CSE 573: Artificial Intelligence
Autumn 2012

Introduction & Search

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With slides from
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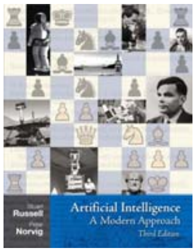
Course Logistics

Textbook:
Artificial Intelligence: A Modern Approach, Russell and Norvig (3rd ed)



Prerequisites:
- Data Structures (CSE 326 or CSE 322) or equivalent
- Understanding of probability, logic algorithms, comlexity

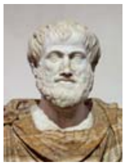
Work:
Readings (text & papers),
Programming assignment (40%),
Written assignments (10%),
Final project (30%),
Class participation (10%)

Topics

- Introduction
- Search Methods & Heuristic Construction
- Game Playing (minimax, alpha beta, expectimax)
- Markov Decision Processes & POMDPs
- Reinforcement Learning
- Knowledge Representation & Reasoning
  - Logic & Planning
  - Contraint Satisfaction
  - Uncertainty, Bayesian Networks, HMMs
- Supervised Machine Learning
- Natural Language Processing
- Mixed Human / Machine Computation

Prehistory

- Logical Reasoning: (4th C BC+) Aristotle, George Boole, Gottlob Frege, Alfred Tarski
- Probabilistic Reasoning: (16th C+) Gerolamo Cardano, Pierre Fermat, James Bernoulli, Thomas Bayes



and

1940-1950: Early Days

1942: Asimov: Positronic Brain; Three Laws of Robotics

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey the orders given to it by human beings, except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws.

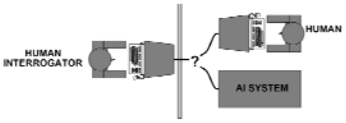
1943: McCulloch & Pitts: Boolean circuit model of brain

1946: First digital computer - ENIAC

The Turing Test

Turing (1950) “Computing machinery and intelligence”

- “Can machines think?” → “Can machines behave intelligently?”
- The *Imitation Game:*



- Suggested major components of AI: knowledge, reasoning, language understanding, learning

1950-1970: Excitement

- 1950s: Early AI programs, including
  - Samuel's checkers program,
  - Newell & Simon's Logic Theorist,
  - Gelernter's Geometry Engine
- 1956: Dartmouth meeting: “Artificial Intelligence” adopted
- 1965: Robinson's complete algorithm for logical reasoning

> “Over Christmas, Allen Newell and I created a thinking machine.”
>
> *-Herbert Simon*

1970-1980: Knowledge Based Systems

- 1969-79: Early development of knowledge-based systems
- 1980-88: Expert systems industry booms
- 1988-93: Expert systems industry busts

  “AI Winter”

> The knowledge engineer practices the art of bringing the principles and tools of AI research to bear on difficult applications problems requiring experts’ knowledge for their solution.
>
> - *Edward Felgenbaum* in “The Art of Artificial Intelligence”

1988--: Statistical Approaches

- 1985-1990: Rise of Probability and Decision Theory

  Eg, Bayes Nets

  Judea Pearl - ACM Turing Award 2011
- 1990-2000: Machine learning takes over subfields:

  Vision, Natural Language, etc.

> "Every time I fire a linguist, the performance of the speech recognizer goes up"
>
> - *Fred Jelinek*, IBM Speech Team

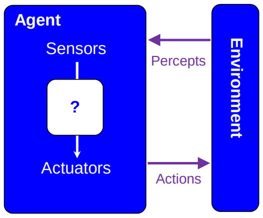
What is AI?

The science of making machines that:

Think like humans	Think rationally
Act like humans	**Act rationally**

Designing Rational Agents

- 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.



- **CSE 573**
  - General AI techniques for a variety of problem types
  - Learning to recognize when and how a new problem can be solved with an existing technique

Rational Decisions

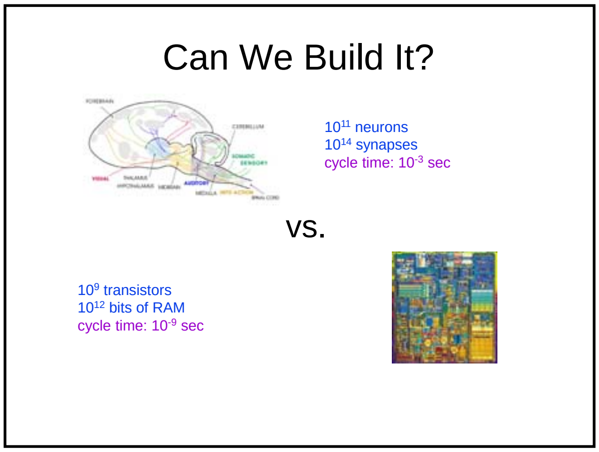
We’ll use the term **rational** in a particular way:

- Rational: maximally achieving pre-defined goals
- Rational only concerns what decisions are made

  (not the thought process behind them)
- Goals are expressed in terms of the **utility** of outcomes
- Being rational means **maximizing your expected utility**

A better title for this course might be:

Computational Rationality



Can We Build It?

10^{11} neurons
10^{14} synapses
cycle time: 10^{-3} sec

vs.

10^{9} transistors
10^{12} bits of RAM
cycle time: 10^{-9} sec

State of the Art

May 1997

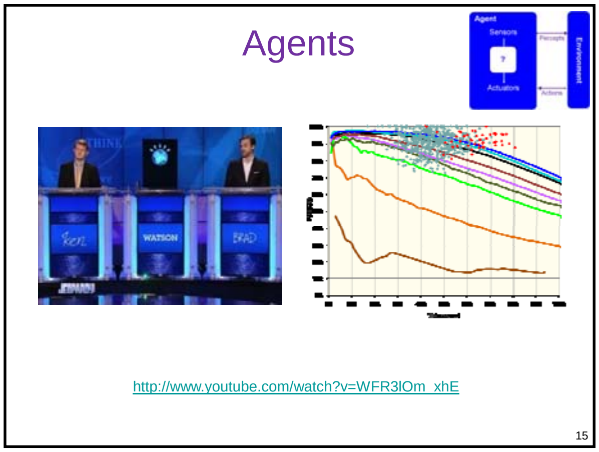
"I could feel – I could smell – a new kind of intelligence across the table"

-Gary Kasparov

MONTY NEWBORN
KASPAROV
VERSUS
DEEP BLUE
COMPUTER CHESS COMES OF AGE
Agent
Sensors
Percepts
?
Actuators
Actions
Environment

Saying Deep Blue doesn't really think about chess is like saying an airplane doesn't really fly because it doesn't flap its wings.

– Drew McDermott



Agents

http://www.youtube.com/watch?v=WFR3lOm_xhE

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Recommendations

Agent
Sensors
Percepts
?
Actuators
Actions
Environment
amazon
Prime
More Top Picks for You
LOOK INSIDE!
PRACTICE EFFECT
NETFLIX

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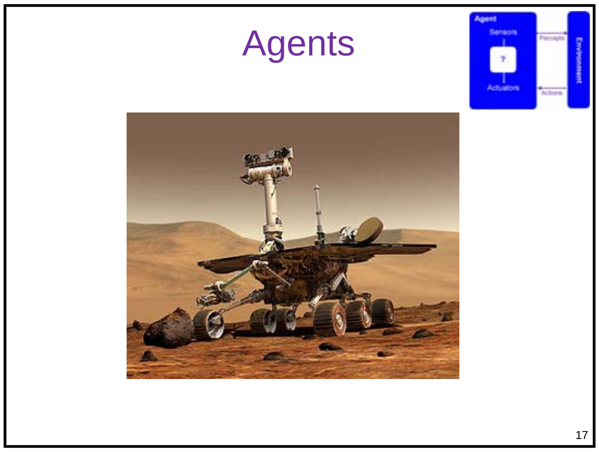

Agents

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Agents

Agent
Sensors
Percepts
?
Actuators
Actions
Environment

Stanford Car
DARPA Grand Challenge

Berkeley Autonomous Helicopter

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What Can AI Do?

Quiz: Which of the following can be done at present?

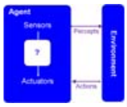
- Play a decent game of Soccer?
- Play a winning game of Chess? Go? Jeopardy?
- Drive safely along a curving mountain road? University Way?
- Buy a week's worth of groceries on the Web? At QFC?
- Make a car? Make a cake?
- Discover and prove a new mathematical theorem?
- Perform a complex surgical operation?
- Unload a dishwasher and put everything away?
- Translate Chinese into English in real time?

Brownies Anyone?

Mathematical Calculation

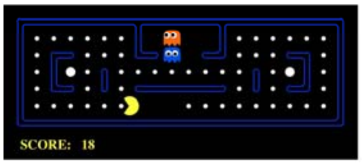
$$
\begin{aligned}
\partial_r^2 u &= -\left[E' - \frac{l(l+1)}{r^2} - r^2\right] u(r) \\
e^{-2s}\left(\partial_s^2 - \partial_s\right) u(s) &= -\left[E' - l(l+1)e^{-2s} - e^{2s}\right] u(s) \\
e^{-2s}\left[e^{\frac{1}{2}s}\left(e^{-\frac{1}{2}s}u(s)\right)'' - \frac{1}{4}u\right] &= -\left[E' - l(l+1)e^{-2s} - e^{2s}\right] u(s) \\
e^{-2s}\left[e^{\frac{1}{2}s}\left(e^{-\frac{1}{2}s}u(s)\right)''\right] &= -\left[E' - \left(l+\frac{1}{2}\right)^2 e^{-2s} - e^{2s}\right] u(s) \\
v'' &= -e^{2s}\left[E' - \left(l+\frac{1}{2}\right)^2 e^{-2s} - e^{2s}\right] v
\end{aligned}
$$

Pacman as an Agent



Utility Function?

Implementation?

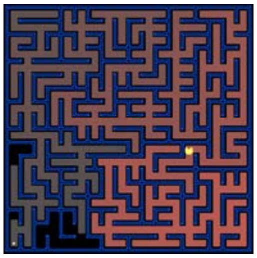


Originally developed at UC Berkeley:
http://www-inst.eecs.berkeley.edu/~cs188/pacman/pacman.html

PS1: Search

Goal:
- Help Pac-man find his way through the maze

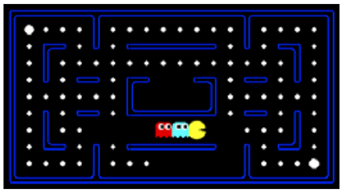
Techniques:
- Search: breadth-first, depth-first, etc.
- Heuristic Search: Best-first, A*, etc.



PS2: Game Playing

Goal:
- Play Pac-man!

Techniques:
- Adversarial Search: minimax, alpha-beta, expectimax, etc.



PS3: Planning and Learning

Goal:

- Help Pac-man learn about the world

Techniques:

- Planning: MDPs, Value Iterations
- Learning: Reinforcement Learning

PS4: Ghostbusters

Goal:

- Help Pac-man hunt down the ghosts

Techniques:

- Probabilistic models: HMMS, Bayes Nets
- Inference: State estimation and particle filtering

Final Project

Your choice

(No final exam)

Advanced topics

- Partially-observable MDPs
- Supervised learning
- Natural language processing
- Mixed human/autonomous computation

Starting… Now!

- Assign 0: Python Tutorial
  - Online, but not graded
- Assign 1: Search
  - On the web.
  - Due Thurs 10/11
  - Start early and ask questions. It's longer than most!

Outline

- Agents that Plan Ahead
- Search Problems
- Uninformed Search Methods (part review for some)
  - Depth-First Search
  - Breadth-First Search
  - Uniform-Cost Search
- Heuristic Search Methods (new for all)
  - Best First / Greedy Search

Agent *vs.* Environment

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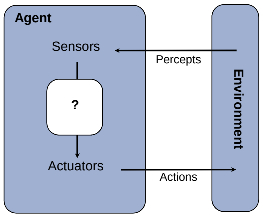


Types of Environments

- Fully observable *vs.* partially observable
- Single agent *vs.* multiagent
- Deterministic *vs.* stochastic
- Episodic *vs.* sequential
- Discrete *vs.* continuous

Fully observable vs. Partially observable

Can the agent observe the complete state of the environment?

vs.

Single agent vs. Multiagent

Is the agent the only thing acting in the world?

vs.

Deterministic vs. Stochastic

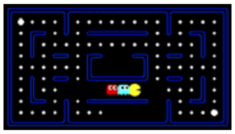
Is there uncertainty in how the world works?

vs.

Episodic vs. Sequential

Does the agent take more than one action?

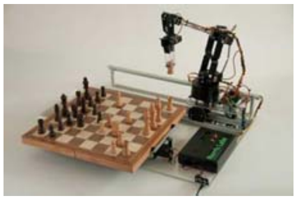
vs.



Discrete vs. Continuous

- Is there a finite (or countable) number of possible environment states?

vs.



Types of Agent

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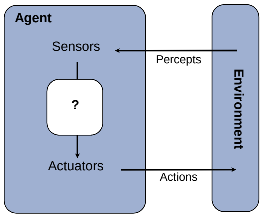
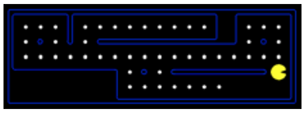
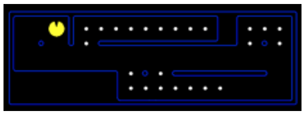


Reflex Agents

- Reflex agents:
  - Choose action based on current percept (and maybe memory)
  - Do not consider the future consequences of their actions
  - Act on how the world IS
- Can a reflex agent be rational?
- Can a non-rational agent achieve goals?

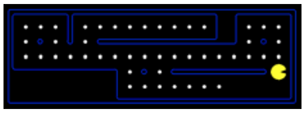


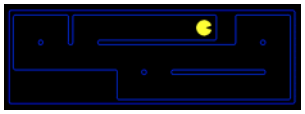


Famous Reflex Agents

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



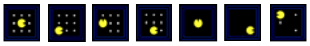


Search thru a Problem Space / State Space

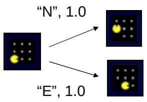
- Input:
  - Set of states
  - Operators [and costs]
  - Start state
  - Goal state [test]
- Output:
  - Path: start ⇒ a state satisfying goal test
  - [May require shortest path]
  - [Sometimes just need state passing test]

Example: Simplified Pac-Man

- Input:
  - A state space



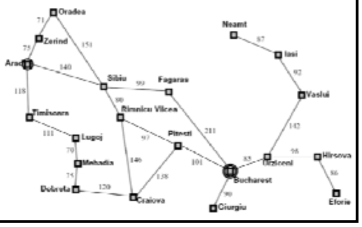
  - A successor function



  - A start state
  - A goal test
- Output:

Ex: Route Planning: Romania → Bucharest

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



Example: N Queens

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

		Q	
Q			
			Q
	Q		

Ex: Blocks World

- Input:
  - Set of states
    Partially specified plans
  - Operators [and costs]
    Plan modification operators
  - Start state
    The null plan (no actions)
  - Goal state (test)
    A plan which provably achieves
    The desired world configuration
- Output:

Multiple Problem Spaces

Real World

States of the world (e.g. block configurations)

Actions (take one world-state to another)

Robot's Head

- Problem Space 1
  - PS states =
    - models of world states
  - Operators =
    - models of actions

- Problem Space 2
  - PS states =
    - partially spec. plan
  - Operators =
    - plan modificat'n ops

Algebraic Simplification

$$
\begin{aligned}
\partial_r^2 u &= -\left[E' - \frac{l(l+1)}{r^2} - r^2\right] u(r) \\
e^{-2s}\left(\partial_s^2 - \partial_s\right) u(s) &= -\left[E' - l(l+1)e^{-2s} - e^{2s}\right] u(s) \\
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v'' &= -e^{2s}\left[E' - \left(l+\frac{1}{2}\right)^2 e^{-2s} - e^{2s}\right] v
\end{aligned}
$$

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

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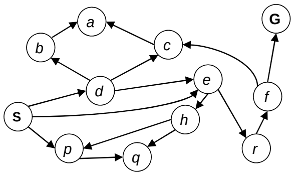
State Space Graphs

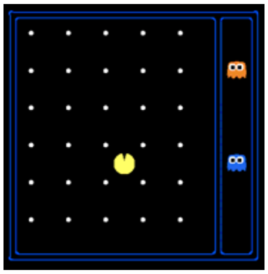
- State space graph:
  - Each node is a state
  - The successor function is represented by arcs
  - Edges may be labeled with costs
- We can rarely build this graph in memory (so we don't)



Ridiculously tiny search graph for a tiny search problem

State Space Sizes?

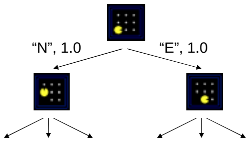
- Search Problem:
  Eat all of the food
- Pacman positions:
  10 x 12 = 120
- Pacman facing:
  up, down, left, right
- Food Count: 30
- Ghost positions: 12



Search Methods

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

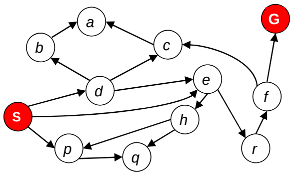
Search Trees



- 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

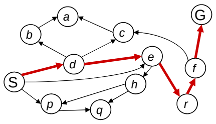
Example: Tree Search

State Graph:



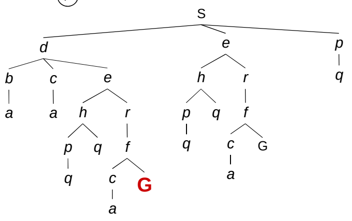
What is the search tree?

State Graphs vs. Search Trees



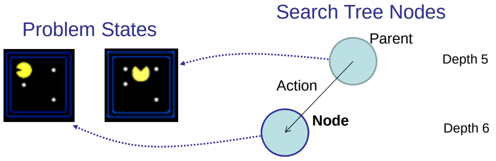
Each NODE in in the search tree denotes an entire PATH in the problem graph.

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

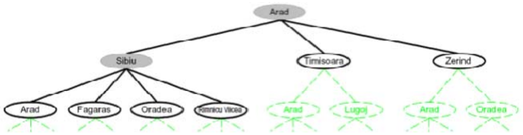


States vs. Nodes

- 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

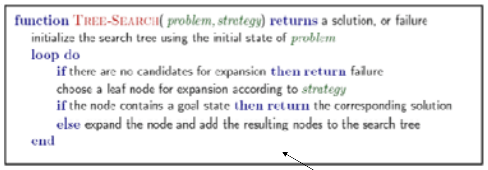


Building Search Trees



- 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
```

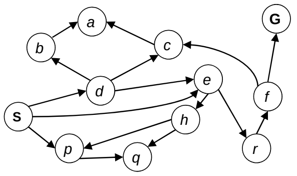
Detailed pseudocode is in the book!

- Important ideas:
  - Fringe
  - Expansion
  - Exploration strategy
- Main question: which fringe nodes to explore?

Review: Depth First Search

Strategy: *expand deepest node first*

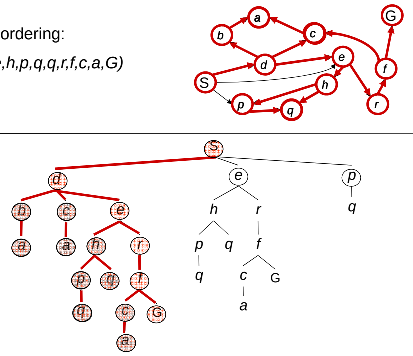
Implementation: *Fringe is a LIFO queue (a stack)*



Review: Depth First Search

Expansion ordering:

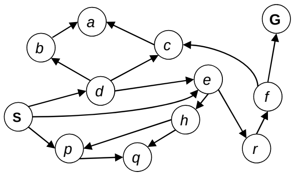
(d,b,a,c,a,e,h,p,q,q,r,f,c,a,G)



Review: Breadth First Search

Strategy: *expand shallowest node first*

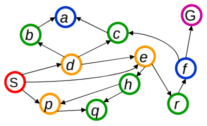
Implementation: *Fringe is a FIFO queue*

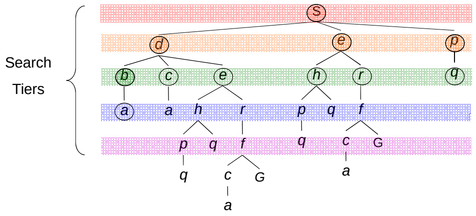


Review: Breadth First Search

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 Algorithm Properties

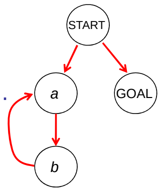
- Complete? Guaranteed to find a solution if one exists?
- Optimal? Guaranteed to find the least cost path?
- Time complexity?
- Space complexity?

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

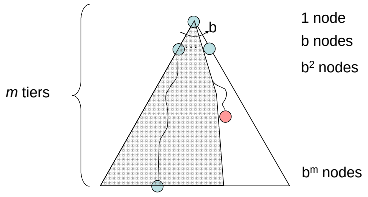
DFS

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

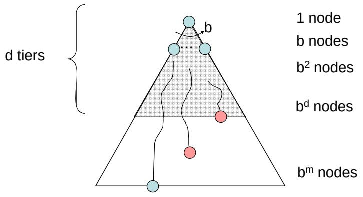


Algorithm		Complete	Optimal	Time	Space
DFS	w/ Path Checking	Y if finite	N	$O(b^m)$	$O(bm)$

* Or graph search – next lecture.

BFS

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



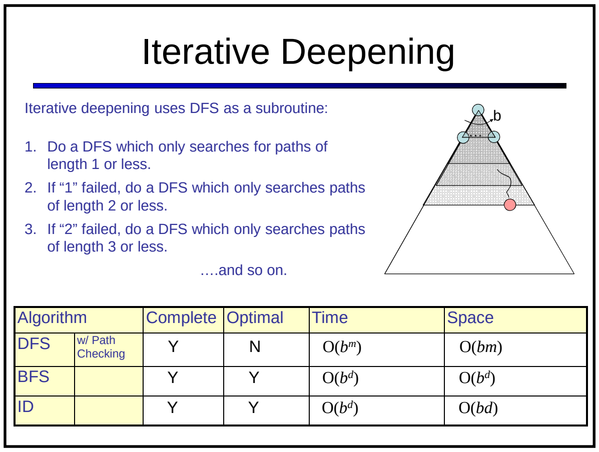
Memory a Limitation?

- 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?



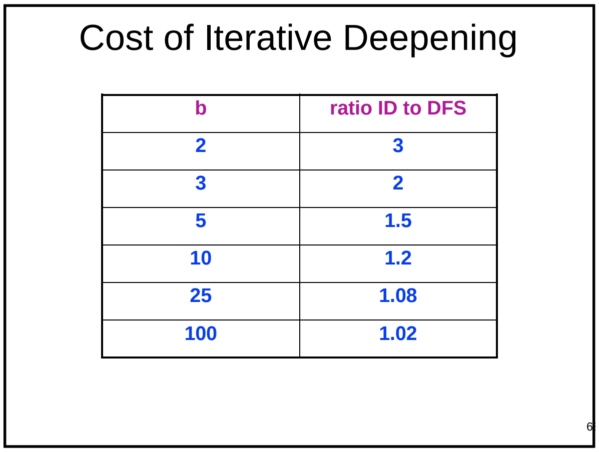
Iterative Deepening

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.

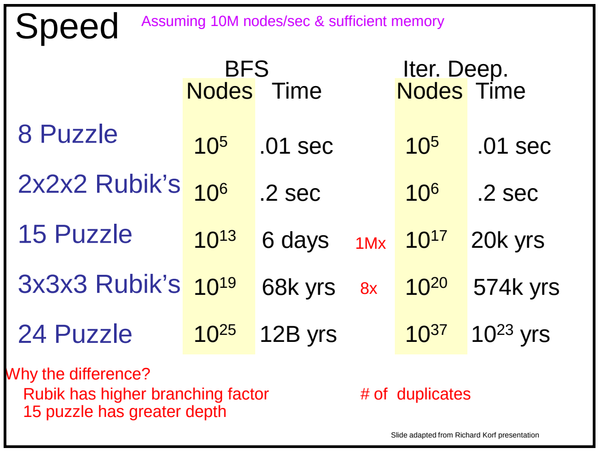
Algorithm		Complete	Optimal	Time	Space
DFS	w/ Path Checking	Y	N	$O(b^m)$	$O(bm)$
BFS		Y	Y	$O(b^d)$	$O(b^d)$
ID		Y	Y	$O(b^d)$	$O(bd)$



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

6



Speed

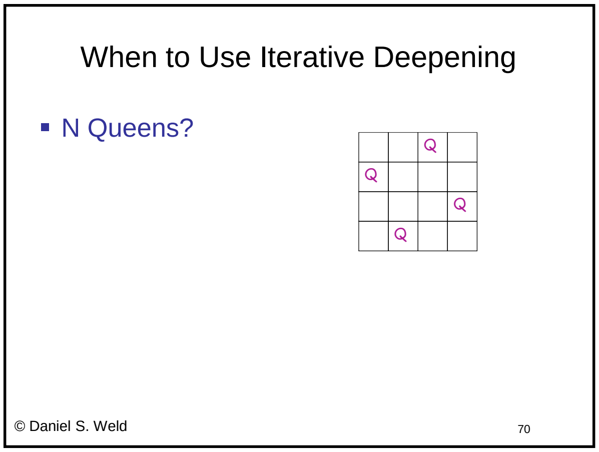
Assuming 10M nodes/sec & sufficient memory

	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
15 puzzle has greater depth

# of duplicates

Slide adapted from Richard Korf presentation



When to Use Iterative Deepening

- N Queens?

		Q	
Q			
			Q
	Q		

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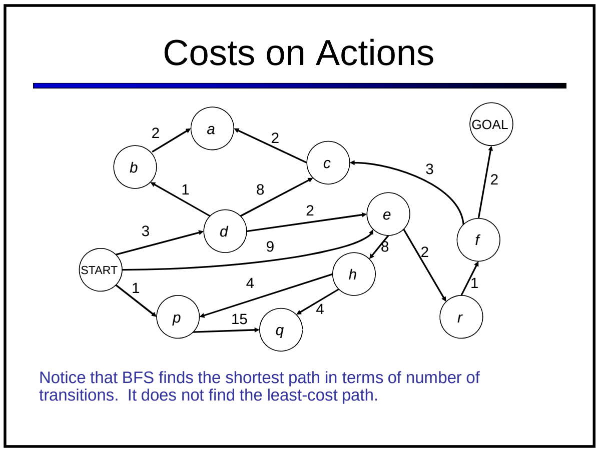
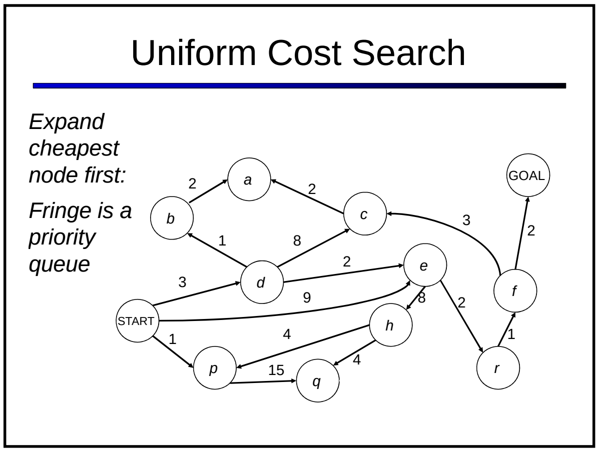


Costs on Actions

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



Uniform Cost Search

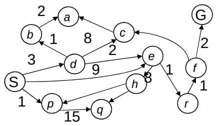
Expand cheapest node first:

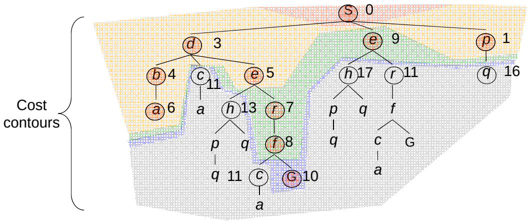
Fringe is a priority queue

Uniform Cost Search

Expansion order:

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





Priority Queue Refresher

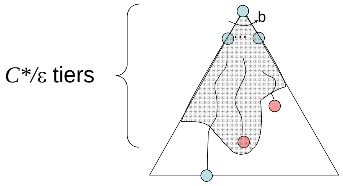
- A priority queue is a data structure in which you can insert and retrieve (key, value) pairs with the following operations:

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

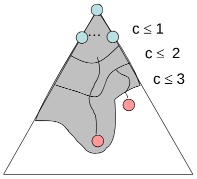
Uniform Cost Search

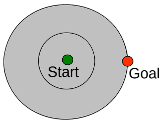
Algorithm		Complete	Optimal	Time	Space
DFS	w/ Path Checking	Y	N	$O(b^m)$	$O(bm)$
BFS		Y	Y	$O(b^d)$	$O(b^d)$
UCS		Y*	Y	$O(b^{C*/\varepsilon})$	$O(b^{C*/\varepsilon})$



Uniform Cost Issues

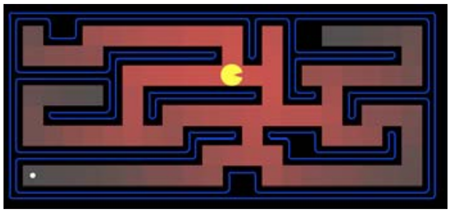
- Remember: explores increasing cost contours
- The good: UCS is complete and optimal!
- The bad:
  - Explores options in every "direction"
  - No information about goal location





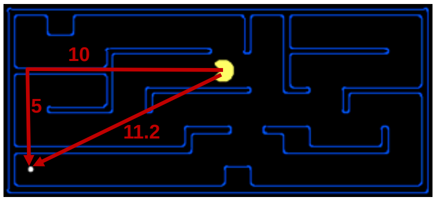
Uniform Cost: Pac-Man

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



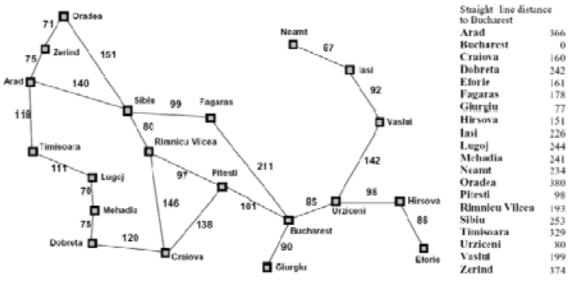
Search Heuristics

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



- Examples: Manhattan distance, Euclidean distance

Heuristics

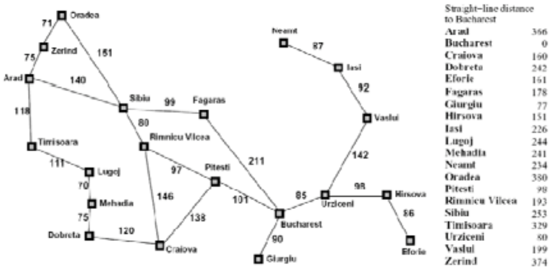


Straight−line distance to Bucharest

Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	98
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

Best First / Greedy Search

Expand closest node first: Fringe is a priority queue



Straight−line distance to Bucharest

Arad	366
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Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
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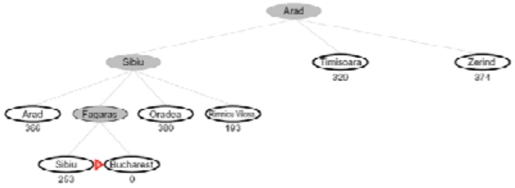
Vaslui	199
Zerind	374

Best First / Greedy Search

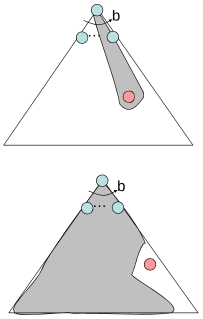
- Expand the node that seems closest…



- 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)

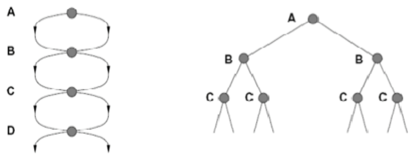


To Do:

- Look at the course website:
  - http://www.cs.washington.edu/cse473/12sp
- Do the readings (Ch 3)
- Do PS0 if new to Python
- Start PS1, when it is posted

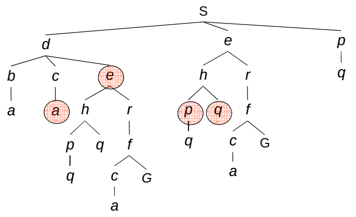
Extra Work?

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



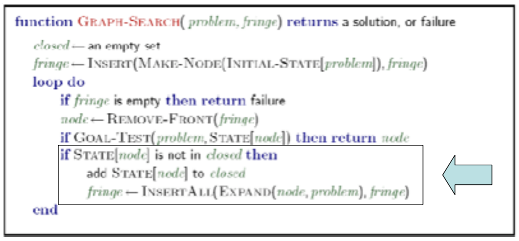
Graph Search

- 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
```

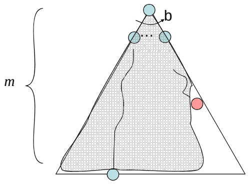
- Can this wreck completeness? Why or why not?
- How about optimality? Why or why not?

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

Best First Greedy Search

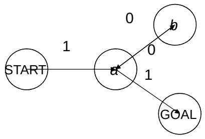
Algorithm	Complete	Optimal	Time	Space
Greedy Best-First Search	Y*	N	$O(b^m)$	$O(b^m)$



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

Uniform Cost Search

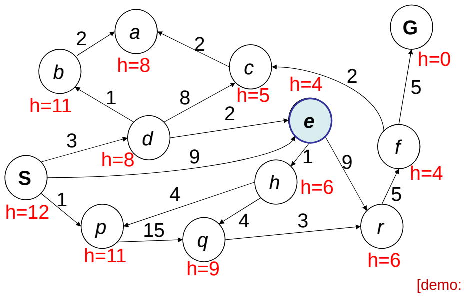
- What will UCS do for this graph?



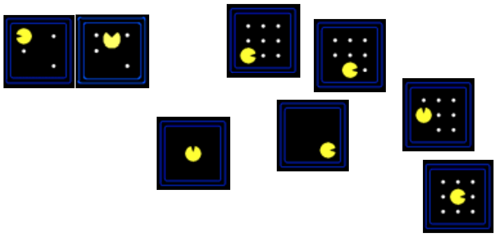
- What does this mean for completeness?

Best First / Greedy Search

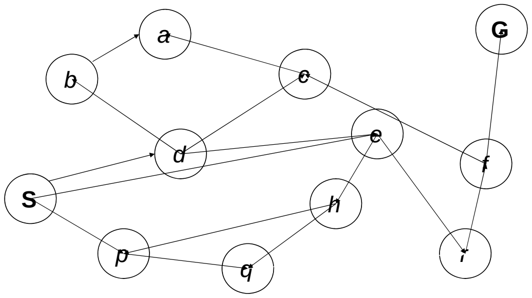
- Strategy: expand the closest node to the goal



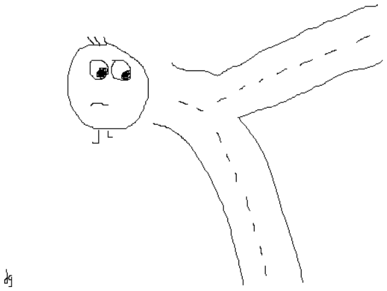
[demo: greedy]



Example: Tree Search



5 Minute Break



A Dan Gillick original