CSCI 5582
Artificial Intelligence

Lecture 5
Jim Martin

Today 9/12

- Review informed searches
- Start on local, iterative improvement search

Review

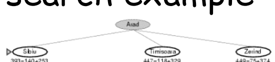
- How is the agenda ordered in the following searches?
  - Uniform Cost
  - Best First
  - A*
  - IDA*

Review: A* search

- Idea: avoid expanding paths that are already expensive
- Evaluation function $f(n) = g(n) + h(n)$
- $g(n)$ = cost so far to reach n
- $h(n)$ = estimated cost from n to goal
- $f(n)$ = estimated total cost of path through n to goal

A* search example

A* search example



A^* search example

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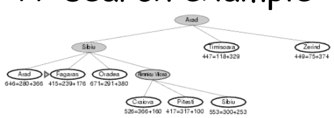
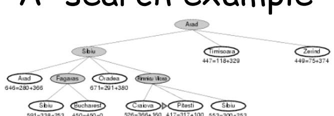
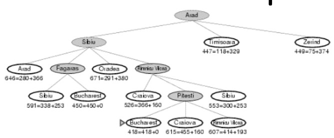


A^* search example



A* search example



Remaining Search Types

- Recall we have…
  - Backtracking state-space search
  - Optimization search
  - Constraint satisfaction search

Optimization

- Sometimes referred to as iterative improvement or local search.
- We'll talk about three simple but effective techniques:
  - Hillclimbing
  - Random Restart Hillclimbing
  - Simulated Annealing

Optimization Framework

- Working with 1 state in memory
  - No agenda/queue/fringe…
    - Usually
- Usually generating new states from this 1 state in an attempt to improve things
- Goal notion is slightly different
  - Normally solutions are easy to find
  - We can compare solutions and say one is better than another
  - Goal is usually an optimization of some function of the "solution" (cost).

Numerical Optimization

- We're not going to consider numerical optimization approaches…
- The approaches we're considering here don't have well-defined objective functions that can be used to do traditional optimization.
- But the techniques used are related

Hill-climbing Search

- Generate nearby successor states to the current state based on some knowledge of the problem.
- Pick the best of the bunch and replace the current state with that one.
- Loop (until?)

Hill-Climbing Search

function HILL-CLIMBING(problem) **return** a state that is a local maximum
input: problem, a problem
local variables: current, a node.
neighbor, a node.

current ← MAKE-NODE(INITIAL-STATE[problem])
loop do
neighbor ← a highest valued successor of current
if VALUE [neighbor] ≤ VALUE[current] **then return** STATE[current]
current ← neighbor

Hill-climbing

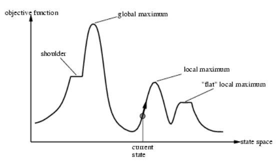
- Implicit in this scheme is the notion of a *neighborhood* that in some way preserves the cost behavior of the solution space…
  - Think about the TSP problem again
  - If I have a current tour what would a neighboring tour look like?
    - This is a way of asking for a successor function.

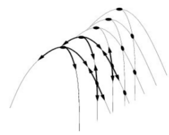
Hill-climbing Search

- The successor function is where the intelligence lies in hill-climbing search
- It has to be conservative enough to preserve significant “good” portions of the current solution
- And liberal enough to allow the state space to be preserved without degenerating into a random walk

Hill-climbing search

- Problem: depending on initial state, can get stuck in various ways





Break

- Questions?
- Python problems?
- My office hours are now
  - Tuesday 2 to 3:30
  - Thursday 12:30 to 2
- Go to cua.colorado.edu to view lectures (Windows and IE only)

Quiz Alert

- The first quiz is on 9/21 (A week from Thursday)
- It will cover Chapters 3 to 6
  - I'll post a list of sections to pay close attention to
- I'll post some past quizzes soon (remind me by email)

Local Maxima (Minima)

- Hill-climbing is subject to getting stuck in a variety of local conditions…
- Two solutions
  - Random restart hill-climbing
  - Simulated annealing

Random Restart Hillclimbing

- Pretty obvious what this is….
  - Generate a random start state
  - Run hill-climbing and store answer
  - Iterate, keeping the current best answer as you go
  - Stopping… when?
- Give me an optimality proof for it.

Annealing

- Based on a metallurgical metaphor
  - Start with a temperature set very high and slowly reduce it.
  - Run hillclimbing with the twist that you can occasionally replace the current state with a worse state based on the current temperature and how much worse the new state is.

Annealing

- More formally…
  - Generate a new neighbor from current state.
  - If it's better take it.
  - If it's worse then take it with some probability proportional to the temperature and the delta between the new and old states.

Simulated annealing

```
function SIMULATED-ANNEALING( problem, schedule) return a solution state
    input: problem, a problem
           schedule, a mapping from time to temperature
    local variables: current, a node.
                     next, a node.
                     T, a "temperature" controlling the probability of downward steps

    current ← MAKE-NODE(INITIAL-STATE[problem])
    for t ← 1 to ∞ do
           T ← schedule[t]
           if T = 0 then return current
           next ← a randomly selected successor of current
           ΔE ← VALUE[next] - VALUE[current]
           if ΔE > 0 then current ← next
           else current ← next only with probability e^(ΔE /T)
```


Properties of simulated annealing search

- One can prove: If *T* decreases slowly enough, then simulated annealing search will find a global optimum with probability approaching 1
- Widely used in VLSI layout, airline scheduling, etc

Coming Up

- Thursday: Constraint satisfaction (Chapter 5)
- Tuesday: Game playing (Chapter 6)
- Thursday: Quiz