Artificial Intelligence

CS 165A
Feb 19, 2019

Instructor: Prof. Yu-Xiang Wang

→ Informed search
→ Adversarial search
Announcements

• MP1 due by midnight today.

• HW3 will be released on Thursday..
  – Mainly problems in Search.
  – Some problems in RL.

• We are grading the midterm.
  – Hopefully some statistics on Thursday.
# Summary table of uninformed search

<table>
<thead>
<tr>
<th>Criteria</th>
<th>BFS</th>
<th>Uniform-cost</th>
<th>DFS</th>
<th>Depth-limited</th>
<th>IDS</th>
<th>Bidirectional</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complete?</td>
<td>Yes#</td>
<td>Yes#&amp;</td>
<td>No</td>
<td>No</td>
<td>Yes#</td>
<td>Yes#+</td>
</tr>
<tr>
<td>Time</td>
<td>$O(b^d)$</td>
<td>$O(b^{1+[C/e]})$</td>
<td>$O(b^m)$</td>
<td>$O(b^l)$</td>
<td>$O(b^d)$</td>
<td>$O(b^{d/2})$</td>
</tr>
<tr>
<td>Space</td>
<td>$O(b^d)$</td>
<td>$O(b^{1+[C/e]})$</td>
<td>$O(bm)$</td>
<td>$O(bl)$</td>
<td>$O(bd)$</td>
<td>$O(b^{d/2})$</td>
</tr>
<tr>
<td>Optimal?</td>
<td>Yes$\S$</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes$\S$</td>
<td>Yes$\S+$</td>
</tr>
</tbody>
</table>

$b$: Branching factor
$d$: Depth of the shallowest goal
$l$: Depth limit
$m$: Maximum depth of search tree
$e$: The lower bound of the step cost

# Complete if $b$ is finite
#&: Complete if step cost $\geq e$
$\S$: Optimal if all step costs are identical
$\S+$: If both direction use BFS

(Section 3.4.7 in the AIMA book.)
Practical note about search algorithms

- The computer can’t “see” the search graph like we can
  - No “bird’s eye view” – make relevant information explicit!
- What information should you keep for a node in the search tree?
  - State
    - (1 2 0)
  - Parent node (or perhaps complete ancestry)
    - Node #3 (or, nodes 0, 2, 5, 11, 14)
  - Depth of the node
    - $d = 4$
  - Path cost up to (and including) the node
    - $g(node) = 12$
  - Operator that produced this node
    - Operator #1
Upcoming next

- Informed search

- Some questions / desiderata
  1. Can we do better with some side information?
  2. We do not wish to make strong assumptions on the side information.
  3. If the side information is good, we hope to do better.
  4. If the side information is useless, we perform as well as an uninformed search method.
Best-First Search (with an Eval-Fn)

function $\text{BEST-FIRST-SEARCH}(\text{problem, Eval-FN})$ returns a solution or failure
QUEUING-FN $\leftarrow$ a function that orders nodes by Eval-FN
return $\text{GENERAL-SEARCH}(\text{problem, QUEUING-FN})$

- Uses a heuristic function, $h(n)$, as the Eval-FN
- $h(n)$ estimates the cost of the best path from state $n$ to a goal state
  - $h(goals) = 0$
Greedy Best-First Search

• Greedy search – always expand the node that appears to be the closest to the goal (i.e., with the smallest $h$)
  – Instant gratification, hence “greedy”

```plaintext
function GREEDY-SEARCH(problem, h) returns a solution or failure
    return BEST-FIRST-SEARCH(problem, h)
```

• Greedy search often performs well, but:
  – It doesn’t always find the best solution / or any solution
  – It may get stuck
  – It performance completely depends on the particular $h$ function
A* Search (Pronounced “A-Star”)

• Uniform-cost search minimizes $g(n)$ (“past” cost)

• Greedy search minimizes $h(n)$ (“expected” or “future” cost)

• “A* Search” combines the two:
  – Minimize $f(n) = g(n) + h(n)$
  – Accounts for the “past” and the “future”
  – Estimates the cheapest solution (complete path) through node $n$

function $A^*$-SEARCH($problem$, $h$) returns a solution or failure
return BEST-FIRST-SEARCH($problem$, $f$)
A* Example

\[ f(n) = g(n) + h(n) \]
A* Example

```
f = 0 + 366 = 366

f = 75 + 374 = 449

f = 0 + 366 = 366

f = 75 + 374 = 449

f = 0 + 366 = 366
```

Oradea

Zerind

Sibiu

Timisoara

Fagaras

Arad

Rimnicu Vilcea
When does A* search “work”?

• Focus on optimality (finding the optimal solution)

• “A* Search” is optimal if $h$ is **admissible**
  - $h$ is optimistic – it never overestimates the cost to the goal
    • $h(n) \leq$ true cost to reach the goal
  - So $f(n)$ never overestimates the actual cost of the best solution passing through node $n$
Visualizing A* search

- A* expands nodes in order of increasing $f$ value
- Gradually adds "$f$-contours" of nodes
- Contour $i$ has all nodes with $f = f_i$, where $f_i < f_{i+1}$
Optimality of A* with an Admissible $h$

- Let OPT be the optimal path cost.
  - All non-goal nodes on this path have $f \leq$ OPT.
    - Positive costs on edges
      - The goal node on this path has $f =$ OPT.

- A* search does not stop until an $f$-value of OPT is reached.
  - All other goal nodes have an $f$ cost higher than OPT.

- All non-goal nodes on the optimal path are eventually expanded.
  - The optimal goal node is eventually placed on the priority queue, and reaches the front of the queue.
Optimal Efficiency of A*

A* is optimally efficient for any particular $h(n)$
That is, no other optimal algorithm is guaranteed to expand fewer nodes with the same $h(n)$.

(More about this in HW3.)

- Need to find a good and efficiently evaluable $h(n)$. 
A* Search with an Admissible $h$

- Optimal? Yes
- Complete? Yes
- Time complexity? Exponential; better under some conditions
- Space complexity? Exponential; keeps all nodes in memory
Recall: Graph Search vs Tree Search

• Tree Search
  – We might repeat some states
  – But we do not need to remember states

• Graph Search
  - We remember all the states that have been explored
  - But we do not repeat some states
Avoiding Repeated States using A* Search

- Is GRAPH-SEARCH optimal with A*?

Graph Search

Step 1: Among B, C, E, Choose C
Step 2: Among B, E, D, Choose B
Step 3: Among D, E, Choose E. (you are not going to select C again)

Try with TREE-SEARCH and GRAPH-SEARCH
Avoiding Repeated States using A* Search

- Is GRAPH-SEARCH optimal with A*?

Solution 1: Remember all paths: Need extra bookkeeping

Solution 2: Ensure that the first path to a node is the best!

Try with TREE-SEARCH and GRAPH-SEARCH
Consistency (Monotonicity) of heuristic $h$

- A heuristic is consistent (or monotonic) provided
  - for any node $n$, for any successor $n'$ generated by action $a$ with cost $c(n,a,n')$
    - $h(n) \leq c(n,a,n') + h(n')$
  - akin to triangle inequality.
  - guarantees admissibility (proof?).
  - values of $f(n)$ along any path are non-decreasing (proof?).
    - Contours of constant $f$ in the state space
- GRAPH-SEARCH using consistent $f(n)$ is optimal.
- Note that $h(n) = 0$ is consistent and admissible.
Memory Bounded Search

- Memory, not computation, is **usually** the limiting factor in search problems
  - Certainly true for A* search
- Why? What takes up memory in A* search?

- Solution: Memory-bounded A* search
  - Iterative Deepening A* (IDA*)
  - Simplified Memory-bounded A* (SMA*)
  - (Read the textbook for more details.)
Heuristics

• What’s a heuristic for
  – Driving distance (or time) from city A to city B?
  – 8-puzzle problem?
  – M&C?
  – Robot navigation?
  – Reaching the summit?

• **Admissible** heuristic
  – Does not overestimate the cost to reach the goal
  – “Optimistic”

• Are the above heuristics admissible? Consistent?
Example: 8-Puzzle

Start State

Goal State
Comparing and combining heuristics

- Heuristics generated by considering relaxed versions of a problem.
- Heuristic $h_1$ for 8-puzzle
  - Number of out-of-order tiles
- Heuristic $h_2$ for 8-puzzle
  - Sum of Manhattan distances of each tile
- $h_2$ dominates $h_1$ provided $h_2(n) \geq h_1(n)$.
  - $h_2$ will likely prune more than $h_1$.
- $\max(h_1, h_2, \ldots, h_n)$ is
  - admissible if each $h_i$ is
  - consistent if each $h_i$ is
- Cost of sub-problems and pattern databases
  - Cost for 4 specific tiles
  - Can these be added for disjoint sets of tiles?
Effective Branching Factor

- Though informed search methods may have poor worst-case performance, they often do quite well if the heuristic is good
  - Even if there is a huge branching factor

- One way to quantify the effectiveness of the heuristic: the effective branching factor, $b^*$
  - $N$: total number of nodes expanded
  - $d$: solution depth
  - $N = 1 + b^* + (b^*)^2 + \ldots + (b^*)^d$

- For a good heuristic, $b^*$ is close to 1
Example: 8-puzzle problem

Averaged over 100 trials each at different solution lengths

<table>
<thead>
<tr>
<th>$d$</th>
<th>IDS</th>
<th>$A^*(h_1)$</th>
<th>$A^*(h_2)$</th>
<th>$A^*(h_1)$</th>
<th>$A^*(h_2)$</th>
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<tr>
<td>2</td>
<td>10</td>
<td>6</td>
<td>6</td>
<td>2.45</td>
<td>1.79</td>
</tr>
<tr>
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<td>112</td>
<td>13</td>
<td>12</td>
<td>2.87</td>
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<td>2.80</td>
<td>1.33</td>
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<td>–</td>
<td>1301</td>
<td>211</td>
<td>–</td>
<td>1.45</td>
</tr>
<tr>
<td>18</td>
<td>–</td>
<td>3056</td>
<td>363</td>
<td>–</td>
<td>1.46</td>
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<td>20</td>
<td>–</td>
<td>7276</td>
<td>676</td>
<td>–</td>
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</tr>
<tr>
<td>22</td>
<td>–</td>
<td>18094</td>
<td>1219</td>
<td>–</td>
<td>1.48</td>
</tr>
<tr>
<td>24</td>
<td>–</td>
<td>39135</td>
<td>1641</td>
<td>–</td>
<td>1.48</td>
</tr>
</tbody>
</table>

Ave. # of nodes expanded

Solution length
Summary of informed search

- How to use a heuristic function to improve search
  - Greedy Best-first search + Uniform-cost search = A* Search

- When is A* search optimal?
  - h is Admissible (optimistic) for Tree Search
  - h is Consistent for Graph Search

- Choosing heuristic functions
  - A good heuristic function can reduce time/space cost of search by orders of magnitude.
  - Good heuristic function may take longer to evaluate.
Games and Adversarial Search

• Games: problem setup

• Minimax search

• Alpha-beta pruning
Game as a search problem

- $S_0$ The initial state
- PLAYER(s): Returns which player has the move
- ACTIONS(s): Returns the legal moves.
- RESULT(s, a): Output the state we transition to.
- TERMINAL-TEST(s): Returns True if the game is over.
- UTILITY(s, p): The payoff of player p at terminal state s.
Two-player, Perfect information, Deterministic, Zero-Sum Game

- Two-player: Tic-Tac-Toe, Chess, Go!
- Perfect information: The State is known to everyone
- Deterministic: Nothing is random
- Zero-sum: The total payoff for all players is a constant.

- The 8-puzzle is a one-player, perfect info, deterministic, zero-sum game.
- How about Monopoly?
- How about Starcraft?
Tic-Tac-Toe

- The first player is \textcolor{red}{X} and the second is \textcolor{green}{O}
- Object of game: get three of your symbol in a horizontal, vertical or diagonal row on a 3x3 game board
- \textcolor{red}{X} always goes first
- Players alternate placing \textcolor{red}{X}s and \textcolor{green}{O}s on the game board
- Game ends when a player has three in a row (a wins) or all nine squares are filled (a draw)

What’s the state, action, transition, payoff for Tic-Tac-Toe?
Partial game tree for Tic-Tac-Toe

- X’s turn
- O’s turn
- X’s turn
- O’s turn
- X’s turn
- X wins
Game trees

• A game tree is like a search tree in many ways …
  – nodes are search states, with full details about a position
    • characterize the arrangement of game pieces on the game board
  – edges between nodes correspond to moves
  – leaf nodes correspond to a set of goals
    • \{ win, lose, draw \}
    • usually determined by a score for or against player
  – at each node it is one or other player’s turn to move

• A game tree is not like a search tree because you have an opponent!
From this slide onwards

- Preview of the next lecture on Thursday
- Things that you will need to start on MP2
Two players: MIN and MAX

• In a zero-sum game:
  – payoff to Player 1 = - payoff to Player 2

• The goal of Player 1 is to maximizing her payoff.

• The goal of Player 2 is to maximizing her payoff as well
  – Equivalent to minimizing Player 1’s payoff.
Minimax search

• Assume that both players play perfectly
  – do not assume player will miss good moves or make mistakes

• Score(s): The score that MAX will get towards the end if both player play perfectly from $s$ onwards.

• Consider MIN’s strategy
  – MIN’s best strategy:
    • choose the move that minimizes the score that will result when MAX chooses the maximizing move
  – MAX does the opposite
Minimaxing

- Your opponent will choose smaller numbers
- If you move left, your opponent will choose 3
- If you move right, your opponent will choose -8
- Thus your choices are only 3 or -8
- You should move left
Minimax example

Which move to choose?

The minimax decision is move $A_1$
Another example

- In the game, it’s your move. Which move will the minimax algorithm choose – A, B, C, or D? What is the minimax value of the root node and nodes A, B, C, and D?
Minimax search

• The *minimax decision* maximizes the utility under the assumption that the opponent seeks to minimize it (if it uses the same evaluation function)

• Generate the tree of minimax values
  – Then choose best (maximum) move
  – Don’t need to keep all values around
    • Good memory property

• Depth-first search is used to implement minimax
  – Expand all the way down to leaf nodes
  – Recursive implementation
Minimax properties

• Optimal?
  Yes, against an optimal opponent, if the tree is finite

• Complete?
  Yes, if the tree is finite

• Time complexity?
  Exponential: $O\left( b^m \right)$

• Space complexity?
  Polynomial: $O\left( bm \right)$
But this could take forever…

- Exact search is intractable
  - Tic-Tac-Toe is $9! = 362,880$
  - For chess, $b \approx 35$ and $m \approx 100$ for “reasonable” games
  - Go is $361! \approx 10^{750}$

- Idea 1: Pruning

- Idea 2: Cut off early and use a heuristic function
Pruning

• What’s really needed is “smarter,” more efficient search
  – Don’t expand “dead-end” nodes!

• **Pruning** – eliminating a branch of the search tree from consideration

• **Alpha-beta pruning**, applied to a minimax tree, returns the same “best” move, while pruning away unnecessary branches
  – Many fewer nodes might be expanded
  – Hence, smaller effective branching factor
  – …and deeper search
  – …and better performance
  • Remember, minimax is *depth-first* search
Alpha pruning
Beta pruning

A

MIN

≤25

B

C

D

MAX

MIN

10

25

15

50

25
Improvements via alpha/beta pruning

- Depends on the ordering of expansion

- Perfect ordering $O(b^{m/2})$

- Random ordering $O(b^{3m/4})$

- For specific games like Chess, you can get to almost perfect ordering.
Heuristic function

• Rather, cut the search off early and apply a heuristic evaluation function to the leaves
  – $h(s)$ estimates the expected utility of the game from a given position (node/state) $s$

• The performance of a game-playing program depends on the quality (and speed!) of its evaluation function
Heuristics (Evaluation function)

• Typical evaluation function for game: weighted linear function
  - \( h(s) = w_1 f_1(s) + w_2 f_2(s) + \ldots + w_d f_d(s) \)
  - weights \cdot features [dot product]

• For example, in chess
  - \( W = \{ 1, 3, 3, 5, 8 \} \)
  - \( F = \{ \# \text{ pawns advantage}, \# \text{ bishops advantage}, \# \text{ knights advantage}, \# \text{ rooks advantage}, \# \text{ queens advantage} \} \)
  - Is this what Deep Blue used?
  - What are some problems with this?

• More complex evaluation functions may involve learning
  - Adjusting weights based on outcomes
  - Perhaps non-linear functions
  - How to choose the features?
Tic-Tac-Toe revisited

a partial game tree for Tic-Tac-Toe
Evaluation functions

• It is usually impossible to solve games completely
• This means we cannot search entire game tree
  – we have to cut off search at a certain depth
    • like depth bounded depth first, lose completeness
• Instead we have to estimate cost of internal nodes
• We do this using an evaluation function
  – evaluation functions are heuristics
• Explore game tree using combination of evaluation function and search
Evaluation function for Tic-Tac-Toe

• A simple evaluation function for Tic-Tac-Toe
  – count the number of rows where X can win
  – subtract the number of rows where O can win

• Value of evaluation function at start of game is zero
  – on an empty game board there are 8 possible winning rows for both X and O

\[ 8 - 8 = 0 \]
Evaluating Tic-Tac-Toe

evalX = (number of rows where X can win) − (number of rows where O can win)

- After X moves in center, score for X is +4
- After O moves, score for X is +2
- After X’s next move, score for X is +4

8-8 = 0  8-4 = 4  6-4 = 2  6-2 = 4
Evaluating Tic-Tac-Toe

evalO = (number of rows where O can win) - (number of rows where X can win)

- After X moves in center, score for O is -4
- After O moves, score for O is +2
- After X’s next move, score for O is -4

8-8 = 0  4-8 = -4  4-6 = -2  2-6 = -4
Search depth cutoff

Tic-Tac-Toe with search depth 2

Evaluations shown for X