

Ryan Smith  
CS 540: AI  
HW #2

2.

(a)

Breadth-First search

Step#	OPEN	CLOSED	X	CHILDREN	RemainingCHILDREN
1	{S}	{}	S	{A, C}	{A, C}
2	{A, C}	{S}	A	{B, G1}	{B, G1}
3	{C, B, G1}	{S, A}	C	{D, F, J}	{D, F, J}
4	{B, G1, D, F, J}	{S, A, C}	B	{G1, J}	{}
5	{G1, D, F, J}	{S, A, C, B}	G1	{}	{}

Goal state reached: G1

States popped off of the OPEN list: S, A, C, B, G1

(b)

Depth-First search

Step#	OPEN	CLOSED	X	CHILDREN	RemainingCHILDREN
1	{S}	{}	S	{A, C}	{A, C}
2	{A, C}	{S}	A	{B, G1}	{B, G1}
3	{B, G1, C}	{S, A}	B	{G1, J}	{J}
3	{J, G1, C}	{S, A, B}	J	{G1, F}	{F}
4	{F, G1, C}	{S, A, B, J}	F	{G2}	{G2}
5	{G2, G1, C}	{S, A, B, J, F}	G2	{}	{}

Goal state reached: G2

States popped off of the OPEN list: S, A, B, J, F, G2

(c)

Iterative Deepening (depth limit 0)

Step#	OPEN	CLOSED	X	CHILDREN	RemainingCHILDREN
1	{S}	{}	S	{A, C}	{A, C}

Iterative Deepening (depth limit 1)

Step#	OPEN	CLOSED	X	CHILDREN	RemainingCHILDREN
1	{S}	{}	S	{A, C}	{A, C}
2	{A, C}	{S}	A	{B, G1}	{B, G1}
3	{C, B, G1}	{S, A}	C	{D, F, J}	{D, F, J}

Iterative Deepening (depth limit 2)

Step#	OPEN	CLOSED	X	CHILDREN	RemainingCHILDREN
1	{S}	{}	S	{A, C}	{A, C}

2	{A, C}	{S}	A	{B, G1}	{B, G1}
3	{B, G1, C}	{S, A}	B	{G1, J}	{J}
4	{G1, C, J}	{S, A, C}	G1	{}	{}

Goal state reached: G1

States popped off of the OPEN list (depth limit 0): S

States popped off of the OPEN list (depth limit 1): S, A, C

States popped off of the OPEN list (depth limit 2): S, A, B, G1

(d)

Uniform Cost (i.e., using  $f = g$ )

Step#	OPEN	CLOSED	X	CHILDREN	RemainingCHILDREN
1	{S_0}	{}	S	{A_4, C_3}	{A_4, C_3}
2	{C_3, A_4}	{S_0}	C	{D_5, F_10, J_12}	{D_5, F_10, J_12}
3	{A_4, D_5, F_10, J_12}	{S_0, C_3}	A	{B_7, G1_12}	{B_7, G1_12}
4	{D_5, B_7, F_10, G1_12, J_12}	{S_0, C_3, A_4}	D	{E_7, F_6}	{E_7, F_6}
5	{F_6, B_7, E_7, J_12, G1_12}	{S_0, C_3, A_4, D_5}	F	{G2_8}	{G2_8}
6	{B_7, E_7, G2_8, J_12, G1_12}	{S_0, C_3, A_4, D_5, F_6}	B	{G1_11, J_9}	{G1_11, J_9}
7	{E_7, G2_8, J_9, G1_11}	{S_0, C_3, A_4, D_5, F_6, B_7}	E	{F_10, G2_13}	{}
8	{G2_8, J_9, G1_11}	{S_0, C_3, A_4, D_5, F_6, B_7, E_7}	G2	{}	{}

Goal state reached: G2

States popped off of the OPEN list: S, C, A, D, F, B, E, G2

(e)

Best-First (using  $f = h$ )

Step#	OPEN	CLOSED	X	CHILDREN	RemainingCHILDREN
1	{S_6}	{}	S	{A_8, C_2}	{A_8, C_2}
2	{C_2, A_8}	{S_6}	C	{D_5, F_2, J_1}	{D_5, F_2, J_1}
3	{J_1, F_2, D_5, A_8}	{S_6, C_2}	J	{G1_0, F_2}	{G1_0}
4	{G1_0, F_2, D_5, A_8}	{S_6, C_2, J_1}	G1	{}	{}

Goal state reached: G1

States popped off of the OPEN list: S, C, J, G1

(f)

Best-First (using  $f = g + h$ )

Step#	OPEN	CLOSED	X	CHILDREN
1	{S_(0+6)}	{}	S	{A_(4+8), C_(3+2)}
2	{C_(3+2), A_(4+8)}	{S_(0+6)}	C	{D_(5+5), F_(10+2), J_(12+1)}

3	{D_(5+5), A_(4+8), F_(10+2), J_(12+1)}	{S_(0+6), C_(3+2)}	D	{E_(7+3), F_(6+2)}
	{E_(7+3), F_(6+2))}			
4	{F_(6+2), E_(7+3), A_(4+8), J_(12+1))}	{S_(0+6), C_(3+2), D_(5+5)}	F	{G2_(8+0)}
	{G2_(8+0)}			
5	{G2_(8+0), E_(7+3), A_(4+8), J_(12+1)}	{S_(0+6), C_(3+2), D_(5+5), F_(6+2)}	G2	{}
	{}			

Goal state reached: G2

States popped off of the OPEN list: S, C, D, F, G2

(g)

Beam Search (with beam width = 2 and  $f = h$ )

Step#	OPEN	CLOSED	X	CHILDREN	RemainingCHILDREN
1	{S_0}	{}	S	{A_8, C_2}	{A_8, C_2}
2	{C_2, A_8}	{S_0}	C	{D_5, F_2, J_1}	{D_5, F_2, J_1}
3	{J_1, F_2}	{S_0, C_2}	J	{F_2, G1_0}	{G1_0}
4	{G1_0, F_2}	{S_0, C_2, J_1}	G1	{}	{}

Goal state reached: G1

States popped off of the OPEN list: S, C, J, G1

(h)

Hill Climbing (using the h function only)

Step#	OPEN	CLOSED	X	CHILDREN	RemainingCHILDREN
1	{S_6}	{}	S	{A_8, C_2}	{A_8, C_2}
2	{C_2}	{S_6}	C	{D_5, F_2, J_1}	{D_5, F_2, J_1}
3	{J_1}	{S_6, C_2}	J	{F_2, G1_0}	{F_2, G1_0}
4	{G1_0}	{S_6, C_2, J_1}	G1	{}	{}

Goal state reached: G1

States popped off of the OPEN list: S, C, J, G1

(i)

No, this h function is not admissible. The h value at D is 5, and there is a path from D to a goal node with cost  $1 + 2 = 3$  (D → F → G2). This cost is less than the h value at D, meaning that h overestimates the cost to get from D to a goal node. Therefore, h is not admissible.

3.

(a)

If you are at Node C and simulated annealing has randomly selected node J for consideration, what is the probability this node is accepted?

Using simulated annealing we would actually go straight to J without needing to calculate a probability since J's score is better than C's. The probability of going to J is therefore 1. For good measure, below is what would be the probability calculation, which comes out to a value greater than 1 (which doesn't make sense as a probability).

$$\begin{aligned} e^{((\text{score}(J) - \text{score}(C)) / \text{Temperature})} &= e^{((-1) - (-2)) / 100} \\ &= e^{(1/100)} \\ &\approx 1.01005016708 \end{aligned}$$

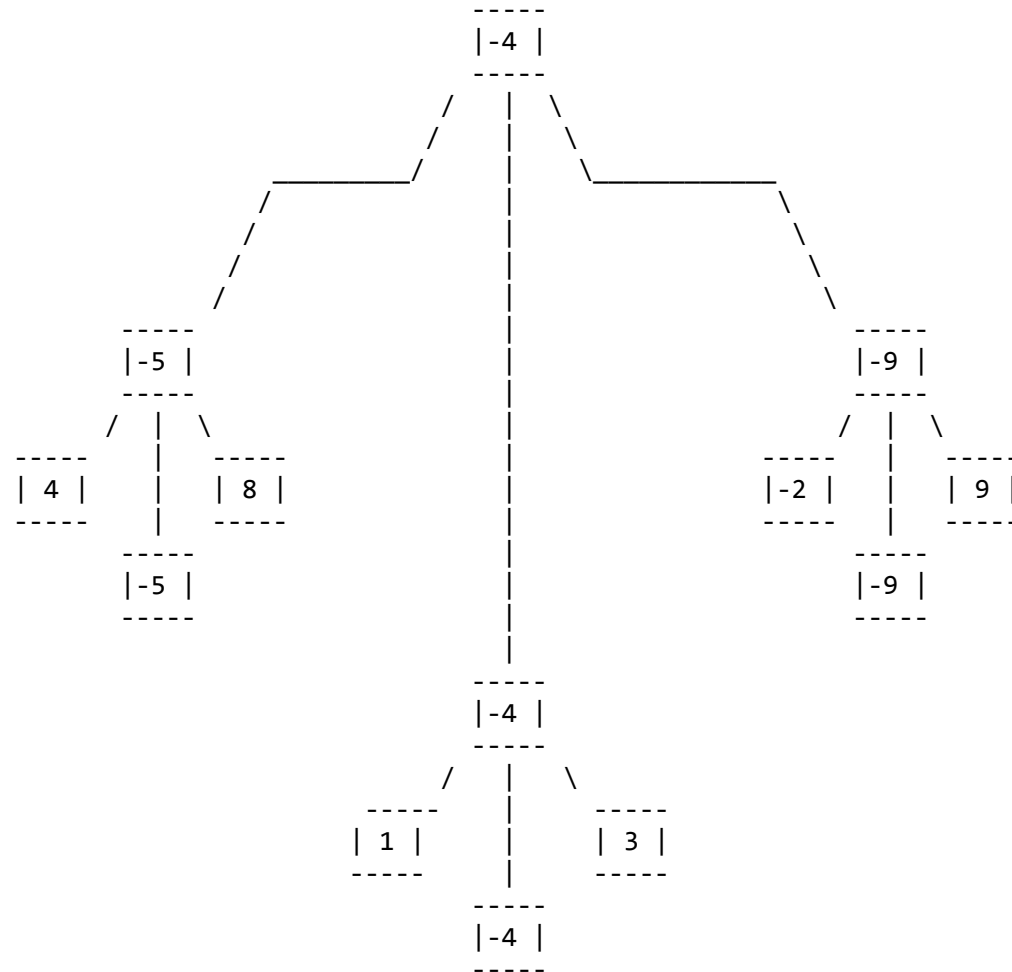
(b)

If you are at Node C and simulated annealing has randomly selected node D for consideration, what is the probability this node is accepted?

$$\begin{aligned} e^{((\text{score}(D) - \text{score}(C)) / \text{Temperature})} &= e^{((-5) - (-2)) / 100} \\ &= e^{-(3/100)} \\ &\approx 0.97044553354 \end{aligned}$$

4.

(a)



Rather than circle it I'll just call it out - the correct move for the maximizer would be to pick the middle arc, going to the intermediate node where I've put -4.

(b)

List one (1) leaf node in the above game tree whose SBE score need not be computed. Explain why.

One such node is the leaf node containing a positive 9.

While it would be great for the maximizer to achieve this value, once we evaluate the leaf node with a value of 9 that shares a parent, we know it won't be possible. If we label the node with value 9 X - the minimizer would choose either the -9

node or X if it turns out X's value is less than -9. Either way, the node in the parent that these two share comes out to at most -9. With this information, the maximizer wouldn't chose the parent no matter the value of X, so there's no need to calculate this node's value.