```
# Datatype Information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6497 entries, 0 to 6496
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   type                  6497 non-null   object
 1   fixed acidity         6487 non-null   float64
 2   volatile acidity      6489 non-null   float64
 3   citric acid           6494 non-null   float64
 4   residual sugar        6495 non-null   float64
 5   chlorides             6495 non-null   float64
 6   free sulfur dioxide   6497 non-null   float64
 7   total sulfur dioxide  6497 non-null   float64
 8   density               6497 non-null   float64
 9   pH                    6488 non-null   float64
 10  sulphates             6493 non-null   float64
 11  alcohol               6497 non-null   float64
 12  quality               6497 non-null   int64
dtypes: float64(11), int64(1), object(1)
memory usage: 660.0+ KB
```

[5]:
```
# Cheak for NULL values
df.isnull().sum()
```

[5]:
```
type                     0
fixed acidity           10
volatile acidity         8
citric acid              3
residual sugar           2
chlorides                2
free sulfur dioxide      0
total sulfur dioxide     0
density                  0
pH                       9
```

```
sulphates               4
alcohol                 0
quality                 0
dtype: int64
```

[6]:

```
# fill the missing values
for col, values in df.items():
    if col!= 'type':
        df[col] = df[col].fillna(df[col].mean())
```

[7]:

```
# Cheak for NULL values ( after fill missing values)
df.isnull().sum()
```

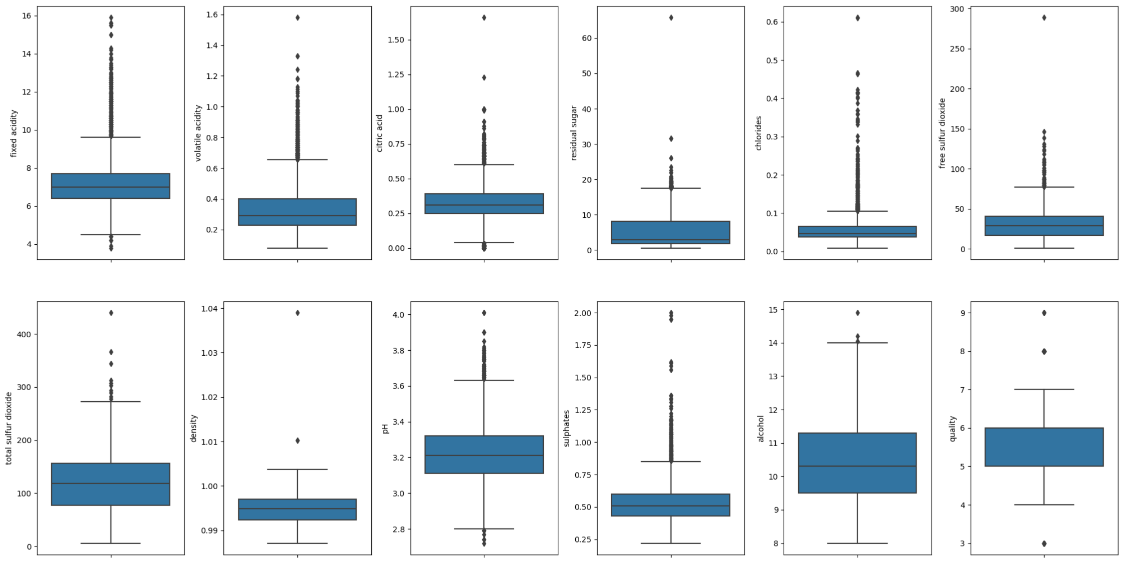
[7]:

```
type                    0
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
```

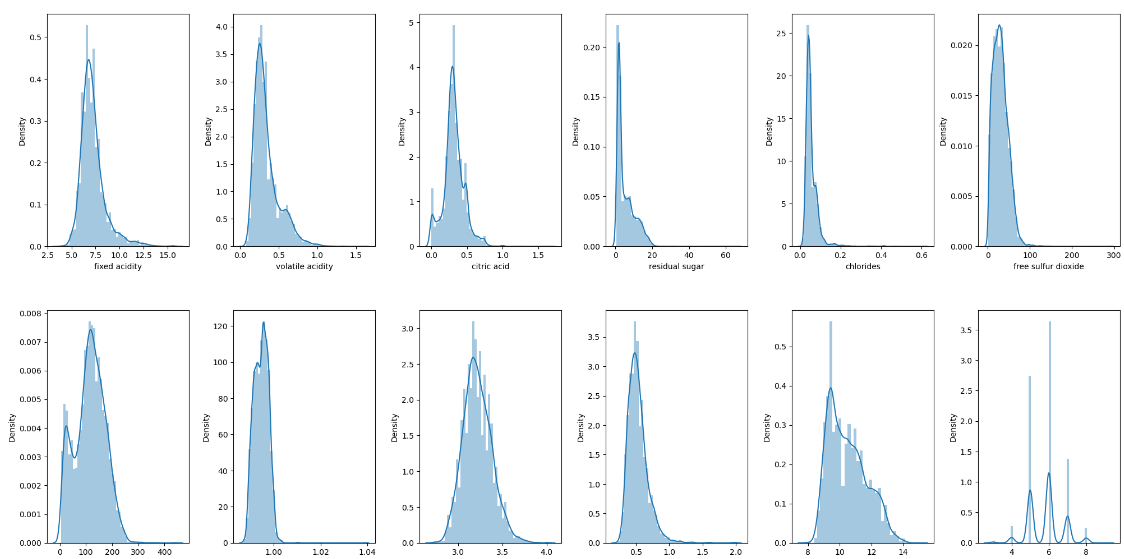
1.4 Expoloratory Data Analysis

[8]:

```
# create box plots
fig, ax = plt.subplots(ncols=6, nrows=2, figsize=(20,10))
index = 0
ax = ax.flatten()

for col, value in df.items():
    if col != 'type':
        sns.boxplot(y=col, data=df, ax=ax[index])
        index += 1
plt.tight_layout(pad=0.5, w_pad=0.7, h_pad=5.0)
```



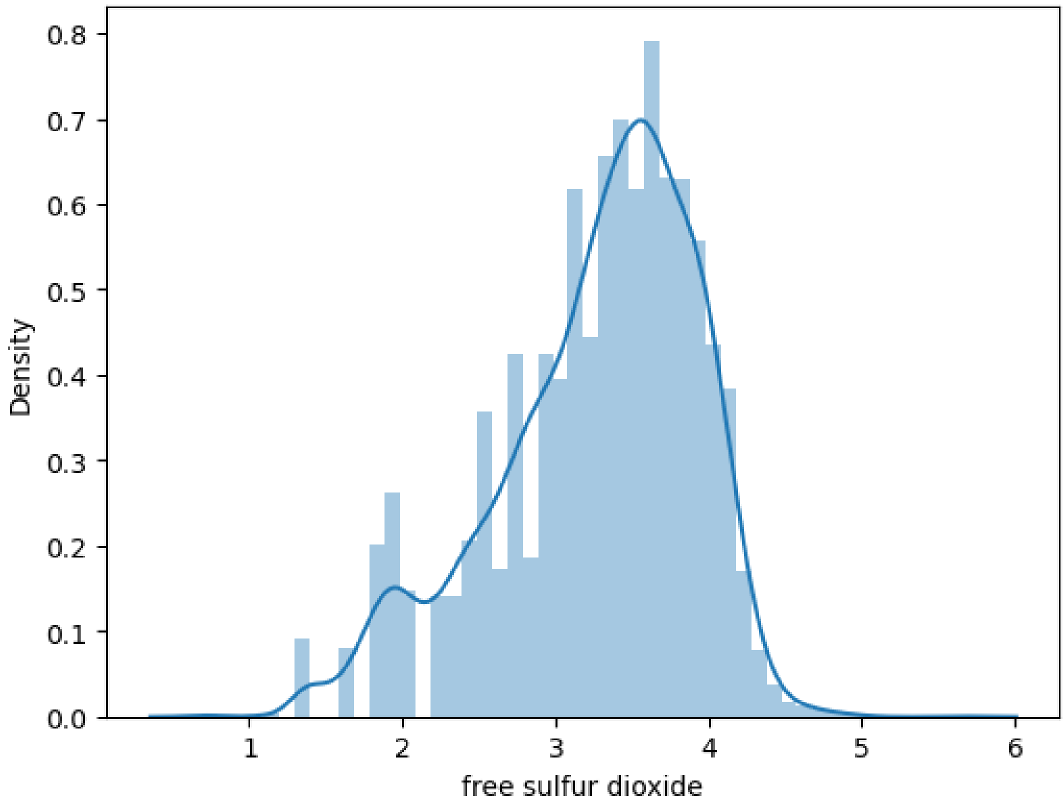
[9]:
```
# create dist plot
fig, ax = plt.subplots(ncols=6, nrows=2, figsize=(20,10))
index = 0
ax = ax.flatten()

for col, value in df.items():
    if col != 'type':
        sns.distplot(value, ax=ax[index])
        index += 1
plt.tight_layout(pad=0.5, w_pad=0.7, h_pad=5.0)
```



[10]:
```
# log transformation
df['free sulfur dioxide'] = np.log(1 + df['free sulfur dioxide'])
```

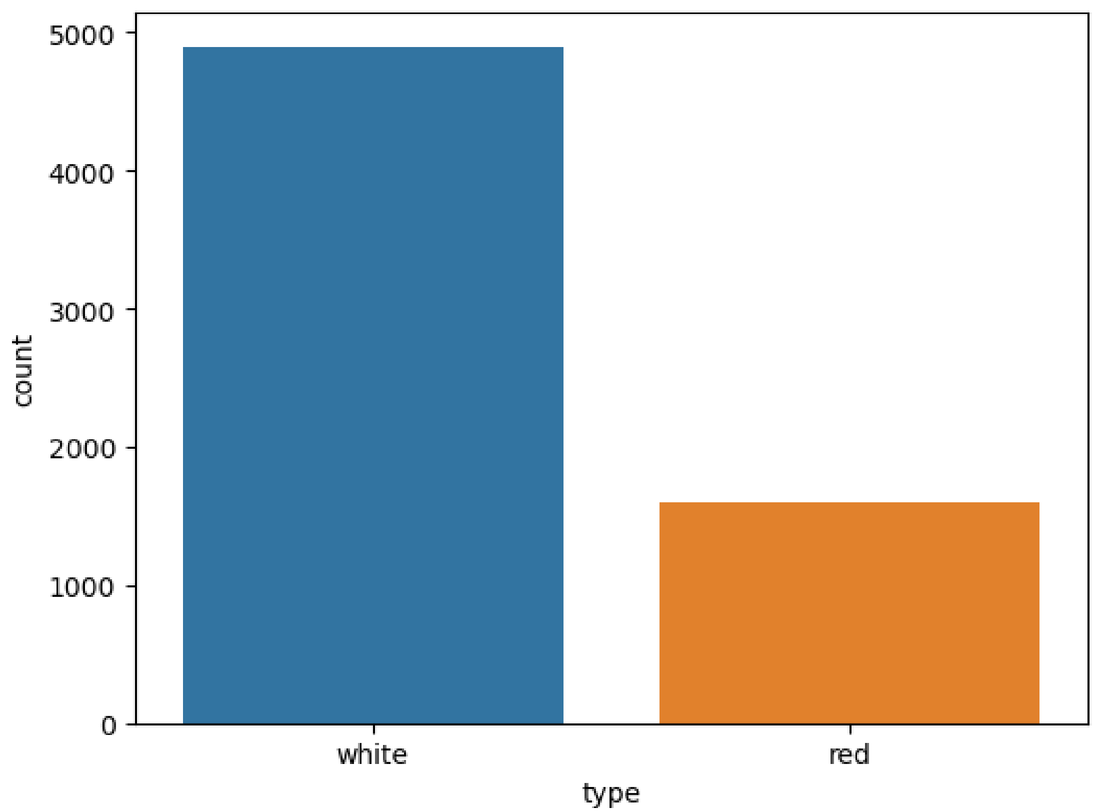
[11]:
```
sns.distplot(df['free sulfur dioxide'])
```

[11]: <Axes: xlabel='free sulfur dioxide', ylabel='Density'>



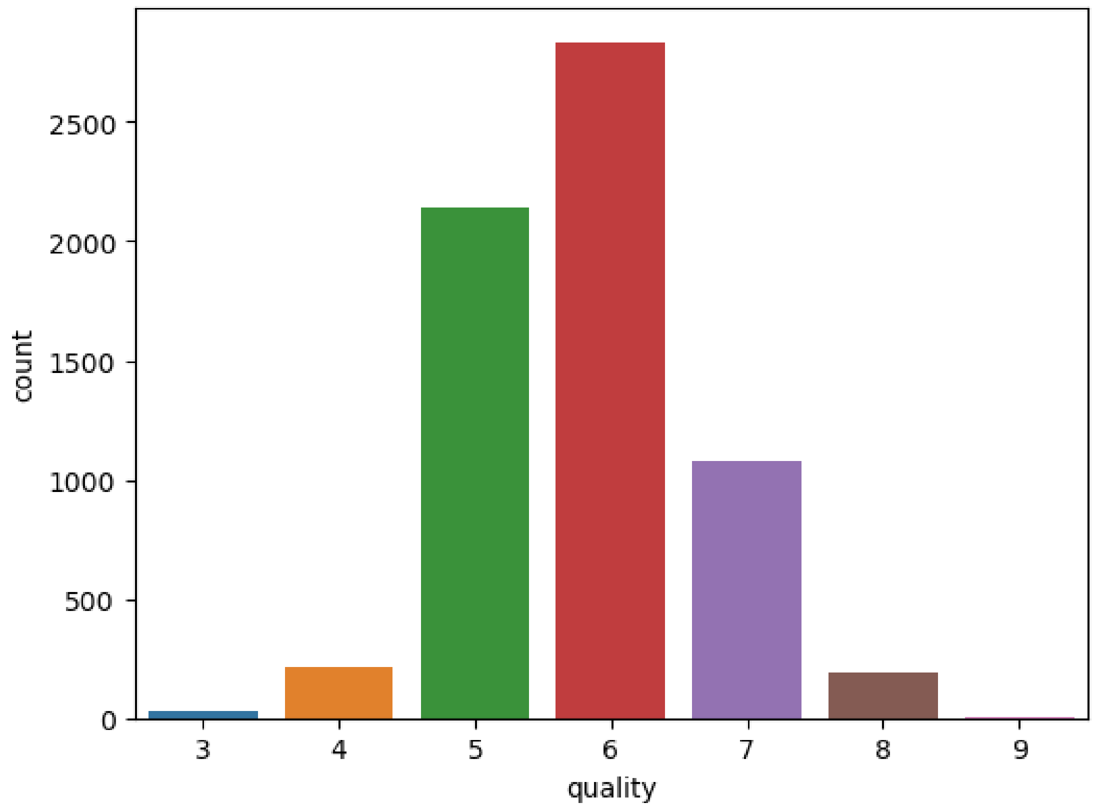
[12]:
```
sns.countplot(data=df, x='type')
```

[12]: <Axes: xlabel='type', ylabel='count'>



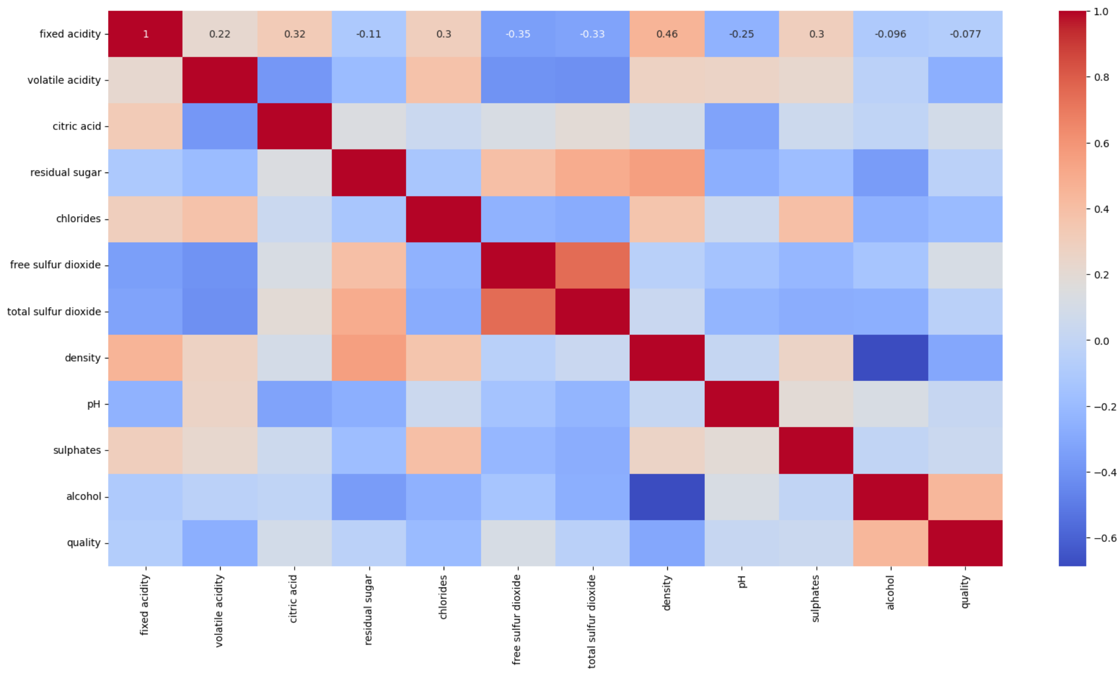
[13]:
```
sns.countplot(data=df, x='quality')
```

[13]: <Axes: xlabel='quality', ylabel='count'>



1.5 Coorelation Matrix

[14]:
```
# Step 1: Identify non-numeric columns
non_numeric_columns = df.select_dtypes(exclude=['float64', 'int64']).columns

# Step 2: Drop non-numeric columns
numeric_df = df.drop(columns=non_numeric_columns)

# Now, calculate the correlation matrix
corr = numeric_df.corr()

# Plot heatmap
plt.figure(figsize=(20, 10))
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.show()
```



1.6 Input split

[15]:
```
X = df.drop(columns=['type','quality'])
y = df['quality']
```

1.7 Class Imbalancement

[16]:
```
y.value_counts()
```

[16]:
```
quality
6    2836
5    2138
7    1079
4     216
8     193
3      30
9       5
Name: count, dtype: int64
```

[17]:
```
from imblearn.over_sampling import SMOTE
oversample = SMOTE(k_neighbors=4)
# transform the dataset
X, y = oversample.fit_resample(X, y)
```

[18]:
```
y.value_counts()
```

[18]: quality
```
6    2836
5    2836
7    2836
8    2836
4    2836
3    2836
9    2836
Name: count, dtype: int64
```

1.8 Model Training

[19]:
```python
# classify function
from sklearn.model_selection import cross_val_score, train_test_split
def classify(model, X, y):
    x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=42)
    # train the model
    model.fit(x_train, y_train)
    print("Accuracy:", model.score(x_test, y_test) * 100)

    # cross-validation
    score = cross_val_score(model, X, y, cv=5)
    print("CV Score:", np.mean(score)*100)
```

[20]:
```python
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
classify(model, X, y)
```

```
Accuracy: 35.05943985492645
CV Score: 32.81264482358561
```

[21]:
```python
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()
classify(model, X, y)
```

```
Accuracy: 80.19343139230304
CV Score: 75.71034965718081
```

[22]:
```python
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
classify(model, X, y)
```

```
Accuracy: 88.01128349788434
CV Score: 82.72220957102722
```

[23]:
```python
from sklearn.ensemble import ExtraTreesClassifier
model = ExtraTreesClassifier()
classify(model, X, y)
```

```
Accuracy: 88.87769494257506
CV Score: 83.65408278025761
```

[ ]:

[ ]: