Final Exam

CSCI 561 Spring 2018: Artificial Intelligence

Instructions:

1. Date: **04/24/2018 from 5:00 pm to 6:20 pm**
2. Maximum credits/points/percentage for this midterm: 100
3. The percentages for each question are indicated in square brackets [ ] near the question.
4. **No books** (or any other material) are allowed.
5. **Write down your name, student ID and USC email address.**
6. **Your exam will be scanned and uploaded online.**
7. **Write within the boxes provided for your answers.**
8. **Do NOT write on the 2D barcode.**
9. **The back of the pages will NOT be graded. You may use it for scratch paper.**
10. No questions during the exam. **If something is unclear to you, write that in your exam.**
11. **Be brief: a few words are often enough if they are precise and use the correct vocabulary studied in class.**
12. When finished, raise completed exam sheets until approached by proctor.
13. **Adhere to the Academic Integrity code.**

Problems	100 Percent total
1. General Knowledge I	10%
2. General Knowledge II	18%
3. Bayesian Networks	20%
4. Decision Trees	16%
5. Markov Decision Process	20%
6. Neural Networks	16%

1. [10%] General AI Knowledge: True/False

For each of the statements below, answer **T** if the statement is **always true**, or **F** otherwise.

F	1. Any preference ordering can be represented by a utility function.
T	2. Bayes' Theorem converts a prior belief into a posterior belief after you've collected some additional evidence.
T	3. There is no training process for *k*-nearest-neighbors classification.
T	4. The minimax algorithm can be considered to be solving a deterministic Markov Decision Process.
F	5. Naive Bayes can capture conditional dependencies between input variables given the output variable.
F	6. Overfitting can result when a machine learning hypothesis space has too few dimensions.
T	7. Q-learning can learn the optimal policy without ever executing it.
T	8. This statement does not contain any examples of coreference.
T	9. C4.5 uses greedy search to learn decision trees.
T	10. Unsupervised learning methods can be applied to labeled training data.

2. [18%] General Knowledge

Each multiple choice question is worth 2% and has one or more correct choices, so circle all correct choices. There will be no partial credit, and you will receive full credit if and only if you choose all of the correct choices and none of the wrong choices.

1. Which of the following statements are true for learning decision trees?
A. The training process is parallel.
B. We use entropy to decide how to split nodes in tree.
C. It can be used in regression problems.
D. It is an unsupervised learning algorithm.

2. Which statements are NOT true about non-parametric methods?
A. They assume a fixed data distribution.
B. Support Vector Machines (SVMs) are one example.
C. They always store all of the training data.
D. They are most often used in unsupervised learning.

3. Which of the following statements regarding Partially Observable Markov Decision Processes (POMDPs) is false?
A. The optimal policy can be written as a function of only the agent's current belief state.
B. The optimal policy can be written as a function of both the agent's current and next belief states.
C. The optimal policy can be written as a function of the agent's history of percepts.
D. A POMDP's belief-state space is continuous.
E. A POMDP's belief-state space is discrete.

4. Consider an adversarial game in which each state s has minimax value $V(s)$. Assume that the maximizer plays according to the optimal minimax policy π, but the opponent (the minimizer) plays according to an unknown, possibly suboptimal policy π′. Which of the following statements are true?

A. The score for the maximizer from a state s when it's the maximizer's turn could be greater than $V(s)$.

B. The score for the maximizer from a state s when it's the maximizer's turn could be less than $V(s)$.

C. Even if the opponent's strategy π′ were known, the maximizer should still play according to π.

D. If π′ is optimal and known, the outcome from any s when it's the maximizer's turn will be $V(s)$.

E. If π′ is optimal, then π and π' form a Nash equilibrium.

5. Which of the following statements are true about Markov Decision Processes (MDPs)?

A. For any MDP with a finite number of states and actions, value iteration is guaranteed to converge if the discount factor $\gamma \in (0, 1]$.

B. Every MDP has at least one optimal policy.

C. The Bellman equation is a recursive descent search tool.

D. The Bellman equation is a greedy search tool.

Each short answer is worth 4%. Partial credit will be awarded for showing work.

6. A despondent millennial was told by his doctor that he has been infected with affluenza, a disease that affects 1% of the population. The test for affluenza has a 99% accuracy rate.

Being a fair-weather skeptic, the millennial went to a second doctor, who administered the same test, but this time, the result was negative. What is the probability that the millennial has affluenza?

P(A) probability of having affluenza

P(E) probability of testing positive

P(T1) probability that first test result is positive

P(T2) probability that second test result is positive

First Doctor

$P(A|T1) = (P(T1|A) * P(A)) / (P(A) * P(T1|A) + P(-A) * P(T1|-A))$

$= (0.99 * 0.01) / (0.01 * 0.99 + 0.99 * 0.01)$

$= 0.5$ or 50%

Second Doctor

$P(A|E) = (0.99 * 0.5) / (0.5 * 0.99 + 0.5 * 0.5)$

$= 0.99$ or 99%

Since, this measures probability of not having the disease, the answer is <u>0.01 or 1%</u> chance of having affluenza.

Alternate solution:

$P(A \mid T1, \neg T2) = \alpha P(T1, \neg T2 \mid A)P(A) = \alpha P(T1 \mid A)P(\neg T2 \mid A)P(A) = \alpha * .99 * .01 * .01$

$P(\neg A \mid T1, \neg T2) = \alpha P(T1, \neg T2 \mid \neg A)P(\neg A) = \alpha P(T1 \mid \neg A)P(\neg T2 \mid \neg A)P(\neg A) =$
$\alpha * .01 * .99 * .99$
$P(A \mid T1, \neg T2) = .99*.01*.01 / (.99*.01*.01+*.01*.99*.99) = .01/(.01+.99) = .01$

Some students will estimate, that is ok. However, anything outside of this range without showing work receives 0. If student shows correct formulation of Bayes theorem they get 2 points. If student shows just numeric answer without work they get 1 point.

7. Consider the contrived (albeit challenging) problem of determining whether a person's name is "creepy".

a. [2%] Give two reasons why this might be a challenging problem for machine learning.

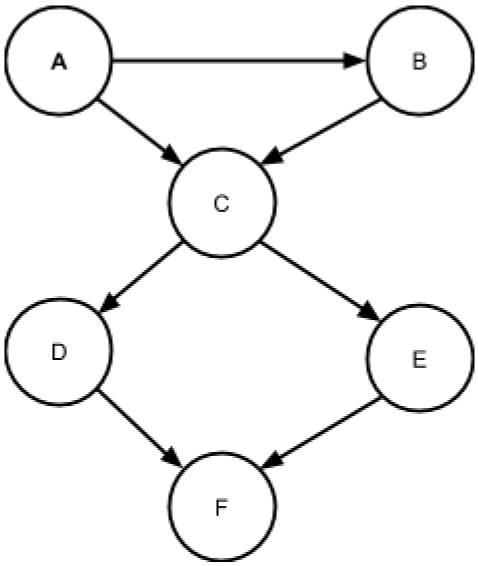
Students only need to list two of four below:

- Phonostylistics -- pronunciation or how it sounds
- Cultural Bias -- social and cultural influence
- How to label data?
- How to evaluate accuracy?
- We should accept other reasonable answers

b. [2%] Would supervised or unsupervised learning be more appropriate for solving this problem? Why?

Although the example is contrived and admittedly difficult, it is still requires <u>supervised training</u> because labeling names as "creepy" or "not creepy" is required.

3. [20%] Bayesian Networks



P(A)
0.3

A	P(B)
T	0.4
F	0.8

C	P(D)
T	0.5
F	0.1

C	P(E)
T	0.2
F	0.6

A	B	P(C)
T	T	0.4
T	F	0.2
F	T	0.1
F	F	0.7

D	E	P(F)
T	T	0.4
T	F	0.7
F	T	0.9
F	F	0.3

Using the provided information on a Bayesian Network, answer the following questions. Be sure to show work or provide an explanation.

1. [3%] Are D and E conditionally independent given A and B? Why or why not?

No, they are not. D and E are conditionally independent given C.
Alternate Acceptable Answer: P(D|A,B,E) != P(D|A,B,not E).

2. [3%] Are D and E conditionally independent given A, B, and C? Why or why not?

Yes, they are. D and E are conditionally independent given C.

3. [3%] Are D and E conditionally independent given C and F? Why or why not?

No, they are not. D and E are conditionally independent given C, but F is a common child of both.

4. [3%] Does P(A, E) = P(A) P(C|A, B) P(E|C)? Why or why not?

No, they are not, because P(B|A), P(not C | ...) and P(not B | A) are missing.
TODO: If students compute the exact values of the left- and right-hand sides and show that they're not equal.

5. [3%] What is $P(A \land \neg B \land \neg C \land D)$? Show your work.

P(D+, C-, A+, B-)
= P(D+|C-) P(C-|A+, B-) P(B-|A+) P(A+)
= 01. * 0.8 * 0.6 * 0.3

$= 1.44 * 10^{-2}$

6. [5%] What is *P(A ∧ ¬B | E)*? Show your work.

$P(A \wedge \neg B \wedge E) = P(A) * P(\neg B \mid A) \ \Sigma_C \ P(C \mid A, \neg B) * P(E \mid C)$

$= 0.0936$

$P(E) = \Sigma_A \ P(A) \ \Sigma_B \ P(B \mid A) * \Sigma_C \ P(C \mid A, B) * P(E \mid C)$

$= 0.5048$

$P(A \wedge \neg B \mid E) = P(A \wedge \neg B \wedge E) / P(E) = 0.1854$

4. [16%] Decision Trees

You are a robot in a lumber yard, and you must learn to discriminate Oak wood from Pine wood. You choose to learn a Decision Tree classifier. The available training data is as follows:

Example	**Density**	**Grain**	**Hardness**	**Class**
Example #1	Heavy	Small	Hard	Oak
Example #2	Heavy	Large	Hard	Oak
Example #3	Heavy	Small	Hard	Oak
Example #4	Light	Large	Soft	Oak
Example #5	Light	Large	Hard	Pine
Example #6	Heavy	Small	Soft	Pine
Example #7	Heavy	Large	Soft	Pine
Example #8	Heavy	Small	Soft	Pine

We also give the approximation of log_2 as follows:

log2(1/8) = -3.00	log2(1/4) = -2.00	log2(1/3) = -1.58	log2(3/8) = -1.42
log2(3/7) = -1.22	log2(1/2) = -1.00	log2(4/7) = -0.81	log2(5/8) = -0.68
log2(2/3) = -0.58	log2(3/4) = -0.42	log2(7/8) = -0.19	log2(1) = 0.00

1. [2%] What is the entropy in the entire data set?

H = -0.5 log(0.5) - 0.5 log(0.5) = 1

2. [6%] Calculate the information gain for splitting on each of the 3 features. Show formulas and steps clearly.

$H(Density) = \frac{6}{8}[-\frac{3}{6}log(\frac{3}{6}) - \frac{3}{6}log(\frac{3}{6})] + \frac{2}{8}[-\frac{1}{2}log(\frac{1}{2}) - \frac{1}{2}log(\frac{1}{2})] = 1$

$IG\ (Density) = 1 - 1 = 0$

$H(Grain) = \frac{4}{8}[-\frac{2}{4}log(\frac{2}{4}) - \frac{2}{4}log(\frac{2}{4})] + \frac{4}{8}[-\frac{2}{4}log(\frac{2}{4}) - \frac{2}{4}log(\frac{2}{4})] = 1$

$IG\ (Grain) = 1 - 1 = 0$

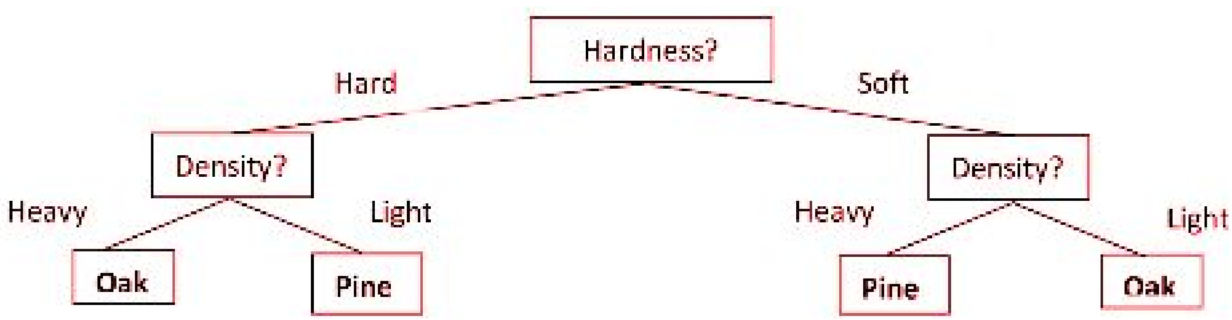
$H(Hardness) = \frac{4}{8}[-\frac{3}{4}log(\frac{3}{4}) - \frac{1}{4}log(\frac{1}{4})] + \frac{4}{8}[-\frac{3}{4}log(\frac{3}{4}) - \frac{1}{4}log(\frac{1}{4})] = 0.815$

$IG\ (Hardness) = 1 - 0.815 = 0.185$

3. [1%] Based on information gain, which attribute should be used as the root of a decision tree?

Hardness

4. [5%] Draw the decision tree that would be constructed by recursively applying information gain to select branches, as in the Decision-Tree-Learning algorithm.



5. [2%] Classify the following new examples as Oak or Pine using your decision tree above.

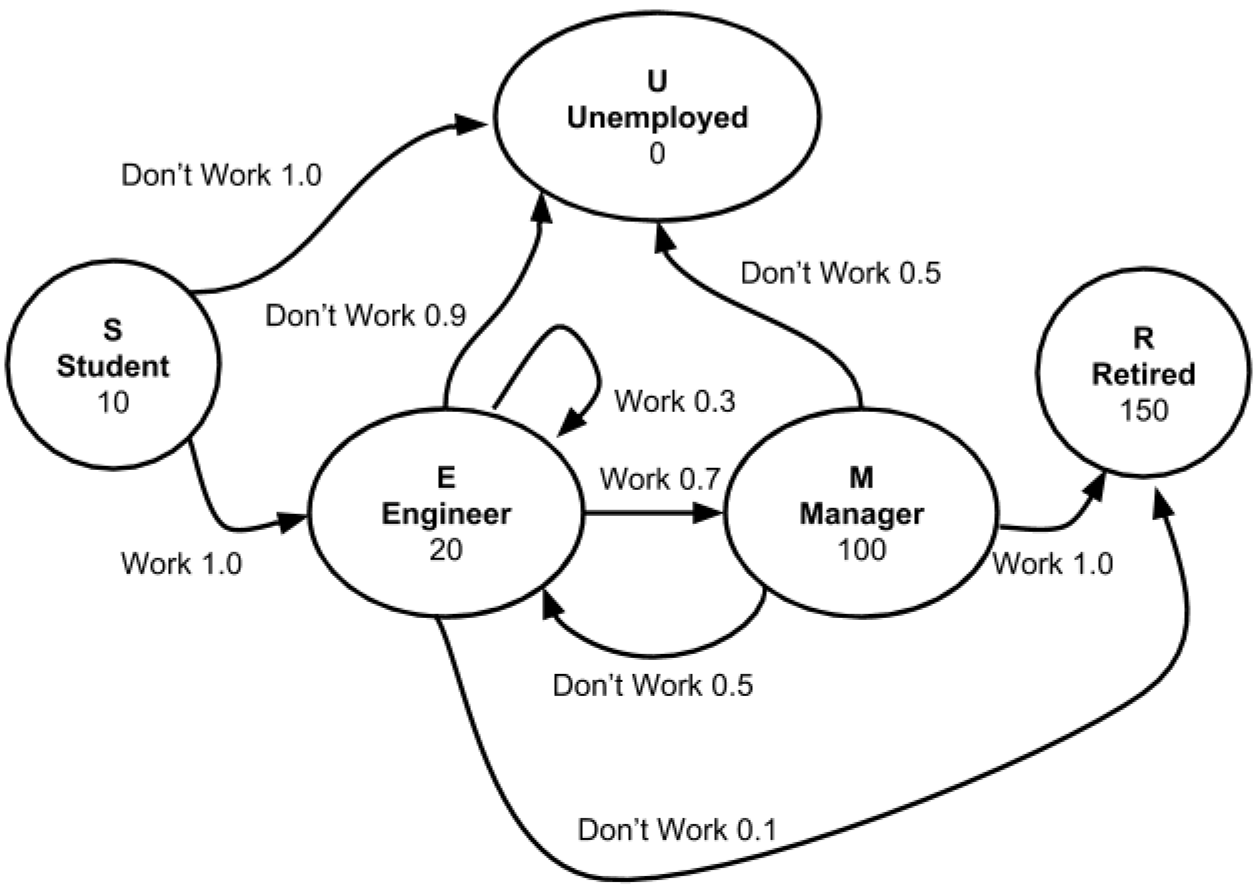
A. What class is [Density=Light, Grain=Small, Hardness=Hard]? Pine

B. What class is [Density=Light, Grain=Small, Hardness=Soft]? Oak

Note: when grading this problem, give students full credits as long as the answers are consistent with the tree in 4 (even if the tree in 4 is wrong).

5. [20%] Markov Decision Process

Consider the professional career of Hal, currently an AI student, captured in the MDP below. Each oval shows a phase of his career and his level of happiness in that phase. Each link from one phase to another is labeled by Hal's decision to work or not and the probability that he makes that transition in the next five years given that decision. Phases with no outgoing links are terminal. Hal feels that being happy five years from now is only 90% as valuable as being happy right now.



1. [2%] What discount factor, γ, should Hal use when computing the expected reward of his actions? 0.9

2. [3%] Hal would like to avoid work. If he never works, what is the probability that he will be able to reach retirement? Please explain.

0% because a career that includes only the “don’t work” action can only lead to unemployment, which is a terminal node. If they answer “0%” they get 1 pt and if they explain correctly they get 2 pts.

3. [3%] If Hal becomes an engineer and decides to always work, what is the probability that he will reach retirement? Please explain.

100% because a career that includes only the “work” action can only lead to retirement. If they answer “100%” they get 1 pt and if they explain correctly they get 2 pts.

4. [12%] Suppose Hal actually hates the idea of becoming a manager. For what happiness levels in phase M would it be optimal for Hal to stop working once he becomes an engineer? You do not need to compute long division, so you may leave your answer in fraction form, e.g. 99/0.75 is acceptable.

U(M) = R(M) + 0.9*150 = R(M)+135

U(E,Work) < U(E,Don't Work) [Including some statement like this is worth 1 or 2 points]

U(E,Work) = 20 + 0.9*(0.3*U(E)+0.7*U(M))

= 20 + 0.27*U(E,Work) + 0.63*R(M) + 0.63*135

= 20/.73 + .63/.73*R(M) + .63*135/.73 [Calculating this correctly is worth some number of points]

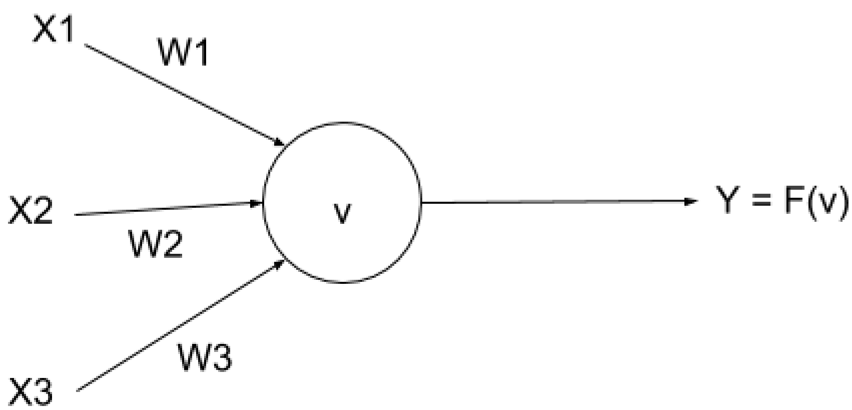
U(E,Don't Work) = 20 + 0.9*(0.9*U(U)+0.1*U(R)) = 20 + 0.09*150 = 33.5 [Calculating this correctly is worth fewer points than U(E,Work)]

20/.73 + .63/.73*R(M) + .63*135/.73 < 33.5 (this would get most of the points, but lose at least 1)

R(M) < 33.5*.73/.63 - 20/.63 - 135 (this could be acceptable too)

6. [16%] Neural Networks

Suppose a single-neuron network is represented as follows:



The node has three inputs ***x*** = (X1, X2, X3) that receive binary signals (either 0 or 1).

1. [2%] How many different input signals can this node receive?

8 (For three inputs the number of combinations of 0 and 1 is 8)

2. [8%] Consider the single neuron network with weights corresponding to the 3 inputs as: W1 = 2, W2 = −4, W3 = 1. And the activation of the unit is given by the step–function:

$$\mathbf{F}(v) = \begin{cases} 1 & \text{if } v \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Calculate what the output value Y of the unit will be for each of the following input data:

Data	P1	P2	P3	P4
X1	1	0	1	1
X2	0	1	0	1
X3	0	1	1	1

P1 : $v=2\cdot1-4\cdot0+1\cdot0=2$, $(2>0)$, $y=F(2)=1$

P2 : $v=2\cdot0-4\cdot1+1\cdot1=-3$, $(-3<0)$, $y=F(-3)=0$

P3 : $v=2\cdot1-4\cdot0+1\cdot1=3$, $(3>0)$, $y=F(3)=1$

P4 : $v=2\cdot1-4\cdot1+1\cdot1=-1$, $(-1<0)$, $y=F(-1)=0$

3. [3%] If the correct output value for P1 is actually 0, which weights would the perceptron learning rule change (if any) and in what direction?

W1 would decrease (partial credit if also saying W2 and W3 would increase)

4. [3%] If the correct output value for P2 is actually 1, which weights would the perceptron learning rule change (if any) and in what direction?

W2 and W3 would increase (partial credit if also saying W1 would decrease)