21bce5283-agginment-4

September 27, 2023

1 Grapes to Greatness: Machine Learning in Wine Quality

```
[1]: import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     df=pd.read_csv('/content/winequality-red.csv')
[1]:
           fixed acidity
                           volatile acidity
                                              citric acid
                                                            residual sugar
                                                                              chlorides
                                                                        1.9
                      7.4
                                       0.700
                                                      0.00
                                                                                  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
                      6.2
                                       0.600
                                                      0.08
                                                                        2.0
                                                                                  0.090
     1594
                      5.9
                                                      0.10
                                                                        2.2
     1595
                                       0.550
                                                                                  0.062
     1596
                      6.3
                                       0.510
                                                      0.13
                                                                        2.3
                                                                                  0.076
     1597
                      5.9
                                                      0.12
                                                                        2.0
                                       0.645
                                                                                  0.075
     1598
                      6.0
                                       0.310
                                                      0.47
                                                                        3.6
                                                                                  0.067
           free sulfur dioxide
                                  total sulfur dioxide
                                                                         sulphates
                                                         density
                                                                     рΗ
     0
                                                   34.0
                                                         0.99780
                                                                   3.51
                                                                               0.56
                           11.0
     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
                                                   44.0 0.99490
     1594
                           32.0
                                                                   3.45
                                                                               0.58
     1595
                           39.0
                                                   51.0 0.99512
                                                                   3.52
                                                                               0.76
                           29.0
     1596
                                                   40.0 0.99574
                                                                   3.42
                                                                               0.75
                           32.0
     1597
                                                   44.0 0.99547
                                                                   3.57
                                                                               0.71
     1598
                           18.0
                                                   42.0 0.99549
                                                                   3.39
                                                                               0.66
           alcohol
                    quality
     0
                9.4
                           5
```

1	9.8	5
2	9.8	5
3	9.8	6
4	9.4	5
•••		
1594	10.5	5
1595	11.2	6
1596	11.0	6
1597	10.2	5
1598	11.0	6

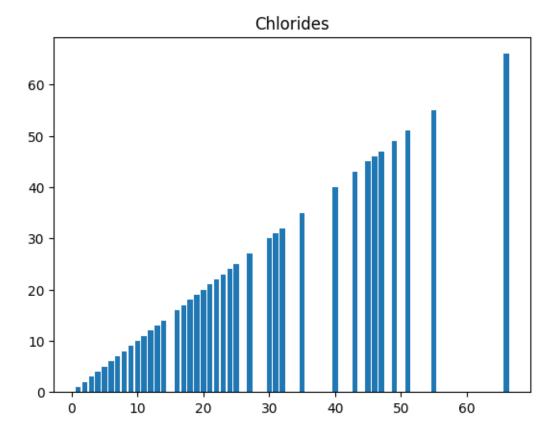
[1599 rows x 12 columns]

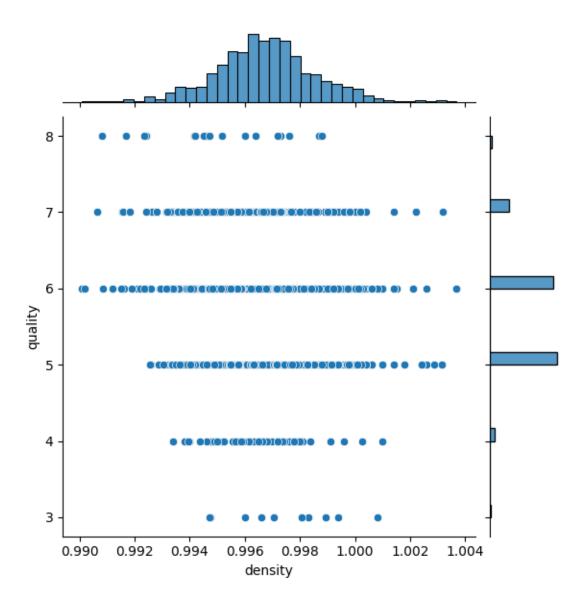
```
[11]: df.describe()
```

```
volatile acidity
                                                                residual sugar
[11]:
              fixed acidity
                                                 citric acid
                1599.000000
                                   1599.000000
                                                 1599.000000
                                                                   1599.000000
      count
                                       0.527821
                                                     0.270976
                                                                      2.538806
      mean
                   8.319637
      std
                   1.741096
                                       0.179060
                                                     0.194801
                                                                      1.409928
      min
                   4.600000
                                       0.120000
                                                     0.000000
                                                                      0.900000
      25%
                                       0.390000
                                                     0.090000
                   7.100000
                                                                      1.900000
      50%
                   7.900000
                                       0.520000
                                                     0.260000
                                                                      2.200000
      75%
                   9.200000
                                       0.640000
                                                     0.420000
                                                                      2.600000
                  15.900000
                                       1.580000
                                                     1.000000
                                                                     15.500000
      max
                chlorides
                            free sulfur dioxide
                                                   total sulfur dioxide
                                                                               density
             1599.000000
                                    1599.000000
                                                            1599.000000
                                                                           1599.000000
      count
                 0.087467
                                       15.874922
                                                               46.467792
                                                                              0.996747
      mean
      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
                                                                              0.997835
      75%
                 0.090000
                                       21.000000
                                                               62.000000
                                                             289.000000
      max
                 0.611000
                                       72.000000
                                                                              1.003690
                       рΗ
                              sulphates
                                              alcohol
                                                            quality
                                          1599.000000
             1599.000000
                            1599.000000
                                                        1599.000000
      count
                               0.658149
      mean
                 3.311113
                                            10.422983
                                                           5.636023
      std
                 0.154386
                               0.169507
                                             1.065668
                                                           0.807569
      min
                 2.740000
                               0.330000
                                             8.400000
                                                           3.000000
      25%
                                             9.500000
                 3.210000
                               0.550000
                                                           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
```

```
[35]: plt.bar(df.chlorides.value_counts(),df.chlorides.value_counts()) plt.title("Chlorides")
```

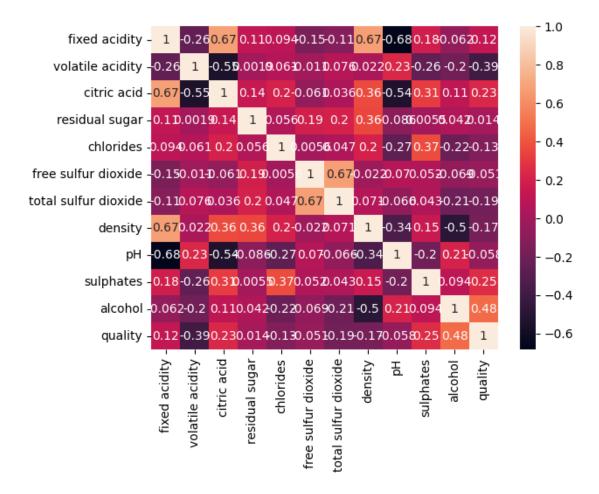
plt.show()





[10]: sns.heatmap(df.corr(),annot=True)

[10]: <Axes: >



```
[14]: from sklearn.model_selection import train_test_split
      from sklearn.preprocessing import StandardScaler
      X=df.drop("quality",axis=1)
      y=df["quality"]
      X.head()
[14]:
         fixed acidity volatile acidity citric acid residual sugar
                                                                         chlorides \
                   7.4
                                     0.70
                                                  0.00
                                                                    1.9
                                                                             0.076
      0
                   7.8
                                                                    2.6
                                     0.88
                                                  0.00
                                                                             0.098
      1
                                                  0.04
      2
                   7.8
                                     0.76
                                                                    2.3
                                                                             0.092
      3
                  11.2
                                     0.28
                                                  0.56
                                                                    1.9
                                                                             0.075
                   7.4
                                     0.70
                                                  0.00
                                                                    1.9
                                                                             0.076
         free sulfur dioxide total sulfur dioxide density
                                                                pH sulphates \
                        11.0
      0
                                               34.0
                                                      0.9978 3.51
                                                                          0.56
      1
                        25.0
                                               67.0
                                                      0.9968
                                                              3.20
                                                                          0.68
                        15.0
                                                                          0.65
      2
                                               54.0
                                                      0.9970
                                                              3.26
                        17.0
                                               60.0
                                                                          0.58
      3
                                                      0.9980
                                                              3.16
```

```
4
                        11.0
                                              34.0 0.9978 3.51 0.56
         alcohol
             9.4
      0
             9.8
      1
             9.8
      2
      3
             9.8
      4
             9.4
[15]: sc=StandardScaler()
      X scaled=sc.fit transform(X)
      X_train, X_test, y_train, y_test=train_test_split(X_scaled, y, test_size=0.
       \hookrightarrow 2, random state=42)
[15]: array([[ 0.21852997, 0.90601191, 0.20039205, ..., 1.09426457,
               0.48302886, 1.10483337],
             [-1.27524919, -1.77549685, 0.66254621, ..., -0.39596939,
              -0.40216729, 1.38643512],
             [ 1.48249695, -0.76993107, 1.02199944, ..., -0.07200549,
               0.54204194, -0.58477711],
             [-0.6432657, 0.51495855, -1.08336951, ..., 1.28864292,
             -0.69723268, -0.86637886],
             [-0.24109439, -1.83136161, 0.4057939, ..., 0.05758008,
               0.83710732, 1.38643512],
             [-1.44760832, -1.32857872, -0.05636026, ..., 0.51112954,
              -0.69723268, 2.8883111 ]])
[19]: from sklearn.linear_model import LogisticRegression
      from sklearn.metrics import confusion_matrix
      le=LogisticRegression()
      model=le.fit(X_train,y_train)
      y_pred = model.predict(X_test)
      cm = confusion_matrix(y_test, y_pred)
     /usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458:
     ConvergenceWarning: lbfgs failed to converge (status=1):
     STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
     Increase the number of iterations (max_iter) or scale the data as shown in:
         https://scikit-learn.org/stable/modules/preprocessing.html
     Please also refer to the documentation for alternative solver options:
         https://scikit-learn.org/stable/modules/linear_model.html#logistic-
     regression
       n_iter_i = _check_optimize_result(
```

```
[19]: array([[ 0, 0, 1, 0, 0, 0],
             [ 0,
                   1, 7, 2,
                               0,
                                   0],
             [ 0, 0, 98, 32,
                               0,
                                   0],
             [ 0, 0, 46, 76, 10,
                                   0],
             [ 0, 0, 3, 30,
                               9,
                                   0],
             [0, 0, 0, 1,
                                   0]])
[21]: from sklearn.metrics import accuracy_score,
      Gonfusion_matrix,classification_report,roc_auc_score,roc_curve
      accuracy_score(y_test,y_pred)
[21]: 0.575
[22]: pd.crosstab(y_test,y_pred)
[22]: col_0
                           7
                   5
      quality
      3
                           0
               0
                   1
                       0
      4
               1
                  7
                       2
                           0
      5
               0 98 32
                           0
      6
               0 46 76
                        10
      7
               0
                   3
                      30
                           9
               0
                   0
                       1
                           4
[25]: print(classification_report(y_test,y_pred))
                                recall f1-score
                                                   support
                   precision
                3
                        0.00
                                  0.00
                                            0.00
                                                         1
                                  0.10
                                            0.18
                4
                        1.00
                                                        10
                5
                        0.63
                                  0.75
                                            0.69
                                                       130
                6
                        0.54
                                  0.58
                                            0.56
                                                        132
                7
                        0.39
                                  0.21
                                            0.28
                                                        42
                8
                        0.00
                                  0.00
                                            0.00
                                                         5
```

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

0.57

0.28

0.55

0.27

0.57

0.43

0.56

320

320

320

accuracy

macro avg

weighted avg

_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to

control this behavior. _warn_prf(average, modifier, msg_start, len(result)) /usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero division` parameter to control this behavior. _warn_prf(average, modifier, msg_start, len(result)) [27]: probability = model.predict proba(X test)[:,1] probability [27]: array([0.02483477, 0.02249377, 0.01574946, 0.01134614, 0.03202448, 0.01491135, 0.00750669, 0.11853224, 0.02170618, 0.04960947, 0.01348905, 0.13794541, 0.02885185, 0.02524655, 0.02042773, 0.00977959, 0.03329229, 0.01903721, 0.00330975, 0.03185402, 0.1797074, 0.03375518, 0.06405695, 0.01701967, 0.07199606, 0.03828524, 0.00477106, 0.08112635, 0.04058424, 0.01038622, , 0.04077697, 0.01130467, 0.04878004, 0.02851514, 0.02944521, 0.01913737, 0.06835138, 0.03249786, 0.02057124,0.02567618, 0.02042431, 0.006988, 0.01425204, 0.01374079,0.03947643, 0.00374969, 0.01676378, 0.08833596, 0.07250037, 0.01094354, 0.02734811, 0.09025171, 0.01177792, 0.04743786,0.01557644, 0.02994908, 0.09684315, 0.02995632, 0.06248571, 0.01361311, 0.02148332, 0.03028016, 0.04898658, 0.00497826, 0.01510166, 0.01183327, 0.04781076, 0.00504487, 0.01450206, 0.00975868, 0.08957871, 0.0110487, 0.03338539, 0.02254037,0.04057309, 0.00302335, 0.00481278, 0.02595905, 0.00514559, 0.06328622, 0.00571601, 0.02323339, 0.03167214, 0.02807292, 0.00498152, 0.01519544, 0.071952, 0.00589653, 0.10965556,0.00579155, 0.04130017, 0.09166548, 0.0216257, 0.00971574, 0.01430115, 0.02018015, 0.02031068, 0.15743163, 0.02627518, 0.1286683, 0.03879046, 0.01325419, 0.10345292, 0.04510503, 0.01106421, 0.01385973, 0.00778097, 0.03758517, 0.03038102, 0.00631245, 0.00592356, 0.00255582, 0.0085207, 0.02894913, 0.01094736, 0.06563413, 0.01373076, 0.05589608, 0.01637058, 0.01182063, 0.0395007, 0.01413268, 0.02768522, 0.0678964, 0.04112568, 0.00826422, 0.02335786, 0.03401157, 0.02896179, 0.0110487, 0.11028868, 0.03168882, 0.00694686, 0.07250037, 0.06947725, 0.03621314, 0.00512094, 0.01887089, 0.0232298, 0.01022772, 0.00711342, 0.00791129, 0.05265072, 0.01430848,0.03762969, 0.05080835, 0.13812178, 0.00655973, 0.01417962, 0.01731361, 0.02659349, 0.03403913, 0.01742294, 0.0110487, 0.00525754, 0.05574201, 0.01837955, 0.02863305, 0.02180492, 0.00855826, 0.01296316, 0.00719941, 0.02473188, 0.02877727, 0.01831045, 0.11902339, 0.03350339, 0.00606012, 0.01003063, 0.01231073, 0.07909799, 0.01248025, 0.00938227, 0.00922779,

0.00984898, 0.00563226, 0.01627412, 0.01257727, 0.26411334,

```
0.09242519, 0.00722218, 0.00895868, 0.0108839, 0.09369835,
            0.00256229, 0.14726728, 0.013673 , 0.00316726, 0.00938227,
            0.05751076, 0.00648566, 0.01672627, 0.00407532, 0.01105994,
            0.04465489, 0.13261131, 0.01265878, 0.02343221, 0.01106421,
            0.04312645, 0.00825491, 0.02558483, 0.04303992, 0.00167707,
            0.06365584, 0.02879044, 0.02108765, 0.02017862, 0.00209676,
            0.04510175, 0.00560467, 0.01235811, 0.00154654, 0.01053313,
            0.03851546, 0.07504775, 0.01853088, 0.04535837, 0.03899463,
            0.0425178, 0.00846753, 0.0104536, 0.00717051, 0.23341551,
            0.04884486, 0.04044068, 0.00566036, 0.00527932, 0.10618048,
            0.00553059, 0.03591392, 0.01170368, 0.03609803, 0.00592857,
            0.01106421, 0.06540582, 0.02807292, 0.06035659, 0.0120259,
            0.04567327, 0.04198665, 0.06234175, 0.0061261, 0.03219853,
            0.02733513, 0.02068696, 0.04479066, 0.00227449, 0.00794547,
            0.00523833, 0.0414681, 0.04079487, 0.02742506, 0.35729187,
            0.02987603, 0.02290243, 0.03998963, 0.01302718, 0.00323973,
            0.01024649, 0.08956821, 0.01627412, 0.00917579, 0.04400462,
            0.00749356, 0.03743595, 0.01220615, 0.00907912, 0.00546852,
            0.0184154, 0.00756899, 0.01566495, 0.01252444, 0.02138715,
            0.04502192, 0.01317294, 0.00726284, 0.00533177, 0.05413836,
            0.00522663, 0.12843439, 0.0386677, 0.02689816, 0.01919488,
            0.02910286, 0.03470307, 0.00711342, 0.03192086, 0.21076717,
            0.0268413, 0.01016235, 0.00992186, 0.01227231, 0.01608297,
            0.00649988, 0.04338943, 0.00832624, 0.0088752, 0.00587206,
            0.00899913, 0.02178773, 0.00842123, 0.01201218, 0.04519739,
            0.05589983, 0.01363781, 0.0050594, 0.03334108, 0.00328764,
            0.03285411, 0.03042666, 0.02367536, 0.04470886, 0.04878004,
            0.0542435, 0.02056979, 0.04453912, 0.00576608, 0.05107761)
[34]: model.predict([[7.4, 0.700, 0.00, 1.9, 0.076, 11.0, 34.0, 0.99780, 3.51, 0.56,
       9.4])
```

[34]: array([5])