Artificial Intelligence 1

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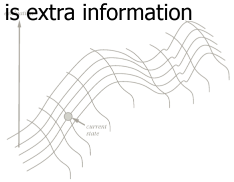
Problem Solving: Local and On-line Search Techniques

Introduction

- We know how to use **heuristics in search**
  - BFS, A*, IDA*, RBFS, SMA*
- **Today**:
  - **What if the path is not important?**
    - Local search: HC, SA, BS, GA
  - **What if the world changes?**
    - on-line search, LRTA*

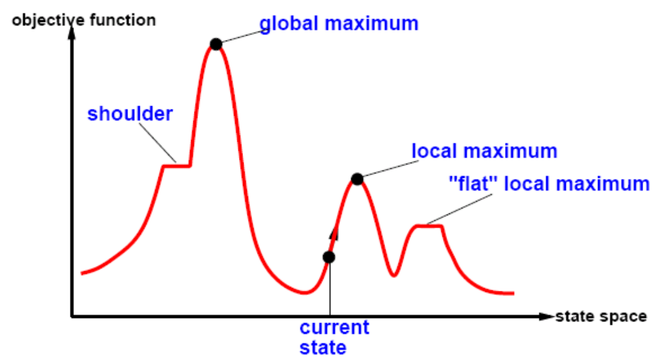
Local search

- So far we systematically explored all paths possibly going to the goal and the path itself was a part of the solution.
- For some problems (e.g. 8-queens) the path is not relevant to the problem, only the goal is important.
- For such problems we can try **local search** techniques.
  - we also keep a single state only (constant memory)
  - in each step we slightly modify the state
  - usually, the path is not stored
  - the method can also look for an **optimal state**, where the optimality is defined by an objective function (defined for states).
    - For example, for the 8-queens problem the objective function can be defined by the number of conflicting queens– this is extra information about the quality of states.



Local search - terminology

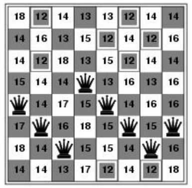
- Local search can be seen as a move in the state-space **landscape**, where coordinates define the state and elevation corresponds to the objective function.



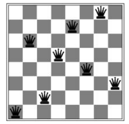
- From the neighboorhood the algorithm selects the state with the best value of the objective function and moves there (**hill climbing**).
  - knows only the neighborhood
  - the current state is forgotten

```
function HILL-CLIMBING(problem) returns a state that is a local maximum
   inputs: 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
```

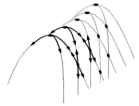
- **# conflicts = 17**
- **state change = change row of a queen**
- **random selection among more best neighbours**



HC is a **greedy algorithm** – goes to the best neighbour with looking ahead



- **local optimum** (the state such that each neighbour is not better)
  - HC cannot escape local optimum
- **ridges** (a sequence of local optima)
  - difficult for greedy algorithms to navigate

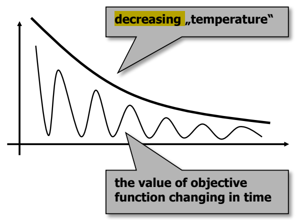


- **plateaux** (a flat area of the state-space landscape)
  - shoulder – progress is still possible
  - HC may not find a solution (cycling)

- **stochastic HC**
  - chooses at random from among the uphill moves; the probability of selection can vary with the steepness of the uphill move
  - usually converges more slowly than steepest ascent
  - in some landscapes, it finds better solutions
- **first-choice HC**
  - implements stochastic HC until a successor better than the current state is generated
  - a good strategy when a state has many (thousands) of successors
- **random-restart HC**
  - conducts a series of HC searches from randomly generated initial states (restart)
  - can escape from a local optimum
  - if HC has a probability p of success then the expected number of restarts required is 1/p
  - a very efficient method for the N-queens problem (p ≈ 0.14 i.e. 7 iterations to find a goal)

- **HC** never makes the "downhill" moves towards states with lower value so the algorithm is not complete (can get stuck on a local optimum).
- **Random walk** – that is moving to a successor chosen randomly – is complete but extremely inefficient.
- **Simulated annealing** combines hill climbing with random walk
  - motivation in metallurgy – process to harden metals by heating them to a high temperature and then gradually cooling them (allowing the material to reach a low-energy crystalline state
  - the algorithm picks a random move and accepts it if:
    - it improves the situation
    - it worsens the situation but this is allowed with a probability given by some temperature value and how much the state worsens; the temperature is decreasing according to a **cooling scheme**

```
function SIMULATED-ANNEALING(problem, schedule) returns a solution state
   inputs: problem, a problem
           schedule, a mapping from time to "temperature"
   local variables: current, a node
                    next, a node
                    T, a "temperature" controlling prob. 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^(Δ E/T)
```



Local beam search

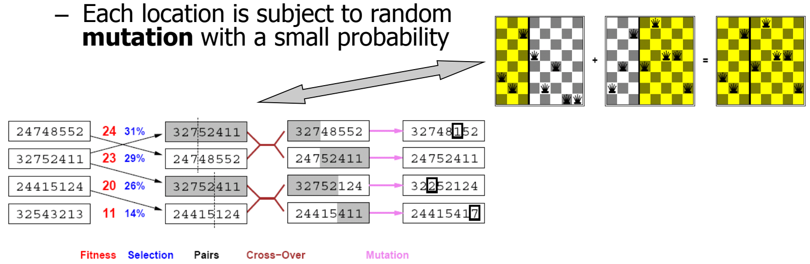
Keeping just one node in memory might seem to be an extreme reaction to the problem of memory limitations.

Can we exploit available memory better?

- **Local beam search** algorithm
  - keeps track of *k* states rather than just one
  - at each step, all the successors of all *k* states are generated
    - if any one is a goal, the algorithm halts
  - otherwise, it selects the *k* best successors and repeats
- **This is not running *k* restarts of HC in parallel!**
  - useful information is passed among the parallel search threads
  - The algorithm quickly abandons unfruitful searches and moves its resources to where the most is being made
  - can suffer from a lack of diversity
    - stochastic beam search helps alleviate this problem (*k* successors are chosen at random with the probability being an increasing function of state value)
    - resemble the process of natural selection

Genetic algorithms

- A variant of stochastic beam search in which successors are generated by combing two parent states (sexual reproduction)
  - Begin with a set of *k* randomly generated states – **population**
    - Each state is represented as a string over a finite alphabet (DNA)
    - **fitness** function evaluates the states (objective function)
  - Select a pair of states for reproduction (probability of selection is given by the fitness function)
  - For each pair choose a **crossover** point from the positions in the string
  - Combine **offsprings** to a new state
  - Each location is subject to random **mutation** with a small probability



Genetic algorithm

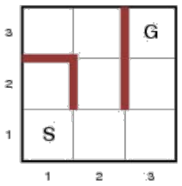
```
function GENETIC-ALGORITHM(population, FITNESS-FN) returns an individual
  inputs: population, a set of individuals
          FITNESS-FN, a function that measures the fitness of an individual

  repeat
     new_population ← empty set
     loop for i from 1 to SIZE(population) do
        x ← RANDOM-SELECTION(population, FITNESS-FN)
        y ← RANDOM-SELECTION(population, FITNESS-FN)
        child ← REPRODUCE(x, y)
        if (small random probability) then child ← MUTATE(child)
        add child to new_population
     population ← new_population
  until some individual is fit enough, or enough time has elapsed
  return the best individual in population, according to FITNESS-FN

function REPRODUCE(x, y) returns an individual
  inputs: x, y, parent individuals

  n ← LENGTH(x)
  c ← random number from 1 to n
  return APPEND(SUBSTRING(x, 1, c), SUBSTRING(y, c + 1, n))
```

Offline vs. online

- So far we have concentrated on **offline search**
  - compute a complete solution
  - then execute the solution without assuming percepts
- **Online search** is different in
  - interleave computation and action
    - select an action
    - execute an action
    - observe the environment
    - compute the next action
  - a good idea in dynamic and semidynamic environments
  - helpful in nondeterministic domains (unknown actions and unknown results of actions)

On-line search

- Online search is useful **for agents executing actions** (useless for pure computation).
- The agent knows only the following **information**:
  - **Actions(s)** – a list of actions allowed in state *s*
  - **c(s,a,s')** – the step cost function (cannot be used until the agent knows state s')
  - **Goal-Test(s)** – identifying the goal state
- We assume the following:
  - agent can **recognize a visited state**
  - (agent can build a world map)
  - actions are deterministic
  - agent has an **admissible heuristic** h(s)



Evaluating on-line algorithms

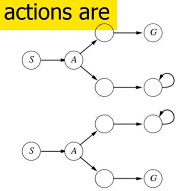
Quality of online algorithms can be measured by **comparing with the offline solution** (knowing the best solution in advance).

- **Competitive ratio**
  = quality if online solution / quality of the best solution
  - can be ∞, for example for a **dead**-end state (if some actions are **irreversible**).

Claim: No algorithm can avoid dead ends in all state spaces.

Proof (adversary argument)

Agent has visited states S and A must make the same decision in both, but in one situation, the agent reaches dead-end.



Assume that the state space is **safely explorable** (some goal state is reachable from every reachable state).

- No bounded competitive ratio can be guaranteed if there are paths of unbounded cost.
- Adversary argument can be used to arbitrarily extend any path.

Hence it is common to describe the performance of online search algorithms in **terms of the size of the entire state space** rather than just the depth of the shallowest goal.

Online DFS

- Opposite to offline algorithms such as A* online algorithms can discover **successors only** for a node that the agent physically occupies.
- It seems better to expand nodes in a **local order** as done for example by DFS.

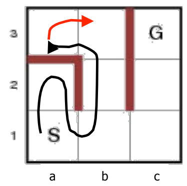
```
function ONLINE-DFS-AGENT(s') returns an action
   inputs: s', a percept that identifies the current state
   static: result, a table, indexed by action and state, initially empty
           unexplored, a table that lists, for each visited state, the actions not yet tried
           unbacktracked, a table that lists, for each visited state, the backtracks not yet tried
           s, a, the previous state and action, initially null

   if GOAL-TEST(s') then return stop
   if s' is a new state then unexplored[s'] ← ACTIONS(s')
   if s is not null then do
      result[a, s] ← s'
      add s to the front of unbacktracked[s']
   if unexplored[s'] is empty then
      if unbacktracked[s'] is empty then return stop
      else a ← an action b such that result[b, s'] = POP(unbacktracked[s'])
   else a ← POP(unexplored[s'])
   s ← s'
   return a
```

learns outcome of actions

The state can be visited more times in a single journey (it is leaved to different states) so we need to remember where to go back – **Ariadna thread**

to go back we need a reverse action to the actions used to reach the state

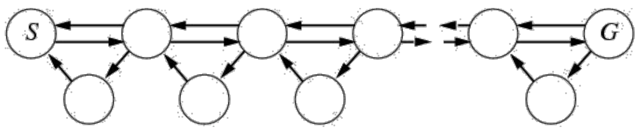
Online DFS



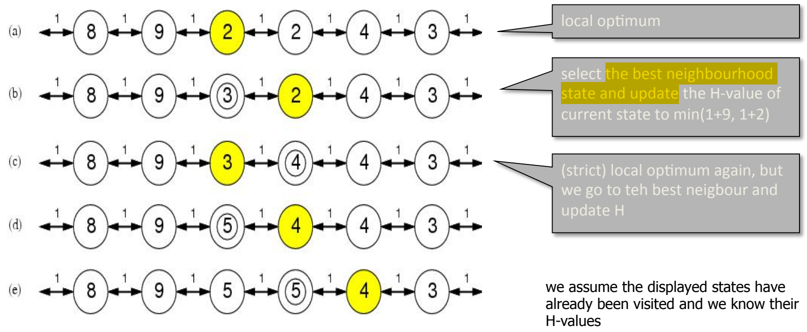
stav	unEX	unBT	rUP	rDN	rLF	rRG
(1,a)	{}	(2,a)	(2,a)	-	-	(1,b)
(2,a)	{}	(1,a)	-	(1,a)	-	-
(1,b)	LF,RG	(1,a)	(2,b)	-		
(2,b)	DW	(1,b)	(3,b)		-	-
(3,b)	DW	(3,a), (2,b)	-		(3,a)	-
(3,a)		(3,b)	-	-	-	(3,b)

- In the worst case, every link is traversed exactly twice (forward and backward).
- This is optimal for exploration, but for finding a goal, the agent's competitive ratio could be arbitrarily bad.
  - an online variant of iterative deepening solves this problem
- On-line DFS works only in state spaces where **actions are reversible**.

- **Hill climbing is an on-line algorithm.**
  - keeps a **single state** (the current physical state)
  - does **local steps** to the neighbouring states
  - in its simplest form **cannot escape local optima**
    - Beware! **Restarts cannot be used in online search!**
    - We can still use **random work**.
      - A random walk will **eventually find a goal** or complete its exploration, provided that the space is finite.
      - The process **can be very slow**.
      - In the following example, a random walk will take exponentially many steps to find the goal (at each step, backward progress is twice as likely as forward progress).



- We can exploit available memory to remember visited states and hence leave local optima.
  - **H(s)** – the current best estimate of path length from *s* to the goal (equals h(s) at the beginning)



- Algorithm LRTA* makes local steps and learns the result of each action as well as a better estimate of distance to the goal (H).

```
function LRTA*-AGENT(s') returns an action
  inputs: s', a percept that identifies the current state
  static: result, a table, indexed by action and state, initially empty
          H, a table of cost estimates indexed by state, initially empty
          s, a, the previous state and action, initially null

  if GOAL-TEST(s') then return stop
  if s' is a new state (not in H) then H[s'] ← h(s')
  unless s is null
      result[a, s] ← s'
      H[s] ←     min      LRTA*-COST(s, b, result[b, s], H)
             b∈ ACTIONS(s)
  a ← an action b in ACTIONS(s') that minimizes LRTA*-COST(s', b, result[b, s'], H)
  s ← s'
  return a

function LRTA*-COST(s, a, s', H) returns a cost estimate
  if s' is undefined then return h(s)
  else return c(s, a, s') + H[s']
```

improve the h-function in the previous state

select the next action with the best cost cile (can also go back); prefer not-yet explored states

if the action has not been applied yet, we optimistically assume that it leads to state with the best cost, i.e. h(s)

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