**ASSIGNMENT 3**

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| Assignment Date | 19 September 2022 |
| Student Name | AJITH M |
| Student Roll Number | 715319106001 |
| Maximum Marks | 2 Marks |

**Artificial intelligence**

**A startlingly effective assistant**

I was given early “preview” access to Copilot about a year ago, and I’ve been using it on and off. It takes some practice to learn exactly how to frame your requests in English so the Copilot AI gives the most useful code output, but it can be startlingly effective.

However, we’re still a *long* way from “Hey Siri, make me a million dollar iPhone app”. It’s still necessary to use my software design skills to figure out what the different bits of code should do in my app.

To understand the level Copilot is working at, imagine writing an essay. You can’t just throw the essay question at it and expect it to produce a useful, well-argued piece. But if you figure out the argument and maybe write the topic sentence for each paragraph, it will often do a pretty good job at filling in the rest of each paragraph automatically.

Depending on the type of coding I’m doing, this can sometimes be a huge time- and brainpower-saver.

*# load dataset (student Portuguese scores)*

**import** pandas **as** pd

d **=** pd**.**read\_csv('student-por.csv', sep**=**';')

len(d)

Out[1]:

649

In [2]:

*# generate binary label (pass/fail) based on G1+G2+G3 (test grades, each 0-20 pts); threshold for passing is sum>=30*

d['pass'] **=** d**.**apply(**lambda** row: 1 **if** (row['G1']**+**row['G2']**+**row['G3']) **>=** 35 **else** 0, axis**=**1)

d **=** d**.**drop(['G1', 'G2', 'G3'], axis**=**1)

d**.**head()

Out[2]:

|  | **school** | **sex** | **age** | **address** | **famsize** | **Pstatus** | **Medu** | **Fedu** | **Mjob** | **Fjob** | **...** | **internet** | **romantic** | **famrel** | **freetime** | **goout** | **Dalc** | **Walc** | **health** | **absences** | **pass** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **0** | GP | F | 18 | U | GT3 | A | 4 | 4 | at\_home | teacher | ... | no | no | 4 | 3 | 4 | 1 | 1 | 3 | 4 | 0 |
| **1** | GP | F | 17 | U | GT3 | T | 1 | 1 | at\_home | other | ... | yes | no | 5 | 3 | 3 | 1 | 1 | 3 | 2 | 0 |
| **2** | GP | F | 15 | U | LE3 | T | 1 | 1 | at\_home | other | ... | yes | no | 4 | 3 | 2 | 2 | 3 | 3 | 6 | 1 |
| **3** | GP | F | 15 | U | GT3 | T | 4 | 2 | health | services | ... | yes | yes | 3 | 2 | 2 | 1 | 1 | 5 | 0 | 1 |
| **4** | GP | F | 16 | U | GT3 | T | 3 | 3 | other | other | ... | no | no | 4 | 3 | 2 | 1 | 2 | 5 | 0 | 1 |

5 rows × 31 columns

In [3]:

*# use one-hot encoding on categorical columns*

d **=** pd**.**get\_dummies(d, columns**=**['sex', 'school', 'address', 'famsize', 'Pstatus', 'Mjob', 'Fjob',

'reason', 'guardian', 'schoolsup', 'famsup', 'paid', 'activities',

'nursery', 'higher', 'internet', 'romantic'])

d**.**head()

Out[3]:

|  | **age** | **Medu** | **Fedu** | **traveltime** | **studytime** | **failures** | **famrel** | **freetime** | **goout** | **Dalc** | **...** | **activities\_no** | **activities\_yes** | **nursery\_no** | **nursery\_yes** | **higher\_no** | **higher\_yes** | **internet\_no** | **internet\_yes** | **romantic\_no** | **romantic\_yes** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **0** | 18 | 4 | 4 | 2 | 2 | 0 | 4 | 3 | 4 | 1 | ... | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| **1** | 17 | 1 | 1 | 1 | 2 | 0 | 5 | 3 | 3 | 1 | ... | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 |
| **2** | 15 | 1 | 1 | 1 | 2 | 0 | 4 | 3 | 2 | 2 | ... | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 |
| **3** | 15 | 4 | 2 | 1 | 3 | 0 | 3 | 2 | 2 | 1 | ... | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |
| **4** | 16 | 3 | 3 | 1 | 2 | 0 | 4 | 3 | 2 | 1 | ... | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |

5 rows × 57 columns

In [4]:

*# shuffle rows*

d **=** d**.**sample(frac**=**1)

*# split training and testing data*

d\_train **=** d[:500]

d\_test **=** d[500:]

d\_train\_att **=** d\_train**.**drop(['pass'], axis**=**1)

d\_train\_pass **=** d\_train['pass']

d\_test\_att **=** d\_test**.**drop(['pass'], axis**=**1)

d\_test\_pass **=** d\_test['pass']

d\_att **=** d**.**drop(['pass'], axis**=**1)

d\_pass **=** d['pass']

*# number of passing students in whole dataset:*

**import** numpy **as** np

print("Passing: %d out of %d (%.2f%%)" **%** (np**.**sum(d\_pass), len(d\_pass), 100**\***float(np**.**sum(d\_pass)) **/** len(d\_pass)))

Passing: 328 out of 649 (50.54%)

In [5]:

*# fit a decision tree*

**from** sklearn **import** tree

t **=** tree**.**DecisionTreeClassifier(criterion**=**"entropy", max\_depth**=**5)

t **=** t**.**fit(d\_train\_att, d\_train\_pass)

In [6]:

*# visualize tree*

**import** graphviz

dot\_data **=** tree**.**export\_graphviz(t, out\_file**=None**, label**=**"all", impurity**=False**, proportion**=True**,

feature\_names**=**list(d\_train\_att), class\_names**=**["fail", "pass"],

filled**=True**, rounded**=True**)

graph **=** graphviz**.**Source(dot\_data)

graph

Out[6]:

b'\n'

In [7]:

*# save tree*

tree**.**export\_graphviz(t, out\_file**=**"student-performance.dot", label**=**"all", impurity**=False**, proportion**=True**,

feature\_names**=**list(d\_train\_att), class\_names**=**["fail", "pass"],

filled**=True**, rounded**=True**)

In [8]:

t**.**score(d\_test\_att, d\_test\_pass)

Out[8]:

0.59731543624161076

In [9]:

**from** sklearn.model\_selection **import** cross\_val\_score

scores **=** cross\_val\_score(t, d\_att, d\_pass, cv**=**5)

*# show average score and +/- two standard deviations away (covering 95% of scores)*

print("Accuracy: %0.2f (+/- %0.2f)" **%** (scores**.**mean(), scores**.**std() **\*** 2))

Accuracy: 0.67 (+/- 0.06)

In [10]:

**for** max\_depth **in** range(1, 20):

t **=** tree**.**DecisionTreeClassifier(criterion**=**"entropy", max\_depth**=**max\_depth)

scores **=** cross\_val\_score(t, d\_att, d\_pass, cv**=**5)

print("Max depth: %d, Accuracy: %0.2f (+/- %0.2f)" **%** (max\_depth, scores**.**mean(), scores**.**std() **\*** 2))

Max depth: 1, Accuracy: 0.64 (+/- 0.05)

Max depth: 2, Accuracy: 0.69 (+/- 0.08)

Max depth: 3, Accuracy: 0.69 (+/- 0.09)

Max depth: 4, Accuracy: 0.66 (+/- 0.10)

Max depth: 5, Accuracy: 0.67 (+/- 0.06)

Max depth: 6, Accuracy: 0.64 (+/- 0.08)

Max depth: 7, Accuracy: 0.67 (+/- 0.02)

Max depth: 8, Accuracy: 0.67 (+/- 0.07)

Max depth: 9, Accuracy: 0.67 (+/- 0.06)

Max depth: 10, Accuracy: 0.63 (+/- 0.12)

Max depth: 11, Accuracy: 0.65 (+/- 0.07)

Max depth: 12, Accuracy: 0.63 (+/- 0.07)

Max depth: 13, Accuracy: 0.63 (+/- 0.07)

Max depth: 14, Accuracy: 0.63 (+/- 0.08)

Max depth: 15, Accuracy: 0.64 (+/- 0.06)

Max depth: 16, Accuracy: 0.62 (+/- 0.05)

Max depth: 17, Accuracy: 0.64 (+/- 0.09)

Max depth: 18, Accuracy: 0.63 (+/- 0.08)

Max depth: 19, Accuracy: 0.63 (+/- 0.06)

In [11]:

depth\_acc **=** np**.**empty((19,3), float)

i **=** 0

**for** max\_depth **in** range(1, 20):

t **=** tree**.**DecisionTreeClassifier(criterion**=**"entropy", max\_depth**=**max\_depth)

scores **=** cross\_val\_score(t, d\_att, d\_pass, cv**=**5)

depth\_acc[i,0] **=** max\_depth

depth\_acc[i,1] **=** scores**.**mean()

depth\_acc[i,2] **=** scores**.**std() **\*** 2

i **+=** 1

depth\_acc

Out[11]:

array([[ 1. , 0.63790456, 0.04848398],

[ 2. , 0.68559869, 0.07148267],

[ 3. , 0.68710174, 0.0865951 ],

[ 4. , 0.6669467 , 0.10726248],

[ 5. , 0.66261518, 0.05307124],

[ 6. , 0.65018859, 0.07040891],

[ 7. , 0.66564494, 0.02029519],

[ 8. , 0.67474598, 0.05984916],

[ 9. , 0.6640118 , 0.03746891],

[ 10. , 0.6346137 , 0.09657669],

[ 11. , 0.6484015 , 0.10475147],

[ 12. , 0.64545485, 0.05529647],

[ 13. , 0.64544256, 0.08167465],

[ 14. , 0.6346614 , 0.07458128],

[ 15. , 0.63463773, 0.08162646],

[ 16. , 0.62853141, 0.05926906],

[ 17. , 0.63622335, 0.05390067],

[ 18. , 0.62548936, 0.06050112],

[ 19. , 0.63004547, 0.07022296]])

In [12]:

**import** matplotlib.pyplot **as** plt

fig, ax **=** plt**.**subplots()

ax**.**errorbar(depth\_acc[:,0], depth\_acc[:,1], yerr**=**depth\_acc[:,2])

plt**.**show()

In [ ]