

# Solution to Decision Trees Prac Sheet

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## Exercise 1

Consider the data table below

**D** =

$X_1$	$X_2$	$X_3$	$X_4$	C
F	F	F	F	P
F	F	T	T	P
F	T	F	T	P
T	T	T	F	P
T	F	F	F	N
T	T	T	T	N
T	T	T	F	N

$$\mathbf{X} = \{X_1, X_2, X_3, X_4\}$$

What is the entropy of  $D$ ?

Write  $P_p$  for the probability of  $C=P$ , and  $P_n$  for the probability of  $C=N$ .

We have  $P_p = 4/7$  and  $P_n = 3/7$

$$H(D) = -P_n \log_2(P_n) - P_p \log_2(P_p)$$

Numerically

$$P_p = 0.5714$$

$$P_n = 0.4286$$

The entropy  $H(D)$  is 0.9852

What is the information gain of  $X_1$ ?

$$H(C | X_1=N) = H([0-,3+]) = 0$$

$$H(C | X_1=P) = H([3-,1+]) = 0.8113$$

$$H(C | X_1) = 3/7 H([0-,3+]) + 4/7 H([3-,1+]) = 0.4636$$

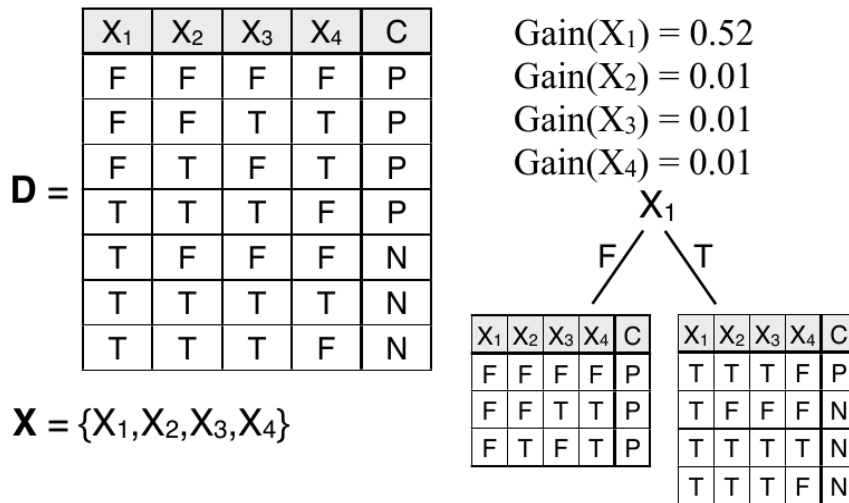
$$\text{Information gain of } X_1 : H(D) - H(C | X_1) = 0.5216$$

What is the information gain of  $X_2$ ?

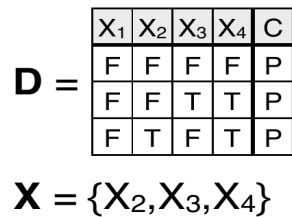
$$\text{Similarly, Gain}(X_2) = 0.9852 - ((4/7)*1 + (3/7)*0.91829) = 0.02$$

Build a DT to a depth of 3.

First split

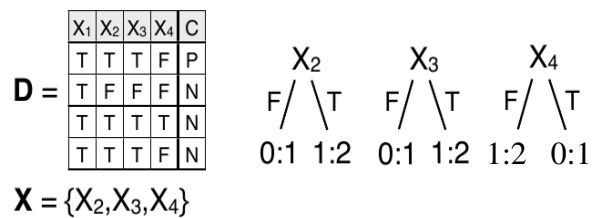


Left subtree,



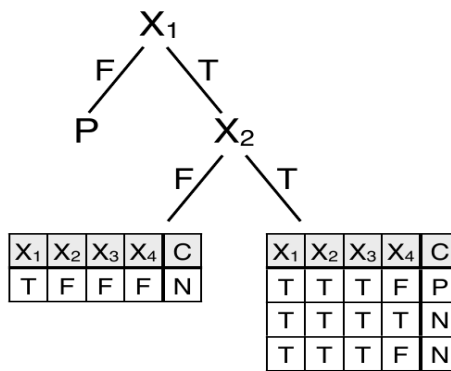
All instances have the same class.  
 Return class P.

Right subtree,



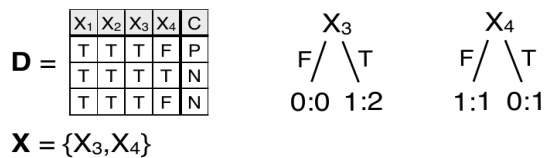
All attributes have same information gain.  
 Break ties arbitrarily.  
 Choose X<sub>2</sub>

So far we have,



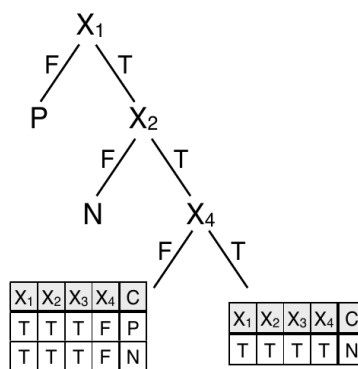
For the left subtree of the tree rooted at X<sub>2</sub>, all instances have the same class, we will return class N.

For the right subtree of the tree rooted at X<sub>2</sub>, we have



X<sub>3</sub> has zero information gain  
X<sub>4</sub> has positive information gain  
Choose X<sub>4</sub>

That is, we now have

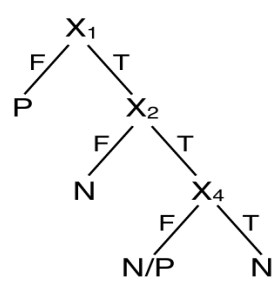


For the left subtree of X<sub>4</sub>, X<sub>3</sub> has zero information gain. No suitable attribute for splitting.

Return most common class (break ties arbitrarily). Note: data is inconsistent!

For the right subtree of X<sub>4</sub>, All instances have the same class. Return N.

The final tree is



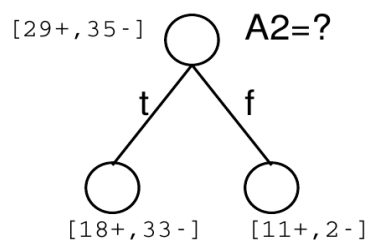
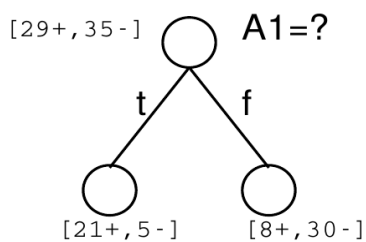
## Exercise 2

Recall that

$Gain(S, A) = \text{expected reduction in entropy due to sorting on } A$

$$Gain(S, A) \equiv Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v)$$

- Compute the information gain of the attribute A1 and A2



The information gain for A1 and A2 can be computed as follows

```
>>> from math import log
```

```
>>> ent = lambda p,n: -p/(p+n)*log(p/(p+n))-n/(p+n)*log(n/(p+n))
```

```
>>> IG1 = ent(29,35) - (21+5)/(29+35)*ent(21,5) - (8+30)/(29+35)*ent(8,30)
```

```
>>> IG1
```

```
0.18429041551228614
```

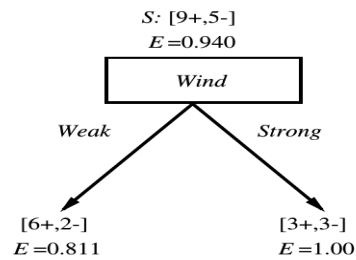
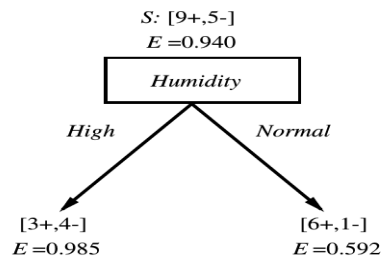
```
>>> IG2 = ent(29,35) - (18+33)/(29+35)*ent(18,33) - (11+2)/(29+35)*ent(11,2)
```

```
>>> IG2
```

```
0.08417016765262439
```

### Exercise 3

- Which attribute is the best classifier?



We have

$$\begin{aligned} \text{Gain}(S, \text{Humidity}) &= .940 - (7/14).985 - (7/14).592 \\ &= .151 \end{aligned}$$

$$\begin{aligned} \text{Gain}(S, \text{Wind}) &= .940 - (8/14).811 - (6/14)1.0 \\ &= .048 \end{aligned}$$

Therefore Humidity is the most informative attribute with respect to class prediction.