6CCS3AIN & 7CCSMAIN, 2018, Tutorial 09 (Version 1.1)

1. The following table gives some examples of recent book selections I have made on the Orinoco website (Orinoco is the world's least well known online bookstore).

Examples	Attributes					Will Buy
	New	Paper	Know	Lang	Type	
X_1	N	N	Y	Eng	Thriller	Y
X_2	N	N	Y	Sp	Romance	N
X_3	Y	N	N	Eng	Detective	Y
X_4	N	Y	Y	Sp	Romance	Y
X_5	N	Y	N	Sp	Thriller	N
X_6	Y	N	Y	Eng	Literature	Y
X_7	Y	N	N	Fr	Detective	N
X_8	N	N	Y	Eng	Romance	Y
X_9	Y	Y	N	Sp	Detective	N
X_{10}	Y	Y	Y	Sp	Literature	N
X_{11}	N	N	N	Fr	Romance	N
X_{12}	Y	Y	Y	Sp	Detective	Y

   This records whether or not the book is *New*ly published, is a *Paper*back or not, whether I *Know* the author (that is whether I have previously bought a book by the same author), what *Lang*uage the book was orginally written in (English, French or Spanish), and what genre the book is from (Thriller, Romance, Dectective, or Literature). The site also records whether or not I actually bought the book (or just browsed it).

   Use the decision tree learning algorithm from the notes to construct a decision tree that Orinoco could use to predict whether I am likely to want to purchase any new books that they start to stock.

   You should explain how the algorithm builds the decision tree, not just give the solution.

2. Consider the data in the table below:

Instance	Features	
	x_1	x_2
X_1	0	3
X_2	2	3
X_3	3	1
X_4	3	3
X_5	3	8
X_6	4	9
X_7	5	7
X_8	7	8
X_9	8	0
X_{10}	8	4
X_{11}	9	1

   Explain how K-means clustering would cluster these examples.

   Given the initial cluster centres $(1, 6)$, $(4, 5)$, and $(9, 3)$, compute the final cluster centres using Manhattan distance as the distance metric.

3. Consider an agent using passive reinforcement learning in the environment from the slides on page 50.

   Consider the following runs:

$$(1,1)_{-0.04} \rightarrow (1,2)_{-0.04} \rightarrow (1,3)_{-0.04} \rightarrow (1,3)_{-0.04} \rightarrow (2,3)_{-0.04} \rightarrow (2,3)_{-0.04} \rightarrow (2,3)_{-0.04} \rightarrow (3,3)_{-0.04}$$
$$\rightarrow (3,2)_{-0.04} \rightarrow (3,3)_{-0.04} \rightarrow (3,2)_{-0.04} \rightarrow (3,3)_{-0.04} \rightarrow (4,3)_{1}$$
$$(1,1)_{-0.04} \rightarrow (1,2)_{-0.04} \rightarrow (1,2)_{-0.04} \rightarrow (1,3)_{-0.04} \rightarrow (2,3)_{-0.04} \rightarrow (3,3)_{-0.04} \rightarrow (4,3)_{1}$$
$$(1,1)_{-0.04} \rightarrow (1,1)_{-0.04} \rightarrow (1,2)_{-0.04} \rightarrow (1,3)_{-0.04} \rightarrow (2,3)_{-0.04} \rightarrow (3,3)_{-0.04} \rightarrow (4,3)_{1}$$

   (a) Use direct utility estimation to estimate the utility of each state along the first run, after that run.

   (b) Calculate the sample estimate of $P(s'|s, \pi(s))$ for each state along the first run.

   (c) Repeat the previous calculations after the second run.
   Note that the values you should compute are the cumulative values after the first and second runs. As a result, you should include utility and probability estimates for every state visited on either run.

(d) Now update your answer to the previous question after the third run.
(e) What do you notice about the estimates?

Note that these runs were randomly generated.