Sp22-CS-221-01 Final Exam

Jason Alexander Chan

TOTAL POINTS

81.3 / 121

QUESTION 1

1 Honor Code **0 / 0**

✓ **- 0 pts Correct**

- 0 pts Missing

QUESTION 2

2 1a(i) **4 / 4**

✓ **- 0 pts Correct**

- 1 pts Right idea with math errors

- 3 pts Some work

- 4 pts No/insuffucient answer

QUESTION 3

3 1a(ii) **2 / 2**

✓ **- 0 pts Correct, k=6**

- 0 pts Incorrect/no answer

QUESTION 4

4 1b(i) **1 / 2**

- 0 pts Correct

✓ **- 1 pts Partially correct**

- 2 pts Incorrect/no answer

All (a) (b) (c) are correct.

QUESTION 5

5 1b(ii) **2 / 2**

✓ **- 0 pts Correct**

- 2 pts Incorrect

- 1 pts Partially correct/not clear.

QUESTION 6

6 1b(iii) **2 / 2**

✓ **- 0 pts Correct**

- 2 pts Incorrect

- 1 pts Partially correct/not clear

QUESTION 7

7 1b(iv) **2 / 3**

- 0 pts Correct

- 3 pts Incorrect

✓ **- 1 pts Partially correct / not clear**

$\partial L/\partial w2 = (x2\ \delta 3 + x3\ \delta 4)\delta 2\ \delta 1\ \delta 0$

QUESTION 8

8 1c **1 / 2**

- 0 pts Correct

✓ **- 1 pts 2, 4 and one extra answer selected or only one of 2 and 4 is picked (one choice differ from the correct answer)**

- 2 pts More than one choice differ from than correct answer/ incorrect/ missing

QUESTION 9

9 2a(i) **2 / 2**

✓ **- 0 pts Correct**

- 0.4 pts One overall incorrect (Did not pick one of (B, C, D, E), or picked A)

- 0.8 pts Two overall incorrect

- 1.2 pts Three overall incorrect

- 1.6 pts Four overall incorrect

- 2 pts Five overall incorrect

QUESTION 10

10 2a(ii) **0.8 / 2**

- 0 pts Correct

- 0.4 pts One incorrect choice (picked (A, B, C) or didn't pick (D, E))

- 0.8 pts Two incorrect choices

✓ **- 1.2 pts Three incorrect choices**

- 1.6 pts Four incorrect choices

- 2 pts Five incorrect choices

QUESTION 11

11 2a(iii) 2 / 2

✓ **- 0 pts** Correct

- 0.4 pts One choice incorrect (Selected one of (A, B, C, E) or didn't select D)

- 0.8 pts Two choices incorrect

- 1.2 pts Three choices incorrect

- 1.6 pts Four choices incorrect

- 2 pts Five choices incorrect

- 2 pts No answer :(

QUESTION 12

12 2b(i) 2 / 3

- 0 pts Correct

- 1.5 pts Does not represent the previous action and the number of times it was taken minimally.

✓ **- 1 pts Missing descriptor for the previous action taken.**

- 1 pts Missing descriptor for the number of times the previous action has been taken consecutively.

- 1 pts Missing descriptor for the location on the grid.

- 0.5 pts Position, previous action, and number of times previous action has been taken consecutively are stated, but extra terms are included in state description (eg: cost).

- 3 pts Incorrect or missing

QUESTION 13

13 2b(ii) 1 / 3

- 0 pts Correct

- 1 pts Correct state in 2b(i) but minor errors

✓ **- 2 pts If 2b(i) state was incorrect but transition is reasonable for the state as defined.**

- 3 pts Incorrect or missing

QUESTION 14

14 2b(iii) 3.5 / 4

+ 4 pts Correct. Mentions that $$h(s_{\text{end}}) = 0$$.

1) Mentions that $$h(succ(s,a)) - h(s) \geq -1$$ since neighbouring states have a difference in L1 distance of at most 1. Since the cost of any action is at least 1, and therefore $$cost(s,a) + h(succ(s,a)) - h(s) \geq 0$$.

OR

2) uses the theorem "consistency of relaxed heuristics", shows that $$ cost_{rel}(s,a) \leq cost(s,a)$$ (using the argument above) and that L1 is the future cost in the relaxed problem because it is the shortest path between locations on the grid such that each location on the path is also on the grid.

✓ **+ 3.5 pts Correct, but doesn't mention that $$h(s_{\text{end}}) = 0$$**

+ 0.5 pts Mentions heuristic is consistent.

+ 0.5 pts States that $$h(s_{\text{end}}) = 0$$

Triangle inequality proof

+ 0.5 pts States the triangle inequality definition of consistency, i.e. $$cost(s,a) + h(succ(s,a)) - h(s) \geq 0$$

+ 1.5 pts Demonstrates admissibility (i.e. mentions that the L1 distance will underestimate future costs of paths), but doesn't prove consistency.

+ 1.5 pts States the definition of consistency and considers heuristic values of neighbouring states, but doesn't correctly justify that the difference is bounded by 1.

+ 0 pts Click here to replace this description.

Theorem of consistency of relaxed heuristics

+ 0.5 pts States that $$cost_{rel}(s,a) \leq cost(s,a)$$ but doesn't justify this.

+ 1.5 pts Mentions $$cost_{rel}(s,a) \leq cost(s,a)$$ because cost between neighbouring states is bounded by 1.

+ 1.5 pts States that the $$h(s) = FutureCost_{rel}(s)$$ without mountains and limits on actions.

+ 0 pts Incorrect or missing.

QUESTION 15

15 2b(iv) 1 / 1

✓ **- 0 pts Correct**

- 0.5 pts Stated that heuristic is not consistent, but incorrect/insufficient justification.

- 1 pts Incorrect or missing.

QUESTION 16

16 3a(i) **2 / 2**

✓ **- 0 pts Correct**

- 2 pts Incorrect

QUESTION 17

17 3a(ii) **2 / 2**

✓ **- 0 pts Correct**

- 2 pts Incorrect

- 1 pts partial correct

QUESTION 18

18 3a(iii) **0 / 2**

- 0 pts Correct

- 1 pts Incorrect/blank explanation

✓ **- 2 pts Incorrect choice and explanation**

- 1 pts correctly explain C but not select B

QUESTION 19

19 3a(iv) **0 / 2**

- 0 pts Correct

- 1 pts Incorrect/blank explanation

✓ **- 2 pts Incorrect choice and explanation**

QUESTION 20

20 3b(i) **1 / 5**

- 0 pts Correct

- 5 pts Answer missing/ incorrect

✓ **- 4 pts Made an incorrect/very incomplete attempt**

- 3 pts A couple of correct steps

- 1 pts Almost correct

QUESTION 21

21 3b(ii) **2 / 2**

✓ **- 0 pts Correct**

- 1 pts Correct answer, wrong/missing explanation

- 2 pts Incorrect

- 0.5 pts Almost correct

QUESTION 22

22 3b(iii) **3 / 3**

✓ **- 0 pts Correct**

- 3 pts Incorrect answer

- 1.5 pts Incorrect explanation

- 1.5 pts Partially correct answer

- 2 pts No explanation

QUESTION 23

23 4a(i) **1 / 2**

+ 2 pts Correct

✓ **+ 1 pts Answering "Yes"**

+ 1 pts Correct justification: Your earnings are your opponent's losses, and your opponent's earnings are your losses. Hence, the sum of the utilities between you and your opponent will always be 0. Insufficient justifications usually do not mention one of the keywords "constant utility" or "you win what your opponent loses"

+ 0 pts Incorrect

QUESTION 24

24 4a(ii) **1 / 2**

+ 2 pts Correct

✓ **+ 1 pts Answering "No"**

+ 1 pts Correct justification: "Again, this scenario has an aspect of cooperation since both cars must avoid crashing into one another. Specifically, if both cars merge, then the sum of the utilities is not 0, violating the conditions for a 0-sum game." Common mistakes: (1) describes the scenario as prisoner's dilemma without further explanation (2) vague statements that don't explain why it is not zero sum

+ 0 pts Incorrect

QUESTION 25

25 4b **6 / 6**

✓ **- 0 pts Correct**

- 1 pts One incorrect node (given nodes below)

- 2 pts 2 incorrect nodes (given nodes below)

- **3 pts** 3 incorrect nodes (given nodes below)
- **4 pts** 4 incorrect nodes (given nodes below)
- **5 pts** 5 incorrect nodes (given nodes below)
- **6 pts** Incorrect

QUESTION 26

26 4c **3 / 6**

- **0 pts** Correct

✓ **- 3 pts 1 of lower or upper bound correct**

- **6 pts** Incorrect

QUESTION 27

27 4d **2 / 2**

✓ **- 0 pts Correct**

- **2 pts** Incorrect

QUESTION 28

28 5a(i) **0 / 2**

- **0 pts** Correct (Power set of students)
- **0.5 pts** Mostly Correct (i.e. size-limited power set or stating that the domain is the the particular assignment of students)
- **1 pts** Only size K subsets

✓ **- 2 pts Incorrect**

QUESTION 29

29 5a(ii) **8 / 8**

✓ **- 0 pts Correct**

- **1 pts** Incorrect/No factor encoding constraint 1
- **0.5 pts** Partially correct constraint 1
- **1 pts** Incorrect/No factor encoding constraint 2
- **0.5 pts** Partially correct constraint 2
- **3 pts** Incorrect/No factor encoding constraint 3
- **1.5 pts** Partially correct constraint 3
- **1 pts** Incorrect/No factor encoding constraint 4
- **0.5 pts** Partially correct constraint 4
- **2 pts** Incorrect/No factor encoding constraint 5
- **1 pts** Partially correct constraint 5
- **8 pts** Incorrect (Blank, Using students as variables, not expressed mathematically)

QUESTION 30

30 6a(i) **2 / 2**

✓ **- 0 pts Correct**

- **2 pts** Incorrect/Missing Answer

QUESTION 31

31 6a(ii) **2 / 2**

✓ **- 0 pts Correct**

- **2 pts** Incorrect Answer

QUESTION 32

32 6a(iii) **2 / 2**

✓ **- 0 pts Correct**

- **2 pts** Incorrect Answer

QUESTION 33

33 6a(iv) **0 / 2**

- **0 pts** Correct

✓ **- 2 pts Incorrect Answer**

- **1 pts** partially incorrect

QUESTION 34

34 6b(i) **2 / 2**

✓ **- 0 pts Correct**

- **2 pts** Incorrect

QUESTION 35

35 6b(ii) **3 / 3**

✓ **- 0 pts Correct ("no" to the word problem and/or "yes" to conditional independence of W and R)**

- **1 pts** Correct but no explanation given
- **3 pts** Incorrect

QUESTION 36

36 6b(iii) {Mislabeled as ii} **2 / 4**

- **0 pts** Fully Correct
- **1 pts** Minor error in final result (e.g. single missing/incorrect coefficient in term in denominator)

✓ **- 2 pts Partially correct reasoning or intermediate result**

- **4 pts** Incorrect/Blank

QUESTION 37

37 6b(iv) {Mislabeled as iii} **0 / 4**

- **0 pts** Correct
- **1 pts** Denominator not fully simplified
- **2 pts** Partially correct reasoning or intermediate result

✓ **- 4 pts Incorrect/Blank**

QUESTION 38

38 6c **2 / 2**

✓ **+ 1 pts Correctly identifying "ethics dumping"**

✓ **+ 1 pts Justification conveys understanding of ethical dumping**

- **2 pts** No concept named
- **2 pts** Incorrect/skipped

QUESTION 39

39 7a(i) **3 / 3**

✓ **+ 3 pts Correct (True)**

- **3 pts** Incorrect/Skipped

QUESTION 40

40 7a(ii) **2 / 2**

✓ **+ 2 pts Correct (c)**

- **2 pts** Incorrect/Skipped

QUESTION 41

41 7a(iii) **0 / 3**

+ **3 pts** Correct (a)

✓ **- 3 pts Incorrect/Skipped**

QUESTION 42

42 7b(i) **2 / 2**

✓ **- 0 pts Correct (d) only**

- **2 pts** Incorrect

QUESTION 43

43 7b(ii) **0 / 2**

- **0 pts** Correct: (-A v -B v C) ^ (-A v -B v D)

✓ **- 2 pts Incorrect**

QUESTION 44

44 7b(iii) **0 / 4**

- **0 pts** Correct (i.e. correct CNF and correct application of MP)
- **2 pts** Partially correct (i.e. correct CNF)

✓ **- 4 pts Incorrect**

QUESTION 45

45 7c **2 / 2**

✓ **- 0 pts Correct**

- **0.5 pts** fail to identify one of civilian or military use.
- **1 pts** fail to identify usages of technology
- **1 pts** fail to identify specific algorithm or technology
- **2 pts** missing/incorrect

CS221 Final Exam

Spring 2022

Please read all of the following information before starting the exam:

- This test has 7 questions, each with multiple subparts.
- **You will have 180 minutes to complete and submit the exam.**
- Note that different questions are worth different amounts of points. Budget your time accordingly!
- Keep your answers precise and concise. We may award partial credit so show all your work clearly and in order.
- Don't spend too much time on one problem. Read through all the problems carefully and do the easier ones first.
- If you are unsure about a problem statement when taking the exam, state your assumptions in your answer. We will take all reasonable assumptions into account when grading.
- You are only allowed a 1-page cheatsheet (front and back) to refer to during this exam.
- Being subject to the provisions of the Honor Code means in part that you must observe the rules established for this exam, which are: you may consult only inanimate sources. You may not consult or collaborate with anyone about the questions. Such collaboration is a violation of the Honor Code.
- Good luck!

Problem	Part	Max Score	Score
	a	6	
	b	9	
	c	2	
1	**Total**	17	
	a	6	
	b	11	
2	**Total**	17	
	a	8	
	b	10	
3	**Total**	18	
	a	4	
	b	6	
	c	6	
	e	2	
4	**Total**	18	
	a	10	
5	**Total**	10	
	a	8	
	b	13	
	c	2	
6	**Total**	23	
	a	8	
	b	8	
	c	2	
7	**Total**	18	

30m/section

bii

→ 90mins mark

→ 2hr.

Honor Code (*0 points*) Please **sign your name** underneath the honor code below. By signing, you agree to abide by the honor code statement as well as the rules stated on Page 1.

Your exam will **not** be graded if this question is not completed.

"I will not consult or collaborate with anyone about the questions. Such collaboration is a violation of the Honor Code."

Jason Chan

8 June 2022
10 12 AM AEST

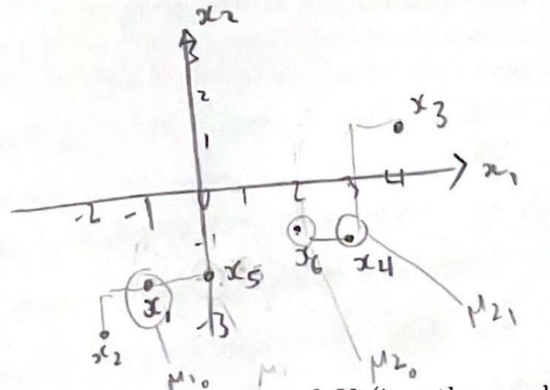
1. Machine Learning (*17 points*)

a. (*6 points*) **K-Means Clustering** You are given the following six points: $x_1 = [-1, -2], x_2 = [-2, -2], x_3 = [4, -1], x_4 = [3, -1], x_5 = [0, -2], x_6 = [2, -1]$. Answer the following questions.

(i) [4 points] In class we saw the use of the L-2 distance for the computation of the K-means objective. Now, we will instead be using the L-1 distance. Recall that the L-1 distance between two points $x = [x_1, x_2]$ and $y = [y_1, y_2]$ is $|x_1 - y_1| + |x_2 - y_2|$. Furthermore, recall that for a group of points, the point that minimizes the sum of the L-1 distance to all of the points is the element-wise median of the points.

If we select x_1 and x_6 as the initial centroids, write down the simulation of the 2-means clustering process until convergence. Include the new positions of the centroids μ_1 and μ_2, the new cluster assignments z and the cost (i.e. K-means objective) at every step of the simulation. Note: you may not need all the rows.

Iteration	μ_1	μ_2	Cluster Assignments z	Cost
0	[-1,-2]	[2,-1]	$z_{\mu_1} = \{x_1, x_2, x_5\}$ $z_{\mu_2} = \{x_3, x_4, x_6\}$	$1+4+1+2=8$
1	[-1,-2]	[3,-1]	$z_{\mu_1} = \{x_1, x_2, x_5\}$ $z_{\mu_2} = \{x_3, x_4, x_6\}$	$1+3+1+2=7$
2				
3				
4				



(ii) [2 points] If we can arbitrarily set the value of K (i.e. the number of clusters) and randomly select K points (without replacement) from the set as initial centroids for each of the clusters, is it possible to achieve the global minimum of the K-means objective cost function? If yes, what is the minimum value of K that achieves the global minimum **for this problem**? If no, what is the minimum cost achieved? .

There exists a case were K = number of all data points, such that at convergence the location of each centroid coincides uniquely to each datapoint, which would result in a cost of 0 for the K-means objective cost function.

the K must be equal to 6 for

Hence min. value of K for this case must be equal to 6 for this problem.

b. (*9 points*) **Neural Networks and Backpropagation** You are trying to classify images to determine whether or not a dog is present (1) or absent (0) using a 2-layer neural network with sigmoid activations.

(i) [2 points] You think that your model is overfitting because your test error is much higher than your train error. Which of the following methods can you use to reduce overfitting? Select all that apply.

(a) Collect more data and increase the size of your dataset m

(b) Use some form of regularization

(c) Reduce the size (number of parameters) in the network

(b), (c)

(ii) [2 points] Suppose you have access to a large training and test set. You do not know what values to use for the hyperparameters of your network (such as the learning rate). What would be an acceptable strategy regarding the dataset splits that you can use to go about choosing the suitable hyperparameters for your network?

An acceptable strategy is to create 3 splits: training, validation &
test sets. Training is of course to train models, Validation set is
used to tweak hyperparameters & compare the effects, finally test
is the 'holden' data set against which a model's performance can be
evaluated against. Typical percentage splits are 70% training, 20%
validation, 10% test, or 70% training 10% validation, 20% test.

You somehow reduce our image down to three *scalar* features x_1, x_2, x_3, and design a neural network (defined by the following equations) to perform the binary classification:

The architecture of your network (in the form of the feed-forward, loss, and cost equations) is given below:

$$a_1 = w_1 x_1 + w_2 x_2$$

$$a_2 = w_1 x_2 + w_2 x_3$$

$$z = max(a_1, a_2)$$
$$a_3 = w_3 z$$
$$y = \sigma(a_3)$$
$$L = y\log(\hat{y}) + (1-y)\log(1-\hat{y})$$

w_1, w_2, w_3, w_4 are the trainable parameters of the network, and L denotes the binary cross-entropy loss function applied on the model's prediction $\hat{y}$ and the true label y.

We will now determine some of the equations required to update the w_is via backpropagation. Suppose that we have already computed the following derivatives:

$$\delta_0 = \partial L/\partial \hat{y}$$
$$\boxed{\delta_1 = \partial \hat{y}/\partial a_3}$$
$$\delta_2 = \partial a_3/\partial z$$
$$\delta_3 = \partial z/\partial a_1$$
$$\delta_3 = \partial z/\partial a_2$$

$$\frac{\partial \hat{y}}{\partial a_3} \times \frac{\partial a_3}{\partial z} \times \frac{\partial z}{\partial a_2}$$
$$\delta_1 \times \partial_2 \times \delta_3$$

(iii) [2 points] What is $\partial L/\partial w_3$? You may use the $\boxed{\delta_i\text{s.}}$ in your answer.

$$L = y\log\hat{y} + (1-y)\log(1-\hat{y})$$
$$= y\log\sigma(a^3) + (1-y)\log(1-\sigma(a_3))$$
$$\frac{\partial L}{\partial w_3} = y\frac{\sigma'(a_3)a_3'}{\sigma(a^3)} + (1-y)\frac{(-\sigma'(a_3)).a_3'}{1-\sigma(a_3)}$$
$$= \frac{y\delta_1 z}{\sigma(a_3)} - \frac{(1-y)\delta_1 z}{1-\sigma(a_3)}$$

(iv) [3 points] What is $\partial L/\partial w_2$? You may use the $\boxed{\delta_i\text{s}}$ in your answer.

$$L = y\log\sigma(w_3 \cdot max(a_1, a_2)) + (1-y)\log(1-\sigma(w_3 \cdot max(a_1, a_2)))$$

$$\frac{\partial L}{\partial w_2} = y\frac{\sigma'(w_3 \cdot max(a_1,a_2))\frac{\partial(w_3 \cdot max(a_1,a_2))}{\partial w_2}}{\sigma(w_3 \cdot max(a_1, a_2))} + (1-y)\frac{-\sigma'(w_3 \cdot max(a_1,a_2)) \times \frac{\partial}{\partial w_2}(w_3 \cdot max(a_1,a_2))'}{1-\sigma(w_3 \cdot max(a_1,a_2))}$$

Mistake here is that I tried to brute force the answer.

The elegant way is to see that this is nothing more than a massive chain rule:

dL/dy_hat x dy_hat/dy_a3 x da3/dz x dz/da1 or dz/da2.

where:

$$\frac{\partial}{\partial w_2} w_3 max(a_1, a_2) = \begin{cases} w_3 x_2 & \text{if } a_1 > a_2 \\ w_3 w_3 & \text{if } a_2 > a_1 \end{cases}$$

$$\therefore \frac{\partial L}{\partial w_2} = \frac{y\delta_1\delta_2\delta_3\frac{\partial}{\partial w_2}(w_3 max(a_1,a_2))}{\sigma(w_3 \cdot max(a_1,a_2))} + \frac{(1-y)\delta_1\delta_2\delta_3\frac{\partial}{\partial w_2}(w_3 max(a_1,a_2))}{\sigma(w_3 \cdot max(a_1,a_2))}$$

c. (*2 points*) **Identifying ethical concerns** Consider a deep learning model trained on public GitHub repositories that can convert natural language instructions into code. On testing, it was discovered that it was possible to make the model output sensitive user information like SSH keys, database passwords, etc. Recall the NeurIPS Ethical Guidelines. Which of the following is the model likely in violation of?
Select all that apply. No explanation required.

1. Directly facilitate injury to living beings
2. Contain any personally identifiable information or sensitive personally identifiable information
3. The dataset used has been discredited by the creators
4. Contain information that could be deduced about individuals that they have not consented to share

Answer is only 2 and 3.

Got this wrong because I tried to be too clever.

2 4 1

∵ injury = financial or physical, both possible

bank accounts

powerstation

2. Search (*17 points*)

a. (*6 points*) **Warm-up** Consider the following search algorithms as they were presented in this course:

A: DFS

B: BFS

C: DFS with iterative deepening

D: Dynamic Programming

E: UCS

For each of the following problems, you may assume that the state graph is acyclic.

(i) [2 points] Suppose you would like to find the minimum cost path between two states s_1, s_2. You know that the cost function is a positive constant α for every edge in the state-graph. Which algorithms can you use to find the optimal path? Select all that apply or **None** from **A, B, C, D, E. No explanation is necessary.**

B C D E

=0

(ii) [2 points] Now you know that the cost is a **non-negative function**. Which algorithms can you use to find the optimal path? Select all that apply or **None** from **A, B, C, D, E. No explanation is necessary.**

~~A~~ B C D E

Non-negative includes zero. I missed the 'optimal path' specification!
D, E dynamic programming and UCS only. DFS doesn't give you optimal and needs to have edge cost exactly zero. BFS doesn't guarantee optimal either.

(iii) [2 points] You now know nothing about the cost, e.g. the cost is an arbitrary function that is bounded. Which algorithms can you use to find the optimal path? Select all that apply or **None** from **A, B, C, D, E**. **No explanation is necessary.**

D

b. (*11 points*) **Encroaching the enemy territory** Samar is at the start position on a 5 × 5 grid and wants to reach the goal position by avoiding the mountains along the way (see figure below). To make things harder for himself, **he decides that he will never take the same action more than 3 times in a row.** Samar decides to model this as a search problem where the actions are {left, right, down, up}. The cost for every legal step he takes is +1. If he tries to run into a wall or a mountain or repeats an action for a fourth time in a row, he incurs a cost of $+\infty$ and the episode ends. Help Samar model the rest of the search problem and reach the enemy camp with the least cost path!

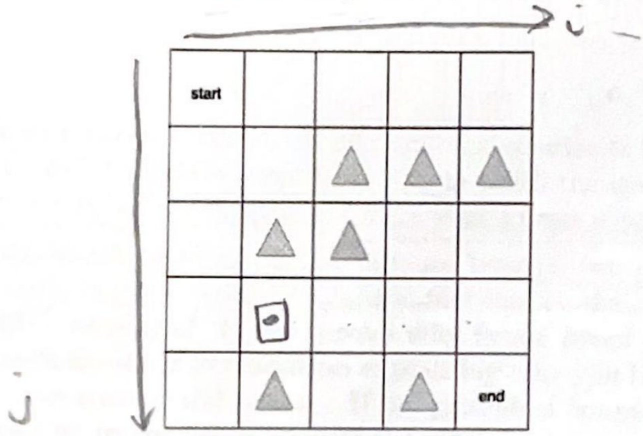


Figure 1: Samar's mission

(i) [3 points] Clearly define a minimal necessary state representation for this problem **as a tuple**.

S: (position, numRepeatedSameAction)

where position = coordinate in the 5x5 grid.
= (i,j)

numRepeatedSameAction = count of repeated same action
resets if currentaction ≠ prevaction

State = (x,y, previous Move, # time previous move taken consecutively).

Without knowing previous move, can't compare to current move to increment the counter !

(ii) [3 points] Clearly define a successor function $T(s'|s,a)$ (where s' is the next state, s is the current state, and a is the action taken) in the form of a piece-wise function. To simplify things, you can ignore the illegal actions (cases where Samar would run into a wall or a mountain or take an action for the fourth consecutive time).
Hint: To simplify notation, assume the actions left, right, up and down can be encoded as tuples $a = (a_1, a_2)$ as $(-1, 0), (1, 0), (0, -1), (0, 1)$ respectively.

$$T(s'|s,a) = \begin{cases} (i+1, j) & \text{if } a = (1,0) \text{ \& numRepeatedSameAction} < 3 \\ (i-1, j) & \text{if } a = (-1,0) \text{ \& ''} \\ (i, j+1) & \text{if } a = (0,+1) \text{ \& ''} \\ (i, j-1) & \text{if } a = (0,-1) \text{ \& ''} \end{cases}$$

(iii) [4 points] We wish to run A^* search to find an optimal solution to this problem. To find a heuristic, we define a relaxed search problem in which the mountains are removed and the infinite cost on repeating actions more than 3 times is removed.

In this relaxed search problem, the L1 distance between two points is the cost of the optimal path and is a potential heuristic function for the original problem. **Is this heuristic consistent? If yes, prove why (your proof should be a clear written or mathematical explanation explaining why you think this heuristic satisfies the consistency definition). If no, provide a counter-example. Your answer should fit in the space provided below.**

consistent if $cost'(s,a) = cost(s,a) + h(succ(s,a)) - h(s) \geq 0$.

The optimal cost can never be less than L_1 distance $\because$ of the obstacles.

- $h(succ(s,a)) \overset{+1}{+} \overset{+1}{h}(s) = 0$ in relaxed condition & L_1 distance
- Therefore $cost(s,a) \geq h(succ(s,a)) - h(s)$

$\therefore cost'(s,a) \geq 0 \quad \therefore$ consistent.

(iv) [1 point] Suppose you change the cost such that the cost for every legal step taken by Samar is c, where $0 < c < 1$. **Is the L1 heuristic consistent in this setting? Provide a brief explanation as to why or why not.**

NO $\because$ you can have very low cost such that

not consistent $\quad cost(s,a) \leq h(succ(s,a) - h(s))$

suppose $c = 0.00001 \times 100 \text{ steps} \Rightarrow$ total cost $= 0.001$

$0.001 \leq L_1$ distance

$\therefore$ inconsistent.

3. MDPs and Reinforcement Learning (*18 points*)

a. (*8 points*) **Debugging Q-learning** Sharon wants to train a Q-learning model for her CS221 project but doesn't quite remember the algorithm. Assume an MDP with finite number of states and actions. **Sharon initializes her Q-value table with all 0s.** She remembers that the update rule is as given below but does not remember how to vary ϵ and η. Remember ϵ is from ϵ-greedy and η is the learning rate. The exploratory policy/ data-generating policy is ϵ-greedy as we have seen in the lectures.

$$\hat{Q}_{opt}(s,a) \leftarrow (1-\eta)\hat{Q}_{opt}(s,a) + \eta(r + \gamma \max_{a'} \hat{Q}_{opt}(s',a'))$$

She tries the following variations of the algorithm:

A: initialize $\epsilon = 1$ and never decrease it during training.

B: initialize $\epsilon = 0$ and never increase it during training.

C: ϵ is initialized to 1 is decayed to 0 during training.

For each of parts i-iv, provide a brief (one-sentence) explanation.

(i) [2 points] Sharon finds that **A** converges *very* slowly to Q_{opt}. What could be the cause of this slow convergence?

Because ϵ=1 means always try a random action which leads to very slow convergence.

(ii) [2 points] Sharon finds that **B** does not converge to Q_{opt}. Why could this be?

Because ϵ=0 means that she never 'exploits' hence Qopt doesn't converge to an optimal solution because she's not on an optimal trajectory / path that takes her to Qopt

(iii) [2 points] In which variations is the data-generating policy changing during the course of training? Select all that apply or **None** from **A**, **B**, **C**.

C

B and C. B because always exploiting is greedy. Even though epsilon isn't changing the Q values are being updated and hence the data-generating policy will change. In A, we are running a policy which is effectively completely random

(iv) [2 points] **For some MDP**, say we know that $Q^{\pi}(s, a_1) > V^{\pi}(s)$. Which of the following is true? Select all that apply. **Note: this part is unrelated to Sharon's experiments.**

(a) action a_1 is the best action that can be taken in state A

(b) π may be an optimal policy

(c) π is not an optimal policy

(d) None of the above

D

A is wrong because we know a1 is better than the average action at s but need not be the best. B is wrong because if true Vpi(s) = max(Q_pi) but question says Qpi > Vpi

(iii) [2 points] In which variations is the data-generating policy changing during the course of training? Select all that apply or **None** from **A, B, C**.

C

(iv) [2 points] **For some MDP**, say we know that $Q^\pi(s, a_1) > V^\pi(s)$. Which of the following is true? Select all that apply. **Note: this part is unrelated to Sharon's experiments.**

(a) action a_1 is the best action that can be taken in state A

(b) π may be an optimal policy

(c) π is not an optimal policy

(d) None of the above

D

b. *(10 points)* **Constantly changing reward functions** Amrita lives in an MDP and wants to find the optimal policy. She uses value-iteration and finds an optimal policy π_{old} with a corresponding value function V_{old}. She wants to determine what happens if she adds a constant scalar C to all rewards in the MDP; to do this, she constructs a new MDP with the new reward function, and computes the optimal policy and value function π_{new} and V_{new}.

(i) [5 points] **Suppose that her MDP is *infinite horizon*, with a discount factor of γ.** Find $\max_{s \in S}(V_{new}(s) - V_{old}(s))$ where S is the set of all the states in the MDP. **Show your work. We expect a mathematical derivation or an explanation.**
Hint: The utility of a infinite horizon trajectory $\tau = (s_1, a_1, r_1), (s_2, a_2, r_2), (s_3, a_3, r_3)\ldots$ is $r_1 + \gamma r_2 + \gamma^2 r_3 + \ldots$

Value Iteration: $V^t_{OPT}(s) \leftarrow \max_{\text{of Actions}} \underbrace{\sum T(s,a,s') \left[\text{Reward}(s,a,s') + \gamma V^{(t-1)}_{OPT}(s') \right]}_{Q^{t-1}_{OPT}(s,a)}$ converges if $\gamma < 1$

The key realisation here is that the value of a policy is the sum of the rewards (DOH). So Vold = r1 + gamma*r2 + ... etc. While Vnew = r1+c + gamma(*r2+c) + ... etc. The diff of Vnew- Vold is simply the algebraic difference!

(ii) [2 points] Is π_{new} the same as π_{old}? Explain why or why not. Assume both policies are deterministic and we break ties in the same way in the new and old MDPs.

Yes, the policy is the same $\because$ adding a scalar to all actions doesn't change the relative reward between each action, so the policy still chooses the same actions in π_{old} & π_{new}

(iii) [3 points] Would your answers to the previous parts change **if the MDP was of *finite horizon***? Explain why or why not.
Hint: Recall that a finite horizon MDP is one in which trajectories are no longer than some length $T \in \mathbb{Z}^+$. You also do not need to re-derive your answer from part (i).

Yes because of the discount factor, we then add more weight to present action which may change the policy vs. an infinite horizon problem.

4. Games (*18 points*)

a. (*4 points*) **Zero-sum or not?** For each of the following scenarios, state whether it can be represented as a zero-sum game. Answer "yes" or "no", and **give a brief (1-2 lines) explanation.**

(i) [2 points] **Heads up Holdem**: You are playing a game of poker against an opponent. If you win the current round, you win the money in the pot, but if you lose, your opponent gets the money in the pot. Both players want to maximize their earnings.

Yes ∵ the pot is shared rewards between each player. If my opponent wins = corresponding loss of the same amount of reward for me.

Correct answer: Yes + you when what your opponent loses, or the sum of you and your opponents utility is zero.

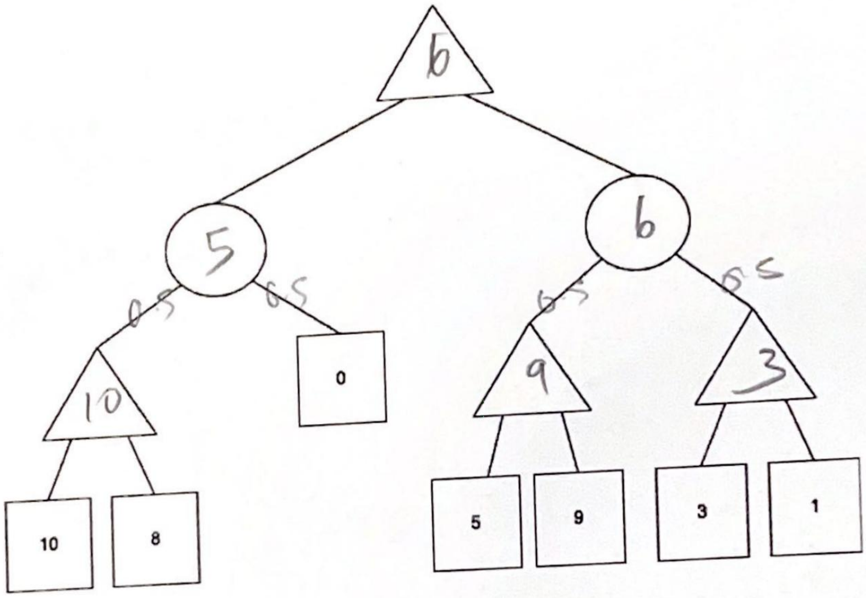
(ii) [2 points] **Autonomous Driving**: Two cars are driving next to one another, and are each trying to merge into the lane ahead of the other (without crashing into one another). Each car has two available actions: merge, or wait. If both cars merge, a crash occurs (resulting in a large negative utility). If one car merges and the other waits, the merged car gets a utility of 10 and the waiting car gets a utility of -10. If both cars wait, they both get a utility of 0.

Prisoners dilemma equivalent

∴ No not zero sum.

In the case where both cars choose action merge then the utilities are +10 each, which does not sum to zero, hence not zero sum.

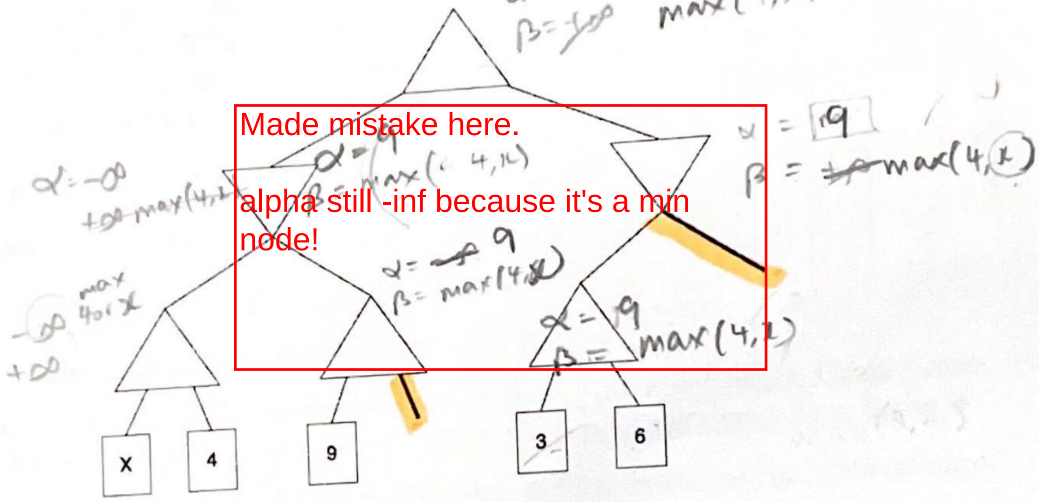
b. (*6 points*) **Expectimax** Consider the following Expectimax game. **Suppose that the chance nodes (circle) play the left and right actions with 0.5 probability each.** Fill in the values of the maximizer (triangle) and chance (circle) nodes in the figure below.



c. (*6 points*) **Alpha-beta pruning**

Consider the following minimax game tree, in which the top node is a maximizer. Determine the range of values for X which could result in the red edges being pruned by left-to-right alpha beta pruning. Fill your answer in the provided blanks (hint: both the upper and lower bounds are finite values).

α = ~~-∞~~ 9
β = ~~+∞~~ max(4, x)



4 ≤ X ≤ 9

6 <= x <= 9

d. (*2 points*) **Wicked Problems** Recall that problems that have multiple, potentially conflicting objectives, a high degree of uncertainty and risk, and stakeholder disagreement about what would count as a solution to the problem are sometimes called "wicked problems." Another characteristic of wicked problems is that each attempt to solve them has consequences for people at the time it is made, even if another choice is made later. Which of the following are wicked problems?
Select all that apply. No explanation required.

1 3

1. Mitigating homelessness in California
2. Developing an agent to play Pac-Man
3. Assigning vaccine priority for Covid-19
4. Creating an optimal chip layout for a circuit board using a simulator

e

5. Constraint Satisfaction Problems (*10 points*)

a. (*10 points*) **Sam and his Sorting CSP** Sam is the new headmaster at Hogwarts and is in charge of splitting the students into houses. However, Hogwarts has expanded and now there are more than just the 4 traditional houses – there are now H houses $X_1, X_2, \ldots X_H$ and N students at Hogwarts. Alice (A), Bob (B), Candice (C), David (D) and Ed (E) are a part of the new cohort of N students at Hogwarts and must be sorted into houses. To add to the problem, Sam needs to adhere to some constraints specified by the school and some students as given below:

$\exists X_i]$

1. Every house must have at-least one student. ✓
2. No house can have more than K students. ✓
3. Every student must be assigned exactly one house. ✓
4. Bob and David must be in the same house.
5. Candice must be in the house right after Alice i.e. if Alice is in house h, Candice must be in house $h+1$. If Alice is in the last house H, then Candice must be in house 1. wrap

$1 \in X_a]$

$\le K_i]$

This problem seems too complex for the Sorting Hat, so Sam decides to model the problem as a CSP and assign the students to different houses. **Model the problem as a CSP where the variables are the houses and help Sam find the optimal assignment in the CSP.**

(i) [2 points] What is the domain of each variable in the CSP? Write it in English or as a set.
Hint: Don't worry about enforcing any constraints here, we will do that when we define factors.

Domain = $\{s_1, s_2, \ldots s_N\}$

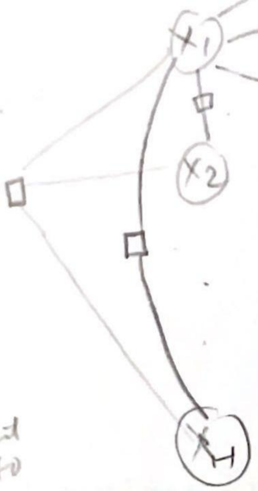
where s is a student.

Each variable has a domain that is the power set of all N students.

Includes null set, and combinations of each element.

(ii) *[8 points]* Express the constraints as factors on the variables. You are allowed to use *only* one n-ary factor. All your other factors must be unary/ binary.
Hint: There may be several correct answers.

let $i = 1 \dots H$



$f_1(x_i) = \mathbb{1}[|x_i| \geq 1]$ — every house must have @ least 1 student.

$f_2(x_i) = \mathbb{1}[|x_i| \leq K]$ — no house can have more than K students

$f_4(x_i) = \mathbb{1}\big[\mathbb{1}[B \in X_i \wedge D \in X_i] \vee \mathbb{1}[B \not\ni X_i \vee D \not\ni X_i]\big]$

BoB & David in same house or not.

$$f_5(X_i, X_{i+1}) = \mathbb{1}\Big[\mathbb{1}[C \in X_{i+1} \wedge A \in X_i] \vee \mathbb{1}[A \in X_H \wedge C \in X_1] \vee \mathbb{1}[C \ni X_i \vee A \ni X_{i+1} \vee C \ni X_{i+1} \vee A \ni X_i]\Big]$$

every student assigned to 1 house.

$$f_3(X_1, X_2, \dots X_H) = \mathbb{1}\Big[\mathbb{1}[S_1 \in X_1 \oplus S_1 \in X_2 \oplus \dots \oplus S_N \in X_H] \wedge \mathbb{1}[S_2 \in X_1 \oplus S_2 \in X_2 \oplus \dots \oplus S_2 \in X_H] \wedge \dots \wedge \mathbb{1}[S_N \in X_1 \oplus S_N \in X_2 \oplus \dots \oplus S_N \in X_H]\Big]$$

$\{E_1, \ldots E_t\}$

6. Bayes Nets (*23 points*)

a. (*8 points*) **Bayes' Casino**

Suppose you are in a casino and have been observing the behavior a slot machine, which at timestep t has a true state of S_t, who's distribution only depends on S_{t-1}. Your observations have resulted in a set of evidence variables $E_1, \ldots, E_t$. You know the distribution $\boxed{P(E_i|S_i)}$.

For each of the following questions, **No explanation is required.**

(i) [2 points] **True or false?** This situation can be modeled as a Hidden Markov Model (HMM).

True.

(ii) [2 points] Suppose you wish to answer the query $P(\boxed{S_t}|\underbrace{E_1, \ldots, E_t}_{\text{up to current timestep}})$. What type of query does this correspond to?

(A) Smoothing

(B) Filtering

(C) None of the above

B

(iii) [2 points] Suppose you wish to answer the query from the previous question. Which of the following algorithms will guarantee you to answer the $\boxed{\text{query } \textbf{exactly}}$?

(A) Gibbs sampling with finite number of iterations. approx

(B) Forward-backward algorithm exact

(C) Particle filtering with finite number of iterations. approx

(D) None of the above

B

(iv) [2 points] Your friend has a crystal ball and tells you what E_{t+5} will be. Suppose you wish to again find the distribution of S_t given this new piece of information, and your observations up till time t. What type of query does this correspond to?

(A) Smoothing

(B) Filtering

(C) None of the above

A $\because$ incorp future evidence.

b. (*13 points*) **Bayesian Sports** You and your friend are fans of the Golden State Warriors and wish to predict the outcome of playoff games. In order to achieve this, you decide to model a Warriors game's outcome with a Bayesian Network with the following variables:

- $H \in \{0, 1\}$: whether the game is being played at home (H = 1) or away (H = 0).
- $C \in \{0, 1\}$: whether Steph Curry scores more than 30 points.
- $R \in \{0, 1\}$: whether refs are helping the Warriors (R = 1) or their opponents (R = 0). haha
- $O \in \{0, 1\}$: whether the Warrior's offense plays well or not.
- $D \in \{0, 1\}$: whether the Warrior's defense plays well or not.
- $W \in \{0, 1\}$: whether the Warriors win the game or not.

With these variables, you model this situation with the following Bayesian Network:

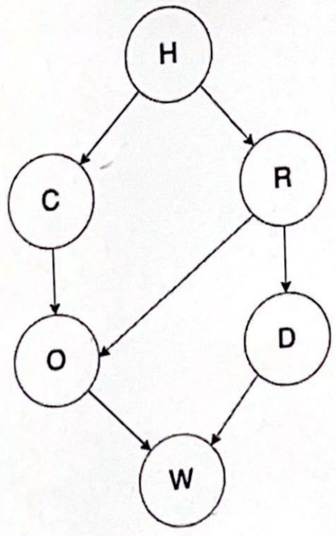
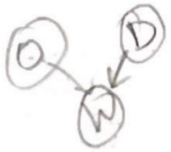


Figure 2: Bayes Net used to model the outcome of a GSW Playoff Game

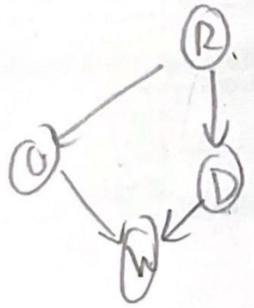
Assume that offense and defense both positively impact winning
(e.g., $P(W=1|O=1) \geq P(W=1|O=0)$ and $P(W=1|D=1) \geq P(W=1|D=0)$).

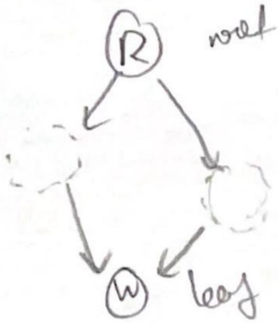
(i) [2 points] **True or false?** $P(O=1|W=1) \geq P(O=1|W=1, D=1)$. Explain your answer briefly (one sentence).



True ∵ explaining away.

(ii) [3 points] You now want to examine the impact the ref can have by siding with the Warriors. Suppose you know that both the offense and defense play well (e.g., you know $O=1$ and $D=1$). Given this evidence, will knowledge of R (whether the ref will help the Warriors) affect the distribution over whether the Warriors win the game? **State yes or no, and explain your answer briefly.**
Hint: this question is asking whether $(W \perp\!\!\!\perp R)|O, D$.





condition on O, D →

disconnected

does knowing O D tell me something about R, W?

True that $(W \perp\!\!\!\perp R) \,||\, O, D$.
ie knowing R won't affect whether warriors win
∵ disconnected graph when conditioned on O & D

Suppose now you do not care about whether the Warriors win and only want to analyze the performance of the Warrior's offense and defense. You remove the W variable and define a new Bayes Net:

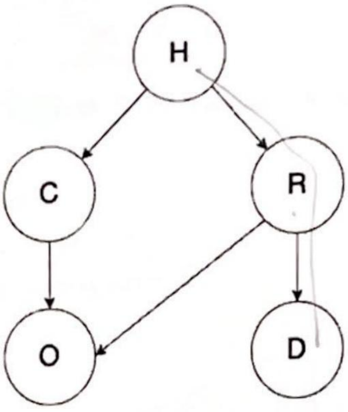


Figure 3: New Bayes Net to model the performance of the offense and defense.

The defense is playing well and you want to determine if the refs have ~~been favoring the~~ Warriors and if the Warriors are playing at home, e.g. you wish to compute $P(R, H|D = 1)$. To do this, you define the following Markov Network. The tables denotes ~~the values of the~~ factors in terms of α, β, θ which are known to you.

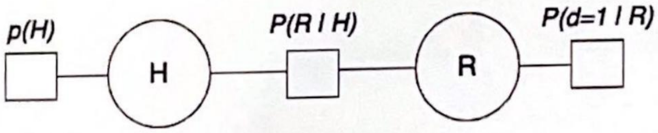


Figure 4: Markov Net for parts (ii) and (iii).

$P(H)$

h	$p(h)$
0	$1-\alpha$
1	α

$P(R \mid H)$

$h \backslash r$	0	1
0	β	$1-\beta$
1	$1-\beta$	β

$P(D \mid R)$

$r \backslash d$	0	1
0	θ	$1-\theta$
1	$1-\theta$	θ

Table 1: The parameters of the Markov Network in Fig. 4.

You realize that you have no idea what values for α, β, θ are, and decide to collect data to estimate them. However, your data collection assistant is careless and forgets to record values for whether the games were played at home or not. However, you have learned the EM algorithm from CS221 and decide to use that the EM algorithm to estimate the parameters. The table below shows your dataset.

i	h_i	r_i	d_i
1	?	1	1
2	?	1	0
...	...	...	...
100	?	0	1

Table 2: The dataset $\mathcal{D}$ containing 100 sample dishes.

(ii) [4 points] **E-Step:** In our situation, the E-step will compute the posterior probability $q_i(h) = \mathbb{P}(H = h \mid R = r_i, D = d_i)$ for each $i \in \{1, 2, ..., 100\}, s \in \{0, 1\}$.

Compute $q_1(1)$, expressing your answer in terms of α, β, θ (i.e., your current estimates). Show your work.

$\underline{q_1(1)}$

$P(H=h \mid R=1_i, D=d) =$

h	r	d	P
1	1	1	$\alpha(\beta)(\theta)$
0	1	1	$(1-\alpha)(1-\beta)(\theta)$

$$q_1(h) = \frac{\alpha(\beta)(\theta)}{(1-\alpha)(\beta)(\theta) + \alpha(1-\beta)(\theta)}$$

$$\therefore q_1(h) = \frac{\alpha\beta}{(1-\alpha)\beta + \alpha[1-\beta)}$$

I MADE A SILLY ALGEBRAIC ERROR!

alpha*beta / (alpha*beta + (1-alpha)*(1-beta))

(iii) [4 points] **M-Step:** Having computed the values of $q_i(h), i \in \{1, 2, ..., 100\}, s \in \{0, 1\}$ from the E-step, what is the value of α after the M-step, expressing your answer in terms of $q_i(h)$? Show your work.

M step: count & normalise

Count and normalise

alpha / (1-alpha) = sigma qi(1) /sigma qi(0)

alpha = sigma qi(1) / (sigma qi(0) + sigma qi(1))

alpha = sigma qi(1) / 100

$$\alpha = \frac{\sum_{i} q_i(h) \times \#\text{times } (r_i = 1 \wedge d_i = 1) \text{ occurs in evidence}}{\sum_{i} q_i(h) \times \#\text{times } (r_i = 1 \wedge d_i = 1) \text{ occurs} + (1 - q_i(h)) \times \#\text{number of times } (r_i = 1 \wedge d_i = 1) \text{ occurs}}$$

c. (*2 points*) **Household Robotics** A robotics company has created a new household robot that can help people with chores at home like washing dishes and cleaning, cooking, etc. However, the company doesn't get approval to test their robot in California. To test their robot, they decide to test it in another country where fire safety laws are not as strict. What ethics concept that you learned in this course would this choice be in violation of, and why?

What we expect: Your answer should be 1-2 sentences and should clearly name the relevant concept, explain why it is in violation in a way that makes it clear that you understand what the concept is.

Ethics Dumping: the company deliberately & knowingly chose to get approval in a state where regulation are less strict to evade the fact that their approval was rejected. If there were just cause for that rejection eg breach safety standards, privacy standards, etc then this is unethical.

7. Logic (*18 points*)

a. (*8 points*) **Knowledge Bases** Consider a setting with four propositional symbols: `Healthy`, `Fatigue`, `Flu`, and `Fever`. Let your current knowledge base be:

$$\mathrm{KB} = \{\texttt{Fatigue} \rightarrow \neg\texttt{Flu}, \texttt{Fever} \wedge \texttt{Flu}\}$$

You are asked by the CDC to update the knowledge base with some new formulas, but the CDC would like to know how the new formulas will change the set of models representing the knowledge base. For each of the following questions, **no explanation is required.**

(i) [3 points] First the CDC would like to know if the knowledge base is satisfiable. True or false: The knowledge base is satisfiable.

Satisfyable if $M(KB) \neq \emptyset$

True.

(ii) [2 points] CDC researcher Sharan gives you the following new formula to compare with your knowledge base: $f_1 = \texttt{Fatigue} \vee \texttt{Healthy}$. Which of the following are true? Circle all that apply.

(a) KB entails f_1 ✗

(b) KB contradicts f_1 ✗

(c) f_1 is consistent

(d) None of the above

c adds new info

¬Fatigue ∨ (¬Flue, Fever ∧ Flue)

(iii) [3 points] The CDC now gives you a new knowledge base:
KB = {`Headache`,
`Headache` ∧ `Fatigue`,
`Headache` ∧ `Fatigue` → `Fever`,
`Fever` ∧ `Headache` ∧ `Fatigue` → `Flu`
`Flu` → *False*}. Which of the following statements are true? Circle the correct answer.

(a) Modus ponens is sound on the given KB, but not necessarily complete. D

(b) Modus ponens is complete on the given KB, but not necessarily sound.

(c) Modus ponens is sound and complete on the given KB.

(d) Modus ponens is neither sound nor complete on the given KB.

sound $\subseteq$

complete $\supseteq$

H	Fat	Fever	Flu
1	0	1	0
1	1	1	1
0	1	1	0

contradict

Answer is A. From A/Prof. Hashimoto: This looks like Horn clauses (and Modus ponens is sound + complete with horn clauses), but note that Headache AND Fatigue is not a Horn clause. This means that you can't derive Fever using Modus ponens. Recall that the most general form of modus ponens is {a, b, c, a AND b AND c -> d} derives d. This can't derive Fever, because we don't have Fatigue as part of the knowledge base. We'd either need some other inference rule that tells us Headache AND Fatigue

We'd either need some other inference rule that tells us Headache AND Fatigue derives Fatigue (not modus ponens) or we need a nonstandard variant of modus ponens that can take {a AND b , a AND b -> c} and derive c.

b. (*8 points*) **Conjunctive Normal Form (CNF)** Modus ponens asserts that if we have two formulas, AB and A in our knowledge base, then we can derive B. Resolution asserts that if we have two formulas, $A \vee B$ and $\neg B \vee C$ in our knowledge base, then we can derive $A \vee C$. If $A \wedge B$ is in the knowledge base, then we can derive both A and B.

Hint: For some of the questions, consider expressing $A \rightarrow B$ in other ways.

(i) [2 points] Your friend Skanda can only read first order logic and needs your help to convert an English sentence into first order logic. Let us consider the following formulas: $Student(x)$ means x is a student, $Classroom(x)$ means x is a classroom, $Safe(x)$ means x is safe, and $Wears(x, mask)$ means x wears a mask. Select the correct conversion(s) of the following English sentence into a first order logic formula. Circle all that apply.

"None of the classrooms are safe if not all students wear masks."

(a) $(\forall s\ Student(s) \wedge \rightarrow Wears(s, mask)) \rightarrow (\forall c\ Classroom(c) \rightarrow \neg Safe(c))$

(b) $(\exists s\ Student(s) \wedge \neg Wears(s, mask)) \rightarrow (\exists c\ Classroom(c) \wedge \neg Safe(c))$

(c) $(\exists s\ Student(s) \rightarrow \neg Wears(s, mask)) \rightarrow (\forall c\ Classroom(c) \wedge \neg Safe(c))$

(d) $(\exists s\ Student(s) \wedge \neg Wears(s, mask)) \rightarrow (\forall c\ Classroom(c) \rightarrow \neg Safe(c))$

D

(ii) [2 points] You are given the symbols A, B, C, D. Convert the following formula to conjunctive normal form (CNF): $(A \wedge B) \rightarrow (C \wedge D)$.

$\neg(A \wedge B) \vee (C \wedge D)$

$= (\neg A \vee B) \vee (C \wedge D)$

I have nfi. Answer is (notA or notB or C) and (notA or B or D))

(iii) [4 points] Suppose the knowledge base contains the following two formulas: KB $= \{(A \vee B) \rightarrow C, A\}$. Convert the KB into CNF and then apply modus ponens to derive C. Show how the KB changes as you apply the derivation rules.

Apply CNF to (A or B) implies C, which results in (notA or C) and (not B or C).

KB = {(notA or C) and (not B or C), A}

KB = {A implies C, B implies C, A}

Apply MP on A implies C and A to derive C.

$A \vee B \rightarrow C$

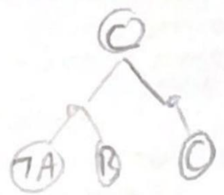
A

$= \neg(A \vee B) \vee C$

$= \neg A \wedge B \vee C$

so $KB = \left\{ \begin{array}{l} \neg A \wedge B \vee C, \\ A \end{array} \right\}$

modus Ponens $\dfrac{A,\ \neg A \wedge B \vee C}{C}$



c. (*2 points*) **Dual-use technologies** Recall that dual-use technologies are technologies that serve two purposes, typically a military and a civilian purpose. In the car-tracking assignment, we saw how a Bayes Net-based tracking system could be used for lethal secondary uses. Give an example of another dual-use AI-based technology related to what we learned in this course (e.g. a technology that includes AI or machine learning). Clearly specify how this technology could be used for both civilian and military purposes. **What we expect:** Your answer should be 2-3 sentences and should (a) clearly describe a specific algorithm or AI-based technology related to what we learned in this course and (b) mention one civilian use and one (actual or plausible) military use of this technology.

The search & MDP techniques can be considered dual use. In civilian application they can be used for guidance ie navigation from starting point A → desired end point B e.g google Maps. Simultaneously, such techniques are already used in military application for path planning & guidance of autonomous / semi-autonomous vehicles in air, land, sea. to move the vehicle to an 'enemy' location to conduct offensive capabilities e.g. 'suicide' loitering drones, or UGVs with remote weapon systems.