ass-4-lokesh

September 21, 2023

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

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

[2]:

	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

[3]:
```
df.describe()
```

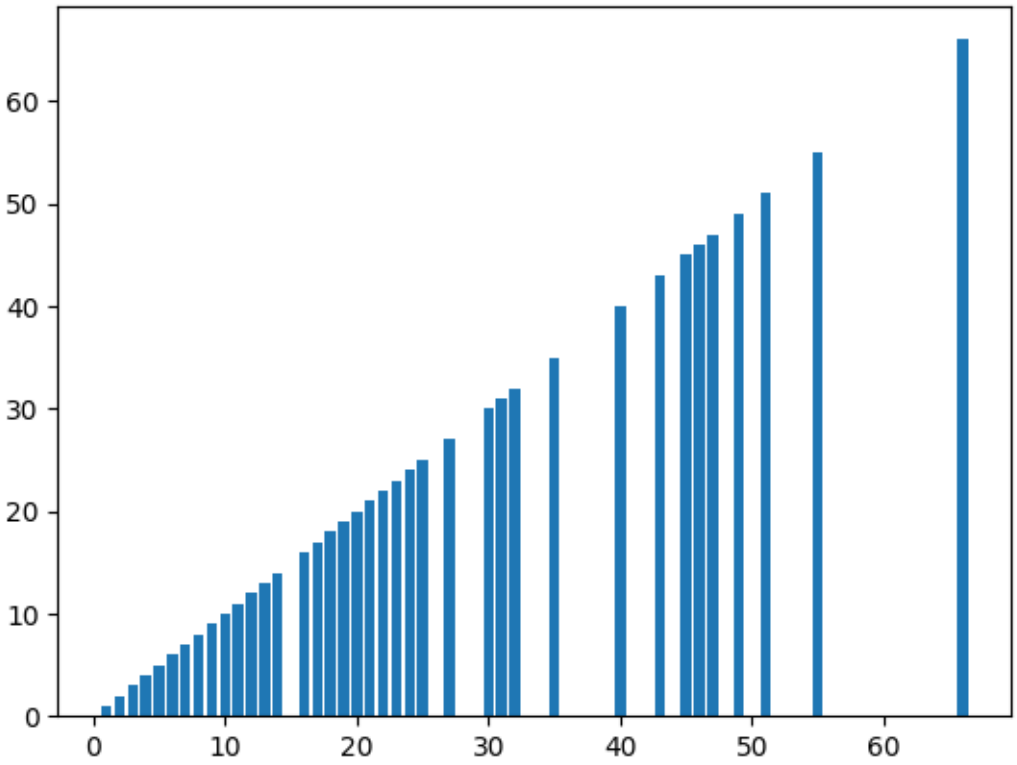
[3]:

	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
```

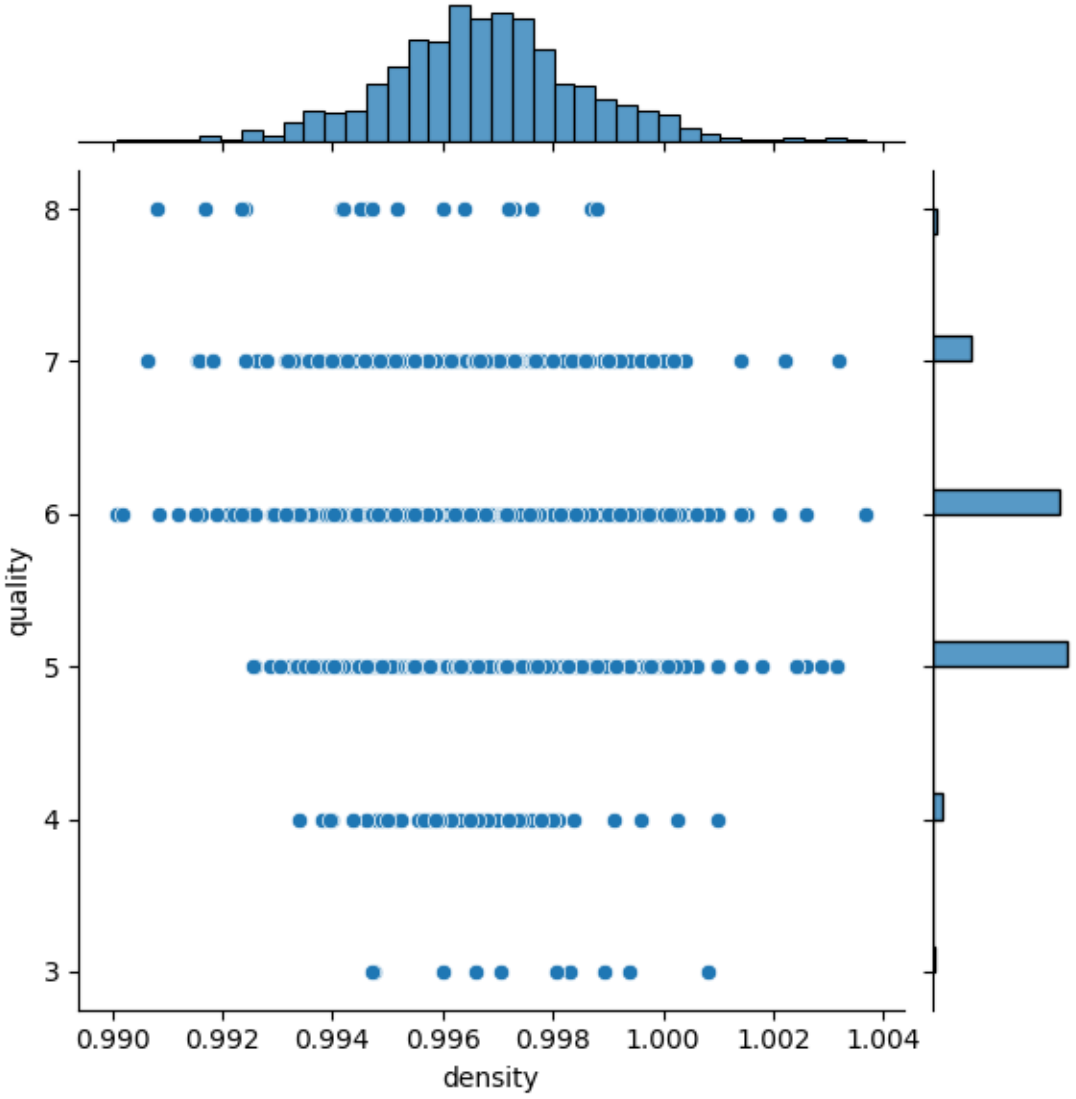
[4]:
```
plt.bar(df.chlorides.value_counts(),df.chlorides.value_counts())
```

[4]:
```
<BarContainer object of 153 artists>
```



[8]:
```
sns.jointplot(x="density",y="quality",data=df)
```

[8]: <seaborn.axisgrid.JointGrid at 0x7e6e96f39c30>



[9]:
```
df.corr()
```

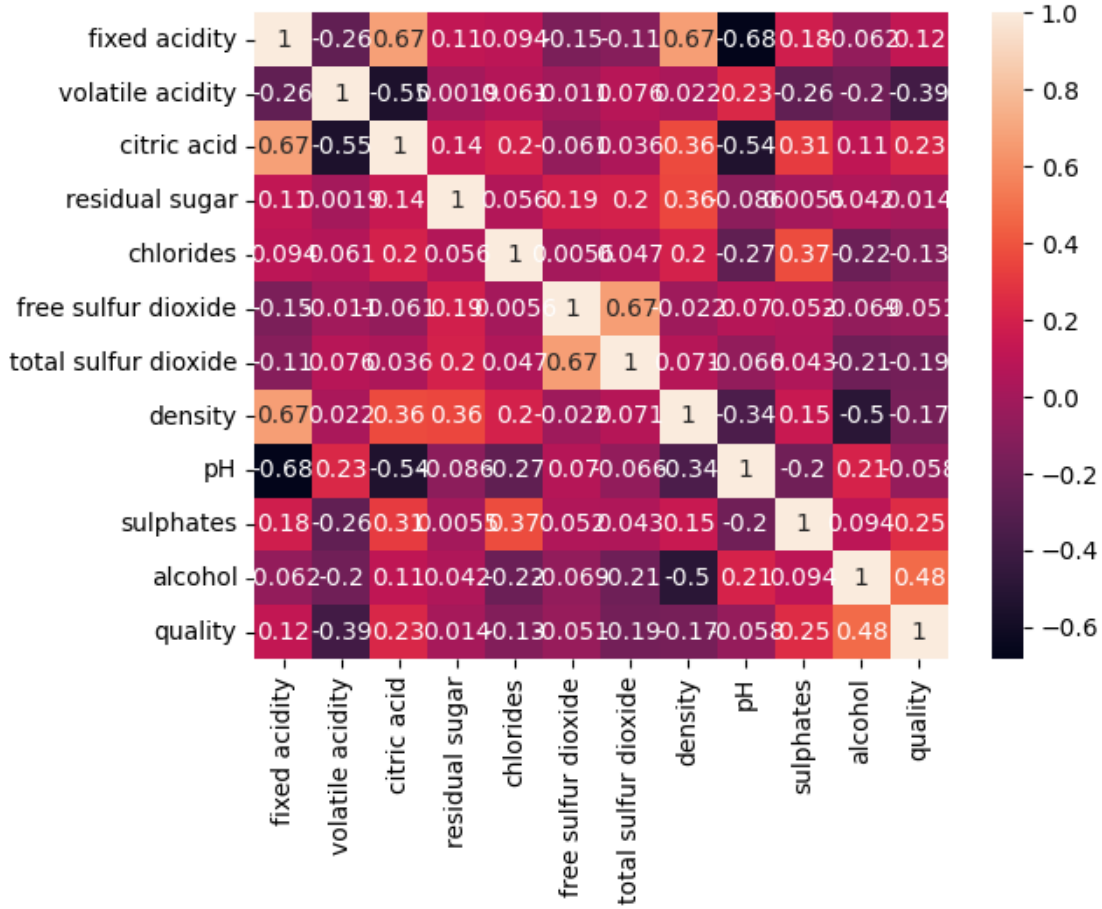
[9]:

	fixed acidity	volatile acidity	citric acid	\
fixed acidity	1.000000	-0.256131	0.671703	
volatile acidity	-0.256131	1.000000	-0.552496	
citric acid	0.671703	-0.552496	1.000000	
residual sugar	0.114777	0.001918	0.143577	
chlorides	0.093705	0.061298	0.203823	
free sulfur dioxide	-0.153794	-0.010504	-0.060978	
total sulfur dioxide	-0.113181	0.076470	0.035533	
density	0.668047	0.022026	0.364947	
pH	-0.682978	0.234937	-0.541904	
sulphates	0.183006	-0.260987	0.312770	

```
alcohol                   -0.061668         -0.202288     0.109903
quality                    0.124052         -0.390558     0.226373

                      residual sugar  chlorides  free sulfur dioxide  \
fixed acidity               0.114777   0.093705            -0.153794
volatile acidity            0.001918   0.061298            -0.010504
citric acid                 0.143577   0.203823            -0.060978
residual sugar              1.000000   0.055610             0.187049
chlorides                   0.055610   1.000000             0.005562
free sulfur dioxide         0.187049   0.005562             1.000000
total sulfur dioxide        0.203028   0.047400             0.667666
density                     0.355283   0.200632            -0.021946
pH                         -0.085652  -0.265026             0.070377
sulphates                   0.005527   0.371260             0.051658
alcohol                     0.042075  -0.221141            -0.069408
quality                     0.013732  -0.128907            -0.050656

                      total sulfur dioxide   density        pH  sulphates  \
fixed acidity                  -0.113181  0.668047 -0.682978   0.183006
volatile acidity                0.076470  0.022026  0.234937  -0.260987
citric acid                     0.035533  0.364947 -0.541904   0.312770
residual sugar                  0.203028  0.355283 -0.085652   0.005527
chlorides                       0.047400  0.200632 -0.265026   0.371260
free sulfur dioxide             0.667666 -0.021946  0.070377   0.051658
total sulfur dioxide            1.000000  0.071269 -0.066495   0.042947
density                         0.071269  1.000000 -0.341699   0.148506
pH                             -0.066495 -0.341699  1.000000  -0.196648
sulphates                       0.042947  0.148506 -0.196648   1.000000
alcohol                        -0.205654 -0.496180  0.205633   0.093595
quality                        -0.185100 -0.174919 -0.057731   0.251397

                       alcohol   quality
fixed acidity        -0.061668  0.124052
volatile acidity     -0.202288 -0.390558
citric acid           0.109903  0.226373
residual sugar        0.042075  0.013732
chlorides            -0.221141 -0.128907
free sulfur dioxide  -0.069408 -0.050656
total sulfur dioxide -0.205654 -0.185100
density              -0.496180 -0.174919
pH                    0.205633 -0.057731
sulphates             0.093595  0.251397
alcohol               1.000000  0.476166
quality               0.476166  1.000000
```

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

[10]: <Axes: >



[11]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
X=df.drop("quality",axis=1)
y=df["quality"]
```

[13]:
```
X.head()
```

[13]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56
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					

```
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
0      9.4
1      9.8
2      9.8
3      9.8
4      9.4
```

[16]:
```
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.
 ↪2,random_state=42)
```

[19]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
le = LogisticRegression()
```

[22]:
```
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(
```

[23]:
```
from sklearn.metrics import accuracy_score,␣
 ↪confusion_matrix,classification_report,roc_auc_score,roc_curve
accuracy_score(y_test,y_pred)
```

[23]:
```
0.575
```

[24]:
```
pd.crosstab(y_test,y_pred)
```

[24]:
```
col_0      4   5   6   7
quality
3          0   1   0   0
```

```
4         1   7   2   0
5         0  98  32   0
6         0  46  76  10
7         0   3  30   9
8         0   0   1   4
```

[26]:
```python
f=classification_report(y_test,y_pred)
print(f)
```

```
              precision    recall  f1-score   support

           3       0.00      0.00      0.00         1
           4       1.00      0.10      0.18        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

    accuracy                           0.57       320
   macro avg       0.43      0.27      0.28       320
weighted avg       0.56      0.57      0.55       320
```

```
/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))
/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))
```

[28]:
```python
probability = model.predict_proba(X_test)[:,1]
probability
```

[28]:
```
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,
```

```
0.03132   , 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])
```

[29]:
```
model.predict([[7.4, 0.700, 0.00, 1.9, 0.076, 11.0, 34.0, 0.99780, 3.51, 0.56,␣
↪9.4]])
```

[29]:
```
array([5])
```

[ ]:
```

```