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Lab: 8

Animal Classification Using Decision Trees

Step:1

```
In [1]: import pandas as pd
In [2]: data = pd.read_csv('Animals.csv')
In [3]: data
```

Out[3]:

	Toothed	hair	breathes	legs	species
0	True	True	True	True	Mammal
1	True	True	True	True	Mammal
2	True	False	True	False	Raptile
3	False	True	True	True	Mammal
4	True	True	True	True	Mammal
5	True	True	True	True	Mammal
6	True	False	False	False	Raptile
7	True	False	True	False	Raptile
8	True	True	True	True	Mammal
9	False	False	True	True	Raptile

```
In [4]: data.shape
```

Out[4]: (10, 5)

In [5]: data.describe()

Out[5]:

	Toothed	hair	breathes	legs	species
count	10	10	10	10	10
unique	2	2	2	2	2
top	True	True	True	True	Mammal
freq	8	6	9	7	6

Step: 2

In [6]: X=data.drop(['species'],axis=1)

```
In [7]: X
```

Out[7]:

Out[/]:	7	Toothed	hair	breathes	legs	
	0	True	True	True	True	
	1	True	True	True	True	
	2	True	False	True	False	
	3	False	True	True	True	
	4	True	True	True	True	
	5	True	True	True	True	
	6	True	False	False	False	
	7	True	False	True	False	
	8	True	True	True	True	
	9	False	False	True	True	
In [8]:	y=da	ta[' <mark>s</mark> p	ecies'].values	5	
In [9]:	у					
Out[9]:	arra					aptile', 'Mammal', 'Mammal', 'Mammal', 'Mammal', 'Raptile'], dtype=object)
In [10]:	from	sklea	rn.mod	del_selec	tion :	import train_test_split
In [11]:	X_tr	ain, X	_test,	y_train	n, y_te	est = train_test_split(X, y, test_size=0.40,random_state=0)
In [12]:	X_tr	ain.sh	ape			
Out[12]:	(6,	4)				
In [13]:	X_te	st.sha	pe			
Out[13]:	(4,	4)				

```
In [14]: y_train.shape
Out[14]: (6,)
In [15]: y_test.shape
Out[15]: (4,)
In [16]: from sklearn.tree import DecisionTreeClassifier
In [17]: data_entropy = DecisionTreeClassifier(criterion ="entropy")
         data_entropy.fit(X_train,y_train)
Out[17]: DecisionTreeClassifier(criterion='entropy')
In [18]: y_pred = data_entropy.predict(X_test)
In [19]: y_pred
Out[19]: array(['Raptile', 'Mammal', 'Mammal', 'Raptile'], dtype=object)
In [21]: from sklearn.metrics import accuracy_score,classification_report
In [22]: | acc = accuracy_score(y_test, y_pred)
         print("Accuracy score :",acc)
```

Accuracy score : 1.0

```
In [23]: clf report= classification report(y test, y pred)
         print("Classification report: ",clf report)
                                                precision
                                                             recall f1-score
         Classification report:
                                                                                support
                                                              2
               Mammal
                             1.00
                                       1.00
                                                 1.00
                                                              2
              Raptile
                             1.00
                                       1.00
                                                 1.00
                                                 1.00
                                                              4
             accuracy
            macro avg
                             1.00
                                       1.00
                                                 1.00
                                                              4
         weighted avg
                             1.00
                                       1.00
                                                 1.00
                                                              4
In [24]: from sklearn import tree
In [26]: with open("tree1.dot",'w') as f:
             f= tree.export graphviz(data entropy,out file=f,max depth=4,impurity= False,
                                     feature names = X.columns.values,class names=['Reptile','Mammal'],filled=True)
In [27]: !type tree1.dot
         digraph Tree {
         node [shape=box, style="filled", color="black"];
         0 [label="hair <= 0.5\nsamples = 6\nvalue = [4, 2]\nclass = Reptile", fillcolor="#f2c09c"];</pre>
         1 [label="samples = 2\nvalue = [0, 2]\nclass = Mammal", fillcolor="#399de5"];
         0 -> 1 [labeldistance=2.5, labelangle=45, headlabel="True"];
         2 [label="samples = 4\nvalue = [4, 0]\nclass = Reptile", fillcolor="#e58139"];
         0 -> 2 [labeldistance=2.5, labelangle=-45, headlabel="False"];
```

```
In [29]: tree.plot_tree(data_entropy)
    Matplotlib is building the font cache; this may take a moment.

Out[29]: [Text(167.4, 163.07999999999999, 'X[1] <= 0.5\nentropy = 0.918\nsamples = 6\nvalue = [4, 2]'),
    Text(83.7, 54.360000000000014, 'entropy = 0.0\nsamples = 2\nvalue = [0, 2]'),
    Text(251.100000000000000, 54.360000000000014, 'entropy = 0.0\nsamples = 4\nvalue = [4, 0]')]

    X[1] <= 0.5
    entropy = 0.918
    samples = 6
    value = [4, 2]

    entropy = 0.0
    samples = 2
    value = [0, 2]</pre>
    entropy = 0.0
    samples = 4
    value = [4, 0]
```

```
step:3
```

```
In [32]: d_test=pd.read_csv("animals_test.csv")
```

```
In [33]: d_test
```

Out[33]:

	Name	toothed	hair	breathes	legs	species
0	Turtile	False	False	True	False	Raptile
1	Blue whales	False	True	True	True	Mammal
2	Crocodile	True	False	True	True	Raptile

```
In [34]: test_x=d_test.drop(['species','Name'],axis=1)
```

In [35]: test_x

Out[35]:

	toothed	hair	breathes	legs
0	False	False	True	False
1	False	True	True	True
2	True	False	True	True

Step:4

```
In [36]: y_pred_test=data_entropy.predict(test_x)
```

```
In [37]: y_pred_test
```

Out[37]: array(['Raptile', 'Mammal', 'Raptile'], dtype=object)

Step:5

```
In [38]: |d_gini = DecisionTreeClassifier(criterion ="gini")
         d_gini.fit(X,y)
Out[38]: DecisionTreeClassifier()
In [39]: y pred test=d gini.predict(test x)
In [40]: y pred test
Out[40]: array(['Raptile', 'Mammal', 'Raptile'], dtype=object)
In [41]: | tree.plot_tree(d_gini)
Out[41]: [Text(167.4, 163.0799999999998, 'X[1] <= 0.5\ngini = 0.48\nsamples = 10\nvalue = [6, 4]'),
         Text(83.7, 54.360000000000014, 'gini = 0.0 \times 10^{-1} = 0.0 \times 10^{-1}),
          Text(251.1000000000002, 54.36000000000014, 'gini = 0.0\nsamples = 6\nvalue = [6, 0]')]
                      gini = 0.48

samples = 10
                      value = [6, 4]
              gini = 0.0
                                   gini = 0.0
            samples = 4 | samples = 6
           value = [0, 4]
                                value = [6, 0]
```

Step:6

```
In [42]: d_zoo=pd.read_csv("zoo.data")
```

Out[43]:

	aardvark	1	0	0.1	1.1	0.2	0.3	1.2	1.3	1.4	1.5	0.4	0.5	4	0.6	0.7	1.6	1.7
0	antelope	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0	1	1
1	bass	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0	0	4
2	bear	1	0	0	1	0	0	1	1	1	1	0	0	4	0	0	1	1
3	boar	1	0	0	1	0	0	1	1	1	1	0	0	4	1	0	1	1
4	buffalo	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0	1	1
	•••																	
95	wallaby	1	0	0	1	0	0	0	1	1	1	0	0	2	1	0	1	1
96	wasp	1	0	1	0	1	0	0	0	0	1	1	0	6	0	0	0	6
97	wolf	1	0	0	1	0	0	1	1	1	1	0	0	4	1	0	1	1
98	worm	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	7
99	wren	0	1	1	0	1	0	0	0	1	1	0	0	2	1	0	0	2

100 rows × 18 columns

```
In [44]: d_zoo.shape
```

Out[44]: (100, 18)

In [45]: d_zoo.describe()

Out[45]:

	1	0	0.1	1.1	0.2	0.3	1.2	1.3	1.4	1.5	0.4	
count	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.00	100.000000	100.000000	100.00000	100.00000	10
mean	0.420000	0.200000	0.590000	0.400000	0.240000	0.360000	0.55	0.600000	0.820000	0.79000	0.08000	
std	0.496045	0.402015	0.494311	0.492366	0.429235	0.482418	0.50	0.492366	0.386123	0.40936	0.27266	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00	0.000000	0.000000	0.00000	0.00000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00	0.000000	1.000000	1.00000	0.00000	
50%	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	1.00	1.000000	1.000000	1.00000	0.00000	
75%	1.000000	0.000000	1.000000	1.000000	0.000000	1.000000	1.00	1.000000	1.000000	1.00000	0.00000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.00	1.000000	1.000000	1.00000	1.00000	

In [47]: X=d_zoo.drop(['aardvark','1.7'],axis=1)

In [49]: X[:5]

Out[49]:

	1	0	0.1	1.1	0.2	0.3	1.2	1.3	1.4	1.5	0.4	0.5	4	0.6	0.7	1.6
0	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0	1
1	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0	0
2	1	0	0	1	0	0	1	1	1	1	0	0	4	0	0	1
3	1	0	0	1	0	0	1	1	1	1	0	0	4	1	0	1
4	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0	1

```
In [53]: d zoo.describe()
Out[53]:
                           1
                                      0
                                                0.1
                                                            1.1
                                                                       0.2
                                                                                   0.3
                                                                                          1.2
                                                                                                      1.3
                                                                                                                 1.4
                                                                                                                           1.5
                                                                                                                                      0.4
                  100.000000
                             100.000000
                                         100.000000
                                                     100.000000
                                                                100.000000
                                                                            100.000000
                                                                                       100.00
                                                                                               100.000000
                                                                                                          100.000000
                                                                                                                     100.00000
                                                                                                                                100.00000
            mean
                    0.420000
                                0.200000
                                           0.590000
                                                       0.400000
                                                                  0.240000
                                                                              0.360000
                                                                                         0.55
                                                                                                0.600000
                                                                                                            0.820000
                                                                                                                       0.79000
                                                                                                                                  0.08000
                    0.496045
                                0.402015
                                           0.494311
                                                       0.492366
                                                                  0.429235
                                                                              0.482418
                                                                                         0.50
                                                                                                0.492366
                                                                                                            0.386123
                                                                                                                       0.40936
                                                                                                                                  0.27266
              std
                    0.000000
                                0.000000
                                           0.000000
                                                                  0.000000
                                                                              0.000000
                                                                                         0.00
                                                                                                0.000000
                                                                                                            0.000000
                                                                                                                       0.00000
                                                                                                                                  0.00000
             min
                                                       0.000000
             25%
                    0.000000
                                0.000000
                                           0.000000
                                                       0.000000
                                                                  0.000000
                                                                              0.000000
                                                                                         0.00
                                                                                                0.000000
                                                                                                            1.000000
                                                                                                                       1.00000
                                                                                                                                  0.00000
             50%
                    0.000000
                                0.000000
                                           1.000000
                                                       0.000000
                                                                  0.000000
                                                                              0.000000
                                                                                         1.00
                                                                                                1.000000
                                                                                                            1.000000
                                                                                                                       1.00000
                                                                                                                                  0.00000
             75%
                     1.000000
                                0.000000
                                           1.000000
                                                       1.000000
                                                                  0.000000
                                                                              1.000000
                                                                                         1.00
                                                                                                1.000000
                                                                                                            1.000000
                                                                                                                       1.00000
                                                                                                                                  0.00000
                                1.000000
                                                                  1.000000
                                                                                         1.00
                                                                                                                                  1.00000
             max
                    1.000000
                                           1.000000
                                                       1.000000
                                                                              1.000000
                                                                                                1.000000
                                                                                                            1.000000
                                                                                                                       1.00000
In [54]: y=d_zoo['1.7'].values
In [55]: y
Out[55]: array([1, 4, 1, 1, 1, 1, 4, 4, 1, 1, 2, 4, 7, 7, 7, 2, 1, 4, 1, 2, 2, 1,
                   2, 6, 5, 5, 1, 1, 1, 6, 1, 1, 2, 4, 1, 1, 2, 4, 6, 6, 2, 6, 2, 1,
                  1, 7, 1, 1, 1, 6, 5, 7, 1, 1, 2, 2, 2, 2, 4, 4, 3, 1, 1, 1, 1,
                   1, 1, 1, 1, 2, 7, 4, 1, 1, 3, 7, 2, 2, 3, 7, 4, 2, 1, 7, 4, 2, 6,
                   5, 3, 3, 4, 1, 1, 2, 1, 6, 1, 7, 2], dtype=int64)
In [56]: X1 train, X1 test, y1 train, y1 test = train test split(X, y, test size=0.33, random state=0)
In [60]: |X1_train.shape
Out[60]: (67, 16)
In [61]: |X1_test.shape
Out[61]: (33, 16)
```

```
In [62]: y1 train.shape
Out[62]: (67,)
In [63]: |y1_test.shape
Out[63]: (33,)
In [64]: | zoo_entropy = DecisionTreeClassifier(criterion ="entropy")
         zoo_entropy.fit(X1_train,y1_train)
Out[64]: DecisionTreeClassifier(criterion='entropy')
In [65]: y1_pred = zoo_entropy.predict(X1_test)
In [66]: y1_pred
Out[66]: array([1, 2, 1, 2, 5, 1, 1, 1, 1, 1, 1, 1, 2, 7, 4, 1, 2, 5, 4, 1, 1, 1,
                1, 6, 7, 1, 4, 2, 2, 7, 4, 7, 3], dtype=int64)
         Accuracy
In [69]: train_acc=zoo_entropy.predict(X1_train)
         train acc
Out[69]: array([1, 5, 1, 1, 2, 1, 1, 4, 3, 2, 6, 1, 2, 4, 2, 6, 1, 4, 4, 1, 1, 1,
                6, 4, 1, 6, 7, 2, 1, 1, 2, 3, 4, 2, 7, 7, 3, 2, 6, 1, 1, 7, 1, 2,
                2, 4, 2, 5, 4, 4, 1, 6, 1, 2, 7, 5, 2, 6, 2, 1, 1, 1, 6, 1, 1, 1,
                1], dtype=int64)
In [70]: |print("Train Accuracy:", accuracy_score(y1_train, zoo_entropy.predict(X1_train)))
         Train Accuracy: 1.0
```

Accuracy score: 0.9393939393939394

```
In [74]: clf_report= classification_report(y1_test, y1_pred)
print("Classification report: ",clf_report)
```

Classification r	report:		precision	recall	f1-score	support
1	1.00	1.00	1.00	1 5		
2	1.00	1.00	1.00	6		
3	1.00	0.50	0.67	2		
4	1.00	1.00	1.00	4		
5	0.50	1.00	0.67	1		
6	0.00	0.00	0.00	0		
7	1.00	0.80	0.89	5		
accuracy			0.94	33		
macro avg	0.79	0.76	0.75	33		
weighted avg	0.98	0.94	0.95	33		

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics_classification.py:1248: UndefinedMetricWarning: Re call and F-score are ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` para meter to control this behavior.

_warn_prf(average, modifier, msg_start, len(result))

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics_classification.py:1248: UndefinedMetricWarning: Re call and F-score are ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` para meter to control this behavior.

_warn_prf(average, modifier, msg_start, len(result))

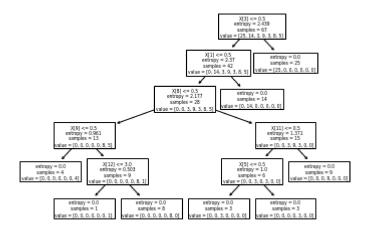
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics_classification.py:1248: UndefinedMetricWarning: Re call and F-score are ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` para meter to control this behavior.

_warn_prf(average, modifier, msg_start, len(result))

ID3

```
In [75]: tree.plot_tree(zoo_entropy)
```

Out[75]: [Text(234.36, 199.32, $X[3] <= 0.5 \le 2.439 \le = 67 \le = 67 \le = [25, 14, 3, 9, 3, 8, 5]$), Text(200.8800000000000, 163.079999999999, 'X[1] <= 0.5\nentropy = 2.37\nsamples = 42\nvalue = [0, 14, 3, 9, 3, 8, 5]'), Text(167.40000000000003, 126.8399999999999, $X[8] \le 0.5 \le 2.177 \le 2.1$ 9, 3, 8, 5]'), Text(66.9600000000001, 90.6, $X[9] <= 0.5 \le 0.961 \le 0$ Text(33.48000000000004, 54.35999999999999, 'entropy = 0.0\nsamples = 4\nvalue = [0, 0, 0, 0, 0, 0, 4]'), Text(100.4400000000001, 54.359999999999985, $X[12] \le 3.0 \neq 0.503 = 0.503 = 9 = 9 = 0.503 = 0.$ 0, 0, 8, 1]'), Text(66.9600000000001, 18.11999999999976, 'entropy = 0.0×1 | 0.0×1 | Text(133.92000000000002, 18.11999999999976, 'entropy = 0.0\nsamples = 8\nvalue = [0, 0, 0, 0, 0, 8, 0]'), Text(267.8400000000003, 90.6, $X[11] <= 0.5 \neq 1.371 = 1.3$ Text(234.36, 54.35999999999985, X[5] <= 0.5 = 1.0 = 6 = 6 = [0, 0, 3, 0, 3, 0, 0]Text(200.8800000000000, 18.11999999999976, 'entropy = 0.0\nsamples = 3\nvalue = [0, 0, 3, 0, 0, 0, 0]'), Text(267.84000000000003, 18.1199999999999976, 'entropy = 0.0×10^{-2} (a) 0.0×10^{-2} (b) 0.0×10^{-2} (c) 0.0×10^{-2} (d) 0.0×10^{-2} (e) 0.0×10^{-2} (f) 0.0×10^{-2} (e) 0.0×10^{-2} (f) 0.0×10^{-2} (f) 0.0Text(301.3200000000005, 54.35999999999995, 'entropy = 0.0\nsamples = 9\nvalue = [0, 0, 0, 0, 0, 0]'), Text(234.36, 126.8399999999999, 'entropy = 0.0×14 , nvalue = [0, 14, 0, 0, 0, 0, 0]'),

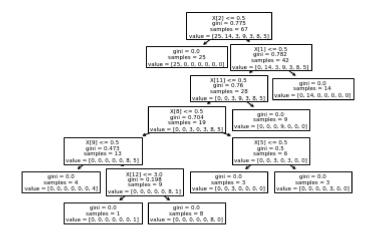


Gini

```
In [77]: X2_train, X2_test, y2_train, y2_test = train_test_split(X, y, test_size=0.33,random_state=0)
In [78]: | zoo2 entropy = DecisionTreeClassifier(criterion = "gini")
         zoo2 entropy.fit(X2 train,y2 train)
Out[78]: DecisionTreeClassifier()
In [79]: y2_pred = zoo2_entropy.predict(X2_test)
In [80]: y2_pred
Out[80]: array([1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 2, 7, 4, 1, 2, 5, 4, 1, 1, 5,
                1, 1, 7, 1, 4, 2, 2, 7, 4, 7, 3], dtype=int64)
In [83]: | train acc=zoo2 entropy.predict(X2 train)
         train acc
Out[83]: array([1, 5, 1, 1, 2, 1, 1, 4, 3, 2, 6, 1, 2, 4, 2, 6, 1, 4, 4, 1, 1, 1,
                6, 4, 1, 6, 7, 2, 1, 1, 2, 3, 4, 2, 7, 7, 3, 2, 6, 1, 1, 7, 1, 2,
                2, 4, 2, 5, 4, 4, 1, 6, 1, 2, 7, 5, 2, 6, 2, 1, 1, 1, 6, 1, 1, 1,
                1], dtype=int64)
In [84]: |print("Train Accuracy:", accuracy score(y2 train, zoo2 entropy.predict(X2 train)))
         Train Accuracy: 1.0
In [86]: | test acc=zoo2 entropy.predict(X2 train)
         test_acc
Out[86]: array([1, 5, 1, 1, 2, 1, 1, 4, 3, 2, 6, 1, 2, 4, 2, 6, 1, 4, 4, 1, 1, 1,
                6, 4, 1, 6, 7, 2, 1, 1, 2, 3, 4, 2, 7, 7, 3, 2, 6, 1, 1, 7, 1, 2,
                2, 4, 2, 5, 4, 4, 1, 6, 1, 2, 7, 5, 2, 6, 2, 1, 1, 1, 6, 1, 1, 1,
                1], dtype=int64)
```

```
In [87]: print("Test Accuracy:", accuracy_score(y2_test, zoo2_entropy.predict(X2_test)))
         Test Accuracy: 0.9090909090909091
In [88]: acc = accuracy_score(y2_test, y2_pred)
         print("Accuracy score :",acc)
         Accuracy score : 0.9090909090909091
In [89]: |clf_report= classification_report(y2_test, y2_pred)
         print("Classification report: ",clf_report)
         Classification report:
                                                            recall f1-score
                                               precision
                                                                               support
                    1
                            0.88
                                      0.93
                                                0.90
                                                            15
                    2
                            1.00
                                      1.00
                                                1.00
                                                             6
                                      0.50
                                                0.67
                    3
                            1.00
                                                             2
                    4
                            1.00
                                      1.00
                                                1.00
                                                             4
```

```
In [90]: | tree.plot tree(zoo2 entropy)
Out[90]: [Text(209.25, 201.90857142857143, 'X[2] <= 0.5\ngini = 0.775\nsamples = 67\nvalue = [25, 14, 3, 9, 3, 8, 5]'),
                                   Text(167.4, 170.84571428571428, 'gini = 0.0\nsamples = 25\nvalue = [25, 0, 0, 0, 0, 0, 0]').
                                   Text(251.10000000000000, 170.84571428571428, 'X[1] \le 0.5 = 0.782 = 42 = 42 = [0, 14, 3, 9, 12]
                                 3, 8, 5]'),
                                    Text(209.25, 139.78285714285715, X[11] \le 0.5 = 0.76 = 28 = 28 = [0, 0, 3, 9, 3, 8, 5]
                                    Text(167.4, 108.72, |X[8]| \le 0.5 \le 0.704 \le 19 \le 19 \le 19
                                   Text(83.7, 77.65714285714284, 'X[9] <= 0.5\ngini = 0.473\nsamples = 13\nvalue = [0, 0, 0, 0, 0, 8, 5]'),
                                    Text(41.85, 46.59428571428572, 'gini = 0.0\nsamples = 4\nvalue = [0, 0, 0, 0, 0, 0, 4]'),
                                   8, 1]'),
                                    Text(83.7, 15.531428571428563, 'gini = 0.0 \times 10^{-1} = 1 \times 10^{-1} Text(83.7, 15.531428571428563, 'gini = 0.0 \times 10^{-1} = 1 \times 10^{-1} Text(83.7, 15.531428571428563, 'gini = 0.0 \times 10^{-1} = 1 \times 10^{-1} Text(83.7, 15.531428571428563, 'gini = 0.0 \times 10^{-1} = 1 \times 10^{-1} Text(83.7, 15.531428571428563, 'gini = 0.0 \times 10^{-1} Text(83.7, 15.531428563, 'gini = 0.0 \times 10^{-1} Text(83.7, 15.7, 15.531428563, 'gini = 0.0 \times 10^{-1} Text(83.7, 15.7, 15.7)
                                   Text(167.4, 15.531428571428563, 'gini = 0.0\nsamples = 8\nvalue = [0, 0, 0, 0, 0, 8, 0]'),
                                   Text(251.1000000000000, 77.65714285714284, 'X[5] <= 0.5\ngini = 0.5\nsamples = 6\nvalue = [0, 0, 3, 0, 3, 0,
                                 0]'),
                                    Text(209.25, 46.59428571428572, 'gini = 0.0\nsamples = 3\nvalue = [0, 0, 3, 0, 0, 0, 0]'),
                                    Text(292.95, 46.59428571428572, 'gini = 0.0\nsamples = 3\nvalue = [0, 0, 0, 0, 3, 0, 0]'),
                                    Text(251.1000000000000, 108.72, 'gini = 0.0 \times 10^{-1} = 0.0 \times
```



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In [ ]:
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