

[illegible]

- (10pts) 1. (Probability) Use the table to calculate the following values. (You need not simplify answers.)

$X_1$	$X_2$	$X_3$	$\Pr(X_1, X_2, X_3)$
0	0	0	0.05
1	0	0	0.1
0	1	0	0.4
1	1	0	0.1
0	0	1	0.1
1	0	1	0.05
0	1	1	0.2
1	1	1	0.0

(a)  $\Pr(X_1 = 1, X_2 = 0) =$  \_\_\_\_\_

(b)  $\Pr(X_3 = 0) =$  \_\_\_\_\_

(c)  $\Pr(X_2 = 1 \mid X_3 = 1) =$  \_\_\_\_\_

(d)  $\Pr(X_1 = 0 \mid X_2 = 1, X_3 = 1) =$  \_\_\_\_\_

(e)  $\Pr(X_1 = 0, X_2 = 1 \mid X_3 = 1) =$  \_\_\_\_\_

2. (Pacman with Feature-Based Q-Learning) Suppose you want to use a Q-learning agent for Pacman, but the state size for a large grid is too massive to hold in memory, so you decide to switch to a feature-based representation of Pacman's state.



Consider the two features:

- $f_g$  = the number of ghosts within 1 step of Pacman
- $f_p$  = the number of food pellets within 1 step of Pacman

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- Hints.* (1) These features depend only on the state, not the actions you take.  
 (2) You are guaranteed at least partial credit if you write down the correct formula for each part of this problem before carrying out the computations.

- (2pts) (a) What are the values of the two features for the game state of the Pacman board shown above.

$$f_g = \underline{\hspace{2cm}} \qquad f_p = \underline{\hspace{2cm}}$$

- (4pts) (b) In Q Learning you train off of a few episodes so your weights begin to take on values. Assume that right now  $w_g = 100$  and  $w_p = -10$ . Calculate the Q value for the game state shown above.

$$Q(s, a) =$$

- (4pts) (c) After receiving an *episode* (start state  $s$ , action  $a$ , end state  $s'$ , and reward  $r$ ), you update your values. The start state of the episode is the state above (for which you already calculated the feature values and the expected Q value). The next state has feature values  $f_g = 0$  and  $f_p = 2$  and the reward is 50. Assuming a discount of  $\gamma = 0.5$ , calculate the new estimate of the Q value for  $s$  based on this episode.

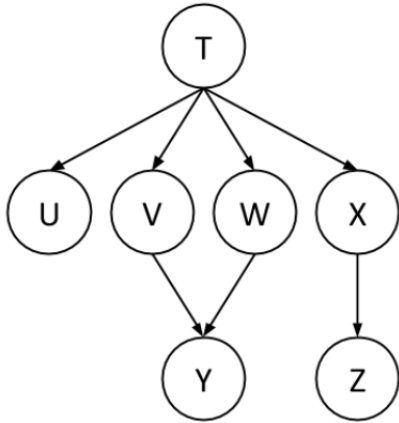
$$Q_{\text{new}}(s, a) =$$

- (4pts) (d) Now use the difference  $Q_{\text{new}}(s, a) - Q(s, a)$ , and learning rate  $\alpha = 0.5$ , to update the weights for each feature.

$$w_g =$$

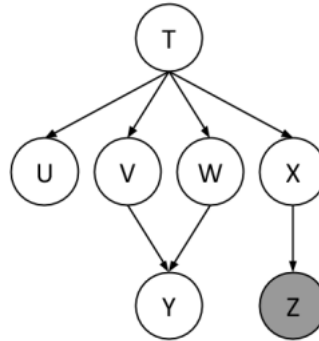
$$w_p =$$

3. (D-Separation) Indicate whether each of the following conditional independence relationships is guaranteed to be true in the Bayes Net below. If the independence relationship does not hold, identify all active (d-connected) paths in the graph; write A-C-D to denote an active path from A to C to D.



- (2pts) (a)  $U \perp\!\!\!\perp X$   
☐ True    ☐ False, because of the active path(s): \_\_\_\_\_
- (2pts) (b)  $U \perp\!\!\!\perp X \mid T$   
☐ True    ☐ False, because of the active path(s): \_\_\_\_\_
- (2pts) (c)  $V \perp\!\!\!\perp W \mid Y$   
☐ True    ☐ False, because of the active path(s): \_\_\_\_\_
- (2pts) (d)  $V \perp\!\!\!\perp W \mid T$   
☐ True    ☐ False, because of the active path(s): \_\_\_\_\_
- (1pts) (e)  $T \perp\!\!\!\perp Y \mid V$   
☐ True    ☐ False, because of the active path(s): \_\_\_\_\_
- (1pts) (f)  $Y \perp\!\!\!\perp Z \mid W$   
☐ True    ☐ False, because of the active path(s): \_\_\_\_\_
- (1pts) (g)  $Y \perp\!\!\!\perp Z \mid T$   
☐ True    ☐ False, because of the active path(s): \_\_\_\_\_

4. (Variable Elimination) Using the same Bayes Net as in the previous problem (and shown below), we want to compute  $\Pr(Y \mid +z)$ . All variables have binary domains. Assume we run variable elimination to compute the answer to this query, with the following variable elimination ordering:  $X, T, U, V, W$ .



After inserting evidence we have the following factors to start with:

$\Pr(T), \Pr(U \mid T), \Pr(V \mid T), \Pr(W \mid T), \Pr(X \mid T), \Pr(Y \mid V, W), \Pr(+z \mid X)$

- (0pts) (a) (example) When eliminating  $X$  we generate a new factor  $f_1$  as follows:

$$f_1(+z \mid T) = \sum_x \Pr(x \mid T) \Pr(+z \mid x)$$

leaving the factors  $\Pr(T), \Pr(U \mid T), \Pr(V \mid T), \Pr(W \mid T), \Pr(Y \mid V, W), f_1(+z \mid T)$ .

- (4pts) (b) Eliminating  $T$  we generate a new factor  $f_2$  as follows (express  $f_2$  as a sum,  $\sum_t$ ):

$$f_2(U, V, W, +z) =$$

leaving the two factors \_\_\_\_\_ and \_\_\_\_\_.

- (4pts) (c) When eliminating  $U$  we generate a new factor  $f_3$  as follows:

$$f_3(V, W, +z) =$$

leaving the two factors \_\_\_\_\_ and \_\_\_\_\_.

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4. (continued)

(3pts) (d) When eliminating  $V$  we generate a new factor  $f_4$  as follows:

$$f_4(W, Y, +z) =$$

leaving the factor \_\_\_\_\_.

(3pts) (e) When eliminating  $W$  we generate a new factor  $f_5$  as follows:

$$f_5(Y, +z) =$$

leaving the factor \_\_\_\_\_.

(3pts) (f) How would we obtain  $\Pr(Y \mid +z)$  from the factor left above?

EXTRA CREDIT

(1pt bonus) (g) What is the largest factor generated during the above process?

(1pt bonus) (h) How many unconditioned variables does it have?

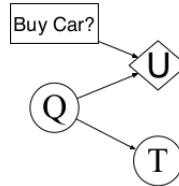
(1pt bonus) (i) How many probability entries will its distribution table have?

(1pt bonus) (j) Does there exist a better elimination ordering (generating smaller largest factors)?

☐ No    ☐ Yes, one such ordering is \_\_\_\_\_.

Score for this page: \_\_\_\_\_ out of 0

5. (Decision Networks and VPI) A used car buyer is deciding whether to carry out test of a car and then, depending on the outcome, decide which car to buy. Assume you (the buyer) are deciding whether to buy car  $c$  and that there is time to carry one test which costs \$50 and which will tell you whether the car is in good shape (quality  $Q = +q$ ) or bad shape (quality  $Q = -q$ ). The test will have one of two outcomes: pass ( $T = \text{pass}$ ) or fail ( $T = \text{fail}$ ). Car  $c$  costs \$1,500, and its market value is \$2,000 if it is already in good shape, and, if it's in bad shape, you would spend \$700 in repairs to get it into good shape. You estimate that  $c$  has 70% chance of being in good shape. The Decision Network is shown below.



- (2pts) (a) Calculate the expected utility (or net gain) from buying car  $c$ , given no test information.

EU(buy) =

- (2pts) (b) Suppose  $\Pr(T = \text{pass} \mid Q = +q) = 0.9$  and  $\Pr(T = \text{pass} \mid Q = -q) = 0.2$ . Calculate the probability that the car will pass or fail. [Hint. Sum  $\Pr(T = \text{pass}, q)$  over  $q$ .]

$\Pr(T = \text{pass}) =$

$\Pr(T = \text{fail}) = 1 - \Pr(T = \text{pass}) =$  \_\_\_\_\_

- (4pts) (c) Calculate the probability the car is in good shape given each test outcome.

$\Pr(Q = +q \mid T = \text{pass}) =$

$\Pr(Q = +q \mid T = \text{fail}) =$

Score for this page: \_\_\_\_\_ out of 8



5. (continued)

- (4pts) (d) Calculate the expected utility of each purchasing decision for each outcome of the test. (“ $\neg$  buy” denotes the decision “don’t buy”)

$$EU(\text{buy} \mid T = \text{pass}) =$$

$$EU(\text{buy} \mid T = \text{fail}) =$$

$$EU(\neg \text{buy} \mid T = \text{pass}) =$$

$$EU(\neg \text{buy} \mid T = \text{fail}) =$$

- (3pts) (e) Use your previous answer to determine the max expected utility for each outcome and identify the optimal decision in each case.

$$MEU(T = \text{pass}) = \underline{\hspace{2cm}} \quad \text{with decision } \square \text{ buy} \quad \square \neg \text{buy}$$

$$MEU(T = \text{fail}) = \underline{\hspace{2cm}} \quad \text{with decision } \square \text{ buy} \quad \square \neg \text{buy}$$

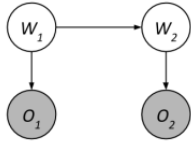
- (3pts) (f) Calculate the value of perfect information of the test and determine whether you should pay to have the test done.

$$VPI(T) =$$

Should you pay for the test? ☐ Yes ☐ No

Score for this page: \_\_\_\_\_ out of 10

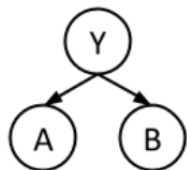
6. (HMM) For the following Hidden Markov Model, use the forward algorithm to compute  $\Pr(W_2 \mid O_1 = A, O_2 = B)$  by following the steps below.



$W_1$	$\Pr(W_1)$	$W_t$	$W_{t+1}$	$\Pr(W_{t+1} \mid W_t)$	$W_t$	$O_t$	$\Pr(O_t \mid W_t)$
0	0.3	0	0	0.4	0	A	0.9
1	0.7	0	1	0.6	0	B	0.1
		1	0	0.8	1	A	0.5
		1	1	0.2	1	B	0.5

- (5pts) (a) Compute  $\Pr(W_1 = w, O_1 = A)$  for each  $w \in \{0, 1\}$ .
- (5pts) (b) Compute  $\Pr(W_2 = w, O_1 = A)$  for  $w \in \{0, 1\}$ . [*Hint.* Sum  $\Pr(x_1, W_2, O_1 = A)$  over  $x_1$ , rewriting summands using independence assumptions of the model.]
- (3pts) (c) Compute  $\Pr(W_2 = w, O_1 = A, O_2 = B)$  for each  $w \in \{0, 1\}$ .
- (3pts) (d) Compute  $\Pr(W_2 = w \mid O_1 = A, O_2 = B)$  for each  $w \in \{0, 1\}$ . [*Hint.* Normalize.]

7. (Naive Bayes) In this question, you will train a Naive Bayes classifier to predict class labels  $Y$  as a function of input features  $A$  and  $B$ . The variables  $Y$ ,  $A$ ,  $B$  are binary; i.e., the domain is  $\{0, 1\}$  in each case. You are given 10 training points from which you will estimate the distribution.



A	1	1	1	1	0	1	0	1	1	1
B	1	0	0	1	1	1	1	0	1	1
Y	1	1	0	0	0	1	1	0	0	0

(10pts)

- (a) Given the data in the table above, compute the maximum likelihood estimates for  $\Pr(Y)$ ,  $\Pr(A \mid Y)$ , and  $\Pr(B \mid Y)$  and write the results (as fractions, not decimals) in the tables below.

Y	$\Pr(Y)$
0	
1	

A	Y	$\Pr(A \mid Y)$
0	0	
1	0	
0	1	
1	1	

B	Y	$\Pr(B \mid Y)$
0	0	
1	0	
0	1	
1	1	

(4pts)

- (b) Consider a new data point ( $A = 1$ ,  $B = 1$ ). What label would this classifier assign to this sample? Write your answer on the line at bottom of the page.  
*[Hint. Compute  $\Pr(Y = y, A = 1, B = 1)$  for each  $y \in \{0, 1\}$ .]*

Classifier predicts label  $Y =$  \_\_\_\_\_.

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EXTRA CREDIT

(4pt bonus)      (c) Recompute the distribution  $\Pr(A \mid Y)$  using Laplace Smoothing with  $k = 2$ .

A	Y	$\Pr(A \mid Y)$
0	0	
1	0	
0	1	
1	1	

– scratch –



– scratch –