Noah Caulfield

CS 460

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3/27/2024

HW4: Classification Search Optimal Parameters

	fixed acidity	volatile acidi	ty citric	acid residua	ıl sugar ci	nlorides f	ree sulfur dioxid	total s	ulfur dioxid	le density	pH su	lphates a	alcohol	qualit	y
0	7.0	0.	27	0.36	20.7	0.045	45.0)	170	.0 1.0010	3.00	0.45	8.8	\$	6
1	6.3		30	0.34	1.6	0.049	14.0		132			0.49	9.5		6
2	8.1		28	0.40	6.9	0.050	30.0		97			0.44	10.1		6
3	7.2	0.	23	0.32	8.5	0.058	47.0)	186	.0 0.9956	3.19	0.40	9.9		6
(48	7.2 898, 12)	Ū.	23	0.32	8.5	0.058	47.(,	186	.0 0.9956	0.13	0.40	9.9		6
			44-4		ah laad daa	fore sulfu			donada	-11			h-1		
count	fixed acidity vo		1tric acid 1898.000000	4898.000000			r dioxide total sulf 98.000000	ur d10x1de 1898.000000	density 4898.000000	pH 4898 000000	sulphate	s alco		quality 98.000000	
nean	6.854788	0.278241	0.334192	6.391415	0.045772		35.308085	138.360657	0.994027	3.188267	0.48984			5.877909	
std	0.843868	0.100795	0.121020	5.072058	0.021848		17.007137	42.498065	0.002991	0.151001	0.11412	6 1.230	621	0.885639	
min	3.800000	0.080000	0.000000	0.600000	0.009000		2.000000	9.000000	0.987110	2.720000	0.22000	0 8.000	000	3.000000	
	6.300000	0.010000		. 700000	0.036000		23.000000	108.000000	0.991723	3.090000	0.41000	0 9.500	000	5.000000	
25%	6.300000	0.210000	0.270000	1.700000	0.000000		23.000000	100.000000	0.551125	0.00000	0.41000	0.000	000	0.00000	
	6.800000	0.210000	0.270000	5.200000	0.043000		34.000000	134.000000	0.993740	3.180000	0.47000			6.000000	
50% 75%												0 10.400 0 11.400	000		
50% 75% max nere are	6.800000 7.300000 14.200000 e no missing valu	0.260000 0.320000 1.100000 ues in the DataFr	0.320000 0.390000 1.660000 ame.	5.200000 9.900000 65.800000	0.043000 0.050000 0.346000	2	34.000000 46.000000	134.000000 167.000000 440.000000	0.993740 0.996100 1.038980	3.180000 3.280000 3.820000	0.47000 0.55000 1.08000	0 10.400 0 11.400	000	6.000000 6.000000 9.000000	
50% 75% max Here are	6.800000 7.300000 14.200000 e no missing valu	0.260000 0.320000 1.100000 ues in the DataFr	0.320000 0.390000 1.660000 ame.	5.200000 9.900000 65.800000 id residual	0.043000 0.050000 0.346000	2	34.00000 46.00000 89.00000	134.000000 167.000000 440.000000	0.993740 0.996100 1.038980 sulfur dio	3.180000 3.280000 3.820000 xide dens	0.47000 0.55000 1.08000	10 10.400 10 11.400 10 14.200 sulphat	000	6.000000 6.000000 9.000000	
50% 75% max Here are	6.800000 7.300000 14.200000 e no missing valu rows of react acidity vola	0.260000 0.320000 1.100000 ues in the DataFr	0.320000 0.390000 1.660000 ame.	5.200000 9.900000 65.800000 id residual	0.043000 0.050000 0.346000 sugar ch	2 Lorides f	34.000000 46.000000 89.000000 ree sulfur dioxid	134.000000 167.000000 440.000000 de total	0.993740 0.996100 1.038980 sulfur dio	3.180000 3.280000 3.820000 xide dens	0.47000 0.55000 1.08000	10 10.400 10 11.400 10 14.200 sulphat	000 000 000	6.000000 6.000000 9.000000	
50% 75% max Here are	6.800000 7.300000 14.200000 e no missing valu acidity vola 7.0	0.260000 0.320000 1.100000 ues in the DataFr wres (A). ttile acidity 0.27	0.320000 0.390000 1.660000 ame.	5.200000 9.900000 65.800000 id residual 36	0.043000 0.050000 0.346000 sugar ch.	lorides f	34,000000 46,000000 89,000000 ree sulfur dioxid	134.000000 167.000000 440.000000 de total .0	0.993740 0.996100 1.038980 sulfur dio	3.180000 3.280000 3.820000 xide dens 70.0 1.0 32.0 0.9	0.47000 0.55000 1.08000 ity pH	10.400 10.11.400 10.14.200 14.200 sulphat 0.	0000 0000 0000	6.000000 6.000000 9.000000	
50% 75% max nere are	6.800000 7.300000 14.200000 e no missing valu rows or react acidity vola 7.0 6.3	0.260000 0.320000 1.100000 ses in the DataFr Units (A). tile acidity 0.27	0.320000 0.390000 1.660000 ame. citric ac:	5,20000 9,90000 65,80000 id residual 36 34	0.043000 0.050000 0.346000 sugar chi 20.7	2 lorides f 0.045 0.049	34,000000 46,000000 89,000000 ree sulfur dioxio 45	134.000000 167.000000 440.000000 de total .0 .0	0.993740 0.996100 1.038980 sulfur dio	3.180000 3.280000 3.820000 xide dens 70.0 1.0 32.0 0.9 97.0 0.9	0.47000 0.55000 1.08000 ity pH 010 3.00 940 3.30	0 10.400 10 11.400 10 14.200 14.200 14.200	000 000 000 000 ees al	6.000000 6.000000 9.000000 .cohol 8.8 9.5	
ot rew	6.800000 7.300000 14.200000 e no missing valu acidity vola 7.0 6.3	0.260000 0.320000 1.100000 uses in the DataFr 41'E5 (A). tile acidity 0.27 0.30 0.28	0.320000 0.390000 1.660000 ame. citric ac: 0.3	5,20000 9,90000 65,80000 iid residual 36 34 40	0.043000 0.050000 0.346000 sugar ch: 20.7 1.6 6.9	20 lorides f 0.045 0.049 0.050	34,000000 46,000000 89,000000 ree sulfur dioxio 45 14	134.000000 167.000000 440.000000 de total .0 .0	0.993740 0.996100 1.038980 sulfur dio	3.180000 3.280000 3.820000 xxide dens 70.0 1.0 32.0 0.9 97.0 0.9 86.0 0.9	0.47000 0.55000 1.08000 ity pH 010 3.00 940 3.30	0 10.400 10 11.400 10 14.200 14.200 14.200 0.0.0	000 000 000 000 ees al 45	6.000000 6.000000 9.000000 8.8 9.5 10.1	
50% 75% max mere are .Clew fixed	6.800000 7.300000 14.200000 e no missing valu acidity vola 7.0 6.3 8.1 7.2	0.260000 0.320000 1.100000 uses in the DataFr Arres (A). title acidity 0.27 0.30 0.28 0.23	0.320000 0.390000 1.660000 citric ac: 0.3	5,20000 9,90000 65,80000 iid residual 36 34 40	0.043000 0.050000 0.346000 sugar ch: 20.7 1.6 6.9 8.5	2 lorides f 0.045 0.049 0.050 0.058	34,00000 46,00000 89,00000 ree sulfur dioxid 45 14 30	134.000000 167.000000 440.000000 de total .0 .0	0.993740 0.996100 1.038980 sulfur dio	3.180000 3.280000 3.820000 xxide dens 70.0 1.0 32.0 0.9 97.0 0.9 86.0 0.9	0.47000 0.55000 1.08000 ity pH 010 3.00 940 3.30 951 3.26	0 10.400 10 11.400 10 14.200 14.200 14.200 0.0.0	0000 0000 0000 0000 ees al .45 .49 .44	6.000000 6.000000 9.000000 ccohol 8.8 9.5 10.1 9.9	

Snlit train and test

```
(3918, 11)
(980, 11)
(3918,)
(980,)
[5.15119310e-01 -1.07623315e+00
-8.13688488e-01 5.34064605e-01 -
-3.28261014e-01 -7.02444738e-01
```

[[5.15119310e-01 -1.07623315e+00 2.27730764e-01 3.40419470e-01 -8.13688488e-01 5.34064605e-01 -6.41932319e-01 -4.47040725e-01 -3.28261014e-01 -7.02444738e-01 1.54037099e+00]
[-6.69188091e-01 -2.88776731e-01 8.95831948e-01 1.00207124e+00 -2.17211567e-01 7.73947112e-01 1.35510550e+00 9.03369755e-01 -6.18856911e-02 2.66074147e-01 -8.21711966e-01]
[-1.49820327e+00 4.00247639e-01 -2.28071805e-02 1.84736700e-01 -4.00742927e-01 -6.05377303e-01 -1.02232048e+00 -4.60280044e-01 4.04271124e-01 1.93263316e-03 4.81506217e-01]
[4.13963498e-02 -8.79369048e-01 1.44218115e-01 -9.24503038e-01 -4.46625767e-01 -1.25612289e-01 -8.79674917e-01 -3.04718052e-01 1.37895801e-01 4.42168490e-01 2.37152807e-01]
[9.88842271e-01 2.03383533e-01 -6.07395717e-01 2.43240669e+00 3.33382515e-01 5.42995912e-02 8.55846045e-01 1.88307932e+00 7.13019704e-02 8.99798045e-02 -8.86517384e-02]

array([0.47959184, 0.4744898 , 0.45535714, 0.45849298, 0.47254151])

Average accuracy: 0.46809465165376496

This is the accuracy of our model using 5 poigh

```
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31]
```

{'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31]}

```
    ▶ GridSearchCV
    ▶ estimator: KNeighborsClassifier
    ▶ KNeighborsClassifier
```

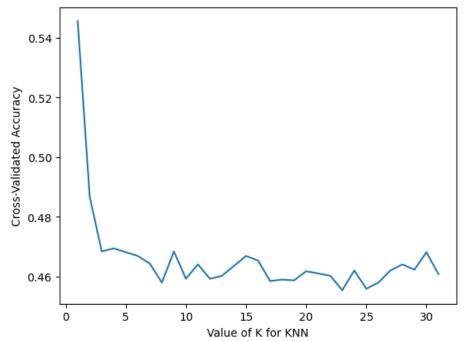
Lat's train the arid with our V train and s

 \Rightarrow

	mean_test_score	std_test_score	params
0	0.545685	0.008051	{'n_neighbors': 1}
1	0.486729	0.018125	{'n_neighbors': 2}
2	0.468358	0.016629	{'n_neighbors': 3}
3	0.469377	0.009407	{'n_neighbors': 4}
4	0.468095	0.009458	{'n_neighbors': 5}
5	0.466822	0.005355	{'n_neighbors': 6}
6	0.464265	0.007483	{'n_neighbors': 7}
7	0.457890	0.008705	{'n_neighbors': 8}
8	0.468353	0.011294	{'n_neighbors': 9}
9	0.459169	0.013004	{'n_neighbors': 10}
10	0.464011	0.011681	{'n_neighbors': 11}
11	0.459161	0.008404	{'n_neighbors': 12}
12	0.460180	0.010164	{'n_neighbors': 13}
13	0.463498	0.010682	{'n_neighbors': 14}
14	0.466817	0.016665	{'n_neighbors': 15}
15	0.465283	0.012302	{'n_neighbors': 16}
16	0.458394	0.010249	{'n_neighbors': 17}
17	0.458905	0.008230	{'n_neighbors': 18}
18	0.458653	0.007690	{'n_neighbors': 19}
19	0.461712	0.007131	{'n_neighbors': 20}
20	0.460946	0 011894	En neighborst 213

/ Lat's visualize the scores

Text(0, 0.5, 'Cross-Validated Accuracy')



Best Score: 0.5456854197617744
Best Parameters: {'n_neighbors': 1}

Best Estimator: KNeighborsClassifier(n_neighbors=1)

{'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31], 'weights': ['uniform', 'distance']}

```
GridSearchCV

GridSearchCV(cv=5, estimator=KNeighborsClassifier(), n_jobs=-1, param_grid={'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, ...], 'weights': ['uniform', 'distance']}, scoring='accuracy')

vestimator: KNeighborsClassifier

KNeighborsClassifier()

KNeighborsClassifier()
```

	mean_test_score	std_test_score	params
0	0.545685	0.008051	{'n_neighbors': 1, 'weights': 'uniform'}
1	0.545685	0.008051	{'n_neighbors': 1, 'weights': 'distance'}
2	0.486729	0.018125	{'n_neighbors': 2, 'weights': 'uniform'}
3	0.545685	0.008051	{'n_neighbors': 2, 'weights': 'distance'}
4	0.468358	0.016629	{'n_neighbors': 3, 'weights': 'uniform'}
57	0.591881	0.008306	$\label{eq:continuous} \mbox{\ensuremath{\text{lower}}} \ensuremath{\text{l$
58	0.468092	0.020879	{'n_neighbors': 30, 'weights': 'uniform'}
59	0.593667	0.011521	$\label{eq:continuous} \mbox{\ensuremath{\text{loweights': 'distance'}}} \mbox{\ensuremath{\text{loweights: 'distance'}}} \mbox{\ensuremath{\text{loweights: 'n_neighbors': 'distance'}}} \mbox{\ensuremath{\text{loweights: 'n_neighbors': 'distance'}}} \mbox{\ensuremath{\text{loweights: 'distance'}}} \mbox{\ensuremath{\text{loweights: 'n_neighbors': 'distance'}}} \mbox{\ensuremath{\text{loweights: 'n_neighbors': 'distance'}}} \mbox{\ensuremath{\text{loweights: 'distance'}}}} \mbox{\ensuremath{\text{loweights: 'distance'}}} \mbox{\ensuremath{\text{loweights: 'distance'}}} \mbox{\ensuremath{\text{loweights: 'distance'}}} \mbox{\ensuremath{\text{loweights: 'distance'}}}} \e$
60	0.460692	0.020216	{'n_neighbors': 31, 'weights': 'uniform'}
61	0.593410	0.015712	$\label{eq:continuous} \mbox{\ensuremath{\text{loweights': 'distance'}}} \mbox{\ensuremath{\text{loweights': 'distance'}}} \mbox{\ensuremath{\text{loweights: n_neighbors': distance'}}} \mbox{\ensuremath{\text{loweights: n_neighbors: distance'}}}} \mbox{\ensuremath{\text{loweights: n_neighbors: distance'}}} \mbox{\ensuremath{\text{loweights: n_neighbors: distance'}}}} \mbox{\ensuremath{\text{loweights: n_neighbors: distance'}}} \mbox{\ensuremath{\text{loweights: n_neighbors: distance'}}} \mbox{\ensuremath{\text{loweights: n_neighbors: distance'}}}} \ensuremath{\text{loweights: n_neighbo$

62 rows x 3 columns

0.5936667578908958

{'n_neighbors': 30, 'weights': 'distance'}

What is the accuracy of your final model using the test dataset?

Write the code for getting that result and answer the following questions

- Does the model prsents overfitting?

Yes, the model does present some overfitting, which is specifically demonstrated by the accuracy of the final model within the test dataset, compared to the best score found above. If the model performs significantly better on the training dataset than on the test dataset, it may indicate overfitting. Overfitting occurs when the model learns the training data too well, including its noise and outliers, making it perform poorly on unseen data. In total the model is relatively in line, however I do feel as though there are some instances of overfitting.

- What could you test to improve your model?

Additional data can always help to strengthen and improve a model- including this one. Hyperparameter tuning can be helpful. Also further addressment of the complexity of the problem/model along with the implementation of different algorithms may be helpful.

- Is accuracy the best metric for this problem? Yes/No and why?

Accuracy is a valid and acceptable metric for this sort of problem, as the "Correctness" of said problem is based on the analysis of the 1-9 input variables per wine type/name. However, the validity of these input variables may be seen as subjective, and the accuracy of identification is contingent concluding with the correct figures/metrics and them being accurately compared. Also, the larger the dataset gets, the harder this level of "Accuracy" will be able to predict- due to crossings within certain identifiable thresholds.

Note: There is another method called RandomizedSearchCV which randomly searches a subset of