2. Unlike Expectimax, Minimax 'can take a risk' and end up in a state with a higher utility as opponents are random. [1 point]

False, based on the nature of expectimax and minimax search algorithms.

3. The importance of an accurate evaluation function increases by increasing the depth. [1 point]

False, because we have more uncertainty further up in the tree; therefore, it is more important to have an accurate evaluation function higher up in the tree.

4. Identify the appropriate type of search for the problems listed below: [3 points]

CPU job scheduling -> goal itself is important

Graph coloring problem -> goal itself is important

Finding the shortest route from city A to city B -> path to goal itself is important

Chess game -> path to goal itself is important (This will be graded manually as the autograder response is incorrect.)

5. Specify two problems with the Hill-climbing algorithm and explain two different methods (one for each problem) that alleviate these problems.

[6 points - 3 points for two problems and 3 points for two reasonable solutions]

- 1. Problem 1
  - a. We get stuck in a local optimum and not the global optimum.
  - b. Solution: We can implement hill-climbing with random restarts, pick the best solution, or use the simulated annealing approach.
- 2. Problem 2
  - a. Plateau points, a flat portion of the state-space landscape hill-climbing tries to find uphill parts, and if there are none, we are stuck.
  - b. Solution: Implement a limited number of side-way movements in an attempt to leave the plateau.
- 6. How is local beam search equivalent to AND different from multiple parallel runs of hill-climbing algorithms? Explain these shared and dissimilar characteristics.

  [4 points 2 points for shared characteristics, 2 points for dissimilarities]

**Similarities**: If k=1, then the beam search is just a single thread of climbing a hill without keeping track of other good choices. They both consider k nodes at any given time.

**Dissimilarities**: Local beam search is not equivalent to parallel runs of several hill-climbing because, in the parallel runs, there is no sense of memory of the best states. Local beam

search is like k parallel runs, but the information is shared, and successors are chosen by considering all neighbors.

7. Simulated annealing is more likely to accept a bad move late in the search than earlier. [1 point]

False, based on the definition of the temperature schedule in the simulated annealing algorithm.

8. Consider the general less-than chain CSP below. Each of the N variables  $X_i$  has the domain  $\{1,\,2,\,\ldots,\,M\}$ . The constraints between adjacent variables  $X_i$  and  $X_{i+1}$  require that  $X_i$  <  $X_{i+1}$  . [10 points]



For now, assume  $N=M_{\perp}$ 

a. How many solutions does the CSP have? [2 points]

One solution: 1<2<3<.....<N

b. What will be the domain of  $X_1$  after enforcing the consistency of only arc  $X_1 \longrightarrow X_2$  ? [3 points]

$$X_1 = \{1,2,3,...,N-1\}$$

c. What will be the domain of  $X_1$  after enforcing the consistency of only arc  $X_2 \longrightarrow X_3$  and then  $X_1 \longrightarrow X_2$ ? [3 points]

$$X_1 = \{1,2,3...N-2\}$$

d. What will be the domain of  $X_1$  after fully enforcing arc consistency in the entire problem? [2 points]

$$X_1$$
 domain =  $\{1\}$ 

9. a. Why do we prefer to change <u>nearly tree-structured CSPs to tree-structured CSPs</u>? How would this conversion happen? [ 3 points]

We prefer tree-structured CSPs because this reduces the time complexity since the arc-consistency algorithm will not backtrack and consistency of arcs will be maintained as variables are assigned.  $O(nd^2)$  vs.  $O(d^n)$ .

We can do this conversion by:

Identify the minimum number of nodes, that if removed, we are left with a tree (cut-set). Then we do cut-set conditioning (pick one of those nodes call it C and assign a value to them (conditioning), then remove conflicting values from the domain of the neighbors), and run the tree-structured algorithm on each instantiated problem.

b. <u>Describe the algorithm</u> for solving a tree-structured CSP and discuss its <u>runtime</u>.

## [3 points]

Given a tree-structured CSP, we apply topological ordering (ordering nodes, from 1 to n, so that all parents come before their children in the sequence). Then:

- i) Do a backward pass, from node n-1 down to 1, enforce arc consistency between the parent of node and the node itself (Parent(Xi)  $\rightarrow$  Xi arc consistency)
- ii) Do a forward pass selecting a value from the domain of each variable that is not conflicting with the values assigned previously.

Solving a tree-structured CSP gives us a quadratic runtime versus an exponential run time because now we have to check each node in the tree and at each node (O(n)), we perform arc consistency in  $O(d^2)$ .

Runtime:  $O(nd^2)$ 

10. If A and B are two events such that P(A) = 0.2, P(B) = 0.6 and P(A|B) = 0.2 then what is the value of  $P(\sim A \mid \sim B)$ ? Show your work.

[3 points]

$$P(A|B) = 0.2$$
 and  $P(B) = 0.6$  so  $P(A, B) = 0.12$  and therefore:  
 $P(A, \sim B) = P(A) - P(A, B) = 0.2 - 0.12 = 0.08$   
 $P(\sim A|\sim B) = 1 - P(A|\sim B)$   
 $P(A|\sim B) = P(A, \sim B)/P(\sim B) = 0.08/0.4 = 0.2 \rightarrow P(\sim A|\sim B) = 1 - 0.2 = 0.8$