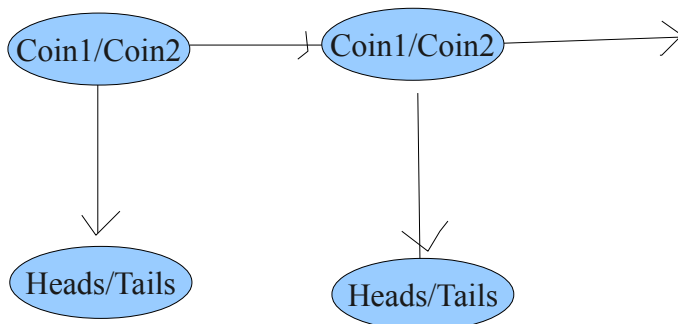
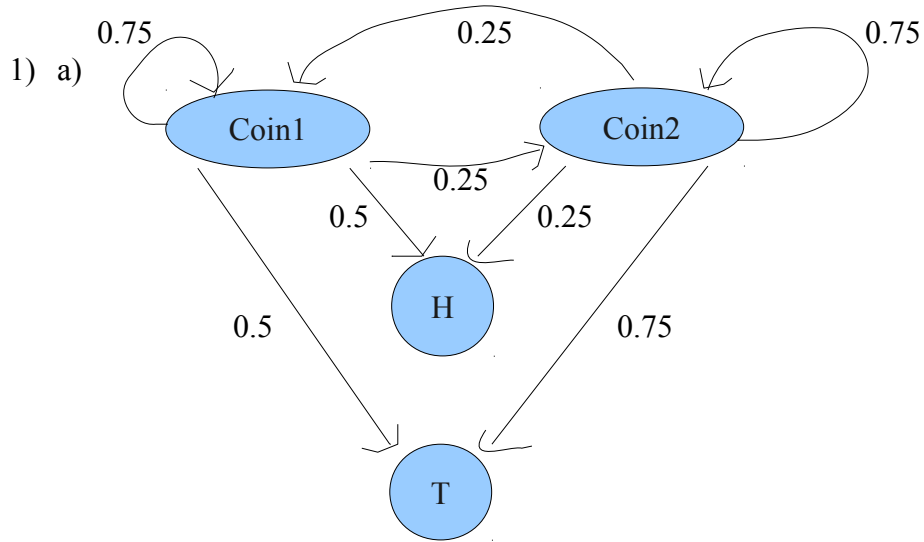


CSE – 730
Assignment – 03
Tarun Ronur Sasikumar



$P(\text{Coin1}_i \text{Coin1}_{i-1})$	0.75
$P(\text{Coin2}_i \text{Coin2}_{i-1})$	0.75
$P(\text{Coin1}_i \text{Coin2}_{i-1})$	0.25
$P(\text{Coin2}_i \text{Coin1}_{i-1})$	0.25

$P(\text{Head} \text{Coin1})$	0.5
$P(\text{Head} \text{Coin2})$	0.75

b) $P(\text{Coin2 Coin2 Coin2} \mid \text{Tails Tails Tails}) = ?$

$P(\text{Coin2 Coin2 Coin2}, \text{Tails Tails Tails}) = P(\text{Coin2} \mid \text{Coin2}) P(\text{Tails} \mid \text{Coin2}) * P(\text{Coin2} \mid \text{Coin2}) P(\text{Tails} \mid \text{Coin2}) * P(\text{Coin2}) P(\text{Tails} \mid \text{Coin2})$

$$\begin{aligned} &= (0.75 * 0.25) * (0.75 * 0.25) * (0.5 * 0.25) \\ &= 0.00439 \\ &= 0.0044 \end{aligned}$$

$$\begin{aligned} P(\text{Tails Tails Tails}) &= (0.5*0.25)*(0.75*0.25)*(0.75*0.25) + (0.5*0.25)*(0.75*0.25)*(0.25*0.5) + \\ &\quad (0.5*0.25)*(0.25*0.5)*(0.25*0.25) + (0.5*0.25)*(0.25*0.5)*(0.75*0.5) + \\ &\quad (0.5*0.5)*(0.75*0.5)*(0.75*0.5) + (0.5*0.5)*(0.75*0.5)*(0.25*0.25) + \\ &\quad (0.5*0.5)*(0.25*0.25)*(0.25*0.5) + (0.5*0.5)*(0.25*0.25)*(0.75*0.25) \end{aligned}$$

$$= 0.0601$$

$$P(\text{Coin2 Coin2 Coin2} \mid \text{Tails Tails Tails}) = 0.0044 / 0.0601 = \mathbf{0.0732}$$

c) Required probability = Probability that the coins were the same given that the sequence was “Heads Tails”
 $= P(\text{Coin1 Coin1} \mid \text{Heads Tails}) + P(\text{Coin2 Coin2} \mid \text{Heads Tails})$

$$P(\text{Heads Tails}) = (0.5*0.75)*(0.75*0.25 + 0.25*0.5) + (0.5*0.5)*(0.75*0.5 + 0.25*0.25) = 0.2266$$

$$\begin{aligned} P(\text{Coin2 Coin2}) &= P(\text{Coin2 Coin2}, \text{Heads Tails}) / P(\text{Heads Tails}) \\ &= 0.5*0.75 * 0.75*0.25 / 0.2266 = 0.3103 \end{aligned}$$

$$\begin{aligned} P(\text{Coin1 Coin1}) &= P(\text{Coin1 Coin1}, \text{Heads Tails}) / P(\text{Heads Tails}) \\ &= 0.5*0.5 * 0.75*0.5 / 0.2266 = 0.4137 \end{aligned}$$

$$P(\text{Coin1 Coin1} \mid \text{Heads Tails}) + P(\text{Coin2 Coin2} \mid \text{Heads Tails}) = 0.3103 + 0.4137 = \mathbf{0.7240}$$

2) No. of records with class label 'No' = 6

No. of records with class label 'Yes' = 10

$$\begin{aligned} \text{Entropy} &= -6/16 * \text{Log}(6/16) - 10/16 * \text{Log}(10/16) \\ &= 0.53063 + 0.42379 \\ &= \mathbf{0.95442} \end{aligned}$$

Split on Device:

– iPod :

No. of records with class label 'No' = 4

No. of records with class label 'Yes' = 1

$$\begin{aligned} \text{Entropy} &= -1/5 \text{Log}(1/5) - 4/5 \text{Log}(4/5) \\ &= 0.46438 + 0.25754 \\ &= \mathbf{0.72192} \end{aligned}$$

– iPhone:

No. of records with class label 'No' = 0

No. of records with class label 'Yes' = 8

$$\begin{aligned} \text{Entropy} &= -0/8 \text{Log}(0) - 8/8 \text{Log}(1) \\ &= \mathbf{0} \end{aligned}$$

- None:
 No. of records with class label 'No' = 2
 No. of records with class label 'Yes' = 1
 $\text{Entropy} = -2/3 \log(2/3) - 1/3 \log(1/3)$
 $= 0.52832 + 0.389975$
 $= \mathbf{0.918245}$

$$\text{Total entropy for splitting on Device} = 5/16 (0.72192) + 8/16 (0) + 3/16 (0.918245) \\ = \mathbf{0.39727}$$

$$\text{Information gain} = 0.95442 - 0.39727 = \mathbf{0.55715}$$

Split on Network:

- Facebook :
 No. of records with class label 'No' = 0
 No. of records with class label 'Yes' = 6
 $\text{Entropy} = 0 * \log(0) - 1 \log(1) = \mathbf{0}$
- Twitter :
 No. of records with class label 'No' = 6
 No. of records with class label 'Yes' = 4
 $\text{Entropy} = -4/10 \log(4/10) - 6/10 \log(6/10)$
 $= \mathbf{0.97095}$

$$\text{Total entropy for split on Network} = 6/16 * 0 + 10/16 * 0.97095 = \mathbf{0.6068}$$

$$\text{Information gain} = 0.95442 - 0.6068 = \mathbf{0.34757}$$

Split of Laptop:

- Mac
 No. of records with class label 'No' = 5
 No. of records with class label 'Yes' = 6
 $\text{Entropy} = -5/11 \log(5/11) - 6/11 \log(6/11)$
 $= \mathbf{0.99398}$
- PC
 No. of records with class label 'No' = 1
 No. of records with class label 'Yes' = 4
 $\text{Entropy} = -1/5 \log(1/5) - 4/5 \log(4/5)$
 $= \mathbf{0.72192}$

$$\text{Total entropy for split on Laptop} = 11/16 * 0.99398 + 5/16 * 0.72192 = \mathbf{0.90896}$$

$$\text{Information gain} = 0.95442 - 0.90896 = \mathbf{0.04546}$$

According to the entropies and Information Gain calculated we would split on **Device**.

3) a. Results of Perceptron Learning rule:

Alpha : 0.001

Bias : 0

Init Weight : 0

Epoch : 100000

Output format: Output-Of-Perceptron (Actual-Output)

Buck-I-Mart	Oxley's	Oxley's cafe	Brennan's	
1 (1)	0 (0)	0 (0)	0 (0)	
1 (0)	0 (1)	0 (0)	0 (0)	Fail
1 (1)	0 (0)	0 (0)	0 (0)	
1 (1)	0 (0)	0 (0)	0 (0)	
1 (1)	0 (0)	0 (0)	0 (0)	
0 (1)	1 (0)	0 (0)	0 (0)	Fail
1 (1)	1 (0)	0 (0)	0 (0)	Fail
0 (1)	0 (0)	0 (0)	0 (0)	Fail
1 (0)	1 (0)	0 (1)	0 (0)	Fail
0 (0)	1 (0)	0 (0)	1 (1)	Fail
1 (1)	0 (0)	0 (0)	0 (0)	
1 (0)	0 (1)	0 (0)	0 (0)	Fail
1 (1)	0 (0)	0 (0)	0 (0)	
1 (1)	0 (0)	0 (0)	0 (0)	
1 (0)	0 (0)	0 (1)	0 (0)	Fail
1 (1)	0 (0)	0 (0)	0 (0)	
1 (1)	1 (0)	0 (0)	0 (0)	Fail
0 (1)	0 (0)	0 (0)	0 (0)	Fail
0 (0)	0 (0)	0 (0)	1 (1)	
0 (1)	0 (0)	1 (0)	0 (0)	Fail
0 (0)	0 (0)	0 (0)	1 (1)	
0 (1)	0 (0)	0 (0)	0 (0)	Fail
0 (1)	0 (0)	0 (0)	0 (0)	Fail
1 (1)	0 (0)	0 (0)	0 (0)	
1 (1)	0 (0)	0 (0)	0 (0)	
1 (0)	0 (1)	0 (0)	0 (0)	Fail
1 (1)	0 (0)	0 (0)	0 (0)	
1 (1)	0 (0)	0 (0)	0 (0)	
1 (1)	0 (0)	0 (0)	0 (0)	
0 (0)	0 (0)	1 (1)	0 (0)	
0 (0)	0 (0)	0 (0)	1 (1)	
1 (0)	0 (0)	0 (0)	1 (1)	Fail
1 (1)	0 (0)	0 (0)	0 (0)	
1 (0)	0 (0)	1 (1)	0 (0)	Fail
1 (1)	0 (0)	0 (0)	0 (0)	
0 (0)	0 (0)	0 (0)	1 (1)	
0 (0)	1 (1)	0 (0)	0 (0)	
0 (0)	0 (0)	0 (0)	0 (1)	Fail
0 (0)	0 (0)	0 (0)	0 (1)	Fail

0 (0)	0 (0)	0 (0)	1 (1)	
0 (0)	0 (0)	0 (0)	1 (1)	
1 (1)	0 (0)	0 (0)	0 (0)	
0 (0)	0 (0)	0 (0)	0 (1)	Fail
1 (1)	0 (0)	0 (0)	0 (0)	
1 (1)	0 (0)	0 (0)	0 (0)	
0 (0)	0 (0)	0 (0)	1 (1)	
0 (1)	0 (0)	0 (0)	1 (0)	Fail
0 (1)	0 (0)	0 (0)	0 (0)	Fail
0 (1)	1 (0)	1 (0)	0 (0)	Fail
0 (0)	0 (0)	0 (0)	1 (1)	

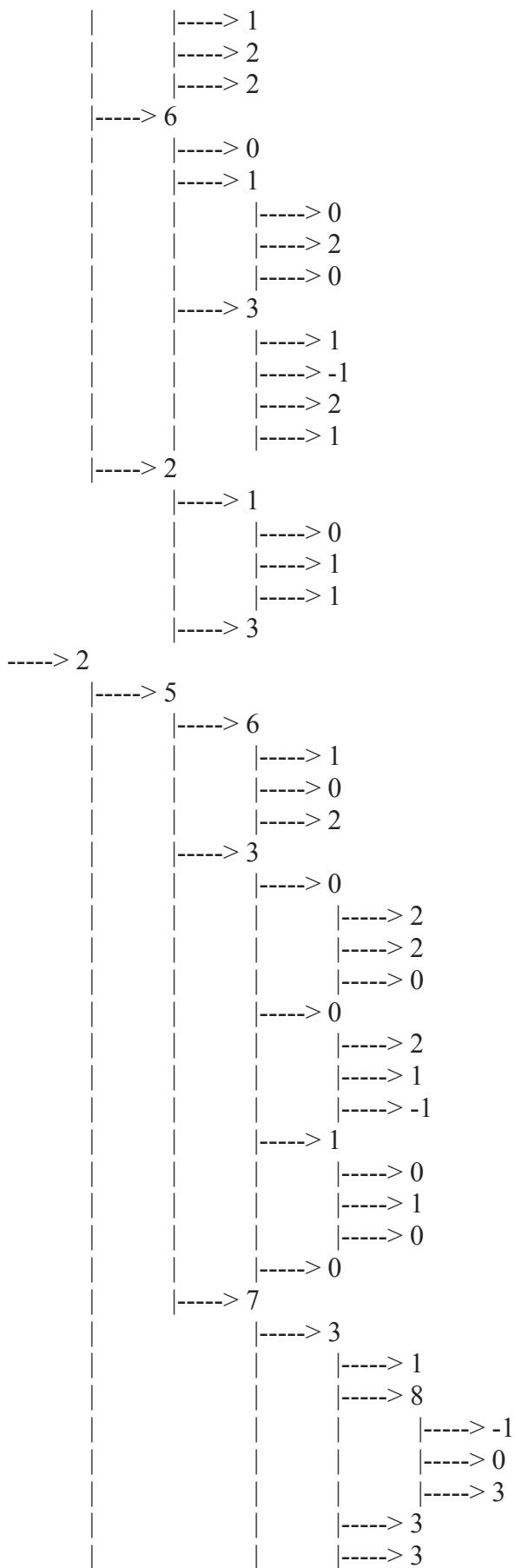
Number of errors = 22

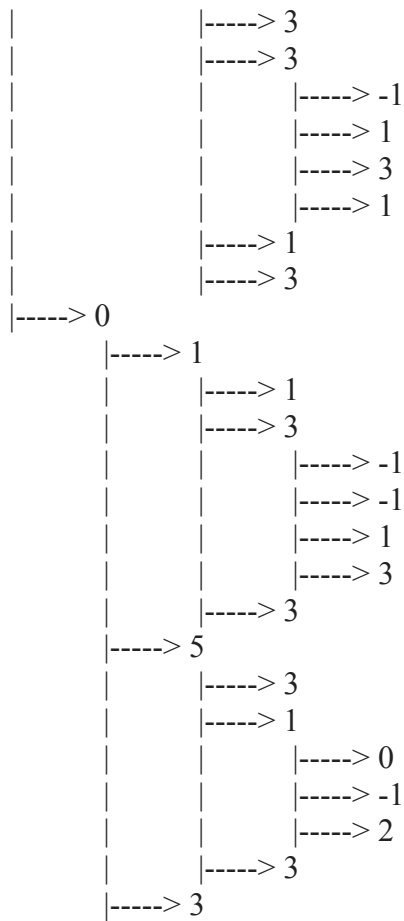
Accuracy = 56%

Weights

w0	0	-0.001	-0.003	-0.003
w1	0.001	0	0.007	-0.007
w2	0.006	-0.001	0.003	-0.007
w3	-0.007	0	-0.013	0.011
w4	0.002	-0.003	-0.001	-0.001
w5	-0.001	0.003	-0.002	-0.001
w6	-0.001	-0.001	0	-0.001
w7	0.005	0	-0.002	-0.007
w8	-0.005	-0.001	-0.001	0.004
w9	-0.003	0.003	0.001	0
w10	0.002	0.002	-0.007	-0.002
w11	0	-0.002	-0.001	0
w12	0.001	-0.004	0.004	-0.001
w13	0.008	-0.004	-0.006	-0.003
w14	0.003	-0.002	-0.003	-0.005
w15	-0.005	0.004	0.006	-0.004
w16	-0.006	0.001	0	0.009
w17	0.004	-0.001	-0.004	0.001
w18	-0.001	-0.002	0	-0.006
w19	-0.003	0.002	0.001	0.002
w20	0.003	-0.004	-0.003	0.004
w21	0	0	-0.001	-0.005
w22	-0.003	0.003	0.001	-0.002
w23	-0.001	0	-0.009	0.003
w24	0	0.001	0.003	-0.006
w25	-0.002	0.001	0	0
w26	0.002	-0.002	0.003	-0.005
w27	0.001	-0.001	0	0.005
w28	-0.002	0	0	-0.002
w29	0.003	0	-0.002	-0.001
w30	-0.001	-0.001	-0.001	0

$$\begin{array}{c} \text{-----} > 0 \\ | \\ | \text{-----} > 3 \\ | \quad | \text{-----} > 1 \end{array}$$





Predicted label : 0 Actual label : 0
 Predicted label : 3 Actual label : 1
 Predicted label : 0 Actual label : 0
 Predicted label : 0 Actual label : 0
 Predicted label : 0 Actual label : 0
 Predicted label : 0 Actual label : 0
 Predicted label : 1 Actual label : 0
 Predicted label : 1 Actual label : 0
 Predicted label : 2 Actual label : 2
 Predicted label : 3 Actual label : 3
 Predicted label : 2 Actual label : 0
 Predicted label : 1 Actual label : 1
 Predicted label : 0 Actual label : 0
 Predicted label : 0 Actual label : 0
 Predicted label : 1 Actual label : 2
 Predicted label : 0 Actual label : 0
 Predicted label : 0 Actual label : 0
 Predicted label : 0 Actual label : 0
 Predicted label : 3 Actual label : 3
 Predicted label : 0 Actual label : 0
 Predicted label : 1 Actual label : 3
 Predicted label : 0 Actual label : 0
 Predicted label : 0 Actual label : 0
 Predicted label : 0 Actual label : 0

Predicted label : 0 Actual label : 0
Predicted label : 0 Actual label : 1
Predicted label : 0 Actual label : 0
Predicted label : 0 Actual label : 0
Predicted label : 0 Actual label : 0
Predicted label : 2 Actual label : 2
Predicted label : 3 Actual label : 3
Predicted label : 3 Actual label : 3
Predicted label : 0 Actual label : 0
Predicted label : 2 Actual label : 2
Predicted label : 0 Actual label : 0
Predicted label : 3 Actual label : 3
Predicted label : 3 Actual label : 1
Predicted label : 3 Actual label : 3
Predicted label : 3 Actual label : 3
Predicted label : 3 Actual label : 3
Predicted label : 3 Actual label : 3
Predicted label : 0 Actual label : 0
Predicted label : 3 Actual label : 3
Predicted label : 0 Actual label : 0
Predicted label : 0 Actual label : 0
Predicted label : 3 Actual label : 3
Predicted label : 0 Actual label : 0
Predicted label : 0 Actual label : 0
Predicted label : 3 Actual label : 0
Predicted label : 0 Actual label : 3

Number mislabeled : 10

Accuracy : 80%

3 records could not be classified and were assigned a Default class label

Note: Leaf nodes that have a label of “-1” indicate that a class label was not predicted due to an empty node and hence will be assigned a default class label.

c) The decision tree has a higher accuracy than the neural network. This maybe be because we treat the different values of a variable as individual variables in a neural network. For example, the variable “How fast do I need it” can take one of 3 values which are mutually exclusive. This mutual exclusivity is captured by the decision tree while the neural network treat these three values as three different binary variables. It could be that since this mutual exclusivity is not captured and also because the size of the training sample is small, the neural network does not perform as well. Since there are 30 binary variables, there are a total of 2^{30} different possible combinations of those variables. With a training set of just 200, it may not be able to model these variables and in particular the mutual exclusivity between certain variables accurately.