Wine Quality Prediction

July 22, 2023

[35]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn import metrics
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression

import warnings
warnings.filterwarnings('ignore')
```

[34]:
```
df = pd.read_csv('winequalityprediction-red.csv')
print(df.head())
```

```
   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
```

[3]:
```
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
```

[4]:
```
df.describe().T
```

[4]:
```
                       count       mean        std      min      25%  \
fixed acidity         1599.0   8.319637   1.741096  4.60000   7.1000
volatile acidity      1599.0   0.527821   0.179060  0.12000   0.3900
citric acid           1599.0   0.270976   0.194801  0.00000   0.0900
residual sugar        1599.0   2.538806   1.409928  0.90000   1.9000
chlorides             1599.0   0.087467   0.047065  0.01200   0.0700
free sulfur dioxide   1599.0  15.874922  10.460157  1.00000   7.0000
total sulfur dioxide  1599.0  46.467792  32.895324  6.00000  22.0000
density               1599.0   0.996747   0.001887  0.99007   0.9956
pH                    1599.0   3.311113   0.154386  2.74000   3.2100
sulphates             1599.0   0.658149   0.169507  0.33000   0.5500
alcohol               1599.0  10.422983   1.065668  8.40000   9.5000
quality               1599.0   5.636023   0.807569  3.00000   5.0000

                           50%        75%        max
fixed acidity          7.90000   9.200000   15.90000
volatile acidity       0.52000   0.640000    1.58000
citric acid            0.26000   0.420000    1.00000
residual sugar         2.20000   2.600000   15.50000
chlorides              0.07900   0.090000    0.61100
free sulfur dioxide   14.00000  21.000000   72.00000
total sulfur dioxide  38.00000  62.000000  289.00000
density                0.99675   0.997835    1.00369
pH                     3.31000   3.400000    4.01000
```

```
sulphates              0.62000   0.730000    2.00000
alcohol               10.20000  11.100000   14.90000
quality                6.00000   6.000000    8.00000
```

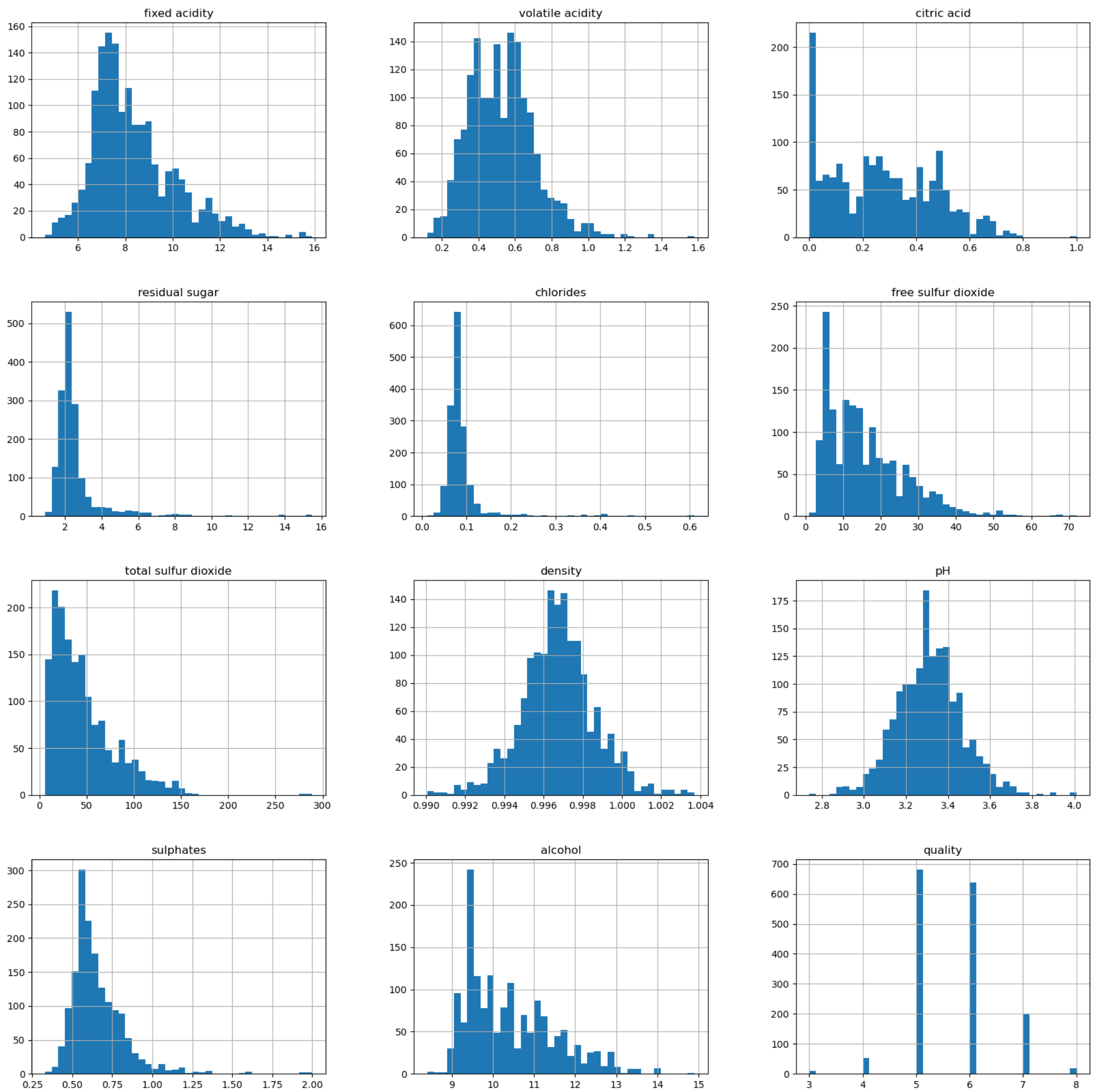
[5]:
```
df.isnull().sum()
```

[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
```

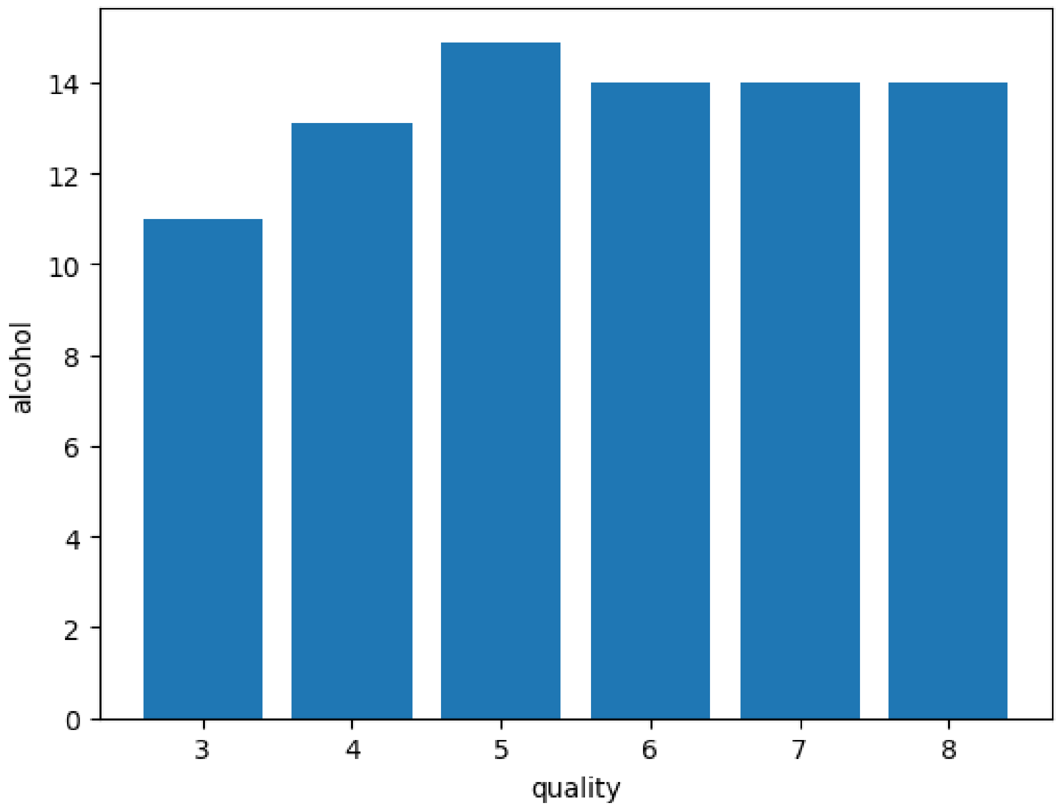
[9]:
```
for col in df.columns:
  if df[col].isnull().sum() > 0:
    df[col] = df[col].fillna(df[col].mean())

df.isnull().sum().sum()
```

[9]:
```
0
```

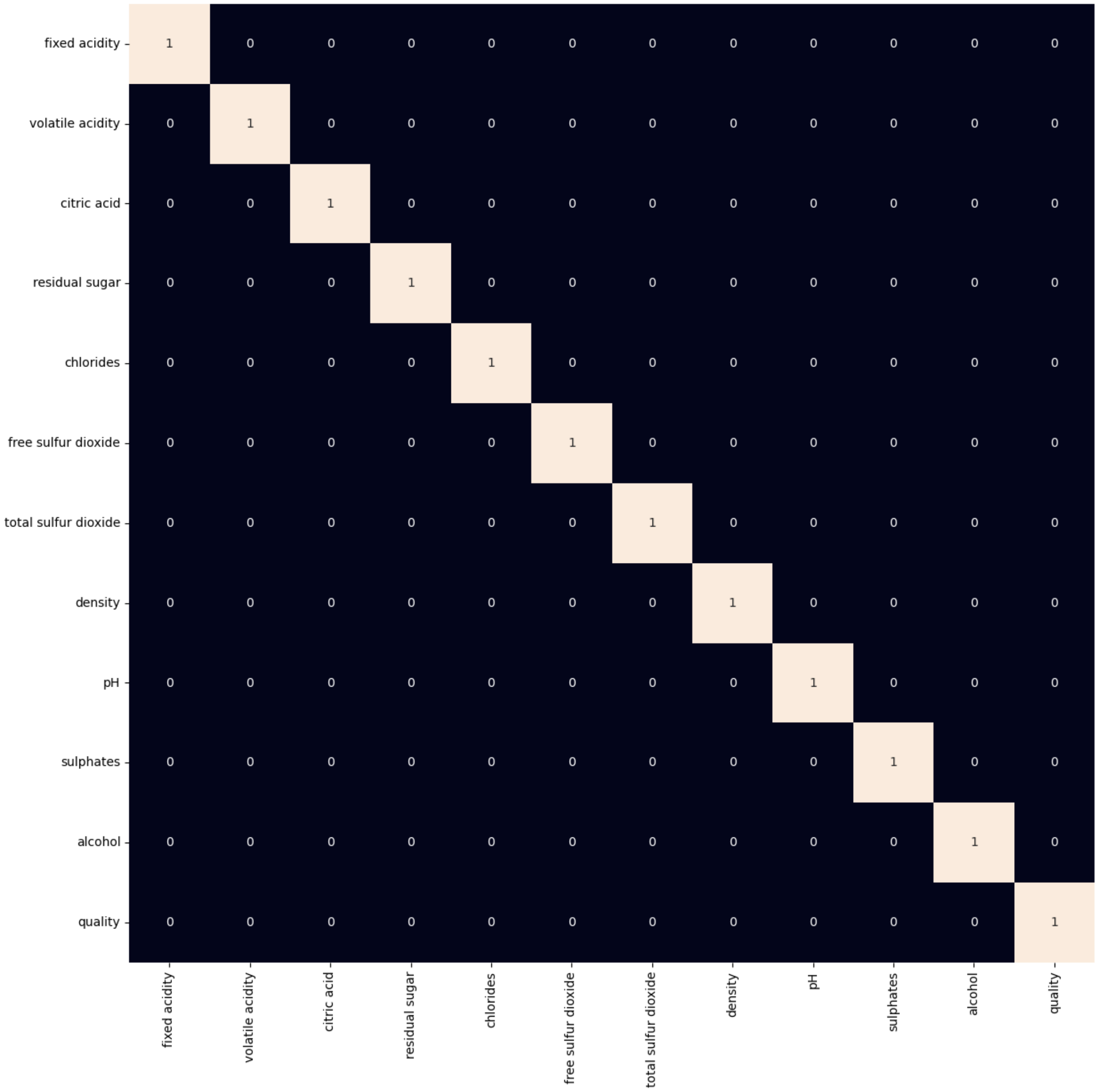
[11]:
```
df.hist(bins=40, figsize=(20, 20))
plt.show()
```



[12]:
```
plt.bar(df['quality'], df['alcohol'])
plt.xlabel('quality')
plt.ylabel('alcohol')
plt.show()
```



[13]:
```
plt.figure(figsize=(14, 14))
sb.heatmap(df.corr() > 0.7, annot=True, cbar=False)
plt.show()
```



[15]:
```
df = df.drop('total sulfur dioxide', axis=1)
```

[16]:
```
df['best quality'] = [1 if x > 5 else 0 for x in df.quality]
```

[17]:
```
df.replace({'white': 1, 'red': 0}, inplace=True)
```

[18]:
```
features = df.drop(['quality', 'best quality'], axis=1)
target = df['best quality']

xtrain, xtest, ytrain, ytest = train_test_split(features, target, test_size=0.
 ↪2, random_state=40)

xtrain.shape, xtest.shape
```

[18]: ((1279, 10), (320, 10))

[19]:
```
norm = MinMaxScaler()
xtrain = norm.fit_transform(xtrain)
xtest = norm.transform(xtest)
```

[36]:
```
models = [LogisticRegression(), XGBClassifier(), SVC(kernel='rbf')]

for i in range(3):
    models[i].fit(xtrain, ytrain)

    print(f'{models[i]} : ')
    print('Training Accuracy : ', metrics.roc_auc_score(ytrain, models[i].
 ↪predict(xtrain)))
    print('Validation Accuracy : ', metrics.roc_auc_score(ytest, models[i].
 ↪predict(xtest)))
    print()
```

```
LogisticRegression() :
Training Accuracy :  0.7286886534333447
Validation Accuracy :  0.765345444536196

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, …) :
Training Accuracy :  1.0
Validation Accuracy :  0.8345523180370414

SVC() :
Training Accuracy :  0.7699408577589806
Validation Accuracy :  0.7930675160237505
```

[ ]:
```

```

[38]:
```
print(metrics.classification_report(ytest,models[1].predict(xtest)))
```

```
              precision    recall  f1-score   support

           0       0.81      0.84      0.82       147
```

```
           1       0.86      0.83      0.84       173

    accuracy                           0.83       320
   macro avg       0.83      0.83      0.83       320
weighted avg       0.84      0.83      0.83       320
```

[ ]: