# Pattern Recognition

- S. S. Samant

#### **Decision Tree Classifier**



These are *multistage* decision systems in which classes are sequentially rejected until we reach a finally accepted class. To this end, the feature space is split into unique regions, corresponding to the classes, *in a sequential manner*.

- A *splitting criterion* must be adopted according to which the best split from the set of candidate ones is chosen.
- A stop-splitting rule is required that controls the growth of the tree, and a node is declared as a terminal one (*leaf*).
- A rule is required that assigns each leaf to a specific class.

### Information gain (entropy)

RID	age	income	student	credit_rating	Class: buys_computer
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 In
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

What if we split on age?

high

low

medium

medium

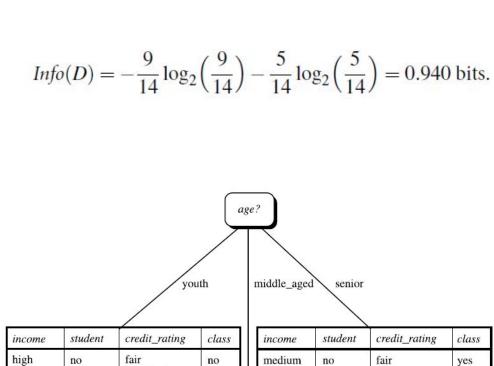
yes

excellent

excellent

fair

fair



income	student	credit_rating	class
high	no	fair	yes
low	yes	excellent	yes
medium	no	excellent	yes
high	yes	fair	yes

low

medium

medium

no

no

yes

yes

fair

fair

excellent

excellent

yes

no

yes

no

yes

yes

yes

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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

$$nfo(D) = -\frac{9}{14}\log_2\left(\frac{9}{14}\right) - \frac{5}{14}\log_2\left(\frac{5}{14}\right) = 0.940 \text{ bits.}$$

$$Info_{age}(D) = \frac{5}{14} \times \left(-\frac{2}{5}\log_2\frac{2}{5} - \frac{3}{5}\log_2\frac{3}{5}\right)$$

$$+\frac{4}{14} \times \left(-\frac{4}{4}\log_2\frac{4}{4} - \frac{0}{4}\log_2\frac{0}{4}\right)$$

$$+\frac{5}{14} \times \left(-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}\right)$$

$$= 0.694 \text{ bits.}$$

$$\mathit{Info}_A(D) = \sum_{j=1}^v rac{|D_j|}{|D|} imes \mathit{Info}(D_j)$$

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13	middle_aged	high	yes	fair	yes
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$$Gain(age) = Info(D) - Info_{age}(D) = 0.940 - 0.694 = 0.246$$
 bits.

Gain(income) = 0.029 bits

$$Gain(student) = 0.151$$
 bits

 $Gain(credit\_rating) = 0.048$  bits.

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

### Representing nominal variables



Python only accepts numeric values for attributes, how to represent **categorical** variables such as age and income?

So, if age takes 3 values **youth**, **middle-aged**, and **senior** We can use 3 - 1 (=2) **dummy variables** for each age-value the variable takes

**Dummy variable :** a numeric variable that represents **categorical** data, such as gender, race, etc.

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**Dummy variable:** a numeric variable that represents **categorical** data, such as gender, race, etc.

For ex. age can take three values, so we can use 2 dummy variables as:

middle-aged	<u>senior</u>	<u>youth</u>
1	0	
0	1	
0	0	

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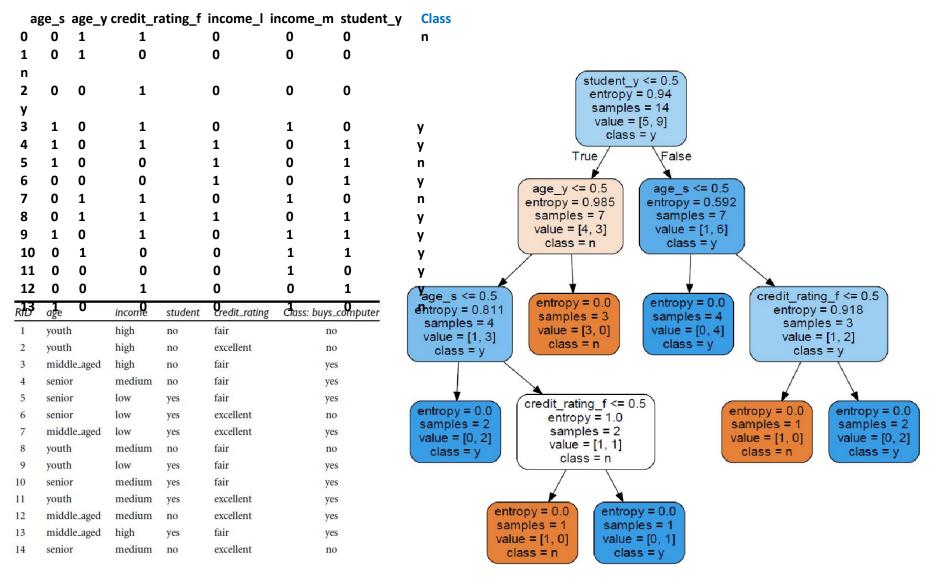
**Dummy variable :** a numeric variable that represents **categorical** data, such as gender, race, etc.

For ex. age can take three values, so we can use 2 dummy variables as:

<u>middle</u>	-aged	<u>senior</u>	<u>youth</u>
4	1	0	
	0	1	
Can infer this value from the other two	0	0	



#### **Attribute Selection Measures**





ā	age_s	age	_y credit_rating	_f incom	e_l income_r	n stud	ent_y Class
0	0	1	1	0	0	0	n
1	0	1	0	0	0	0	n
2	0	0	1	0	0	0	У
3	1	0	1	0	1	0	У
4	1	0	1	1	0	1	У
5	1	0	0	1	0	1	n
6	0	0	0	1	0	1	У
7	0	1	1	0	1	0	n
8	0	1	1	1	0	1	У
9	1	0	1	0	1	1	У
10	0	1	0	0	1	1	у
11	0	0	0	0	1	0	у
12	0	0	1	0	0	1	у
13	1	0	0	0	1	0	n

Initial entropy = 0.9402, entropy on splits (ages\_s=?, age\_y=?, credit\_rating\_f=?, income\_l=?, income\_m=?, student\_y=?)



a	ge_s	age	_y credit_rating	g_f income_	_l income_r	n stud	ent_y Class
0	0	1	1	0	0	0	n
1	0	1	0	0	0	0	n
2	0	0	1	0	0	0	у
3	1	0	1	0	1	0	у
4	1	0	1	1	0	1	у
5	1	0	0	1	0	1	n
6	0	0	0	1	0	1	у
7	0	1	1	0	1	0	n
8	0	1	1	1	0	1	у
9	1	0	1	0	1	1	у
10	0	1	0	0	1	1	У
11	0	0	0	0	1	0	У
12	0	0	1	0	0	1	У
13	1	0	0	0	1	0	n

Initial entropy = 0.9402, entropy on splits (ages\_s=0.9371, age\_y=0.838, credit\_rating\_f=0.8921, income\_l=0.9253, income\_m=0.9389, student\_y=0.7884)

	age_s	age_	_y credit_rating_t	income_l	income_m	stu	dent_y Class
0	0	1	1	0	0	0	n
1	. 0	1	0	0	0	0	n
2	. 0	0	1	0	0	0	У
3	1	0	1	0	1	0	У
7	0	1	1	0	1	0	n
1	1 0	0	0	0	1	0	у
1	3 1	0	0	0	1	0	n

Initial entropy = 0.9852, entropy on splits (ages\_s=0.9792, age\_y=0.4635, credit\_rating\_f=0.9649, income\_I=0.9852, income\_m=0.9649)

n

#### **Dataset**

13 1 0

 age\_s age\_y credit\_rating\_f income\_l income\_m student\_y Class

 2
 0
 0
 1
 0
 0
 y

 3
 1
 0
 1
 0
 y

 11
 0
 0
 0
 y

Initial entropy = 0.8112, entropy on splits ( ages\_s=0.5, credit\_rating\_f=0.5, income\_l=0.8112, income\_m=0.6887)

age\_s age\_y credit\_rating\_f income\_l income\_m student\_y Class

2 0 0 1 0 0 0 y 11 0 0 0 0 1 0 y

Initial entropy = 0, so Class='y'

### **DT** implementation

```
install graphviz from anaconda prompt by running
      conda install python-graphviz
      conda install graphviz
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import export graphviz
import graphviz
data = pd.DataFrame()
            = ['y','y','m','s','s','s','m','y','y','s','y','m','m','s']
data['age']
#print (data)
df = pd.DataFrame([['s','m','y','f'], ['s','m','y','e']],
columns=['age','income','student','credit rating'])
df2 = data.append(df,ignore index=True )
fea = pd.get dummies(df2,drop first=True)
df train, df test = fea[:14], fea[14:]
dt = DecisionTreeClassifier(criterion='entropy', random state=1)
dt.fit(df train, y)
dot data = export graphviz(dt, out file=None,
   feature names =list(fea.columns.values), class names = ['n', 'y'], filled=True,
rounded=True)
graph = graphviz.Source(dot data)
graph.render('buys computer') # saves Dtree in a file buys computer.pdf
```



## Thank You!