Online search algorithms

CS4881 Artificial Intelligence

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Outline

- Online search
- Exploratory search
- Sample applications
- Online search problems
- Online-DFS-Agent
- Online local search
- Random walk
- LTRA*

Online search

- We have concentrated on agents that use offline search algorithms.
  - They compute a complete solution before setting foot in the real world.
  - Then execute the solution without recourse of their percepts.
  - Talk about analysis paralysis!

- In contrast, an online search agent operates by interleaving computation and action.
  - First it takes an action
  - Then it observes the environment and computes the next action.

In what types of environments is online search required?

Online search

- *Online search* is a good idea in dynamic or semidynamic domains –
  - Domains where there is a penalty for sitting around and computing too long.

- *Online search* is an even better idea for stochastic domains – *think taxi cab agent!*

- In general, *offline search* would need to come up with an *exponentially* large contingency plan that considers all possible happenings.

- *Online search* need only consider what actually *does* happen. Example:
  - A chess playing agent is well advised to make its first move long before it has figured out the complete course of the game. *Why?*

Exploratory Search

- Online search is necessary for any *exploration* problem.
- States and actions are *unknown* to the agent.
- An agent in this state of *ignorance* must use its actions as experiments to determine what to do next.
- Requires agent to interleave *computation and action*.
- *Exploration and exploitation as the agent build a model.*
- Discovery of how the world works, is in part, an *online search process*.

Sample Problems

Examples:

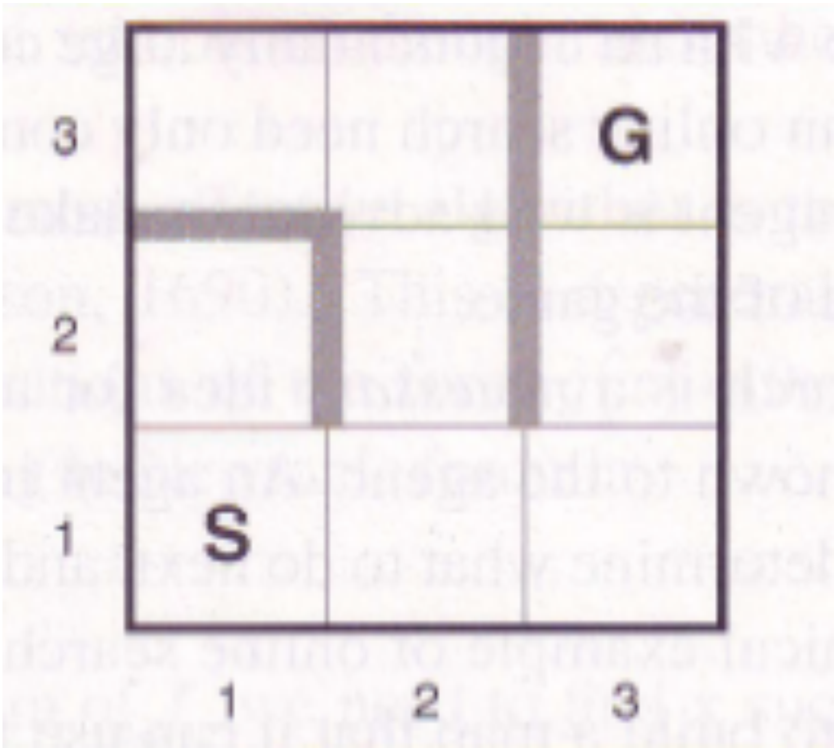
- Robot that is placed in a new building and must explore it to build a map that it can use for getting from A to B.
- Methods for escaping from labyrinths!
- Web search agent builds knowledge and structure of the problem as it explores environment to achieve desired goal, receives feedback from user (relevance feedback).
- Newborn exploring their environment:
  - Has many actions, does not know outcomes of actions, and has experience in only a few of the possible states it can reach.
- Model for human language acquisition.
- Adaptive ML for dynamic sensor data.

Online Search Problems

- Online search problem can be solved *only* by an agent executing actions, rather than by a purely computational process.
- Assume agent knows the following:
  - *ACTIONS(s),* which returns a list of actions allowed in state *s*.
  - The *step-cost* function *c(s, a, s').*
    - Note: can not be used until agent knows s'.
  - *GOAL-TEST(s).*

Online Search Problems

- Agent cannot access the successors of a state except by actually trying all the actions in the state.
- In *maze* problem, agent does not know that going *Up* from (1,1) leads to (1,2).
- *Ignorance can be reduced* – robot explorer might know how its movement actions work, but may be ignorant of the location of obstacles.



Online Search Problems

Assumptions:

- Agent can recognize state it has visited before.
- Actions are *deterministic*.
- Agent may have access to admissible heuristic *h(s).*
- Agent's objective is to *reach goal state while minimizing cost.*
- Cost is the *total path cost* agent travels.

Online Search Problems

- Common to compare online path cost with the cost of the path the agent would take if it knew the search space in advance.
  - Just plug in an informed search algorithm.
  - Known as *“competitive ratio”*

- *In a worst-case scenario what is the best competitive ratio you can achieve?*
- *In what circumstances would this occur?*

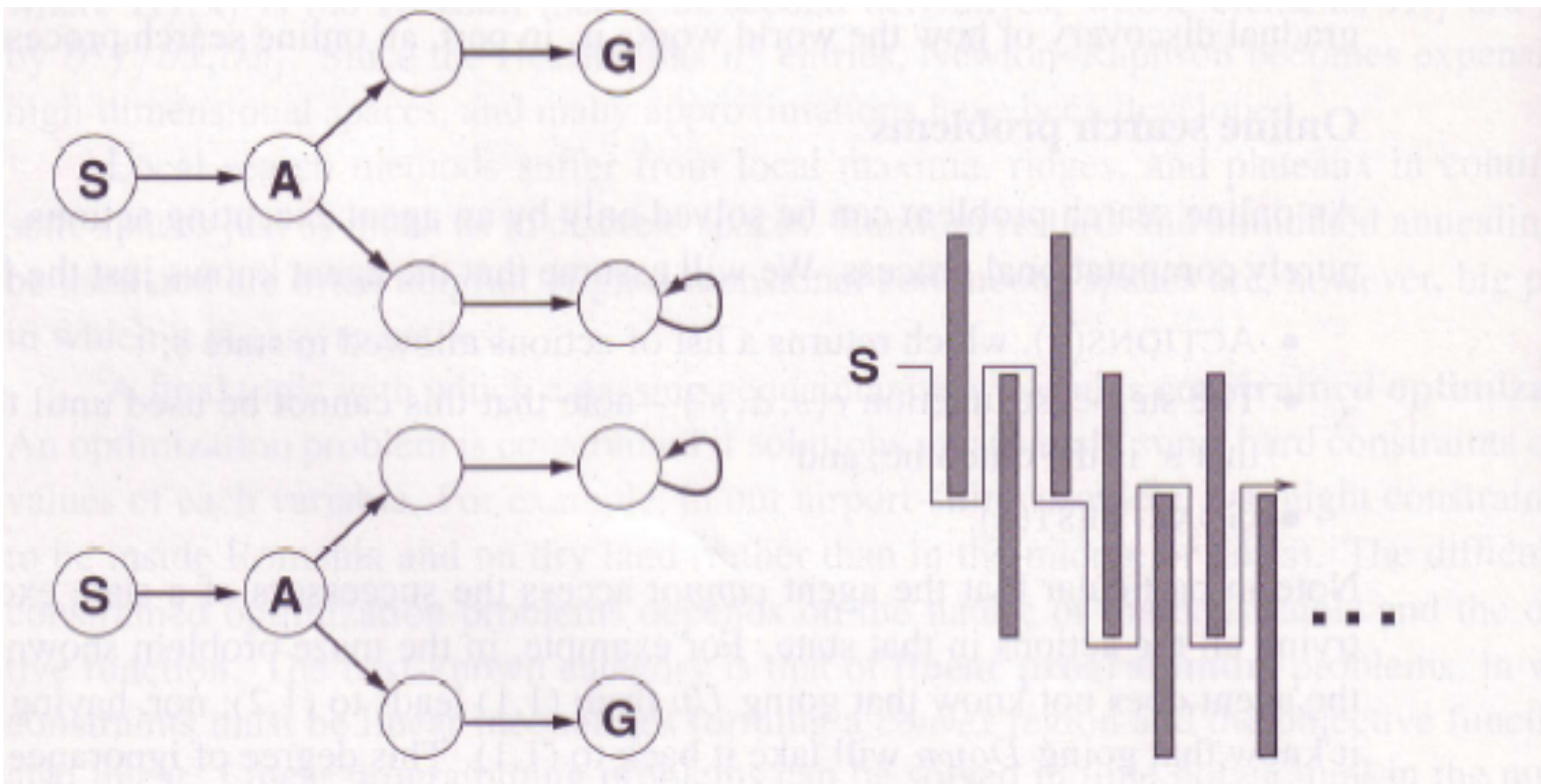
Online Search Problems

- Worst case competitive ratio can be infinite.
  - Some actions can be *irreversible* – can reach dead-end state from which goal state is unreachable.
- Claim:
  - *No algorithm can avoid dead ends in all state spaces.*
- Adversary argument:
  - Imagine an adversary that constructs the state space while the agent explores it and can put the goals and dead ends wherever it likes.
  - *Major research problem in natural terrain robotics – staircases, cliffs, ramps.*

- ***For now we assume state space is safely explorable and reversible.***

Online Search Problems

a) ***State space that can lead to dead end***
b) ***Adversary blocks route to goal with wall in 2D environment.***



(a) (b)

Online search agent

- After each *action*, agent receives *percept* (feedback) defining *state* reached.
- Agent augments it's *map of the environment* with this information.
- Current map is used to decide where to go next.
- Online agent can *only expand a node it occupies* –
  - Can't just jump around a search tree like A* informed search.
  - Better to expand nodes in local order – depth-first search.

Online Search Problems

```
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
```

LRTA*-AGENT selects an action according to the value of neighboring states, which are updated as the agent moves about the state space.

```
function ONLINE-DFS-AGENT(s') returns an action
   inputs: s', a percept that identifies the current state
   persistent: result, a table, indexed by state and action, initially empty
            untried, a table that lists, for each state, the actions not yet tried
            unbacktracked, a table that lists, for each 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 (not in untried) then untried[s'] <- ACTIONS(s')
   if s is not null then
      result[s, a] <- s'
      add s to the front of the unbacktracked[s']
   if untried[s'] is empty then
      if unbacktracked[s'] is empty then return stop
      else a <- an action b such that result[s', b] = POP(unbacktracked[s'])
   else a <- POP(untried[s'])
   s <- s'
   return a
```

Online-DFS-Agent

- Trace through maze problem with Online-DFS-Agent.
  - *How many links* in state-space will *Online-DFS-Agent* visit for worst case scenario in reaching it's goal?
  - Will *Online-DFS-Agent* work in environments where actions are irreversible?
  - Do any such agents have a *bounded* competitive ratio?

Online-Local Search

- Like *depth-first search*, *local hill-climbing search* has the property of *locality* in its node expansions.
  - Unfortunately, it can easily leave agent at *local maxima*.
  - Random restart does not work, since *agent can't teleport itself to remote node in search space*.

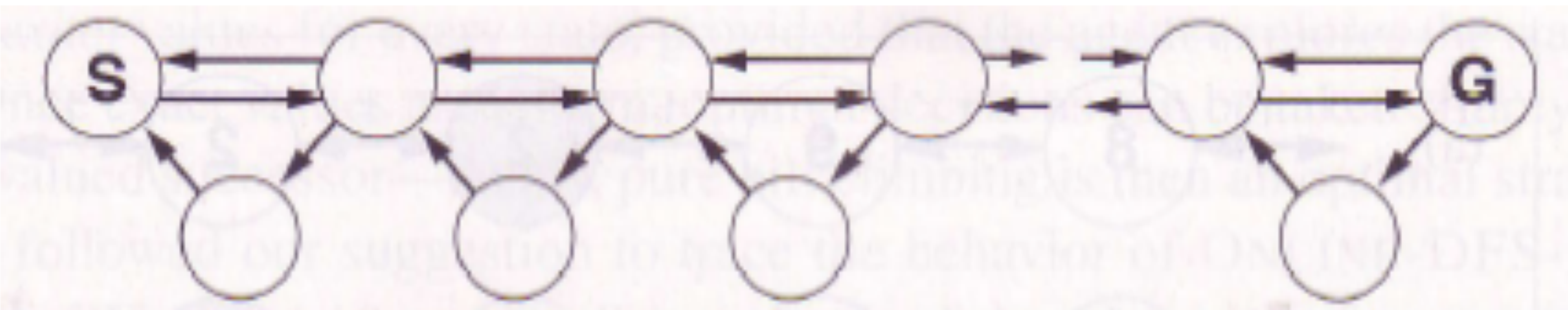
Random Walk

- Random walk *randomly selects one of the available actions* from the current state.
- Preferences can be given to actions that have not yet been tried.
- Random walk will *eventually* find a goal or complete its exploration if state-space is *finite**.
- Can be very slow, can be surprisingly fast.

**Infinite case is tricky: Complete in 1D & 2D, chance of 0.3405 in 3D – see Hughes 1995.*

Random Walk

- Environment where random walk will take exponential many states to the goal. *Why?*



Random Walk

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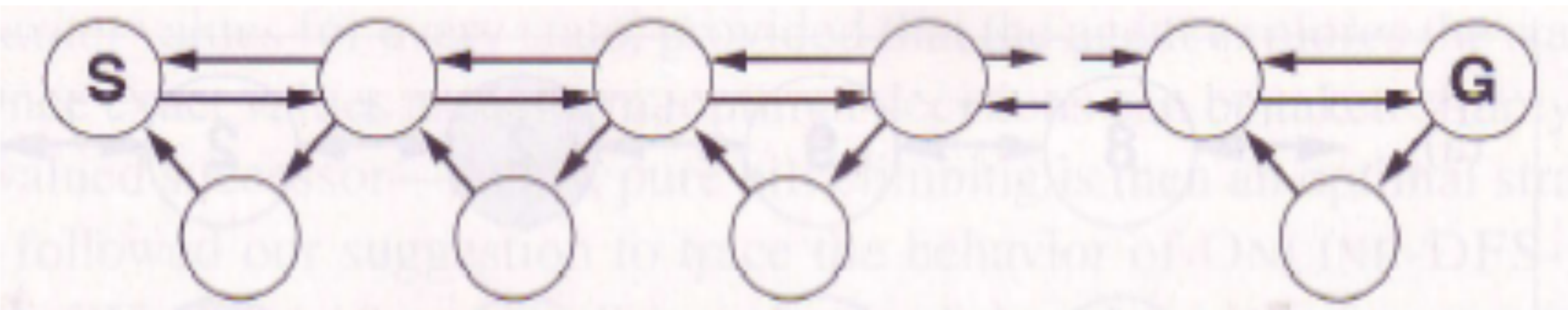


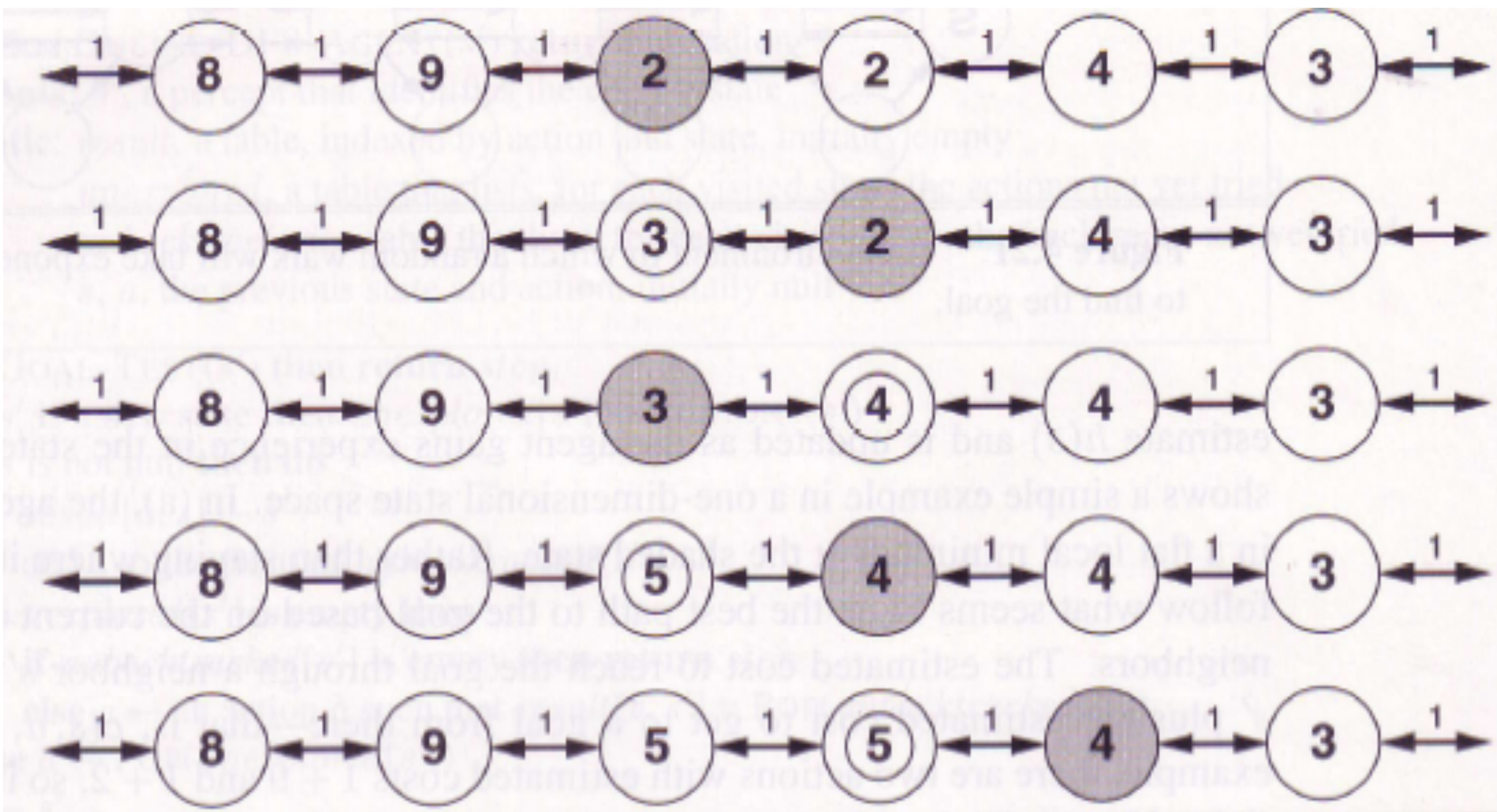
- *At each step, backward progress twice as likely as forward progress.*

*Learning realtime A**

- Augmenting *hill climbing* with *memory* rather than randomness is more effective.
- Idea: store current best estimate *h(s)* of the cost to reach goal.
- Heuristic estimate *h(s)* updated as agent gains experience in the state-space.
- Cost to reach goal through a neighbor *s'* is cost to get to *s'* + estimated cost to goal – $c(s, a, s') + H(s')$.
- Called *learning realtime A* (LTRA*)*

*Learning realtime A**

LRTA*-AGENT selects an action according to the value of neighboring states, which are updated as the agent moves about the state space.



LRTA*-AGENT selects an action according to the value of neighboring states, which are updated as the agent moves about the state space.

```
function LRTA*-AGENT(s') returns an action
    inputs: s', a percept that identifies the current state
    persistent: result, a table, indexed by state and action, 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')
    if s is not null
      result[s, a] <- s'
      H[s] <-       min LRTA*-COST(s, b, result[s, b], H)
               b (element of) ACTIONS(s)
    a <- an action b in ACTIONS(s') that minimizes LRTA*-COST(s', b, result[s', b], 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']
```

Summary

- Exploration problems arise when the *agent has no idea about the states and actions of its environments*.
- For safely explorable environments, online search agents can *build a map* and *find a goal **if*** it exists.
- *Updating heuristic estimates* from *experience* provides an effective method to escape from local minima.

Summary

- Many opportunities for learning:
  - Agent learns map of environment
  - Learn more accurate estimates of the value of a state.
  - Would be nice if agent could develop general rules it learned from exploring one state space to a similar state space, e.g., what does *up* mean?
  - More fun ahead!