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Class: Comp 4431-1
Assignment: Exercise 6
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Part 1

For the decision tree in the book in example 8.2, during class I just showed how to calculate the root node Gain(A) values for A in {income,age,student,credit}. Also found here: exercise6A_start.pdf Download exercise6A_start.pdf

Hand calculate the Gain(A) values, for each of the 4 attributes, for the left subtree split (i.e. for the tuples 1,2,8,9 and 11 which are in the "youth" category after the first split.

301
```
import math
import pandas as pd

columns = ['RID', 'Age', 'income', 'student', 'credit_rating', 'Class: buys_computer']
data_info = [[1, 'youth', 'high', 'no', 'fair', 'no'],
             [2, 'youth', 'high', 'no', 'excellent', 'no'],
             [3, 'middle_aged', 'high', 'no', 'fair', 'yes'],
             [4, 'senior', 'medium', 'no', 'fair', 'yes'],
             [5, 'senior', 'low', 'yes', 'fair', 'yes'],
             [6, 'senior', 'low', 'yes', 'excellent', 'no'],
             [7, 'middle_aged', 'low', 'yes', 'excellent', 'yes'],
             [8, 'youth', 'medium', 'no', 'fair', 'no'],
             [9, 'youth', 'low', 'yes', 'fair', 'yes'],
             [10, 'senior', 'medium', 'yes', 'fair', 'yes'],
             [11, 'youth', 'medium', 'yes', 'excellent', 'yes'],
             [12, 'middle_aged', 'medium', 'no', 'excellent', 'yes'],
             [13, 'middle_aged', 'high', 'yes', 'fair', 'yes'],
             [14, 'senior', 'medium', 'no', 'excellent', 'no']]

df = pd.DataFrame(data_info, columns=columns)
df = df.set_index("RID")
df
```

301

	Age	income	student	credit_rating	Class: buys_computer
RID					
1	youth	high	no	fair	no
2	youth	high	no	excellent	no
3	middle_aged	high	no	fair	yes
4	senior	medium	no	fair	yes

	Age	income	student	credit_rating	Class: buys_computer
RID					
5	senior	low	yes	fair	yes
6	senior	low	yes	excellent	no
7	middle_aged	low	yes	excellent	yes
8	youth	medium	no	fair	no
9	youth	low	yes	fair	yes
10	senior	medium	yes	fair	yes
11	youth	medium	yes	excellent	yes
12	middle_aged	medium	no	excellent	yes
13	middle_aged	high	yes	fair	yes
14	senior	medium	no	excellent	no

302
```
subset = df[df["Age"] =="youth"]
subset
```

302

	Age	income	student	credit_rating	Class: buys_computer
RID					
1	youth	high	no	fair	no
2	youth	high	no	excellent	no
8	youth	medium	no	fair	no
9	youth	low	yes	fair	yes
11	youth	medium	yes	excellent	yes

$$Info(D) = -\sum_{i=1}^{m} p_i log_2 p_i$$

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j)$$

$$Info(D) = -[\frac{2}{5}log_2(\frac{2}{5})] - [\frac{3}{5}log_2(\frac{3}{5})] = 0.9709506$$

$$Gain(A) = Info(D) - Info_A(D)$$

303
```
Info_i_D = -((2/5)*math.log(2/5,2))-((3/5)*math.log(3/5,2))
Info_i_D
```

303
```
0.9709505944546686
```

Computation of gain ratio for the *Credit attribute*

304
```
subset_credit_e = subset[subset['credit_rating'] =="excellent"]
subset_credit_e
```

304

	Age	income	student	credit_rating	Class: buys_computer
RID					
2	youth	high	no	excellent	no
11	youth	medium	yes	excellent	yes

305
```
subset_credit_f = subset[subset['credit_rating'] =="fair"]
subset_credit_f
```

305

	Age	income	student	credit_rating	Class: buys_computer
RID					
1	youth	high	no	fair	no
8	youth	medium	no	fair	no
9	youth	low	yes	fair	yes

$$Info_{Credit}(D) = \frac{2}{5}Info_{Credit=Excellent} + \frac{3}{5}Info_{Credit=Fair} = 0.9509775$$

$$Info_{Credit=Excelent} = -\frac{1}{2}log_2(\frac{1}{2}) - \frac{1}{2}log_2(\frac{1}{2}) = 1$$

$$Info_{Credit=Fair} = -\frac{1}{3}log_2(\frac{1}{3}) - \frac{2}{3}log_2(\frac{2}{3}) = 0.9182958$$

$$Info_{Credit}(D) = \frac{2}{5}[-\frac{1}{2}log_2(\frac{1}{2}) - \frac{1}{2}log_2(\frac{1}{2})] + \frac{3}{5}[-\frac{1}{3}log_2(\frac{1}{3}) - \frac{2}{3}log_2(\frac{2}{3})] = 0.9509775$$

$$Gain(Credit\ Rating) = Info(D) - Info_{income}(D) = 0.01997309$$

$$Gain(Credit\ Rating) = 0.9709506 - 0.9509775 = 0.01997309$$

306
```
Info_Credit_Fair = -((1/3)*math.log(1/3,2))-((2/3)*math.log(2/3,2))
Info_Credit_Fair
```

306
```
0.9182958340544896
```

307
```
Info_Credit_Excellent = -((1/2)*math.log(1/2,2))-((1/2)*math.log(1/2,2))
Info_Credit_Excellent
```

307
```
1.0
```

308
```
Info_Credit = ((2/5)*Info_Credit_Excellent) + ((3/5)*Info_Credit_Fair)
Info_Credit
```

308
```
0.9509775004326937
```

309
```
Gain_Credit = Info_i_D-Info_Credit
Gain_Credit
```

309
```
0.01997309402197489
```

Computation of gain ratio for the ***Student attribute***

310
```
subset_student_y = subset[subset["student"] == "yes"]
subset_student_y
```

310

	Age	income	student	credit_rating	Class: buys_computer
RID					
9	youth	low	yes	fair	yes
11	youth	medium	yes	excellent	yes

311
```
subset_student_n = subset[subset["student"] == "no"]
subset_student_n
```

311

	Age	income	student	credit_rating	Class: buys_computer
RID					
1	youth	high	no	fair	no

	Age	income	student	credit_rating	Class: buys_computer
RID					
2	youth	high	no	excellent	no
8	youth	medium	no	fair	no

$$Info_{Student}(D) = \frac{2}{5}Info_{Student=Yes} + \frac{3}{5}Info_{Student=No} = 0$$

$$Info_{Student=Yes} = -\frac{2}{2}log_2(\frac{2}{2}) - \frac{0}{2}log_2(\frac{0}{2}) = 0$$

$$Info_{Student=No} = -\frac{0}{3}log_2(\frac{0}{3}) - \frac{3}{3}log_2(\frac{3}{3}) = 0$$

$$Info_{Student}(D) = \frac{2}{5}[-\frac{2}{2}log_2(\frac{2}{2}) - \frac{0}{2}log_2(\frac{0}{2})] + \frac{3}{5}[-\frac{0}{3}log_2(\frac{0}{3}) - \frac{3}{3}log_2(\frac{3}{3})] = 0$$

$$Gain(Student) = Info(D) - Info_{Student}(D) = 0.9709506$$

$$Gain(Student) = 0.9709506 - 0 = 0.9709506$$

312
```
Info_Student = 0
Gain_Student = Info_i_D - Info_Student
Gain_Student
```

312
```
0.9709505944546686
```

Computation of gain ratio for the ***Income attribute***

313
```
subset_income_high = subset[subset["income"] == "high"]
subset_income_high
```

313

	Age	income	student	credit_rating	Class: buys_computer
RID					
1	youth	high	no	fair	no
2	youth	high	no	excellent	no

314
```
subset_income_medium = subset[subset["income"] == "medium"]
```

```
subset_income_medium
```

314

	Age	income	student	credit_rating	Class: buys_computer
RID					
8	youth	medium	no	fair	no
11	youth	medium	yes	excellent	yes

315
```
subset_income_low = subset[subset["income"] == "low"]
subset_income_low
```

315

	Age	income	student	credit_rating	Class: buys_computer
RID					
9	youth	low	yes	fair	yes

$$Info_{Income}(D) = \frac{1}{5}Info_{Income=Low} + \frac{2}{5}Info_{Income=Medium} + \frac{2}{5}Info_{Income=High} = .4$$

$$Info_{Income=Low} = -\frac{1}{1}log_2(\frac{1}{1}) - \frac{0}{1}log_2(\frac{0}{1}) = 0$$

$$Info_{Income=Medium} = -\frac{1}{2}log_2(\frac{1}{2}) - \frac{1}{2}log_2(\frac{1}{2}) = 1$$

$$Info_{Income=High} = -\frac{0}{2}log_2(\frac{0}{2}) - \frac{2}{2}log_2(\frac{2}{2}) = 0$$

$$Info_{Income}(D) = \frac{1}{5}[-\frac{1}{1}log_2(\frac{1}{1}) - \frac{0}{1}log_2(\frac{0}{1})]+$$

$$\frac{2}{5}[-\frac{1}{2}log_2(\frac{1}{2}) - \frac{1}{2}log_2(\frac{1}{2})]+$$

$$\frac{2}{5}[-\frac{0}{2}log_2(\frac{0}{2}) - \frac{2}{2}log_2(\frac{2}{2})] = .4$$

$$Gain(Income) = Info(D) - Info_{Income}(D) = 0.5709506$$

$$Gain(Income) = 0.9709506 - .4 = 0.5709506$$

316
```
Info_Income_Low = 0
Info_Income_High = 0
Info_Income_Medium = -((1/2)*math.log(1/2,2))-((1/2)*math.log(1/2,2))
Info_Income_Medium
```

316
```
1.0
```

317
```
Info_Income = ((1/5)*Info_Income_Low) + ((2/5)*Info_Income_Medium) + ((2/5)*Info_Income_High)
Info_Income
```

317
```
0.4
```

318
```
Gain_Income = Info_i_D - Info_Income
Gain_Income
```

318
```
0.5709505944546686
```

Comparing all of the Gain's together

$$Gain(Student) = 0.9709506 - 0 = 0.9709506$$

$$Gain(Income) = 0.9709506 - .4 = 0.5709506$$

$$Gain(Credit\ Rating) = 0.9709506 - 0.9509775 = 0.01997309$$

These are all of the subtree splits on the left of the tree in which is under "youth" The next split that we will want to make is off of student as it has the highest gain value

Part 2

You are to create a set of 8..12 training tuples, including the classification of each, and then run through sklearn to build a decision and print out the resultant decision tree. You should craft your tuples and classification array such that the decision tree has at least 3 levels (including the root) and explain which tuples end up in which leaf level node. Feel free to draw a picture or use the graph viewer if you prefer.

The problem is to classify college student applicants based on likelihood of finishing in 6 years as "yes" or "no". Assume a tuple has the following information:

[GPA, RANK, WORKED] where: GPA = high school grade point average

RANK = rank in class expressed as a decimal percentile (e.g. 0.99 means top 99%)

WORKED = { 0 , 1} where 0 means did not work a job in HS, 1 means did

For example:

[3.4,0.85,1] means an applicant has a 3.4 gpa, was in the top 85 percentile, and worked while in high school.

319
```
# Importing Libraries

import pandas as pd
import random
import numpy as np
import graphviz
from sklearn import tree
from sklearn.tree import export_text
from sklearn.tree import export_graphviz
from sklearn import metrics
```

Setting Up Random Data to have biases

GPA's are assigned randomly in between a scale of 1 and 4

320
```
# Setting Random Seed
random.seed(16)

# Creating a list of 12 Random GPAS
GPA = [round(random.uniform(1, 4), 2) for _ in range(12)]  # Creating List of Random GPA
GPA_testing = [round(random.uniform(1, 4), 2) for _ in range(12)]
print("GPA's", GPA, ";", len(GPA))
print("GPA's Testing", GPA_testing, ";", len(GPA_testing))
```

```
GPA's [2.08, 2.44, 2.25, 2.34, 2.23, 2.97, 1.78, 2.9, 1.03, 1.91, 2.01, 1.43] ; 12
GPA's Testing [3.23, 1.93, 3.37, 3.87, 1.76, 3.68, 3.42, 3.0, 1.08, 2.37, 2.88, 1.89] ; 12
```

Rankings are assigned on tier basis. Within those tiers there is some variability
-If the GPA is above 3.5 the student is in the top 90-100%
-If the GPA is above 3.0 but below 3.5 the student is in the top 80-90%
-If the GPA is above 2.5 but below 3 the student is in the top 70-80%
-If the GPA is above 2.0 but below 2.5 the student is in the top 60-70%
-If the GPA is below 2.0 the student is in the bottom 0-60%

321
```
def get_rankings(GPA):
    """This Function Randomizes rankings with weights"""
    RANK = []
    for grade in GPA:
        if grade > 3.5:
            RANK.append(round(random.uniform(.9, 1), 2))
        elif grade > 3:
            RANK.append(round(random.uniform(.8, .9), 2))
        elif grade > 2.5:
            RANK.append(round(random.uniform(.7, .8), 2))
        elif grade > 2:
            RANK.append(round(random.uniform(.6, .7), 2))
        else:
```

```
            RANK.append(round(random.uniform(0, .6), 2))
    return RANK

RANK = get_rankings(GPA)
RANK_testing = get_rankings(GPA_testing)

print("Rankings", RANK)
print("Ranking Testing", RANK_testing)
```

```
Rankings [0.62, 0.63, 0.63, 0.68, 0.63, 0.74, 0.39, 0.79, 0.18, 0.03, 0.7, 0.5]
Ranking Testing [0.88, 0.31, 0.82, 0.92, 0.18, 0.95, 0.81, 0.77, 0.44, 0.6, 0.78, 0.29]
```

For assigning working values. 1 indicates that the student did work, 0 indicates the student did not.
-If the students GPA is above 2.0, there is a random 0-60 value assigned. If that value is above 50 they did work. (1)
-If the students GPA is below 2.0, there is a random 30-100 value assigned. If that value is above 50 they did work. (1)

322
```
# Setting up Random Work 0 did not work 1 did, Scaling it toward working have lower GPA
def get_working(GPA):
    """Determining if they worked based off of GPA, with some randomness"""
    WORKED = []
    for num in enumerate(GPA):
        if num[1] > 2:
            rand_work = random.randint(0, 60)
            if rand_work > 50:
                WORKED.append(1)
            else:
                WORKED.append(0)
        else:
            if random.randint(30, 100) > 50:
                WORKED.append(1)
            else:
                WORKED.append(0)
    return  WORKED

WORKED = get_working(GPA)
WORKED_testing = get_working(GPA_testing)
print("Worked", WORKED)
print("Worked Testing", WORKED_testing)
```

```
Worked [1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0]
Worked Testing [0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1]
```

Compressing the GPA, RANKING and WORKED into a list

323
```
def compress_list(GPA, RANK, WORKED):
    """Compressing the lists"""
    list_o_list = []
    for num in range(len(GPA)):
        list_o_list.append([GPA[num], RANK[num], WORKED[num]])
    return list_o_list

list_o_list = compress_list(GPA, RANK, WORKED)
list_o_training = compress_list(GPA_testing, RANK_testing, WORKED_testing)
print("List_o_list", list_o_list)
print("List_o_training", list_o_training)
```

```
List_o_list [[2.08, 0.62, 1], [2.44, 0.63, 1], [2.25, 0.63, 0], [2.34, 0.68, 0], [2.23, 0.63, 0], [2.97,
List_o_training [[3.23, 0.88, 0], [1.93, 0.31, 1], [3.37, 0.82, 1], [3.87, 0.92, 0], [1.76, 0.18, 1], [3.
```

Graduating in 6 years is based on the sum of GPA, RANK and WORKED.
If the sum of these three variables is above 3.5 They graduate with in 6 years
Graduate Training is made so that we can see how well our decision tree works

324

```
def grad_in_6(list_o_list):
    """Creating a classifier if they graduate in 6 years """
    graduate = []
    for person in enumerate(list_o_list):
        if sum(person[1]) > 3.5:
            graduate.append(1)
        else:
            graduate.append(0)
    return graduate

graduate = grad_in_6(list_o_list)
graduate_training = grad_in_6(list_o_training)

print('Graduate', graduate)
print('Graduate Training', graduate_training)
```

```
Graduate [1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0]
Graduate Training [1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0]
```

First Example

Setting up a decision tree and looking at the predictions. Then comparing them to what they should be to analysize model accuracy

325

```
X = list_o_list
Y = graduate
labels = ["GPA", "RANK", "WORKED"]

clf = tree.DecisionTreeClassifier()
clf = clf.fit(X,Y)
print(type(clf))
print(clf)

foo = clf.predict_proba(list_o_training)

print("output of classifying 3 new items (should be): ", graduate_training)
foo = pd.DataFrame(data=foo, columns=["Something","Graduate"])
predict_graduating = foo["Graduate"].to_list()
predict_graduating = [int(i) for i in predict_graduating]
print("Printing out the prediction for graduating     ",predict_graduating)
```

```
<class 'sklearn.tree._classes.DecisionTreeClassifier'>
DecisionTreeClassifier()
output of classifying 3 new items (should be):  [1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0]
Printing out the prediction for graduating      [1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0]
```

Second Example

This example is looking at the prediction tree using entropy

326
```
Xnum = list_o_list
classifications = graduate
clf2 = tree.DecisionTreeClassifier(criterion="entropy")
clf2 = clf2.fit(Xnum,classifications)
print(type(clf2))
print(clf2)

print("\nNow 'predicting class' of the first 6 elements of the training data.")
testData = list_o_training
foo = clf2.predict_proba( testData )
print("test data = " + str(testData))
print("data are classified as:")
print(foo)

# Turning Foo into a list so that it can be compared
foo = pd.DataFrame(data=foo, columns=["Something","Graduate"])
predict_graduating = foo["Graduate"].to_list()
predict_graduating = [int(i) for i in predict_graduating]

print("Printing out the prediction for graduating     ",predict_graduating)
print("output of classifying 3 new items (should be): ", graduate_training)

treeStruct = export_text(clf2)
print("\nNow printing export_text(clf2)")
print(treeStruct)
```

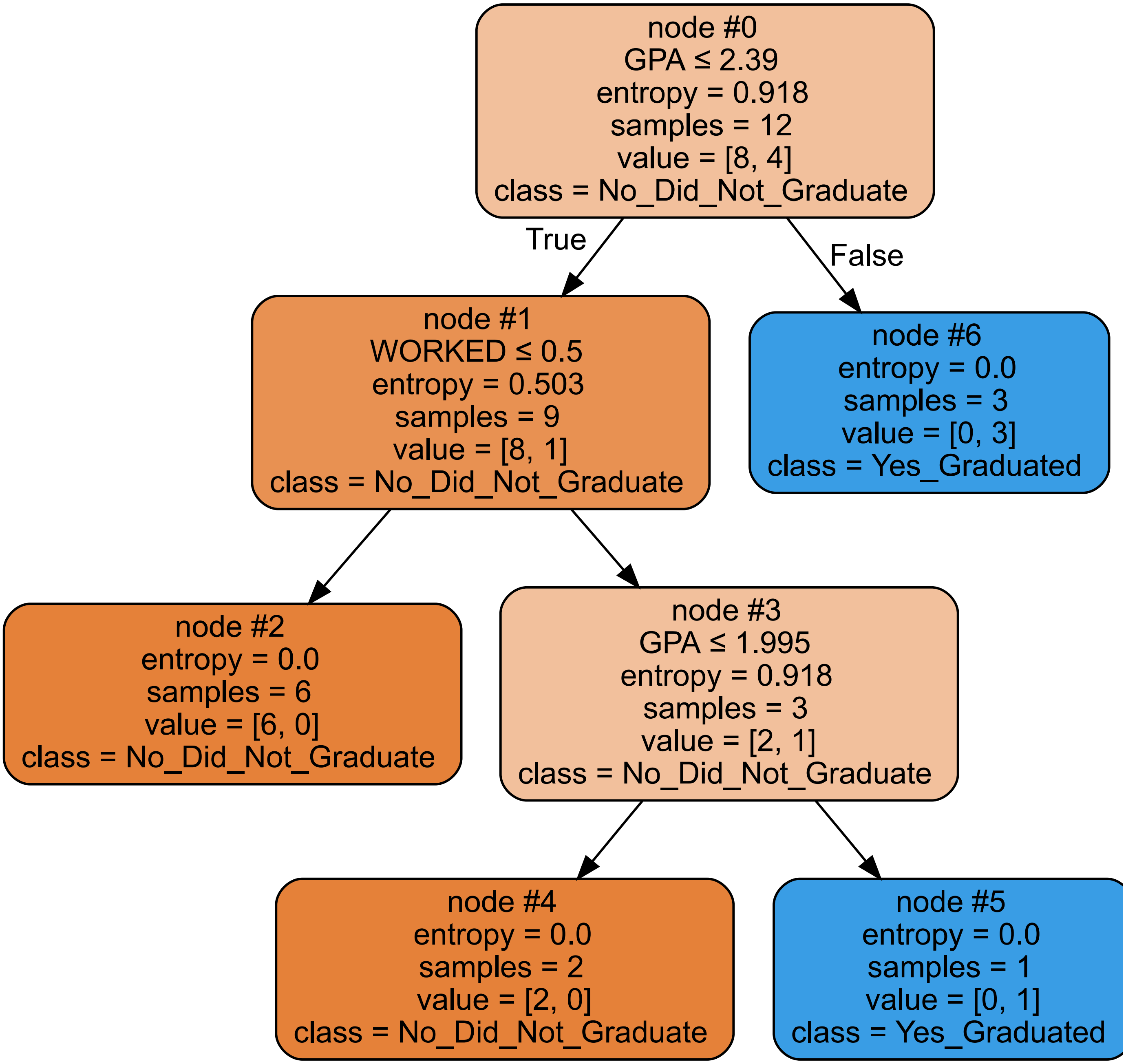
```
<class 'sklearn.tree._classes.DecisionTreeClassifier'>
DecisionTreeClassifier(criterion='entropy')

Now 'predicting class' of the first 6 elements of the training data.
test data = [[3.23, 0.88, 0], [1.93, 0.31, 1], [3.37, 0.82, 1], [3.87, 0.92, 0], [1.76, 0.18, 1], [3.68,
data are classified as:
[[0. 1.]
 [1. 0.]
 [0. 1.]
 [0. 1.]
 [1. 0.]
 [0. 1.]
 [0. 1.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
 [0. 1.]
 [1. 0.]]
Printing out the prediction for graduating      [1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0]
output of classifying 3 new items (should be):  [1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0]

Now printing export_text(clf2)
|--- feature_0 <= 2.39
|   |--- feature_2 <= 0.50
|   |   |--- class: 0
|   |--- feature_2 >  0.50
|   |   |--- feature_0 <= 1.99
|   |   |   |--- class: 0
|   |   |--- feature_0 >  1.99
|   |   |   |--- class: 1
|--- feature_0 >  2.39
|   |--- class: 1
```

```
# Code to look at the tuples within the decision tree and printing out the decision tree
```

327
```
foo = clf2.apply( Xnum )   # passing in full list of training tuples
print("clf2.apply( Xnum ):")
print(foo)
# now print out line by line as pair:  tuple, which leaf node
print("\nNow printing each tuple with the decision tree node it ends up in:")
for i in range(len(foo)):
    print(str(Xnum[i]) + "," + str(foo[i]))

# NOTE - adding in node_ids and class_names as options to make tree viz more robust
dot_data = tree.export_graphviz(clf2, node_ids="true",
                                feature_names=labels,
                                class_names=('No_Did_Not_Graduate','Yes_Graduated'),
                                out_file=None,
                                filled=True,
                                rounded=True,
                                special_characters=True)
graph = graphviz.Source(dot_data)

graph
```

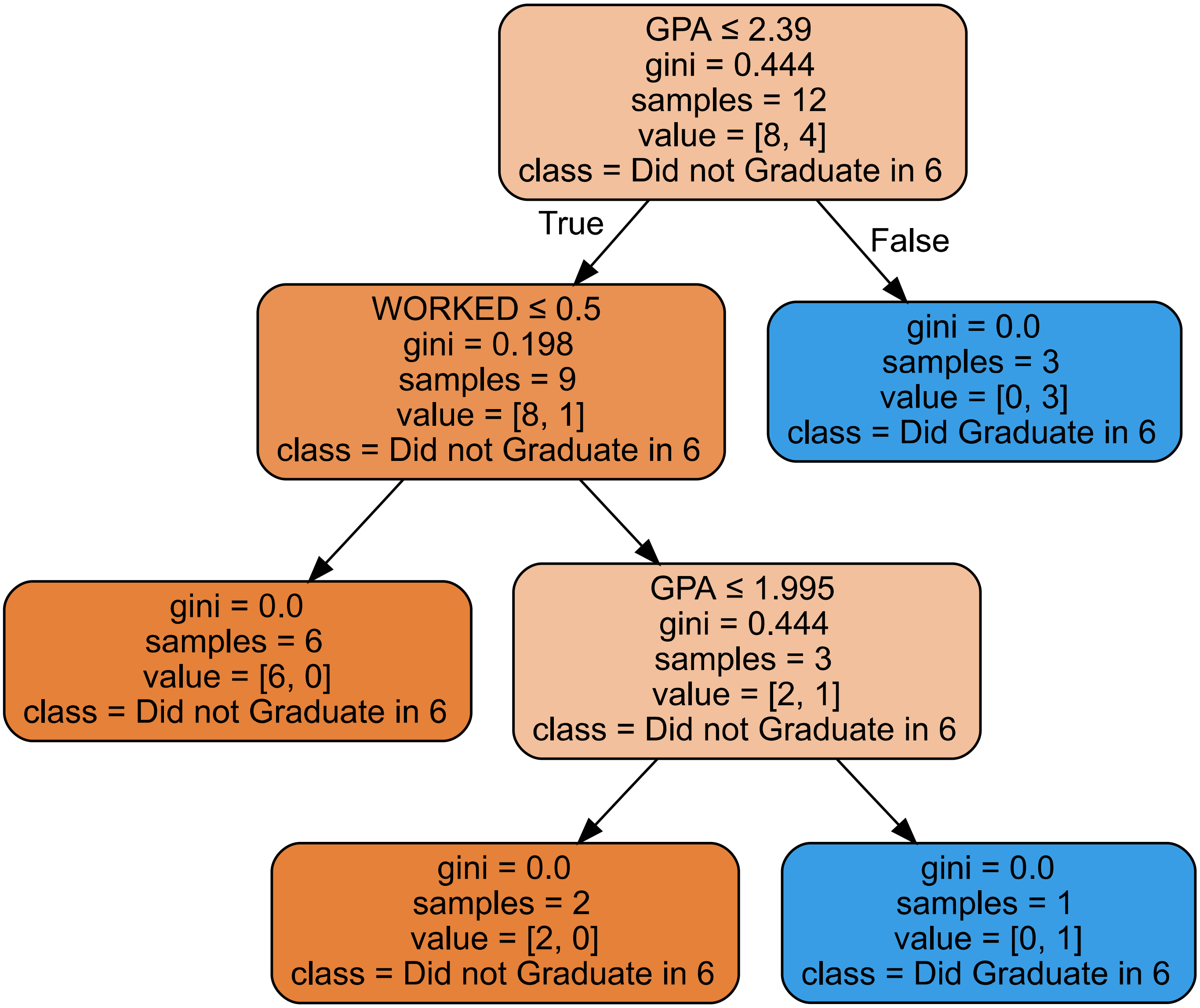
```
clf2.apply( Xnum ):
[5 6 2 2 2 6 4 6 2 4 2 2]

Now printing each tuple with the decision tree node it ends up in:
[2.08, 0.62, 1],5
[2.44, 0.63, 1],6
[2.25, 0.63, 0],2
[2.34, 0.68, 0],2
[2.23, 0.63, 0],2
[2.97, 0.74, 0],6
[1.78, 0.39, 1],4
[2.9, 0.79, 1],6
[1.03, 0.18, 0],2
[1.91, 0.03, 1],4
[2.01, 0.7, 0],2
[1.43, 0.5, 0],2
```

327



Example 3 Creating a tree with "gini" instead of entropy

328
```
clf3 = tree.DecisionTreeClassifier(criterion="gini")
clf3 = clf3.fit(Xnum,classifications)
dotData3 = tree.export_graphviz(clf3,
                                feature_names=labels,
                                class_names=("Did not Graduate in 6", "Did Graduate in 6"),
                                out_file=None,
                                filled=True,
                                rounded=True,
                                special_characters=True)
foo = clf3.predict_proba(Xnum)

graph = graphviz.Source(dotData3)
graph
```


GPA ≤ 2.39
gini = 0.444
samples = 12
value = [8, 4]
class = Did not Graduate in 6
True
False
WORKED ≤ 0.5
gini = 0.198
samples = 9
value = [8, 1]
class = Did not Graduate in 6
gini = 0.0
samples = 3
value = [0, 3]
class = Did Graduate in 6
gini = 0.0
samples = 6
value = [6, 0]
class = Did not Graduate in 6
GPA ≤ 1.995
gini = 0.444
samples = 3
value = [2, 1]
class = Did not Graduate in 6
gini = 0.0
samples = 2
value = [2, 0]
class = Did not Graduate in 6
gini = 0.0
samples = 1
value = [0, 1]
class = Did Graduate in 6