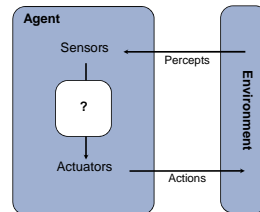# CSE 573: Artificial Intelligence
Autumn 2012

Introduction & Search

Dan Weld

With slides from
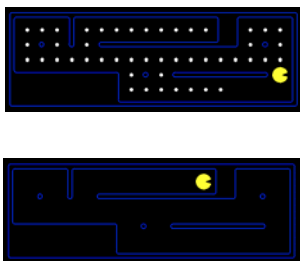Dan Klein, Stuart Russell, Andrew Moore, Luke Zettlemoyer

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Agent *vs.* Environment

- An **agent** is an entity that *perceives* and *acts*.
- A **rational agent** selects actions that maximize its **utility function**.
- Characteristics of the **percepts, environment,** and **action space** dictate techniques for selecting rational actions.

Goal Based Agents

- Plan ahead
- Ask "what if"

- Decisions based on (hypothesized) consequences of actions
- Must have a model of how the world evolves in response to actions
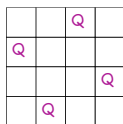
- Act on how the world WOULD BE

Search thru a
Problem Space / State Space

- Input:
  - Set of states
  - Operators [and costs]
  - Start state
  - Goal state [test]

- Output:
  - Path: start $\Rightarrow$ a state satisfying goal test
  - [May require shortest path]
  - [Sometimes just need state passing test]

Example: N Queens

- Input:
  - Set of states

  - Operators [and costs]
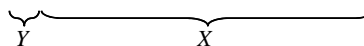
  - Start state

  - Goal state (test)

- Output

Machine Learning : predict fuel efficiency
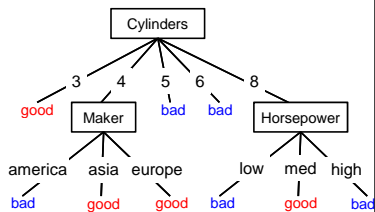
Discrete Data

Predict MPG

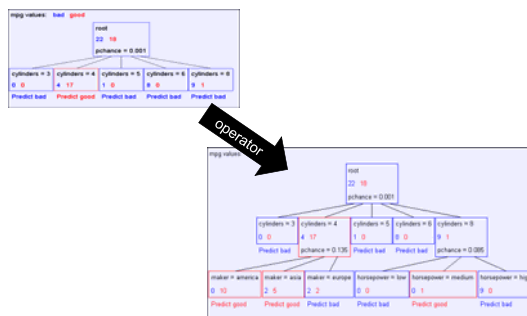| mpg	cylinders	displacement	horsepower	weight	acceleration	modelyear	maker
good	4	low	low	low	high	75to78	asia
bad	6	medium	medium	medium	medium	70to74	america
bad	4	medium	medium	medium	low	75to78	europe
bad	8	high	high	high	low	70to74	america
bad	6	medium	medium	medium	medium	70to74	america
bad	4	low	medium	low	medium	70to74	asia
bad	4	low	medium	low	low	70to74	asia
bad	8	high	high	high	low	75to78	america
:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:
bad	8	high	high	high	low	70to74	america
good	8	high	medium	high	high	79to83	america
bad	8	high	high	high	low	75to78	america
good	4	low	low	low	low	79to83	america
bad	6	medium	medium	medium	high	75to78	america
good	4	medium	low	low	low	79to83	america
good	4	low	low	medium	high	79to83	america
bad	8	high	high	high	low	70to74	america
good	4	low	medium	low	medium	75to78	europe
bad	5	medium	medium	medium	medium	75to78	europe

Y X

Need to find "Hypothesis": $f : X \rightarrow Y$

Hypotheses: decision trees $f : X \rightarrow Y$

- Each internal node tests an attribute x_i
- Each branch assigns an attribute value $x_i = v$
- Each leaf assigns a class y
- To classify input x?

  traverse the tree from root to leaf, output the labeled y

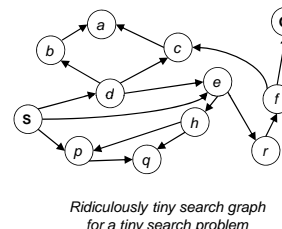## Search thru Space of Decision Trees

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Search Methods

- **Blind Search**
  - Depth first search
  - Breadth first search
  - Iterative deepening search
  - Uniform cost search
- **Local Search**
- **Informed Search**
- **Constraint Satisfaction**
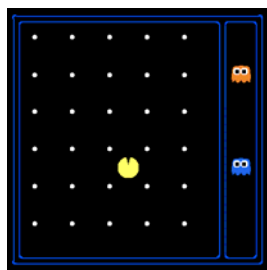- **Adversary Search**

State Space Graphs

- State space graph:
  - Each node is a state
  - The successor function is represented by arcs
  - Edges may be labeled with costs
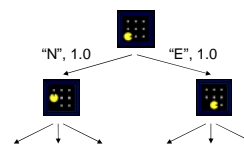- We can rarely build this graph in memory (so we don't)

Ridiculously tiny search graph for a tiny search problem

State Space Sizes?

- Search Problem: Eat all of the food
- Pacman positions: 10 x 12 = 120
- Pacman facing: up, down, left, right
- Food Count: 30
- Ghost positions: 12

Search Trees

"N", 1.0   "E", 1.0

- A search tree:
  - Start state at the root node
  - Children correspond to successors
  - Nodes contain states, correspond to PLANS to those states
  - Edges are labeled with actions and costs
  - For most problems, we can never actually build the whole tree

Example: Tree Search

State Graph:

What is the search tree?

State Graphs vs. Search Trees

Each NODE in in the search tree denotes an entire PATH in the problem graph.

We construct both on demand – and we construct as little as possible.

States vs. Nodes

- Nodes in state space graphs are problem states
    - Represent an abstracted state of the world
    - Have successors, can be goal / non-goal, have multiple predecessors
- Nodes in search trees are plans
    - Represent a plan (sequence of actions) which results in the node's state
    - Have a problem state and one parent, a path length, a depth & a cost
    - The same problem state may be achieved by multiple search tree nodes

Problem States

Search Tree Nodes
Parent
Depth 5
Action
Node
Depth 6

Building Search Trees

- Search:
    - Expand out possible plans
    - Maintain a fringe of unexpanded plans
    - Try to expand as few tree nodes as possible

General Tree Search

```
function TREE-SEARCH( problem, strategy) returns a solution, or failure
    initialize the search tree using the initial state of problem
    loop do
        if there are no candidates for expansion then return failure
        choose a leaf node for expansion according to strategy
        if the node contains a goal state then return the corresponding solution
        else expand the node and add the resulting nodes to the search tree
    end
```

- Important ideas:
    - Fringe
    - Expansion
    - Exploration strategy

Detailed pseudocode is in the book!

- Main question: which fringe nodes to explore?

Review: Depth First Search

***Strategy**: expand deepest node first*

***Implementation**: Fringe is a LIFO queue (a stack)*

Review: Depth First Search

Expansion ordering:

(d,b,a,c,a,e,h,p,q,q,r,f,c,a,G)

Review: Breadth First Search

Strategy: *expand shallowest node first*

Implementation: *Fringe is a FIFO queue*

Review: Breadth First Search

Expansion order:

(S,d,e,p,b,c,e,h,r,q,a,a ,h,r,p,q,f,p,q,f,q,c,G)

Search Tiers

Search Algorithm Properties

- Complete?   Guaranteed to find a solution if one exists?
- Optimal?   Guaranteed to find the least cost path?
- Time complexity?
- Space complexity?

Variables:

n	Number of states in the problem
b	The maximum branching factor B (the maximum number of successors for a state)
$C*$	Cost of least cost solution
d	Depth of the shallowest solution
m	Max depth of the search tree

DFS

Algorithm		Complete	Optimal	Time	Space
DFS	Depth First Search	No	No	Infinite	Infinite

- Infinite paths make DFS incomplete...
  - How can we fix this?
  - Check new nodes against path from S
- Infinite search spaces still a problem

DFS

Algorithm		Complete	Optimal	Time	Space
DFS	w/ Path Checking	Y if finite	N	$O(b^m)$	$O(bm)$

* Or graph search – next lecture.

4

BFS

Algorithm		Complete	Optimal	Time	Space
DFS	w/ Path Checking	Y	N	$O(b^m)$	$O(bm)$
BFS		Y	Y	$O(b^d)$	$O(b^d)$

d tiers

1 node
b nodes
b^2 nodes

b^d nodes

b^m nodes

Extra Work?

- Failure to detect repeated states can cause exponentially more work (why?)

Graph Search

- In BFS, for example, we shouldn't bother expanding the circled nodes (why?)

Graph Search

- Very simple fix: never expand a state type twice


```
function GRAPH-SEARCH( problem, fringe) returns a solution, or failure
    closed ← an empty set
    fringe ← INSERT(MAKE-NODE(INITIAL-STATE[problem]), fringe)
    loop do
        if fringe is empty then return failure
        node ← REMOVE-FRONT(fringe)
        if GOAL-TEST(problem, STATE[node]) then return node
        if STATE[node] is not in closed then
            add STATE[node] to closed
            fringe ← INSERTALL(EXPAND(node, problem), fringe)
    end
```

- Can this wreck completeness? Why or why not?
- How about optimality? Why or why not?

Some Hints

- Graph search is almost always better than tree search (when not?)

- Implement your closed list as a dict or set!

- Nodes are conceptually paths, but better to represent with a state, cost, last action, and reference to the parent node

Memory a Limitation?

- Suppose:
  - 4 GHz CPU
  - 6 GB main memory
  - 100 instructions / expansion
  - 5 bytes / node

  - 400,000 expansions / sec
    - Memory filled in 300 sec … 5 min
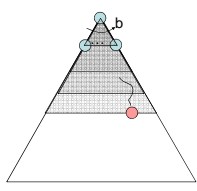
Comparisons

- When will BFS outperform DFS?

- When will DFS outperform BFS?

Iterative Deepening

Iterative deepening uses DFS as a subroutine:

1. Do a DFS which only searches for paths of length 1 or less.
2. If "1" failed, do a DFS which only searches paths of length 2 or less.
3. If "2" failed, do a DFS which only searches paths of length 3 or less.

….and so on.

Algorithm		Complete	Optimal	Time	Space
DFS	w/ Path Checking	Y	N	$O(b^m)$	$O(bm)$
BFS		Y	Y	$O(b^d)$	$O(b^d)$
ID		Y	Y	$O(b^d)$	$O(bd)$

Cost of Iterative Deepening

b	ratio ID to DFS
2	3
3	2
5	1.5
10	1.2
25	1.08
100	1.02

Speed

Assuming 10M nodes/sec & sufficient memory

	BFS		Iter. Deep.	
	Nodes	Time	Nodes	Time
8 Puzzle	10^5	.01 sec	10^5	.01 sec
2x2x2 Rubik's	10^6	.2 sec	10^6	.2 sec
15 Puzzle	10^{13}	6 days 1Mx	10^{17}	20k yrs
3x3x3 Rubik's	10^{19}	68k yrs 8x	10^{20}	574k yrs
24 Puzzle	10^{25}	12B yrs	10^{37}	10^{23} yrs

Why the difference?
 Rubik has higher branching factor   # of duplicates
 15 puzzle has greater depth
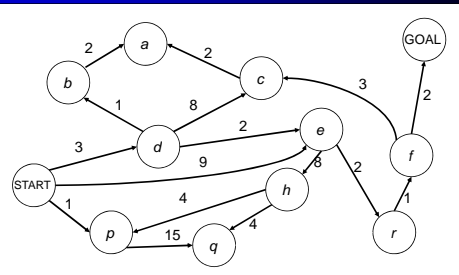
Slide adapted from Richard Korf presentation

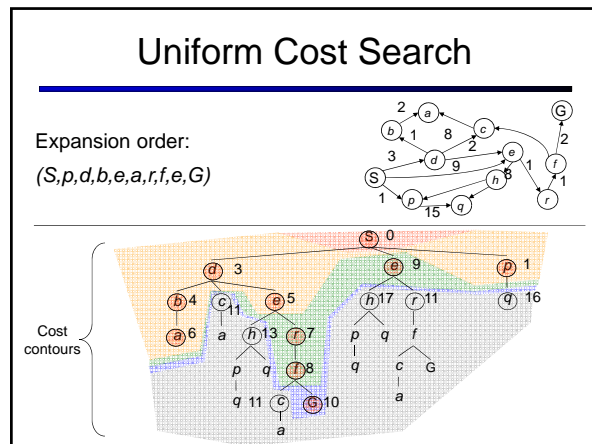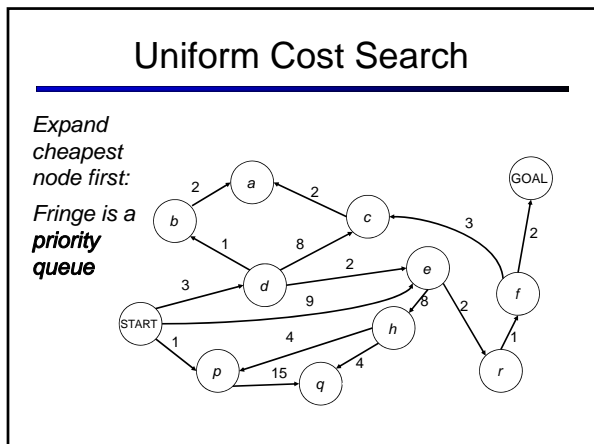## When to Use Iterative Deepening

- N Queens?

35

Costs on Actions

Notice that BFS finds the shortest path in terms of number of transitions. It does not find the least-cost path.

Uniform Cost Search

Expand cheapest node first:

*Fringe is a **priority queue***

Uniform Cost Search

Expansion order:

(S,p,d,b,e,a,r,f,e,G)

Cost contours

Priority Queue Refresher

- A priority queue is a data structure in which you can insert and retrieve (key, value) pairs with the following operations:

pq.push(key, value)	inserts *(key, value)* into the queue.
pq.pop()	returns the key with the lowest value, and removes it from the queue.

- You can decrease a key's priority by pushing it again
- Unlike a regular queue, insertions aren't constant time, usually O(log *n*)
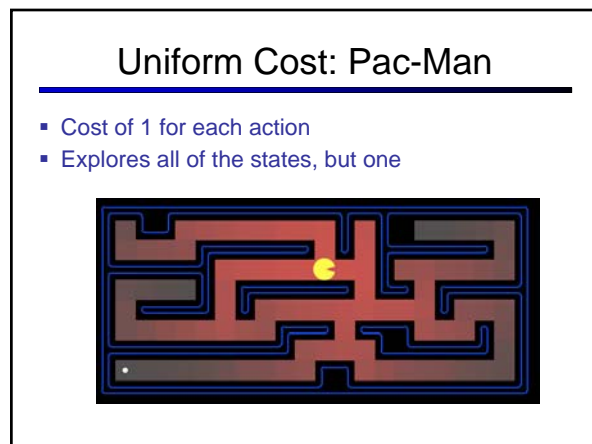- We'll need priority queues for cost-sensitive search methods

Uniform Cost Search

Algorithm		Complete	Optimal	Time	Space
DFS	w/ Path Checking	Y	N	$O(b^m)$	$O(bm)$
BFS		Y	Y	$O(b^d)$	$O(b^d)$
UCS		Y*	Y	$O(b^{C^*/\varepsilon})$	$O(b^{C^*/\varepsilon})$

C^*/ε tiers

Uniform Cost Issues

- Remember: explores increasing cost contours
- The good: UCS is complete and optimal!
- The bad:
  - Explores options in every "direction"
  - No information about goal location

Uniform Cost: Pac-Man

- Cost of 1 for each action
- Explores all of the states, but one

7

Exponentials Everywhere

"I think we're going to need a stronger donkey…"
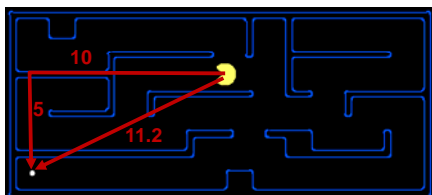
43

Heuristics

RULE OF THUMB

If your extended thumb is too small to block your view of the hazmat incident, you're not far enough away.

44

Search Heuristics

- Any *estimate* of how close a state is to a goal
- Designed for a particular search problem

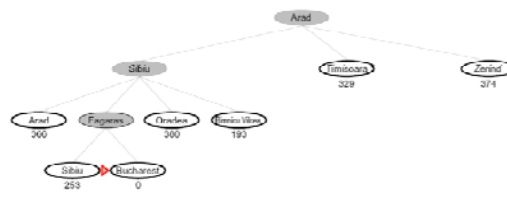- Examples: Manhattan distance, Euclidean distance

Heuristics

Best First / Greedy Search

Expand closest node first: Fringe is a priority queue

Best First / Greedy Search

- Expand the node that seems closest…

- What can go wrong?

Greedy Search

Expand the node that seems closest…

What can go wrong?

Best First / Greedy Search

- A common case:
  - Best-first takes you straight to the (wrong) goal

- Worst-case: like a badly-guided DFS in the worst case
  - Can explore everything
  - Can get stuck in loops if no cycle checking

- Like DFS in completeness (finite states w/ cycle checking)

Best First Greedy Search

Algorithm	Complete	Optimal	Time	Space
Greedy Best-First Search	Y*	N	$O(b^m)$	$O(b^m)$

- What do we need to do to make it complete?
- Can we make it optimal?

A* Search

Hart, Nilsson & Rafael 1968

Best first search with $f(n) = g(n) + h(n)$

- $g(n)$ = sum of costs from start to n
- $h(n)$ = estimate of lowest cost path n → goal
  $h(goal) = 0$

If h(n) is admissible and monotonic
then A* is optimal

Underestimates cost of reaching goal from node

f values increase from node to descendants (triangle inequality)

Graph Search Detail

When do we check for goals?
- When adding to queue?
- When removing from queue?

European Example

54

A* Example

Arad
366=0+366

55

A* Example

Arad

Sibiu
393=140+253

Timisoara
447=118+329

Zerind
449=75+374

56

A* Example

Arad

Sibiu

Timisoara
447=118+329

Zerind
449=75+374

Arad
646=280+366

Fagaras
415=239+176

Oradea
671=291+380

Rimnicu Vilcea
413=220+193

57

A* Example

Arad

Sibiu

Timisoara
447=118+329

Zerind
449=75+374

Arad
646=280+366

Fagaras
415=239+176

Oradea
671=291+380

Rimnicu Vilcea

Craiova
526=366+160

Pitesti
417=317+100

Sibiu
553=300+253

58

A* Example

Arad

Sibiu

Timisoara
447=118+329

Zerind
449=75+374

Arad
646=280+366

Fagaras

Oradea
671=291+380

Rimnicu Vilcea

Sibiu
591=338+253

Bucharest
450=450+0

Craiova
526=366+160

Pitesti
417=317+100

Sibiu
553=300+253

59

A* Example

Arad

Sibiu

Timisoara
447=118+329

Zerind
449=75+374

Arad
646=280+366

Fagaras

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671=291+380

Rimnicu Vilcea

Sibiu
591=338+253

Bucharest
450=450+0

Craiova
526=366+160

Pitesti

Sibiu
553=300+253

Bucharest
418=418+0

Craiova
615=455+160

Rimnicu Vilcea
607=414+193

60

10

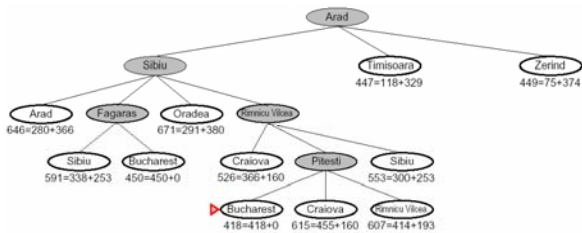## Optimality of A*

Suppose some suboptimal goal G_2 has been generated and is in the queue. Let n be an unexpanded node on a shortest path to an optimal goal G_1.

$$
\begin{aligned}
f(G_2) &= g(G_2) & \text{since } h(G_2) = 0 \\
&> g(G_1) & \text{since } G_2 \text{ is suboptimal} \\
&\geq f(n) & \text{since } h \text{ is admissible}
\end{aligned}
$$

Since $f(G_2) > f(n)$, A* will never select G_2 for expansion

61

Optimality Continued

Lemma: A* expands nodes in order of increasing f value*

Gradually adds "f-contours" of nodes (cf. breadth-first adds layers)
Contour i has all nodes with $f = f_i$, where $f_i < f_{i+1}$

A* Summary

- Pros

- Cons

63

Iterative-Deepening A*

- Like iterative-deepening depth-first, but...
- Depth bound modified to be an f-limit
  - Start with f-limit = h(start)
  - Prune any node if f(node) > f-limit
  - Next f-limit = min-cost of any node pruned

64

IDA* Analysis

- Complete & Optimal (ala A*)
- Space usage ∝ depth of solution
- Each iteration is DFS - no priority queue!
- # nodes expanded relative to A*
  - Depends on # unique values of heuristic function
  - In 8 puzzle: few values ⇒ close to # A* expands
  - In traveling salesman: each f value often unique
    ⇒ 1+2+…+n = $O(n^2)$ where n=nodes A* expands
    if n is too big for main memory, n^2 is too long to wait!
- Generates duplicate nodes in cyclic graphs

65

Forgetfulness

- A* used exponential memory
- How much does IDA* use?
  - During a run?
  - In between runs?

66

SMA*

- Use all available memory
- Start like A*
- When memory is full…
  - Erase node with highest f-value
  - First, backup parent with this f-value
  - So… parent knows cost-bound on best child

67

Alternative Approach to Finite Memory…

- Optimality is nice to have, but…

68

Depth-First Branch & Bound

- Single DF search
  - → uses linear space
- Keep track of best solution so far
- If $f(n) = g(n)+h(n) \geq cost(best\text{-}soln)$
  - Then prune n

  Tradeoff:
  Prune space, but…
  Must apply test to each node

- Requires
  - Finite search tree, or
  - Good upper bound on solution cost
- Generates duplicate nodes in cyclic graphs
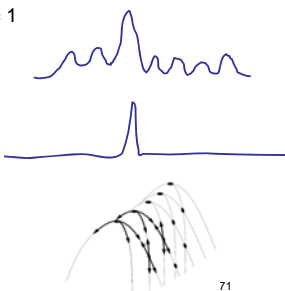
Adapted from Richard Korf presentation

69

Beam Search

- Idea
  - Best first but only keep N best items on priority queue
- Evaluation
  - Complete?

  - Time Complexity?

  - Space Complexity?

70

Hill Climbing *"Gradient ascent"*

- Idea
  - Always choose best child; no backtracking
  - Beam search with |queue| = 1
- Problems?
  - Local maxima

  - Plateaus

  - Diagonal ridges

71

Randomizing Hill Climbing
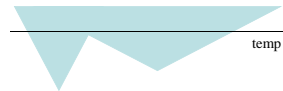
- Randomly disobeying heuristic
- Random restarts

  (heavy tailed distributions)

  → Local Search

72

Simulated Annealing

- Objective: avoid local minima
- Technique:
  - For the most part use hill climbing
  - When no improvement possible
    - Choose random neighbor
    - Let Δ be the decrease in quality
    - Move to neighbor with probability $e^{-\Delta/T}$
  - Reduce "temperature" (T) over time
- Optimal?
  - If T decreased slowly enough, *will* reach optimal state
- Widely used
  - See also WalkSAT

temp

73

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