#NIPS2018 The main conference sold out in 11 minutes 38 seconds

9/4/18, 12:17 PM

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Jason Yosinski @jasonyo · 4h
Replying to @NipsConference
About three times faster. Oh, sorry, I must have misheard; I thought you asked how much faster #NIPS2018 sold out than #burningman2018.
Intelligent Agents, Search Problem Formulation and Uninformed Search

AIMA, Chapters 2, 3.1-3.2
Outline for today’s lecture

• Intelligent Agents (AIMA 2.1-2)

• Task Environments

• Formulating Search Problems

• Uninformed Search (AIMA 3.1-3.4)
Review: What is AI?

Views of AI fall into four categories:

<table>
<thead>
<tr>
<th>Thinking humanly</th>
<th>Thinking rationally</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acting humanly</td>
<td>Acting rationally</td>
</tr>
</tbody>
</table>

We will focus on "acting rationally"
Review: Acting rationally: rational agents

- **Rational** behavior: doing the right thing

- The right thing: that which is *expected to maximize goal achievement, given the available information*

- **Rational agent**: An agent is an entity that perceives and acts rationally

This course is about *effective programming techniques* for designing *rational agents*
• An agent is anything that perceives its environment through sensors and can act on its environment through actuators.

• A percept is the agent’s perceptual inputs at any given instance.
Agents and environments

- An agent is specified by an **agent function** \( f : P \rightarrow a \) that maps a sequence of percept vectors \( P \) to an action \( a \) from a set \( A \):

\[
P = [p_0, p_1, \ldots, p_t]
\]
\[
A = \{a_0, a_1, \ldots, a_k\}
\]
Agents

- An *agent* is anything that can be viewed as
  - *perceiving* its *environment* through *sensors* and
  - *acting* upon that environment through *actuators*

- **Human agent:**
  - Sensors: eyes, ears, ...
  - Actuators: hands, legs, mouth, ...

- **Robotic agent:**
  - Sensors: cameras and infrared range finders
  - Actuators: various motors

- **Agents include humans, robots, softbots, thermostats, ...**
Agent function & program

- The *agent program* runs on the physical *architecture* to produce $f$
  - $agent = architecture + program$

- “Easy” solution: table that maps every possible sequence $P$ to an action $a$
  - One small problem: exponential in length of $P$
Rational agents

- **Rational Agent**: For each possible percept sequence $P$, a rational agent selects an action $a$ to **maximize its performance measure**

- **Performance measure**: An objective criterion for success of an agent's behavior, given the evidence provided by the percept sequence.
Performance measure - example

- A performance measure for a vacuum-cleaner agent might include e.g. some subset of:
  - +1 point for each clean square in time T
  - +1 point for clean square, -1 for each move
  - -1000 for more than $k$ dirty squares
Rationality is *not* omniscience

- Ideal agent: maximizes *actual* performance, but needs to be *omniscient*.
  - Usually impossible…..
    - But consider tic-tac-toe agent…
  - Rationality ≠ Guaranteed Success

- Caveat: *computational limitations make complete rationality unachievable*
  - design best *program* for given machine resources

- In Economics:
  “Bounded Rationality” → “Behavioral Economics”
Rational agents 2

- **Rational Agent**: For each possible percept sequence $P$, a rational agent selects an action $a$ to *maximize its performance measure*

- **Performance measure**: An objective criterion for success of an agent's behavior, given the evidence provided by the percept sequence.

Revised:

- **Rational Agent**: For the current percept sequence $P$, a rational agent selects an action $a$ that *maximizes the expected value of its performance measure*
Outline for today’s lecture

- Intelligent Agents

- *Task Environments (AIMA 2.3)*

- Formulating Search Problems
Task environments

- To design a rational agent we need to specify a *task environment*
  - a problem specification for which the agent is a solution

- **PEAS**: to specify a task environment
  - *Performance measure*
  - *Environment*
  - *Actuators*
  - *Sensors*
**PEAS: Specifying an automated taxi driver**

**Performance measure:**
- ?

**Environment:**
- ?

**Actuators:**
- ?

**Sensors:**
- ?
**PEAS: Specifying an automated taxi driver**

- **Performance measure:**
  - safe, fast, legal, comfortable, maximize profits

- **Environment:**
  - roads, other traffic, pedestrians, customers

- **Actuators:**
  - steering, accelerator, brake, signal, horn

- **Sensors:**
  - cameras, LiDAR, speedometer, GPS
**PEAS:** Medical diagnosis system

- **Performance measure:** Healthy patient, minimize costs, lawsuits
- **Environment:** Patient, hospital, staff
- **Actuators:** Screen display (form including: questions, tests, diagnoses, treatments, referrals)
- **Sensors:** Keyboard (entry of symptoms, findings, patient's answers)

From: The New Yorker April 2017
The rational agent designer’s goal

• Goal of AI practitioner who designs rational agents: given a PEAS task environment,

1. Construct agent function $f$ that maximizes the expected value of the performance measure,

2. Design an agent program that implements $f$ on a particular architecture
Environment types: Definitions 1

- **Fully observable** (vs. partially observable): An agent's sensors give it access to the complete state of the environment at each point in time.

- **Deterministic** (vs. stochastic): The next state of the environment is completely determined by the current state and the action executed by the agent.
  - If the environment is deterministic except for the actions of other agents, then the environment is *strategic*.

- **Episodic** (vs. sequential): The agent's experience is divided into atomic "episodes" during which the agent perceives and then performs a single action, and the choice of action in each episode does not depend on any previous action. (example: classification task)
Environment types: Definitions 2

- Static (vs. dynamic): The environment is unchanged while an agent is deliberating.
  - The environment is *semidynamic* if the environment itself does not change with the passage of time but the agent's performance score does.

- Discrete (vs. continuous): A limited number of distinct, clearly defined percepts and actions.

- Single agent (vs. multiagent): An agent operating by itself in an environment.
### Examples

<table>
<thead>
<tr>
<th>Task Environment</th>
<th>Observable</th>
<th>Agents</th>
<th>Deterministic</th>
<th>Episodic</th>
<th>Static</th>
<th>Discrete</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crossword puzzle Chess with a clock</td>
<td>Fully</td>
<td>Single</td>
<td>Deterministic</td>
<td>Sequential</td>
<td>Static</td>
<td>Discrete</td>
</tr>
<tr>
<td></td>
<td>Fully</td>
<td>Multi</td>
<td>Deterministic</td>
<td>Sequential</td>
<td>Semi</td>
<td>Discrete</td>
</tr>
<tr>
<td>Poker Backgammon</td>
<td>Partially</td>
<td>Multi</td>
<td>Stochastic</td>
<td>Sequential</td>
<td>Static</td>
<td>Discrete</td>
</tr>
<tr>
<td></td>
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<td>Sequential</td>
<td>Static</td>
<td>Discrete</td>
</tr>
<tr>
<td>Taxi driving Medical diagnosis</td>
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<td>Continuous</td>
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<td></td>
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<td>Sequential</td>
<td>Dynamic</td>
<td>Continuous</td>
</tr>
<tr>
<td>Image analysis Part-picking robot</td>
<td>Fully</td>
<td>Single</td>
<td>Deterministic</td>
<td>Episodic</td>
<td>Semi</td>
<td>Continuous</td>
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<td>Dynamic</td>
<td>Continuous</td>
</tr>
<tr>
<td>Refinery controller Interactive English tutor</td>
<td>Partially</td>
<td>Single</td>
<td>Stochastic</td>
<td>Sequential</td>
<td>Dynamic</td>
<td>Continuous</td>
</tr>
<tr>
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<td>Stochastic</td>
<td>Sequential</td>
<td>Dynamic</td>
<td>Discrete</td>
</tr>
</tbody>
</table>
Environment Restrictions for Now

- We will assume environment is
  - *Static*
  - *Fully Observable*
  - *Deterministic*
  - *Discrete*
Problem Solving Agents & Problem Formulation

AIMA 3.1-3.2
Example search problem: 8-puzzle

• **Formulate goal**
  • Pieces to end up in order as shown…

• **Formulate search problem**
  • **States:** configurations of the puzzle (9! configurations)
  • **Actions:** Move one of the movable pieces (≤4 possible)
  • **Performance measure:** minimize total moves

• **Find solution**
  • Sequence of pieces moved: 3,1,6,3,1,…
Example search problem: holiday in Romania

You are here

You need to be here
Holiday in Romania

- On holiday in Romania; currently in Arad
  - Flight leaves tomorrow from Bucharest
- **Formulate** goal
  - Be in Bucharest
- **Formulate** search problem
  - States: various cities
  - Actions: drive between cities
  - Performance measure: minimize travel time / distance
- **Find** solution
  - Sequence of cities; e.g. Arad, Sibiu, Fagaras, Bucharest, …
More formally, a problem is defined by:

1. **States**: a set $S$
2. An *initial state* $s_i \in S$
3. **Actions**: a set $A$
   - $\forall s \, \text{Actions}(s) = \text{the set of actions that can be executed in } s$, that are *applicable* in $s$.
4. **Transition Model**: $\forall s \, \forall a \in \text{Actions}(s) \, \text{Result}(s, a) \rightarrow s_r$
   - $s_r$ is called a *successor* of $s$
   - $\{s_i\} \cup \text{Successors}(s_i)^* = \text{state space}$
5. **Path cost (Performance Measure)**: Must be additive
   - e.g. sum of distances, number of actions executed, ...
   - $c(x, a, y)$ is the step cost, assumed $\geq 0$
     - (where action $a$ goes from state $x$ to state $y$)
6. **Goal test**: $\text{Goal}(s)$
   - Can be implicit, e.g. *checkmate*(s)
   - $s$ is a *goal state* if $\text{Goal}(s)$ is true
Solutions & Optimal Solutions

- A **solution** is a sequence of **actions** from the **initial state** to a **goal state**.

- **Optimal Solution**: A solution is **optimal** if no solution has a lower **path cost**.
Art: Formulating a Search Problem

Decide:

- Which properties matter & how to represent
  - Initial State, Goal State, Possible Intermediate States
- Which actions are possible & how to represent
  - Operator Set: Actions and Transition Model
- Which action is next
  - Path Cost Function

Formulation greatly affects combinatorics of search space and therefore speed of search
Example: 8-puzzle

- States??
- Initial state??
- Actions??
- Transition Model??
- Goal test??
- Path cost??
Example: 8-puzzle

- States??
- Initial state??
- Actions??
- Transition Model??
- Goal test??
- Path cost??
Example: 8-puzzle

- States??  List of 9 locations- e.g., [7,2,4,5,-,6,8,3,1]
- Initial state??  [7,2,4,5,-,6,8,3,1]
- Actions??  \{Left, Right, Up, Down\}
- Transition Model??  ...
- Goal test??  Check if goal configuration is reached
- Path cost??  Number of actions to reach goal
Hard subtask: Selecting a state space

- Real world is absurdly complex
  State space must be *abstracted* for problem solving

- (abstract) \textit{State} = set (equivalence class) of real world states

- (abstract) \textit{Action} = equivalence class of combinations of real world actions
  - e.g. \textit{Arad} \rightarrow \textit{Zerind} represents a complex set of possible routes, detours, rest stops, etc
  - The abstraction is valid if the path between two states is reflected in the real world

- Each abstract action should be “easier” than the real problem
Outline for today’s lecture

- Intelligent Agents
- Task Environments
- Formulating Search Problems
- *Search Fundamentals (AIMA 3.3)*
Useful Concepts

- **State space**: the set of all states reachable from the initial state by *any* sequence of actions
  - *When several operators can apply to each state, this gets large very quickly*
  - *Might be a proper subset of the set of configurations*

- **Path**: a sequence of actions leading from one state $s_j$ to another state $s_k$

- **Frontier**: those states that are available for expanding (for applying legal actions to)

- **Solution**: a path from the initial state $s_i$ to a state $s_f$ that satisfies the goal test
Basic search algorithms: *Tree Search*

- Generalized algorithm to solve search problems
- Enumerate in some order all possible paths from the initial state
  - Here: search through *explicit tree generation*
    - ROOT = initial state.
    - Nodes in search tree generated through *transition model*
    - Tree search treats different paths to the same node as distinct
Generalized tree search

function TREE-SEARCH(problem, strategy) return a solution or failure
  Initialize frontier to the initial state of the problem
  do
    if the frontier is empty then return failure
    choose leaf node for expansion according to strategy & remove from frontier
    if node contains goal state then return solution
    else expand the node and add resulting nodes to the frontier
8-Puzzle: States and Nodes

- A **state** is a (representation of a) **physical configuration**
- A **node** is a data structure constituting **part of a search tree**
  - Also includes **parent, children, depth, path cost g(x)**
  - Here **node** = <**state, parent-node, children, action, path-cost, depth**>
- States do not have parents, children, depth or path cost!

- The **EXPAND** function
  - uses the Actions and Transition Model to create the corresponding states
    — creates new nodes,
    — fills in the various fields
8-Puzzle **Search Tree**

- (Nodes show state, parent, children - leaving *Action*, *Cost*, *Depth* Implicit)
- Suppressing useless “backwards” moves
Problem: Repeated states

- Failure to detect *repeated states* can turn a linear problem into an *exponential* one!
Solution: Graph Search!

- **Graph search**
  - Simple Mod from tree search: Check to see if a node has been visited before adding to search queue
  - must keep track of all possible states (can use a lot of memory)
  - e.g., 8-puzzle problem, we have $9!/2 \approx 182K$ states
Graph Search vs Tree Search

function POP-SEARCH \( (\text{problem}) \) returns a solution, or failure
initialize the frontier using the initial state of \( \text{problem} \)
loop do
  if the frontier is empty then return failure
  choose a leaf node and remove it from the frontier
  if the node contains a goal state then return the corresponding solution
  expand the chosen node, adding the resulting nodes to the frontier

function GRAP-SEARCH \( (\text{problem}) \) returns a solution, or failure
initialize the frontier using the initial state of \( \text{problem} \)
initialize the explored set to be empty
loop do
  if the frontier is empty then return failure
  choose a leaf node and remove it from the frontier
  if the node contains a goal state then return the corresponding solution
  add the node to the explored set
  expand the chosen node, adding the resulting nodes to the frontier
  only if not in the frontier or explored set

Figure 3.7 An informal description of the general tree-search and graph-search algorithms. The parts of GRAPH-SEARCH marked in bold italic are the additions needed to handle repeated states.
Uninformed Search Strategies

AIMA 3.3-3.4
Uninformed search strategies:

- AKA “Blind search”
- Uses only information available in problem definition

Informally:

- *Uninformed search*: All non-goal nodes in frontier look equally good
- *Informed search*: Some non-goal nodes can be ranked above others.
Search Strategies

• **Review: Strategy** = order of tree expansion
  • Implemented by different queue structures (LIFO, FIFO, priority)

• **Dimensions for evaluation**
  • *Completeness* - always find the solution?
  • *Optimality* - finds a least cost solution (lowest path cost) first?
  • *Time complexity* - # of nodes generated *(worst case)*
  • *Space complexity* - # of nodes simultaneously in memory *(worst case)*

• **Time/space complexity variables**
  • \( b \), *maximum branching factor* of search tree
  • \( d \), *depth* of the shallowest goal node
  • \( m \), maximum length of any path in the state space (potentially \( \infty \))
Introduction to space complexity

• You know about:
  • “Big O” notation
  • Time complexity

• Space complexity is analogous to time complexity

• Units of space are arbitrary
  • Doesn’t matter because Big O notation ignores constant multiplicative factors
  • Plausible Space units:
    — One Memory word
    — Size of any fixed size data structure
      — eg Size of fixed size node in search tree
Review: Breadth-first search

• **Idea:**
  • Expand *shallowest* unexpanded node

• **Implementation:**
  • *frontier* is FIFO (First-In-First-Out) Queue:
    — Put successors at the end of *frontier* successor list.

Image credit: Dan Klein and Pieter Abbeel
http://ai.berkeley.edu
Breadth-first search (simplified)

function BREADTH-FIRST-SEARCH(problem) returns a solution, or failure

node <- a node with STATE = problem.INITIAL-STATE, PATH-COST=0
if problem.GOAL-TEST(node.STATE) then return SOLUTION(node)

frontier <- a FIFO queue with node as the only element

loop do
  if EMPTY?(frontier) then return failure
  node <- POP(frontier) // chooses the shallowest node in frontier
  add node.STATE to explored
  for each action in problem.ACTIONS(node.STATE) do
    child <- CHILD-NODE(problem, node, action)
    if problem.GOAL-TEST(child.STATE) then return SOLUTION(child)
  frontier <- INSERT(child, frontier)

From Figure 3.11 Breadth-first search (ignores loops, repeated nodes)
Properties of breadth-first search

- **Complete?** Yes (if $b$ is finite)
- **Time Complexity?** $1+b+b^2+b^3+\ldots+b^d = O(b^d)$
- **Space Complexity?** $O(b^d)$ (keeps every node in memory)
- **Optimal?** Yes, if cost = 1 per step (not optimal in general)

$b$: maximum branching factor of search tree
$d$: depth of the least cost solution
$m$: maximum depth of the state space ($\infty$)
Exponential Space (and time) Not Good...

- Exponential complexity uninformed search problems cannot be solved for any but the smallest instances.
- *(Memory* requirements are a bigger problem than *execution time.*)

<table>
<thead>
<tr>
<th>DEPTH</th>
<th>NODES</th>
<th>TIME</th>
<th>MEMORY</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>110</td>
<td>0.11 milliseconds</td>
<td>107 kilobytes</td>
</tr>
<tr>
<td>4</td>
<td>11110</td>
<td>11 milliseconds</td>
<td>10.6 megabytes</td>
</tr>
<tr>
<td>6</td>
<td>(10^6)</td>
<td>1.1 seconds</td>
<td>1 gigabyte</td>
</tr>
<tr>
<td>8</td>
<td>(10^8)</td>
<td>2 minutes</td>
<td>103 gigabytes</td>
</tr>
<tr>
<td>10</td>
<td>(10^{10})</td>
<td>3 hours</td>
<td>10 terabytes</td>
</tr>
<tr>
<td>12</td>
<td>(10^{12})</td>
<td>13 days</td>
<td>1 petabyte</td>
</tr>
<tr>
<td>14</td>
<td>(10^{14})</td>
<td>3.5 years</td>
<td>99 petabytles</td>
</tr>
</tbody>
</table>

Fig 3.13  Assumes b=10, 1M nodes/sec, 1000 bytes/node
Review: Depth-first search

- **Idea:**
  - Expand *deepest* unexpanded node

- **Implementation:**
  - *frontier* is LIFO (Last-In-First-Out) Queue:
    —Put successors at the *front* of *frontier* successor list.

Image credit: Dan Klein and Pieter Abbeel
http://ai.berkeley.edu
Properties of depth-first search

- **Complete?** No: fails in infinite-depth spaces, spaces with loops
  - Modify to avoid repeated states along path
    → complete in finite spaces

- **Time?** \( O(b^m) \): terrible if \( m \) is much larger than \( d \)
  - but if solutions are dense, may be much faster than breadth-first

- **Space?** \( O(b^m) \), i.e., linear space!

- **Optimal?** No

---

\( b \): maximum branching factor of search tree  
\( d \): depth of the least cost solution  
\( m \): maximum depth of the state space (\( \infty \))
Depth-first vs Breadth-first

- **Use depth-first if**
  - *Space is restricted*
  - There are many possible solutions with long paths and wrong paths are usually terminated quickly
  - Search can be fine-tuned quickly

- **Use breadth-first if**
  - *Possible infinite paths*
  - Some solutions have short paths
  - Can quickly discard unlikely paths
Outline for today’s lecture

- Formulating Search Problems – An Example

- Search Fundamentals

- Introduction to Uninformed Search
  - Review of Breadth first and Depth-first search

- Iterative deepening search (AIMA 3.4.4-5)
  - Strange Subroutine: Depth-limited search
  - Depth-limited search + iteration = WIN!!
Search Conundrum

• **Breadth-first**
  - ✓ Complete,
  - ✓ Optimal
  - ✗ *but* uses $O(b^d)$ space

• **Depth-first**
  - ✗ Not complete *unless m is bounded*
  - ✗ Not optimal
  - ✗ Uses $O(b^m)$ time; terrible if $m >> d$
  - ✓ *but* only uses $O(b \times m)$ space

How can we get the best of both?
Depth-limited search: A building block

- Depth-First search *but with depth limit $l$*
  - i.e. nodes at depth $l$ *have no successors.*
  - No infinite-path problem!

- If $l = d$ (by luck!), then optimal
  - But:
    - If $l < d$ then incomplete 😞
    - If $l > d$ then not optimal 😞

- **Time complexity:** $O(b^l)$
- **Space complexity:** $O(bl)$ 😊
Iterative deepening search

• A general strategy to find best depth limit $l$.
  • Key idea: use *Depth-limited search* as subroutine, with increasing $l$.

  For $l = 0$ to $\infty$ do
  
  depth-limited-search to level $l$
  
  if it succeeds
  
  then return solution

• *Complete & optimal*: Goal is always found at depth $d$, the depth of the shallowest goal-node.

*Could this possibly be efficient?*
Nodes constructed at each deepening

- Depth 0: 0 (Given the node, doesn’t construct it.)

- Depth 1: $b^1$ nodes

- Depth 2: $b$ nodes + $b^2$ nodes

- Depth 3: $b$ nodes + $b^2$ nodes + $b^3$ nodes

- ...
Total nodes constructed:

- Depth 0: 0 (Given the node, doesn’t construct it.)
- Depth 1: \( b^1 = b \) nodes
- Depth 2: \( b \) nodes + \( b^2 \) nodes
- Depth 3: \( b \) nodes + \( b^2 \) nodes + \( b^3 \) nodes
- ...

Suppose the first solution is the last node at depth 3:
Total nodes constructed:
\[ 3b \text{ nodes} + 2b^2 \text{ nodes} + 1b^3 \text{ nodes} \]
ID search, Evaluation II: Time Complexity

- More generally, the time complexity is
  - \((d)b + (d-1)b^2 + \ldots + (1)b^d = O(b^d)\)

- As efficient in terms of \(O(\ldots)\) as Breadth First Search:
  - \(b + b^2 + \ldots + b^d = O(b^d)\)
ID search, Evaluation III

- Complete: YES (no infinite paths)
- Time complexity: $O(b^d)$
- Space complexity: $O(bd)$
- Optimal: YES if step cost is 1.
## Summary of algorithms

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Breadth-First</th>
<th>Depth-First</th>
<th>Depth-limited</th>
<th>Iterative deepening</th>
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</thead>
<tbody>
<tr>
<td>Complete?</td>
<td>YES</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
</tr>
<tr>
<td>Time</td>
<td>$b^d$</td>
<td>$b^m$</td>
<td>$b^l$</td>
<td>$b^d$</td>
</tr>
<tr>
<td>Space</td>
<td>$b^d$</td>
<td>$b^m$</td>
<td>$b^l$</td>
<td>$b^d$</td>
</tr>
<tr>
<td>Optimal?</td>
<td>YES</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
</tr>
</tbody>
</table>