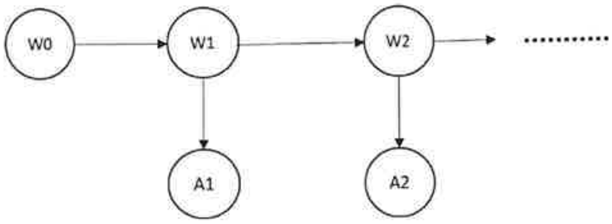
CS 561 Artificial Intelligence QUIZ II

19 April 2024 (Friday) **Max. Marks: 20** **Time: 40 mins** A

Roll No. ______________________ Name: ______________________

Q 4 Set-B

1. Sam is a football player (goalkeeper). His coach wants to evaluate his performance after each of his weekly practice matches, and he does so based on Sam's actions (offensive or defensive) during a match. He models this scenario by using an HMM as shown below: **[5 marks]**



W_0	$P(W_0)$
+w	0.6
-w	0.4

A_i	W_i	$P(A_i\|W_i)$
+a	+w	0.5
-a	+w	0.5
+a	-w	0.9
-a	-w	0.1

W_{i+1}	W_i	$P(W_{i+1}\|W_i)$
+w	+w	0.7
-w	+w	0.3
+w	-w	0.4
-w	-w	0.6

Wi is a binary random variable representing whether Sam played well during Week i. Ai is another binary random variable representing his action (+a : offensive, -a : defensive) in Week i. His actions during Week 0 are not observed. The coach uses particle filtering to analyse this HMM.

(a) At timestep t = 3, the coach has observed the following evidence: A1 = +a, A2 = −a, and A3 = +a. Following the particle filtering algorithm, assign weights to particles in the following states at t = 3:

Particles in state +w will have weight: 0.5

Particles in state -w will have weight: 0.9

2 marks

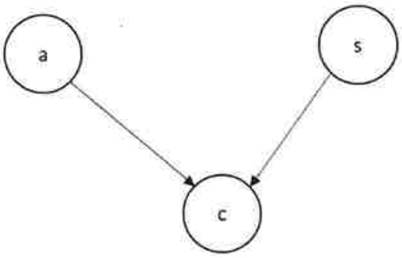
(b) At timestep t = 6, the coach observes 3 particles in state +w and 5 particles in state −w, and A6 = −a. Fill in the table describing the distribution that we resample our new particles from for t = 7.

W7	P(W7)
+w	0.75
-w	0.25

3 marks

2. Let **D** denote all the data, with observed value and H denote the hypothesis with possible values $h_1, h_2, \ldots$ The hypothesis (or model), h_i that ~~d~~ maximizes $P(h_i|\boldsymbol{d})$ is often called maximum a posterior or MAP hypothesis. **(True/ False)** True **[2 marks]**

3. Consider the following network where a: exposure to asbestos, s: being a smoker, c: incidence of lung cancer. We assume that there is no direct relationship between smoking and exposure to asbestos. The list of patients' records is shown in the following table. **[8 marks]**



a	s	c
1	1	1
1	0	0
0	1	1
0	1	0
1	1	1
0	0	0
1	0	1

Table 1

We would like to learn the appropriate parameters for the CPTs, which are given as $\theta_a, \theta_b, \theta_c^{11}, \theta_c^{01}, \theta_c^{10}, \theta_c^{00}$. Here, $P(c = 1 \mid a = 1, s = 1) = \theta_c^{11}$.

Use maximum likelihood (ML) parameter learning and Bayesian parameter learning with beta distribution as hypothesis prior to fill in the following table of parameters. The hyperparameters of beta distribution are denoted by α and β and assume an initial prior to be uniform with $\alpha = 1$ and $\beta = 1$.

	θ_a	θ_c^{11}	θ_c^{01}
ML	4/7	1	1/2
Bayesian	5/9	3/4	1/2

} 3 marks

1 mark 4 marks

Q 3
Set B

4. Consider the same network, now assume that the states of the variable a are never observed. So, for this problem use only the columns with labels s and c from the table (Table 1). Show one iteration of Expectation Maximization to estimate the parameter θ_a. Assume the initial parameter value to be $\theta_a = 0.5$. **[5 marks]**

E step:

$$\hat{N}(a=1) = 3 \times 0.5 + 2 \times 0.5 + 1 \times 0.5 + 1 \times 0.5$$
$$= 3.5$$

M step:

$$\hat{\theta}_a = \frac{\hat{N}(a=1)}{N} = \frac{3.5}{7} = 0.5$$

CS 561 Artificial Intelligence QUIZ II

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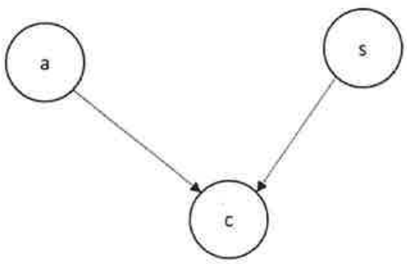
1. Let **D** denote all the data, with observed value and H denote the hypothesis with possible values $h_1, h_2, \ldots$ The hypothesis (or model), h_i that **d** maximizes $P(h_i|\mathbf{d})$ is often called as maximum-likelihood hypothesis. **(True/ False)** False **[2 marks]**

2. Consider the following network, a: exposure to asbestos, s: being a smoker, c: incidence of lung cancer. We assume that there is no direct relationship between smoking and exposure to asbestos. The list of patients' records is shown in the following table. **[8 marks]**



a	s	c
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Table 1

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Use maximum likelihood (ML) parameter learning and Bayesian parameter learning with beta distribution as hypothesis prior to fill in the following table of parameters. The hyperparameters of beta distribution are denoted by α and β and assume an initial prior to be uniform with $\alpha = 1$ and $\beta = 1$.

	θ_b	θ_c^{10}	θ_c^{00}
ML	4/7	1/2	0
Bayesian	5/9	2/3	1/3

3 marks

1 mark

4 marks

3. Consider the same network, now assume that the states of the variable a are never observed. So, for this problem use only the columns with labels s and c from the table. Show one iteration of Expectation Maximization to estimate the parameter θ_a. Assume the initial parameter to be $\theta_a = 0.5$. **[5 marks]**

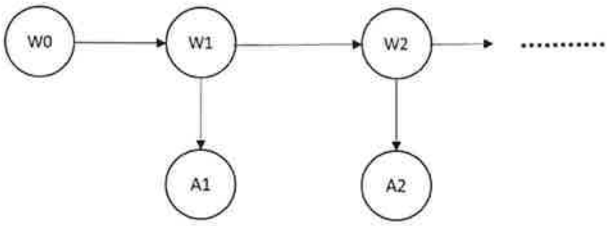
E step: $\hat{N}(a=1) = 3 \times 0.5 + 2 \times 0.5 + 1 \times 0.5 + 1 \times 0.5$

$= 3.5$

E step (contd.):

M step: $\hat{\theta}_a = \frac{\hat{N}(a=1)}{N} = \frac{3.5}{7} = 0.5$

4. Sam is a football player (goalkeeper). His coach wants to evaluate his performance after each of his weekly practice matches, and he does so based on Sam's actions (offensive or defensive) during a match. He models this scenario by using an HMM as shown below: **[5 marks]**



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W_{i+1}	W_i	$P(W_{i+1} \mid W_i)$
+w	+w	0.7
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