CSE 415–Autumn 2022 — Final Exam Solutions

(Version of Dec. 10 at 11:00 PM)

by the Staff of CSE 415, Autumn 2022

1 Heuristics

On the left, you're given the following 8 puzzle that is unsolved (for reference, the solved version is on the right):

4		2
3	6	1
7	8	5

	1	2
3	4	5
6	7	8

(a) (6 points)

Let $h_1(state)$ = sum of Manhattan distances from correct position for each tile (not counting the empty space).

Calculate the value of h_1 for the above state of the 8 puzzle. Show your work for each tile.

SOLUTION: $2 + 0 + 0 + 2 + 1 + 2 + 1 + 1 = 9$

(b) (10 points)

In English, describe a heuristic h_2 that would be dominated by h_1. Recall that for h_1 to dominate h_2, $h_1 \geq h_2$ for all states except the goal, where they should both be 0. Provide a justification for why the dominance relation holds.

SOLUTION: Answers may vary. An example is $h_2(state) = 0$, which is in effect using uniform cost search.

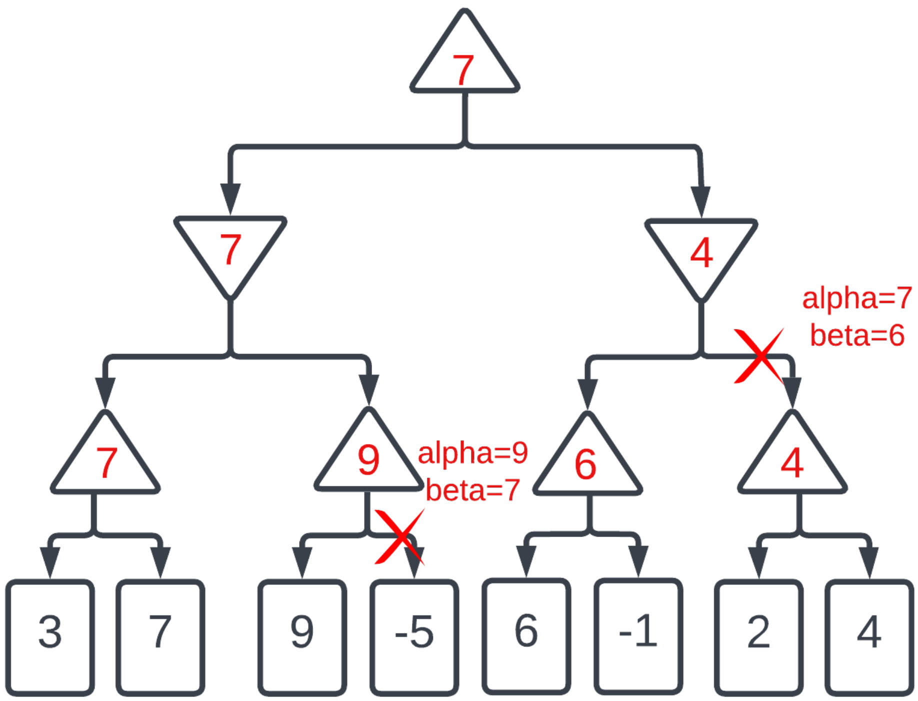
(c) (4 points)

Consider the heuristic $h_3(state)$ = the Manhattan distance of the empty space from the goal (the top left). Is h_3 admissible? Why or why not?

SOLUTION: Yes. h_3 is admissible as the heuristic always gives an underestimate of the true distance/cost to the goal. The edge cases fall into two categories: a) the empty space is in the correct location but the other pieces are not and b) the empty space is in the incorrect location. For the former, moving the other pieces to the correct location requires a nonzero number of moves, meaning the heuristic is admissible. For the latter case, the heuristic remains admissible as even with free movement of pieces, there requires a nonzero number of moves to get the empty space to the right location, in addition to the moves required to place the rest of the pieces.

2 Adversarial Search

Consider the tree below in answering the questions.



(a) (8 points) Show the values of all internal nodes, as would be computed by a standard minimax search (without any alpha-beta pruning).

(b) (6 points) Now reconsider the search, applying alpha-beta pruning to determine where subtrees could be cut off. Wherever a subtree can be cut off, draw mark across the tree edge where the pruning would occur.

(c) (6 points) Wherever a cutoff occurred in (b), give the corresponding α and β values. Recall that a cutoff occurs when $\alpha \geq \beta$ at a node. Write each (α, β) pair as an ordered pair next to the node at which it occurs.

3 MDPs and Values

Consider the following MDP environment, in which there are two exit states giving rewards of 100 and 10, respectively. An agent can move left or right in all states except the leftmost and rightmost, where they can take the exit action. Actions are taken deterministically, meaning $T(s, a, s') = 1$ for all available actions between two different states.

a	b	c	d	e
100				10

(a) (12 points)

(i) (6 points) Fill in the optimal action at each state for $\gamma = 1$. Use L for left, R for right, and E for exit. Show your work.

a	b	c	d	e
E	L	L	L	E

(ii) (6 points) Fill in the optimal action at each state for $\gamma = 0.1$. Use L for left, R for right, and E for exit. Show your work.

a	b	c	d	e
E	L	L	R	E

(b) (8 points) For what value of γ are left and right equally good in state B? Show your work.

SOLUTION: $\gamma * 100 = \gamma^3 * 10$ which yields $\gamma = \sqrt{10}$.

4 Q-Learning

Consider an "unknown" MDP with three states (A, B and C) and two actions ($\leftarrow$ and $\rightarrow$). The agent knows what states there are an what actions there are but does not know either the T function or the R function. Suppose the agent chooses actions according to some policy π in the unknown MDP, collecting a dataset consisting of samples (s, a, s', r) representing taking action a in state s resulting in a transition to state s' and a reward of r. (We'll process these in the order given, even though they may not have come from a sequence of consecutive transitions.)

s	a	s'	r
A	$\rightarrow$	B	4
C	$\leftarrow$	B	4
B	$\rightarrow$	C	-4
A	$\rightarrow$	B	8

You may assume a discount factor of $\gamma = 1$.

(a) Recall the update function of Q-learning is:

$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + \alpha\left(R(s,a,s') + \gamma \max_{a'} Q(s',a')\right)$$

Assume that all Q-values are initialized to 0, and use a learning rate of $\alpha = \frac{1}{2}$.

(i) (10 points) Run Q-learning on the above experience table and fill in the following Q-values (Show your Q-learning derivations for each step!):
The first of the four Q-updates is done for you.

$$Q_1(A,\rightarrow) = \frac{1}{2}\cdot Q_0(A,\rightarrow) + \frac{1}{2}\left(4 + \gamma \max_{a'} Q(B,a')\right) = \frac{1}{2}(0) + \frac{1}{2}(4+0) = 2$$

$Q_1(C,\leftarrow) =$

$Q_1(B,\rightarrow) =$

$Q_2(A,\rightarrow) =$

SOLUTION: The algorithm updates Q-values as follows:

$$Q_1(A,\rightarrow) = \frac{1}{2}\cdot Q_0(A,\rightarrow) + \frac{1}{2}\left(4 + \gamma \max_{a'} Q(B,a')\right) = \frac{1}{2}(0) + \frac{1}{2}(4+0) = 2$$
$$Q_1(C,\leftarrow) = \frac{1}{2}\cdot Q_0(C,\leftarrow) + \frac{1}{2}\left(4 + \gamma \max_{a'} Q(B,a')\right) = \frac{1}{2}(0) + \frac{1}{2}(4+0) = 2$$
$$Q_1(B,\rightarrow) = \frac{1}{2}\cdot Q_0(B,\rightarrow) + \frac{1}{2}\left(-4 + \gamma \max_{a'} Q(C,a')\right) = \frac{1}{2}(0) + \frac{1}{2}(-4+2) = -1$$
$$Q_2(A,\rightarrow) = \frac{1}{2}\cdot Q_1(A,\rightarrow) + \frac{1}{2}\left(8 + \max_{a'} Q(B,a')\right) = \frac{1}{2}(2) + \frac{1}{2}(8+0) = 5.$$

$Q(A, \rightarrow) = \boxed{5}$ $\qquad$ $Q(B, \rightarrow) = \boxed{-1}$

(ii) (4 points) After running Q-learning and producing the above Q-values, you construct a policy π_Q that maximizes the Q-value in a given state:

$$\pi_Q(s) = \arg\max_a Q(s, a)$$

What are the actions chosen by the policy in states A and B? (Pick one answer for each state)

$\pi_Q(A)$ is equal to:

- ○ $\pi_Q(A) = \leftarrow$.
- ● $\pi_Q(A) = \rightarrow$.
- ○ $\pi_Q(A) =$ Undefined.

$\pi_Q(B)$ is equal to:

- ● $\pi_Q(B) = \leftarrow$.
- ○ $\pi_Q(B) = \rightarrow$.
- ○ $\pi_Q(B) =$ Undefined.

SOLUTION:
Note that $Q(A, \rightarrow) = 5 > 0 = Q(A, \leftarrow)$.
Similarly, $Q(B, \leftarrow) = 0 > -1 = Q(B, \rightarrow)$.

(b) (6 points) Use the empirical frequency count approach to obtain an estimate of the transition function $\hat{T}(s, a, s')$ and and estimate of the reward function $\hat{R}(s, a, s')$. (If a transition is not observed, it has a count of 0.)

Write down the following quantities. You may write N/A for undefined quantities.

$\hat{T}(A, \rightarrow, B) = \boxed{1}$ $\qquad$ $\hat{R}(A, \rightarrow, B) = \boxed{6}$

$\hat{T}(B, \rightarrow, A) = \boxed{0}$ $\qquad$ $\hat{R}(B, \rightarrow, A) = \boxed{N/A}$

$\hat{T}(B, \leftarrow, A) = \boxed{N/A}$ $\qquad$ $\hat{R}(B, \leftarrow, A) = \boxed{N/A}$

SOLUTION:

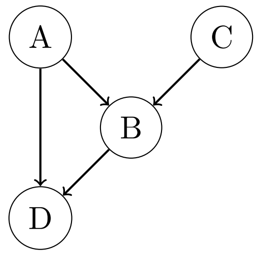
$\hat{T}(A, \rightarrow, B) = 1$, because $(A, \rightarrow, B)$ occurred in 2 samples and no other samples has $(A, \rightarrow)$.
$\hat{R}(A, \rightarrow, B) =$ Avg(4, 8) $= 6$

$\hat{T}(B, \rightarrow, A) = 0$, because $(B, \rightarrow)$ occurred in 1 sample but $(B, \rightarrow)$ only leads to state C. Thus, the reward function is undefined.

$\hat{T}(B, \leftarrow, A) =$ N/A, because $(B, \leftarrow)$ occurred in 0 samples. Thus, the transition function and reward function are both undefined.

5 Joint Distributions and Bayes' Net

Consider the Bayes net graph depicted below with *binary* variables:



(a) (2 points) What is the size of the factor $P(D|B,C)$? (i.e., how many probability values will be in the conditional probability table?)

$2^3 = 8$

(b) (3 points) What is the **minimum** number of parameters needed to fully specify the distribution $P(D|B,C)$? (i.e., what is the number of "free" parameters?)

$(2-1)2^2 = 4$

(c) (5 points) Select all conditional independences that are enforced by this Bayes net graph. (Hint: Consider the D-Separation rules.)

[ ] $A \perp\!\!\!\perp B$	[ ] $A \perp\!\!\!\perp C \mid B$	[x] $D \perp\!\!\!\perp C \mid A, B$	[ ] $D \perp\!\!\!\perp C$
[x] $A \perp\!\!\!\perp C$	[ ] $A \perp\!\!\!\perp C \mid D$	[ ] $A \perp\!\!\!\perp C \mid B, D$	[ ] $D \perp\!\!\!\perp C \mid B$

(d) (4 points) Because of these conditional independences, there are some distributions that cannot be represented by this Bayes net. Find a minimal set of edges that would need to be added such that the resulting Bayes net could represent any distribution. (Hint: think about how the normal chain rule for joint distributions differs from the factored distribution represented by the graph.)

[x] $A \to C$	[ ] $B \to C$	[ ] $B \to A$	[x] $C \to A$
[x] $C \to D$	[ ] $D \to C$	[ ] $D \to A$	[ ] $D \to B$

SOLUTION: Either ($C \to A$ AND $C \to D$) OR ($A \to C$ AND $C \to D$)

(e) (6 points) Here are some partially-filled conditional probability tables that provide information about a joint probability distribution involving four random variables A, B, C, and D. Note that these are not necessarily factors of the Bayes net above. Fill in the six blank entries such that this distribution can be represented by the Bayes net.

A	B	C	$P(C \mid A, B)$
$+a$	$+b$	$+c$	0.5
$+a$	$+b$	$-c$	0.5
$+a$	$-b$	$+c$	0.2
$+a$	$-b$	$-c$	0.8
$-a$	$+b$	$+c$	0.9
$-a$	$+b$	$-c$	0.1
$-a$	$-b$	$+c$	0.4
$-a$	$-b$	$-c$	0.6

A	B	D	$P(D \mid A, B)$
$+a$	$+b$	$+d$	0.6
$+a$	$+b$	$-d$	0.4
$+a$	$-b$	$+d$	0.1
$+a$	$-b$	$-d$	0.9
$-a$	$+b$	$+d$	0.2
$-a$	$+b$	$-d$	0.8
$-a$	$-b$	$+d$	0.5
$-a$	$-b$	$-d$	0.5

A	C	$P(C \mid A)$
$+a$	$+c$	0.8
$+a$	$-c$	0.2
$-a$	$+c$	0.8
$-a$	$-c$	0.2

C	$P(C)$
$+c$	**(i)**
$-c$	**(ii)**

A	B	C	D	$P(D, C \mid A, B)$
$+a$	$+b$	$+c$	$+d$	**(iii)**
$+a$	$+b$	$-c$	$-d$	**(iv)**
$+a$	$-b$	$+c$	$+d$	**(v)**
$+a$	$-b$	$-c$	$-d$	**(vi)**
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$

(i) 0.8

(ii) 0.2

(iii) $0.6 * 0.5 = 0.3$

(iv) $0.4 * 0.5 = 0.2$

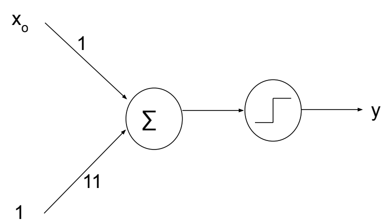
(v) $0.1 * 0.2 = 0.02$

(vi) $0.9 * 0.8 = 0.72$

6 Perceptrons

For all parts of this question perceptrons should output 1 if $\sum w_i x_i \geq 0$ and 0 otherwise.

(a) (3 points) Draw a perceptron, with weights, that accepts a single integer x_0 and outputs 1 if and only if the input is greater than or equal to -11.



(b) (3 points) Assuming there will be two inputs x_0 and x_1, each with possible values in $\{0, 1\}$, give values for a triple of weights $\langle w_0, w_1, w_2 \rangle$ such that the corresponding perceptron would act as an OR gate for the two inputs. (Weight w_2 is the bias weight.) Note that an OR gate outputs 1 when at least one of the inputs is 1; it outputs 0 otherwise.

$\langle w_0, w_1, w_2 \rangle = \langle 1, 1, -1 \rangle$

(c) (4 points) Describe, using words and/or pseudocode, what the perceptron training algorithm does when the model receives as training input a) an example it classifies correctly and b) an example it classifies as a false positive and c) an example it classifies as a false negative. Describe the updates to the weights and bias that take place in terms of the input x vector and the learning rate.

The weights do not change if the model classifies the example correctly. If the model receives a false positive, we subtract each the training example vector times learning rate from the weight vector and subtract the learning rate from the bias term. If the model receives a false negative, we add each the training example vector times learning rate from the weight vector and add the learning rate to the bias term.

(d) (4 points) Consider the problem of categorizing sentences according to topic. For features, we can count the numbers of occurrences of keywords in an example. We can train on example data using the multiclass perceptron training algorithm. Use the three given training examples to update the weights below. Note that all weights have been started at 0, except the first bias weight, which we've set to 1, so that we don't have to do any tie-breaking in this presentation. The initial weights are generally arbitrary, since they will be automatically adjusted in accordance with the training data. 3 classes (topics): astronomy, cooking, health.

Training examples:

Example	vector representation							
	`[bias,`	`black,`	`discover,`	`donut,`	`hole,`	`spice],`	`class`	
"Black hole discovered!"	$e_1 =$ `[ 1,`	`1,`	`1,`	`0,`	`1,`	`0 ],`	`astronomy`	
"Discover donut holes"	$e_2 =$ `[ 1,`	`0,`	`1,`	`1,`	`1,`	`0 ],`	`cooking`	
"A spicy discovery"	$e_3 =$ `[ 1,`	`0,`	`1,`	`0,`	`0,`	`1 ],`	`cooking`	

Let $w_{a,0}$ represent the initial weight vector for astronomy, and let $w_{a,i}$ represent the weight vector after i cycles of training (with one presentation of some training example in each cycle). In similar fashion, we define $w_{c,i}$ and $w_{h,i}$ for the cooking and health topics, respectively. The initial weight vectors are given in the table below.

	`[bias,`	`black,`	`discover,`	`donut,`	`hole,`	`spice]`
$w_{a,0} =$	`[ 1,`	`0,`	`0,`	`0,`	`0,`	`0 ]`
$w_{c,0} =$	`[ 0,`	`0,`	`0,`	`0,`	`0,`	`0 ]`
$w_{h,0} =$	`[ 0,`	`0,`	`0,`	`0,`	`0,`	`0 ]`

Perform one step of training, using e_1 as the training example. Reminder: first you will classify e_1 by computing its dot product with each of the current weight vectors. (Show these dot products.) Then you will determine the maximum among these, and the predicted class that goes with it. If the example is correctly classified, then there will be no changes to the weight vectors for the cycle. However, if the classification comes out, say J, when it was supposed to be K, then J's vector needs to have a fraction of the training example vector SUBTRACTED from the weight vector for J, and the same fraction should be ADDED to the weight vector for K. Use the fraction 1 (i.e., $\alpha = 1$) for this problem. If nothing changes, write $w_{q,1} = w_{q,0}$ where $q \in \{a, c, h\}$ to show that the vectors are unchanged. If there is any change, write the new vectors in the space provided.

$e_1 \bullet w_{a,0} = 1$; $e_1 \bullet w_{c,0} = 0$; $e_1 \bullet w_{h,0} = 0$; class of the argmax is: astronomy

$w_{a,1} = w_{a,0}$

$w_{c,1} = w_{c,0}$

$w_{h,1} = w_{h,0}$

(e) (4 points) Now, starting with the weight vectors $w_{q,1}$ that you just found, train with example e_2. $e_2 \bullet w_{a,1} = 1$; $e_2 \bullet w_{c,1} = 0$; $e_2 \bullet w_{h,1} = 0$; class of the argmax is: astronomy

$w_{a,2} = [0,\ 0,\ -1,\ -1,\ -1,\ 0]$

$w_{c,2} = [1,\ 0,\ 1,\ 1,\ 1,\ 0]$

$w_{h,2} = w_{h,1}$

(f) (2 points) Finally, from the $w_{q,2}$ that you just found, train with example e_3. $e_3 \bullet w_{a,2} = -1$; $e_3 \bullet w_{c,2} = 2$; $e_3 \bullet w_{h,2} = 0$; class of the argmax is: cooking

$w_{a,3} = w_{a,2}$

$w_{c,3} = w_{c,2}$

$w_{h,3} = w_{h,2}$

7 Markov Models

According to an unnamed source about an online video game, the quality of teammates in a sequence of matches can be modeled using a Markov model, where there are two states "good" and "bad." The dynamics of the model are given:

S_{t-1}	S_t	$P(S_t \mid S_{t-1})$
good	good	0.2
good	bad	0.8
bad	good	0.6
bad	bad	0.4

(a) (7 points) Suppose Bill got good teammates in match 0 (S_0). Compute the probability that Bill gets good teammates in match 2 (S_2).

First, $P(S_1 = \text{good}) = 0.2$, and $P(S_1 = \text{bad}) = 0.8$. Then, $P(S_2 = \text{good}) = P(S_1 = \text{good}) \cdot 0.2 + P(S_1 = \text{bad}) \cdot 0.6 = 0.2 \cdot 0.2 + 0.8 \cdot 0.6 = 0.52$.

(b) (7 points) Compute the stationary probabilities for states good and bad.

$P_\infty(\text{ good }) = P_\infty(\text{ good }) \cdot 0.2 + P_\infty(\text{ bad }) \cdot 0.6$.
$P_\infty(\text{ bad }) = 1 - P_\infty(\text{ good })$.
$P_\infty(\text{ good }) = 3/7$. $P_\infty(\text{ bad }) = 4/7$.

(c) (6 points)Now suppose that whenever Bill gets good teammates, he wins the match with probability 0.7 and loses the match with probably 0.3.

When Bill gets bad teammates, he wins with probability 0.1 and loses with probability 0.9.

Suppose Bill cannot directly tell whether his teammates are good or bad, but can only see whether he wins or loses the match.

State S	Observation Q	$P(Q \mid S)$
good	win	0.7
good	lose	0.3
bad	win	0.1
bad	lose	0.9

Suppose Bill gets good teams in match 0 (S_0) with a probability of 0.5. If the observation at match 1 is "lose," what is the belief in Bill's teammates are good right after the observation?

First compute $P(S_1 = \text{good})$ without the observation using the forward transitions from $S_0 = \text{good}$ and $S_0 = \text{bad}$. $P(S_1 = \text{good }) = 0.5 * 0.2 + 0.5 * 0.6 = 0.40$. and $P(S_1 = \text{bad }) = 0.5 * 0.8 + 0.5 * 0.4 = 0.60$.
Now take the observation into account using Bayes' rule:
$P(S_1 = \text{good } \mid Q_1 = \text{lose }) = P(S_1 = \text{good}, Q_1 = \text{lose })/P(Q_1 = \text{lose })$
$= P(Q_1 = \text{lose } \mid S_1 = \text{good })P(S_1 = \text{good })/P(Q_1 = \text{lose })$
Here $P(Q_1 = \text{lose }) = P(S_1 = \text{good}, Q_1 = \text{lose }) + P(S_1 = \text{bad}, Q_1 = \text{lose }) = P(Q_1 = \text{lose } \mid S_1 = \text{good})P(S_1 = \text{good}) + P(Q_1 = \text{lose } \mid S_1 = \text{bad})P(S_1 = \text{bad}) = 0.3 \cdot 0.4 + 0.9 \cdot 0.6 = 0.12 + 0.54 = 0.66$.
So, $P(S_1 = \text{good } \mid Q_1 = \text{lose }) = 0.12/0.66 = 0.182$.

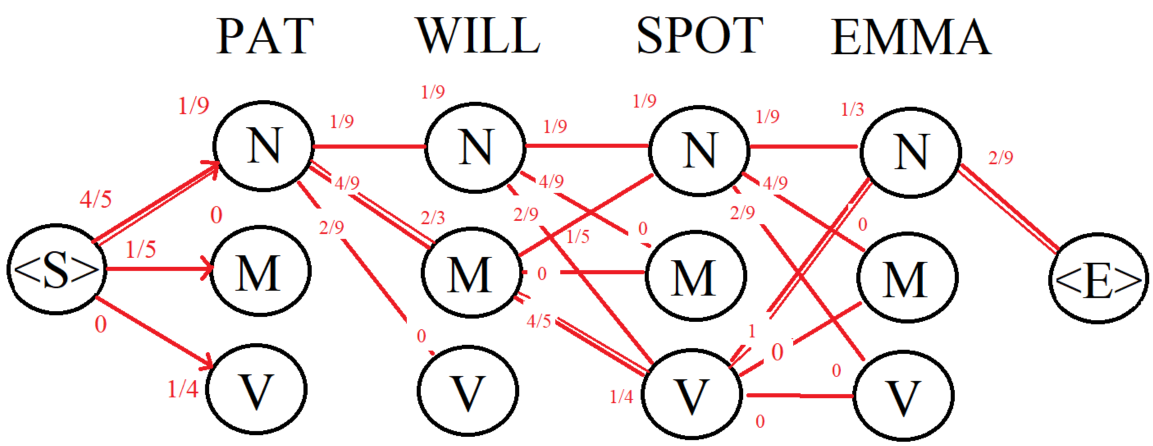
8 Hidden Markov Models

8.1 Viterbi Algorithm and POS Tagging

Consider the partial trellis diagram below.

	N	M	V	⟨E⟩
⟨S⟩	4/5	1/5	0	0
N	1/9	4/9	2/9	2/9
M	1/5	0	4/5	0
V	1	0	0	0

	N	M	V
JOHN	1/3	0	0
EMMA	1/3	0	0
WILL	1/9	2/3	0
SPOT	1/9	0	1/4
CAN	10	1/3	1/4
SEE	0	0	1/4
PAT	1/9	0	1/4



(a) (10 points) Perform the steps of the Viterbi algorithm using the given transition model and emission model, to find a most likely sequences of POS tags to give correspond to the sequence of emissions given by the sentence above the trellis. As you do this, draw all edges except those where the probability of coming to the tail of the edge is 0. Show on each drawn edge the new factors that should be multiplied to get the probability of a path including that edge so far. The first cycle (with edges from $\langle S \rangle$) is done for you. Show the most likely path (from S to E) by highlighting the trellis edges that appear in the path.

(b) (2 points) Give an expression that represents the probability of the most likely path, given the emissions represented by the sentence. Your expression should be similar to the following, which represents the probability of one of the incorrect paths:

$$(1/5)(0)(4/9)(1/9)(4/9)(0)(1)(1/4)(0)$$

$$(4/5)(1/9)(4/9)(2/3)(4/5)(1/4)(1)(1/3)(2/9)$$

8.2 The Forward Algorithm

Consider the following Hidden Markov Model representing a robot's knowledge of its own location on the top floor of a building. There are only two rooms (room A and room B), and they are connected by a wide doorway. It will make somewhat random moves from one room to another, and it will receive observations (based on an emission model) that relate to what room it is in. Initially, the robot does not know anything and so it uses a belief vector of $\langle 0.5, 0.5 \rangle$ to represent its current belief about which room it is in. The observations are sounds: { click, ding }.

S_{t-1}	S_t	$P(S_t \mid S_{t-1})$
A	A	0.8
A	B	0.2
A	B	0.6
B	B	0.4

A	click	0.9
A	ding	0.1
B	click	0.5
B	ding	0.5

(c) (2 points) From its starting situation, the robot makes one move, and then it hears a sound. What should its belief vector be after it moves but before it hears the sound? (no need here to normalize)

$$\left\langle \begin{array}{c} 0.5 \cdot 0.8 + 0.5 \cdot 0.6 \\ 0.5 \cdot 0.6 + 0.5 \cdot 0.4 \end{array} \right\rangle = \left\langle \begin{array}{c} 0.7 \\ 0.3 \end{array} \right\rangle$$

(d) (4 points) Then, suppose the sound it hears is a click. What should its belief vector be after that? (Do not normalize, yet.)

$$\left\langle \begin{array}{c} 0.7 \cdot 0.9 \\ 0.3 \cdot 0.5 \end{array} \right\rangle = \left\langle \begin{array}{c} 0.63 \\ 0.15 \end{array} \right\rangle$$

(e) (2 points) Now express the belief vector in normalized form (i.e., as a valid probability distribution). You don't need to calculate ratios here; simply express any ratios that might be involved.

$$\left\langle \begin{array}{c} 0.63/0.78 \\ 0.15/0.78 \end{array} \right\rangle$$

9 AI and Ethics

Asimov's Laws of Robotics:

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws.

You are a medical student who has had to move to virtual schooling due to a viral pandemic. Your well-endowed medical school, in partnership with faculty and industry collaborators, has presented you and all your classmates with "Standardized Patient Robots" – beta version humanoid personal assistant robots that they had quickly modified with knowledge of medical conditions, symptoms, and treatments (along with other enhancements) to enable you to continue your training while in quarantine. Since you studied computer science as an undergraduate, you decided to modify your robot to obey Asimov's Laws.

(a) (10 points) You have been struggling to get into "student mode" while being isolated at home. Before you realize it, the school term is over and you have final exams. You do not feel ready for your exams, so you start wondering how you can get your robot to help you. You decide you can just order the robot to give you the answers to your exam questions. How does this strategy work when you try it out during the exam? **Describe how you think your robot would respond in this scenario (short answer). Justify your prediction by referring to the relevant law(s) of robotics.**

Different responses are possible for this question:

Example 1: The robot will obey the command, in accordance with Asimov's 2nd Law. The 2nd Law is not in conflict with the first law in this case because the robot can help the student do well in the exam, which will be to his benefit. As there are no rules saying that the student cannot use the robot in this way, there should be no penalties that would harm the student.

Example 2: The robot won't obey the student, because doing so, although it would be in accordance with the 2nd law, would violate the first law by being harmful to the student. The student needs to know the material on the exam to do well in his/her academic career, and, presumably, later in his/her career as a doctor. Not knowing this information could harm the student in the future. Furthermore, although there may be no rules specifically saying it is not allowed to use the robot in this way, the robot realizes that the student is supposed to take the exam without any outside assistance and could face penalties if it is determined that he had help from the robot.

(b) (10 points) Discuss one or two ethical issues that come to mind related to the scenario described above – the robot is a tool intended to enhance your (human) performance, but you can assume that this use of the robot was not anticipated or explicitly approved (or forbidden) by the school administration. **Is the student in the scenario behaving ethically in attempting to use the robot this way or not? Please briefly discuss your reasoning in coming to your conclusion.**

Different responses are possible for this question:

Example 1: The student understands that he/she is supposed to complete the exam without help from others, including the help he/she is planning to get from the robot. By being a student in the class, the student has agreed to follow the rules concerning proper behavior that apply to all students. By trying to pass the robot's knowledge off as his/her own, the student is intentionally breaking the agreed upon rules of conduct and misrepresenting himself/herself. This is not ethical behavior.

Example 2: This might seem like more of a stretch, but imagine the student happens upon a real-life medical emergency. In such a situation, the student realizes that the robot could significantly improve the student's ability to help, and asks the robot for assistance. In such a case, not doing so, and relying only on his/her own skills and knowledge would be unethical behavior, as it could harm the person(s) in need of medical attention. In the case of the exam, there is no risk of harm to any other person(s), but by not calling on the robot for assistance, the student is not accurately demonstrating the full extent of what she/he is capable of, if allowed to use all the tools at his/her disposal. As there are (presumably) no rules against using other tools, such as stethoscopes, X-rays, etc., there should be no ethical issues surrounding the use of the robot either.

10 Multiple Choice

Each of the 5 following subquestions in this overall question is worth 4 points. For each subquestion, circle the letter of the one *best* answer. (More than one choice might seem correct, but credit will only be given for the best answer, and if more than one answer gets circled, no credit will be given for that subquestion.)

(a) When searching in a tree, which is not an advantage of iterative deepening search over straight depth-first search to the same maximum depth?

- (A) In game-playing, it can provide an anytime algorithm for computing a good move within the available time.
- (B) When searching for a goal, when it does find a goal, it can immediately identify a shortest path.
- (C) It might take longer to find a goal node.
- (D) Its memory requirements are no greater, and on average, less.

C is correct.

(b) We can consider perceptron training to be a kind of search for some kind of hyperplane. Which of the following is most likely to prevent finding a solution?

- (A) The existence of extra dimensions in the vector representation of the data items, such that these dimensions contain irrelevant features.
- (B) A learning rate that is following a harmonic sequence $1, \frac{1}{2}, \frac{1}{3}, \ldots$
- (C) A training set in which the positive and negative examples cannot be completely separated by any hyperplane.
- (D) An iterative algorithm that has no limit on the number of iterations it might use during training.

C is correct.

(c) Which of these is not part of Kurzweil's "singularity"?

- (A) Robots will have been improving their own designs.
- (B) Robots are expected to fully control humans.
- (C) Artificial intelligence will help spread human values.
- (D) Great strides will have been made in neuroscience.

B is correct.

(d) Which of these stand in the way of using Asimov's laws for self-driving cars?

  (A) The laws are written in English and therefore irrelevant to robots and computers that don't perform natural language understanding.

  (B) The laws need to be adopted by national governments before they can be applied.

  (C) A car cannot be a robot, and vice versa.

  (D) Robots cannot always predict the consequences of their actions accurately.

  D is correct.

(e) Knowing you have (human) enemies who want to do you harm through personal, physical attacks, you purchase an XL1000 Personal Defense Bot. You select the "Obeys Asimov's Laws" optional add-on feature. Your enemies find about about your purchase through one of their spies. Which of the following outcomes is likely?

  (A) Your enemies, who are well-acquainted with Asimov's Laws, give up any thoughts of attacking you.

  (B) Your enemies, who are well-acquainted with Asimov's Laws, laugh as they plan their next attack.

  (C) Your bodyguard robot kills all potential attackers before they can harm you.

  (D) Your bodyguard robot kills you.

  The correct response is B, since the robot will be presented with an unsolvable scenario - to protect its owner and prevent harm from occurring to the owner, while also not harming any human attackers.