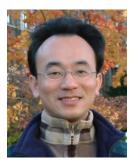




(Artificial Intelligence) 問題解決 (Problem Solving)

1092AI03 MBA, IM, NTPU (M5010) (Spring 2021) Wed 2, 3, 4 (9:10-12:00) (B8F40)



Min-Yuh Day 戴敏育

Associate Professor

副教授

Institute of Information Management, National Taipei University

國立臺北大學 資訊管理研究所



https://web.ntpu.edu.tw/~myday 2021-03-09





- 週次(Week) 日期(Date) 內容(Subject/Topics)
- 1 2021/02/24 人工智慧概論 (Introduction to Artificial Intelligence)
- 2 2021/03/03 人工智慧和智慧代理人 (Artificial Intelligence and Intelligent Agents)
- 3 2021/03/10 問題解決 (Problem Solving)
- 4 2021/03/17 知識推理和知識表達 (Knowledge, Reasoning and Knowledge Representation)
- 5 2021/03/24 不確定知識和推理 (Uncertain Knowledge and Reasoning)

6 2021/03/31 人工智慧個案研究 I (Case Study on Artificial Intelligence I)





- 週次(Week) 日期(Date) 內容(Subject/Topics)
- 7 2021/04/07 放假一天 (Day off)
- 8 2021/04/14 機器學習與監督式學習 (Machine Learning and Supervised Learning)
- 9 2021/04/21 期中報告 (Midterm Project Report)
- 10 2021/04/28 學習理論與綜合學習
 - (The Theory of Learning and Ensemble Learning)
- 11 2021/05/05 深度學習
 - (Deep Learning)
- 12 2021/05/12 人工智慧個案研究 II (Case Study on Artificial Intelligence II)





週次(Week) 日期(Date) 內容(Subject/Topics) 13 2021/05/19 強化學習 (Reinforcement Learning) 14 2021/05/26 深度學習自然語言處理 (Deep Learning for Natural Language Processing) 15 2021/06/02 機器人技術 (Robotics) 16 2021/06/09 人工智慧哲學與倫理,人工智慧的未來 (Philosophy and Ethics of AI, The Future of AI) 17 2021/06/16 期末報告 | (Final Project Report I) 18 2021/06/23 期末報告 || (Final Project Report II)

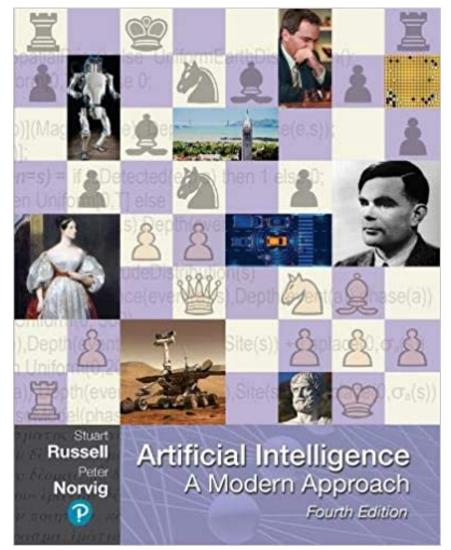
Artificial Intelligence Problem Solving

Outline

- Solving Problems by Searching
- Search in Complex Environments
- Adversarial Search and Games
- Constraint Satisfaction Problems

Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach,

4th Edition, Pearson



Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

https://www.amazon.com/Artificial-Intelligence-A-Modern-Approach/dp/0134610997/

Artificial Intelligence: A Modern Approach

- 1. Artificial Intelligence
- 2. Problem Solving
- 3. Knowledge and Reasoning
- 4. Uncertain Knowledge and Reasoning
- 5. Machine Learning
- 6. Communicating, Perceiving, and Acting
- 7. Philosophy and Ethics of AI

Artificial Intelligence: Problem Solving

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

Artificial Intelligence: 2. Problem Solving

- Solving Problems by Searching
- Search in Complex Environments
- Adversarial Search and Games
- Constraint Satisfaction Problems

Intelligent Agents

4 Approaches of Al

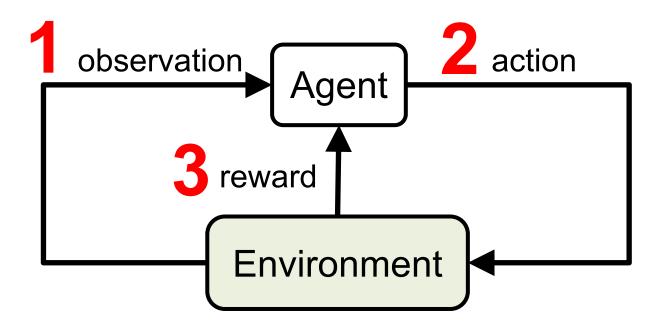
2.	3.
Thinking Humanly:	Thinking Rationally:
The Cognitive	The "Laws of Thought"
Modeling Approach	Approach
1.	4.
Acting Humanly:	Acting Rationally:
The Turing Test	The Rational Agent
Approach (1950)	Approach

Reinforcement Learning (DL)

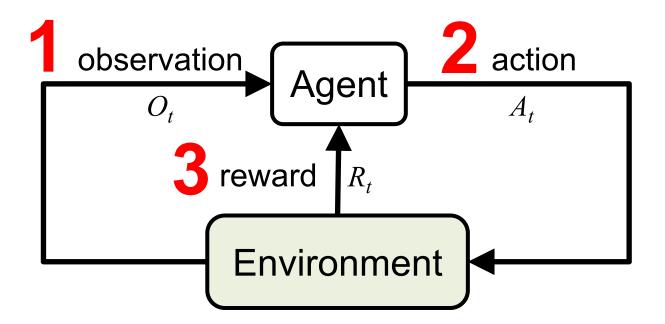


Environment

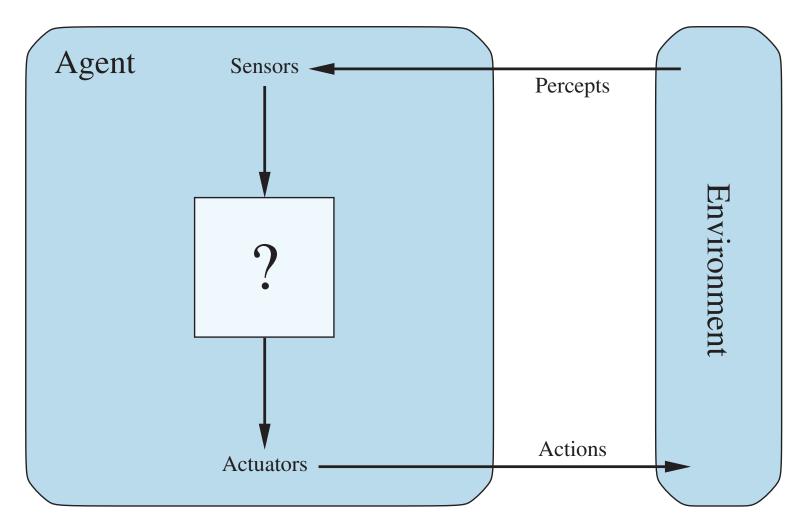
Reinforcement Learning (DL)



Reinforcement Learning (DL)



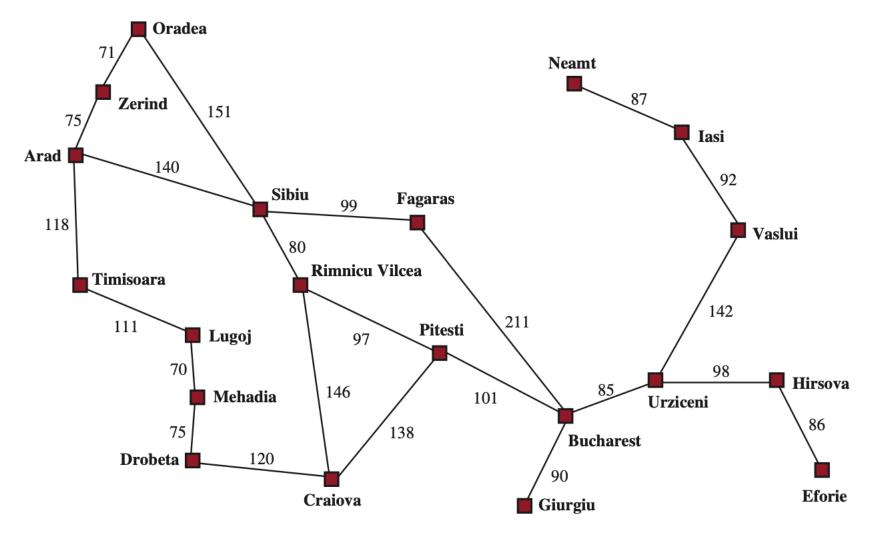
Agents interact with environments through sensors and actuators



Solving Problems by Searching

AI: Solving Problems by Searching

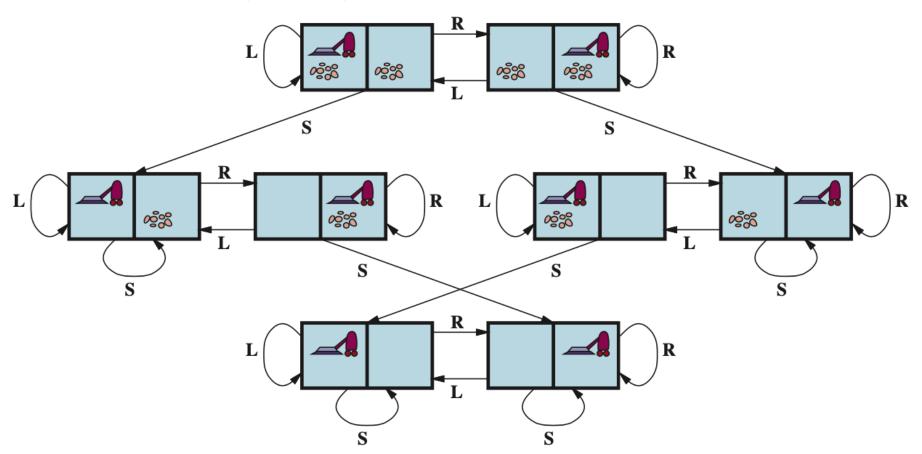
A simplified road map of part of Romania, with road distances in miles.



Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

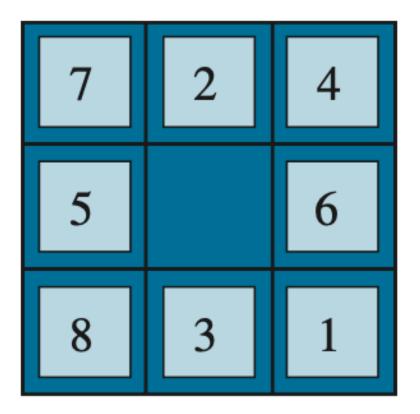
The state-space graph for the two-cell vacuum world

There are 8 states and three actions for each state: L = Left, R = Right, S = Suck.

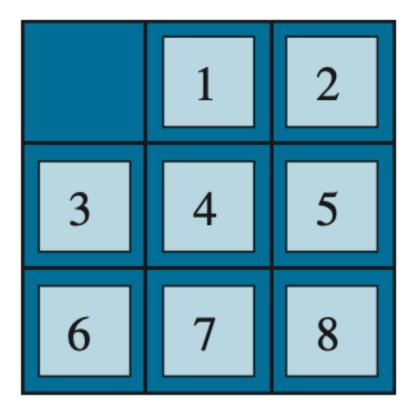


Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

A typical instance of the 8-puzzle

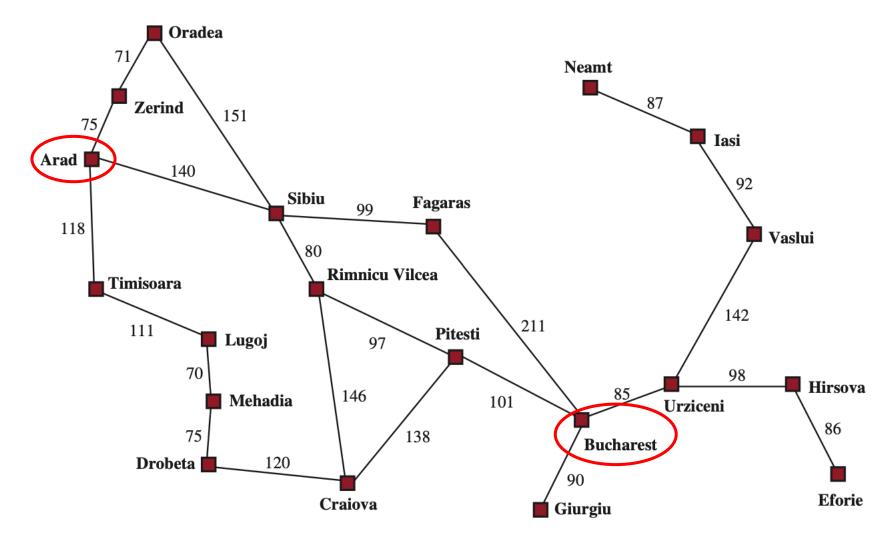


Start State

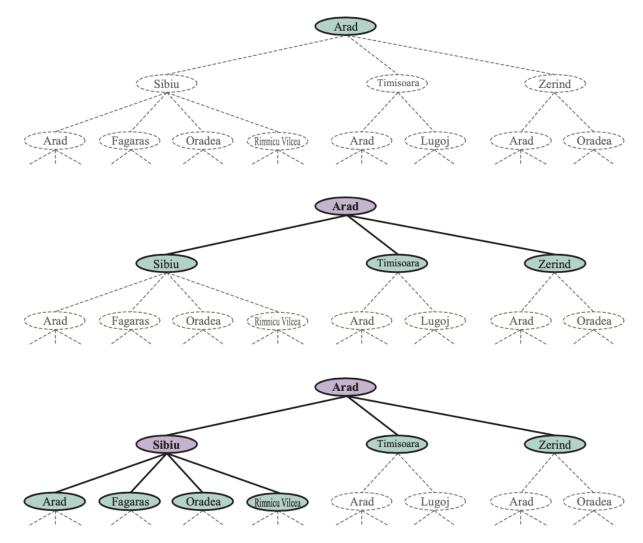


Goal State

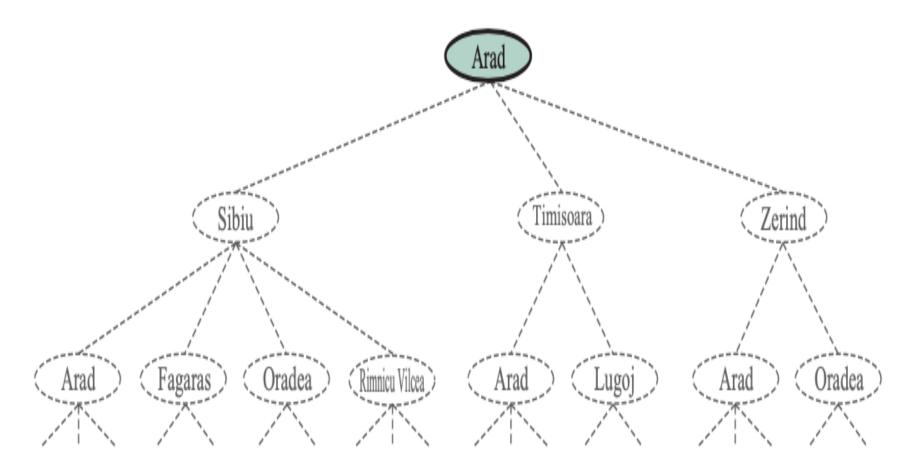
Arad to Bucharest

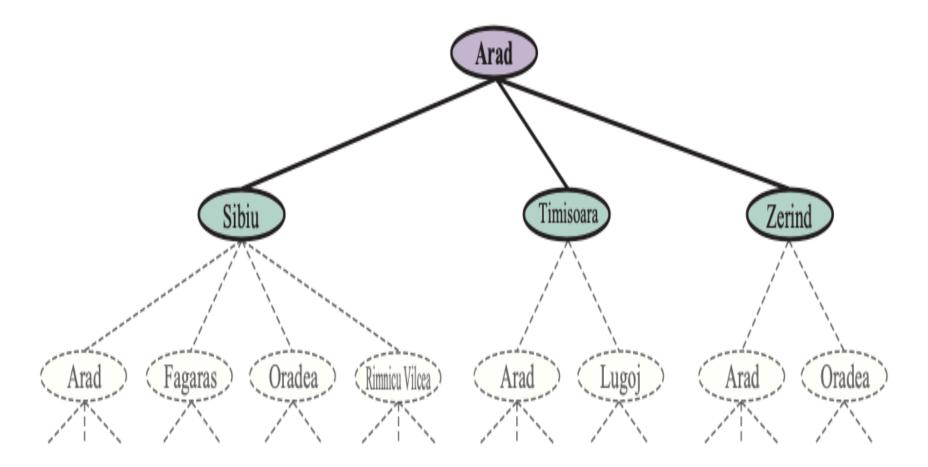


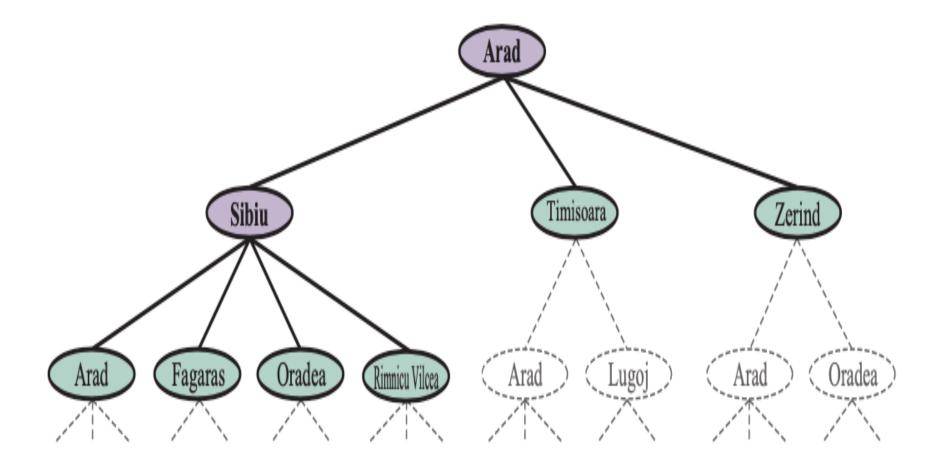
Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson



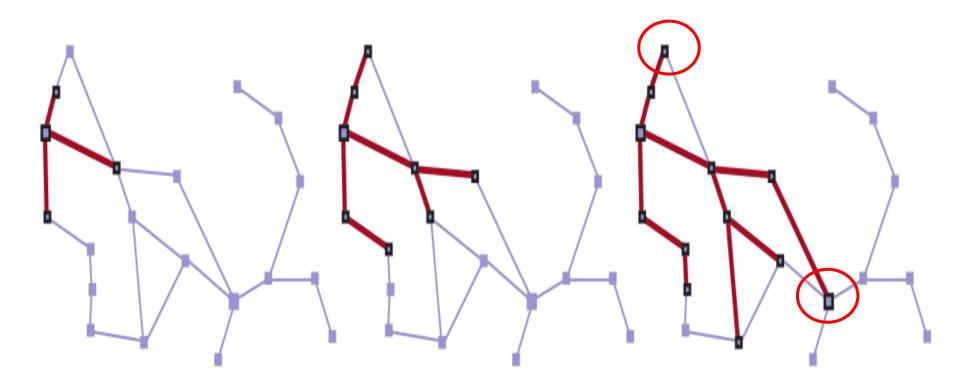
Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson







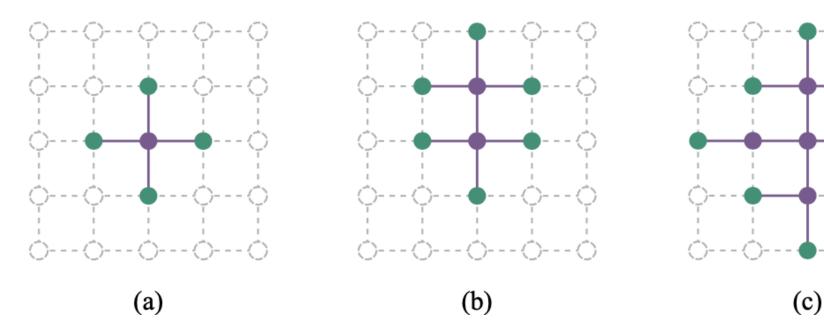
A sequence of search trees generated by a graph search on the Romania problem



The Separation Property of Graph Search

illustrated on a rectangular-grid problem

The frontier (green) separates the interior (lavender) from the exterior (faint dashed)



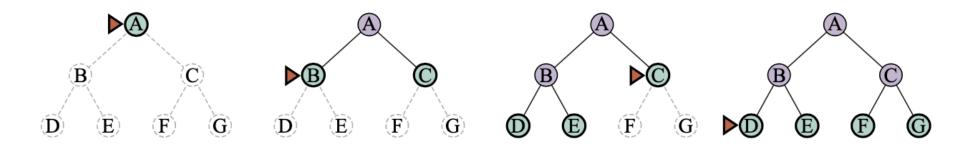
Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

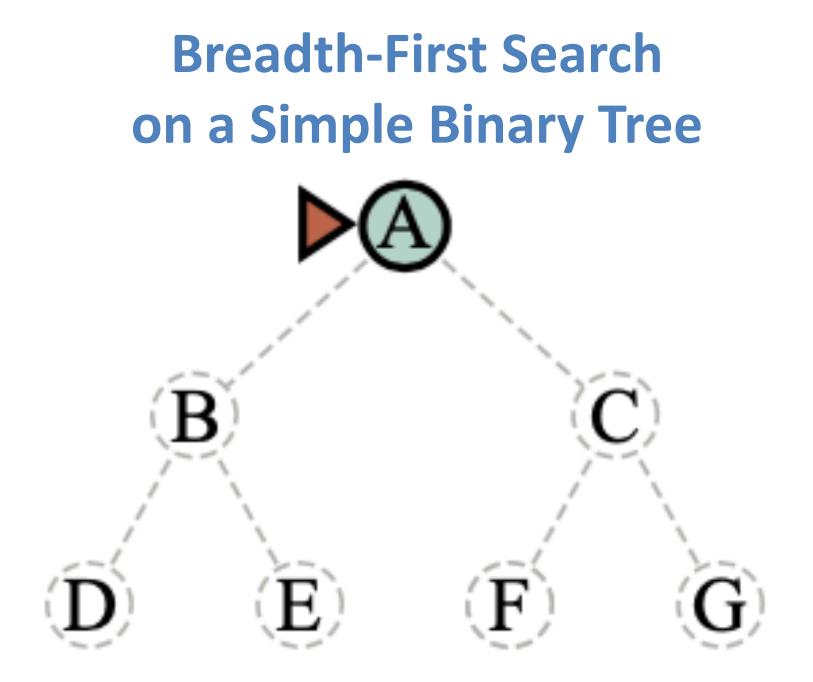
The Best-First Search (BFS) Algorithm

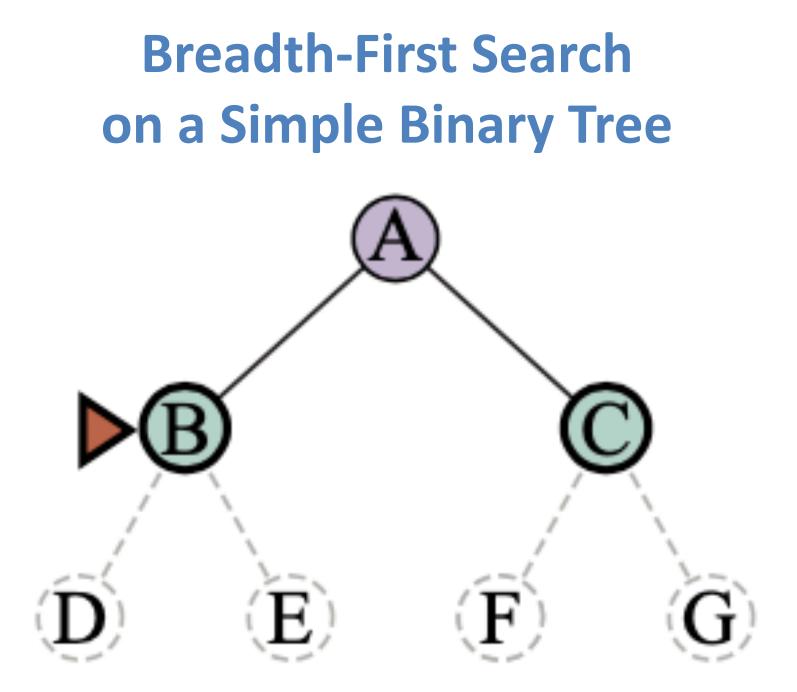
function BEST-FIRST-SEARCH(problem, f) returns a solution node or failure $node \leftarrow \text{NODE}(\text{STATE}=problem.INITIAL})$ *frontier* \leftarrow a priority queue ordered by f, with node as an element $reached \leftarrow$ a lookup table, with one entry with key problem.INITIAL and value node while not IS-EMPTY(frontier) do $node \leftarrow POP(frontier)$ if problem.IS-GOAL(node.STATE) then return node for each *child* in EXPAND(*problem*, *node*) do $s \leftarrow child$.STATE if s is not in reached or child.PATH-COST < reached[s].PATH-COST then $reached[s] \leftarrow child$ add child to frontier **return** failure

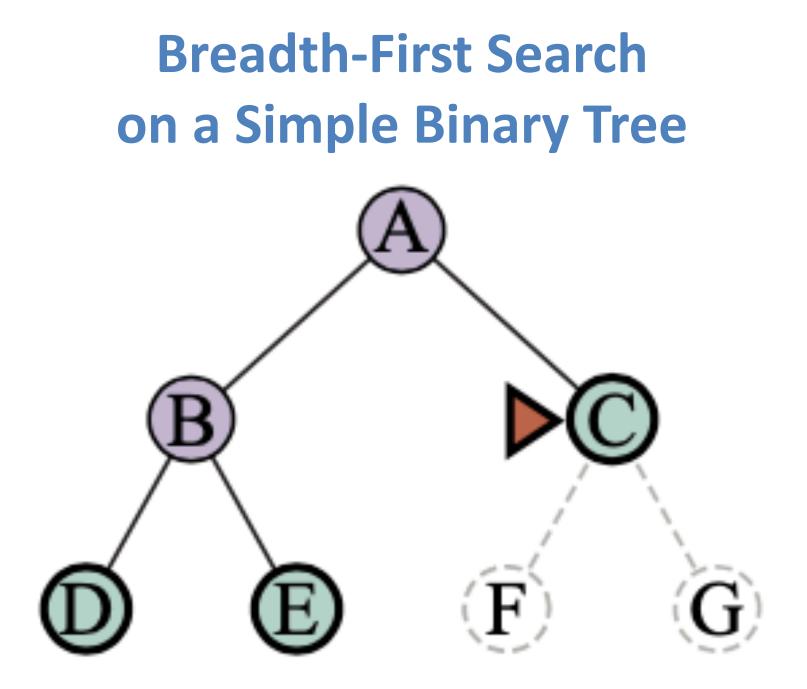
function EXPAND(problem, node) yields nodes $s \leftarrow node.STATE$ for each action in problem.ACTIONS(s) do $s' \leftarrow problem.RESULT(s, action)$ $cost \leftarrow node.PATH-COST + problem.ACTION-COST(s, action, s')$ yield NODE(STATE=s', PARENT=node, ACTION=action, PATH-COST=cost)

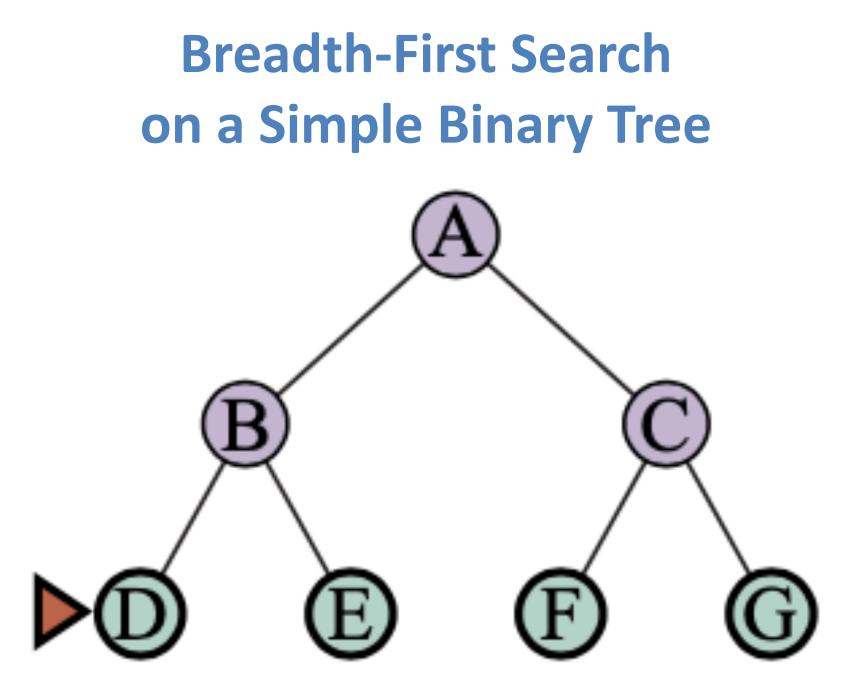
Breadth-First Search on a Simple Binary Tree









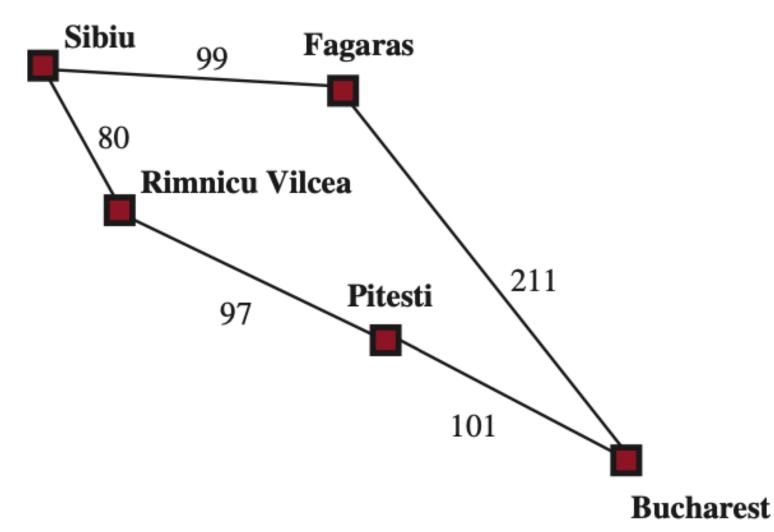


Breadth-First Search and Uniform-Cost Search Algorithms

function BREADTH-FIRST-SEARCH(*problem*) returns a solution node or *failure* $node \leftarrow NODE(problem.INITIAL)$ if problem.Is-GOAL(node.STATE) then return node *frontier* \leftarrow a FIFO queue, with *node* as an element $reached \leftarrow \{problem.INITIAL\}$ while not IS-EMPTY(frontier) do $node \leftarrow POP(frontier)$ for each *child* in EXPAND(*problem*, *node*) do $s \leftarrow child.STATE$ **if** problem.IS-GOAL(s) **then return** child if s is not in reached then add s to reached add child to frontier **return** failure

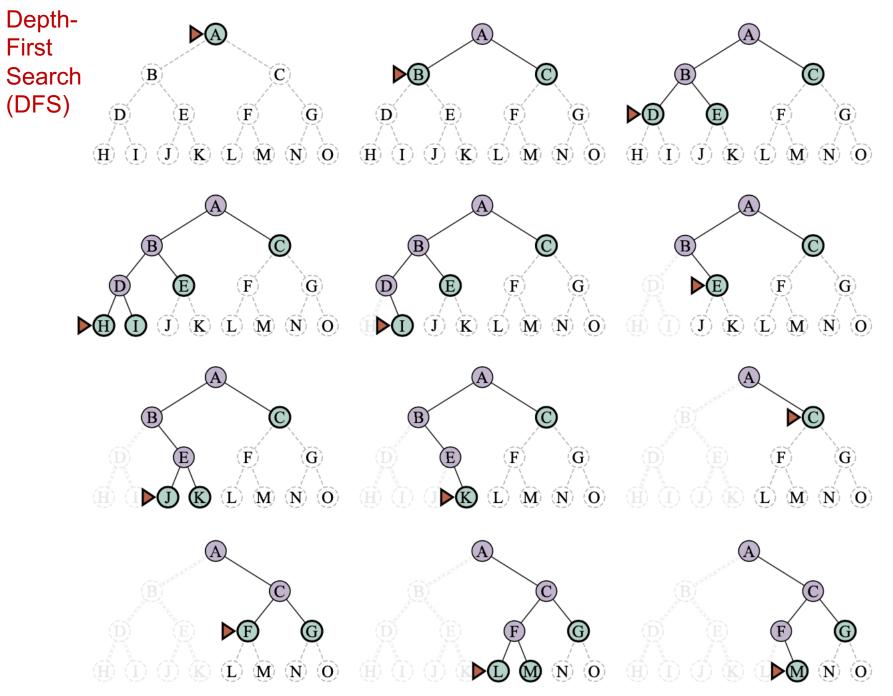
function UNIFORM-COST-SEARCH(*problem*) **returns** a solution node, or *failure* **return** BEST-FIRST-SEARCH(*problem*, PATH-COST)

Part of the Romania State Space Uniform-Cost Search



Depth-First Search (DFS)

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

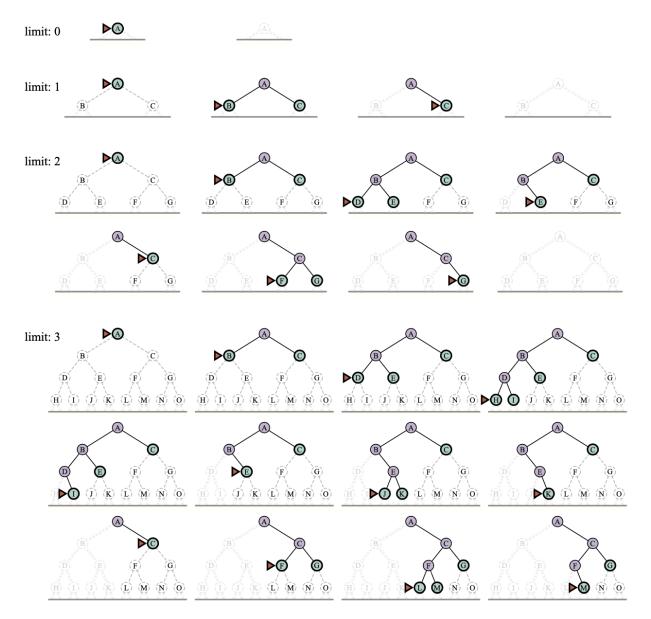


Iterative deepening and depth-limited tree-like search

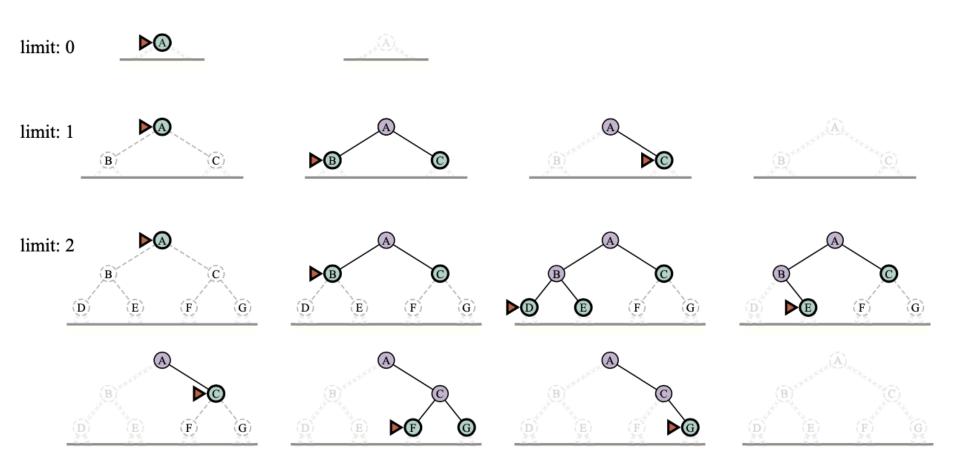
function ITERATIVE-DEEPENING-SEARCH(*problem*) returns a solution node or *failure* for depth = 0 to ∞ do result \leftarrow DEPTH-LIMITED-SEARCH(*problem*, depth) if result \neq cutoff then return result

function DEPTH-LIMITED-SEARCH(problem, l) returns a node or failure or cutoff
frontier ← a LIFO queue (stack) with NODE(problem.INITIAL) as an element
result ← failure
while not Is-EMPTY(frontier) do
node ← POP(frontier)
if problem.Is-GOAL(node.STATE) then return node
if DEPTH(node) > l then
result ← cutoff
else if not Is-CYCLE(node) do
for each child in EXPAND(problem, node) do
add child to frontier
return result

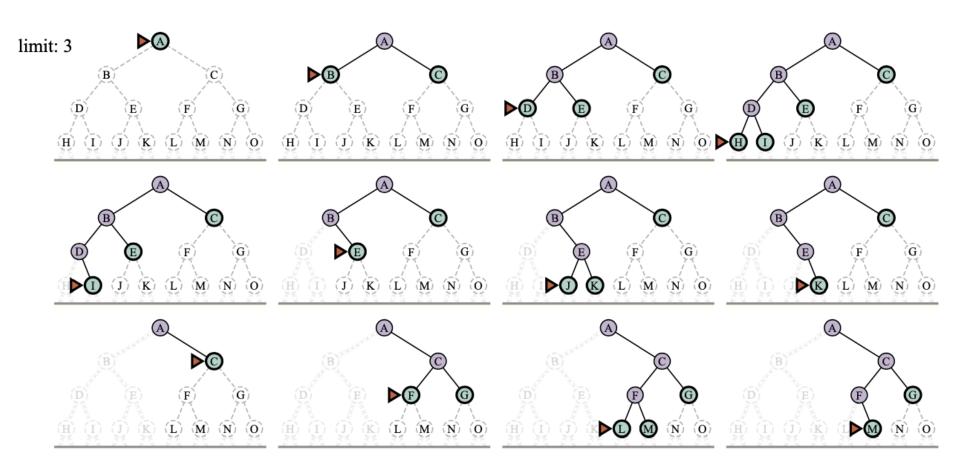
Four iterations of iterative deepening search



Four iterations of iterative deepening search



Four iterations of iterative deepening search



Bidirectional Best-First Search

keeps two frontiers and two tables of reached states

function BIBF-SEARCH(*problem*_F, f_F, *problem*_B, f_B) **returns** a solution node, or *failure* $node_F \leftarrow \text{NODE}(problem_F.INITIAL)$ // Node for a start state $node_B \leftarrow \text{NODE}(problem_B.INITIAL)$ // Node for a goal state frontier $_F \leftarrow$ a priority queue ordered by f_F , with $node_F$ as an element frontier $_B \leftarrow$ a priority queue ordered by f_B , with $node_B$ as an element $reached_F \leftarrow$ a lookup table, with one key $node_F.STATE$ and value $node_F$ $reached_B \leftarrow$ a lookup table, with one key $node_B.STATE$ and value $node_B$ $solution \leftarrow failure$

while not TERMINATED(solution, frontier_F, frontier_B) do

if $f_F(\text{TOP}(frontier_F)) < f_B(\text{TOP}(frontier_B))$ then

 $solution \leftarrow PROCEED(F, problem_F frontier_F, reached_F, reached_B, solution)$ else $solution \leftarrow PROCEED(B, problem_B, frontier_B, reached_B, reached_F, solution)$ return solution

Bidirectional Best-First Search keeps two frontiers and two tables of reached states

function PROCEED(dir, problem, frontier, reached, reached₂, solution) returns a solution // Expand node on frontier; check against the other frontier in reached₂. // The variable "dir" is the direction: either F for forward or B for backward. $node \leftarrow POP(frontier)$ for each *child* in EXPAND(*problem*, *node*) do $s \leftarrow child.$ STATE if s not in reached or PATH-COST(child) < PATH-COST(reached[s]) then $reached[s] \leftarrow child$ add *child* to *frontier* if s is in $reached_2$ then $solution_2 \leftarrow JOIN-NODES(dir, child, reached_2[s]))$ if $PATH-COST(solution_2) < PATH-COST(solution)$ then $solution \leftarrow solution_2$ **return** solution

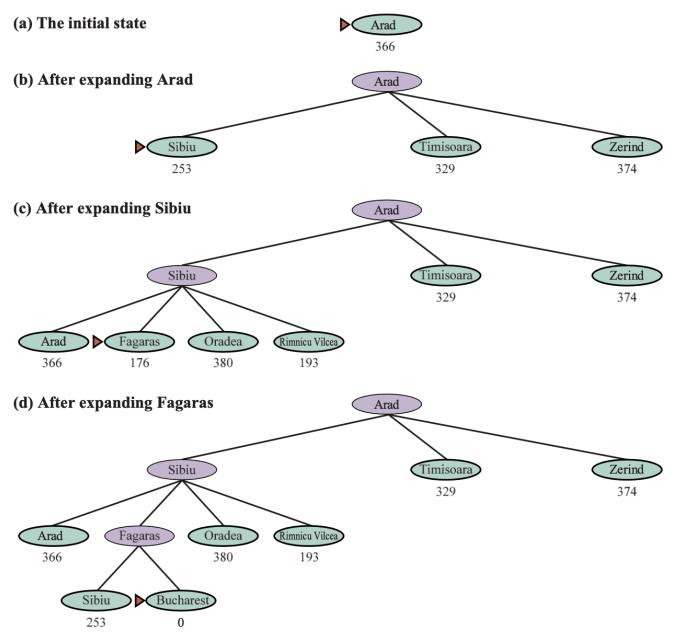
Evaluation of search algorithms

Criterion	Breadth- First	Uniform- Cost	Depth- First	Depth- Limited	Iterative Deepening	Bidirectional (if applicable)
Complete?	Yes ¹	$ m Yes^{1,2}$	No	No	Yes ¹	Yes ^{1,4}
Optimal cost?	Yes ³	Yes	No	No	Yes ³	Yes ^{3,4}
Time	$O(b^d)$	$O(b^{1+\lfloor C^*/\epsilon floor})$	$O(b^m)$	$O(b^\ell)$	$O(b^d)$	$O(b^{d/2})$
Space	$O(b^d)$	$O(b^{1+\lfloor C^*/\epsilon floor})$	O(bm)	$O(b\ell)$	O(bd)	$O(b^{d/2})$

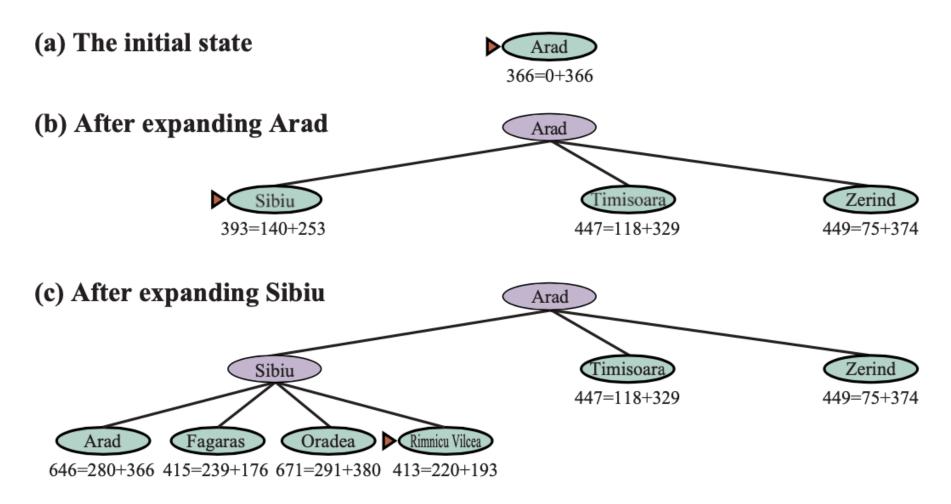
b is the branching factor; *m* is the maximum depth of the search tree; *d* is the depth of the shallowest solution, or is *m* when there is no solution; ℓ is the depth limit

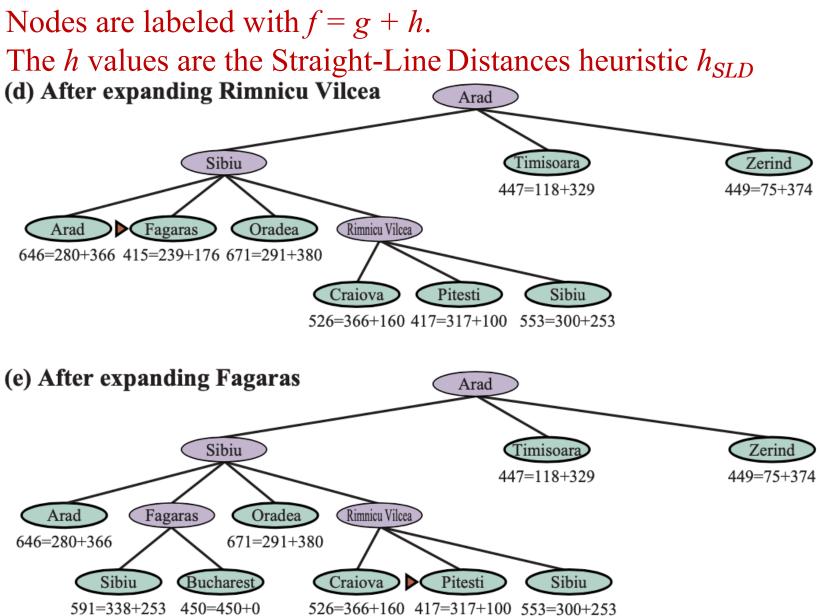
Values of *hSLD* —straight-line distances to Bucharest.

Arad	366	Mehadia	241
Bucharest	0	Neamt	234
Craiova	160	Oradea	380
Drobeta	242	Pitesti	100
Eforie	161	Rimnicu Vilcea	193
Fagaras	176	Sibiu	253
Giurgiu	77	Timisoara	329
Hirsova	151	Urziceni	80
Iasi	226	Vaslui	199
Lugoj	244	Zerind	374



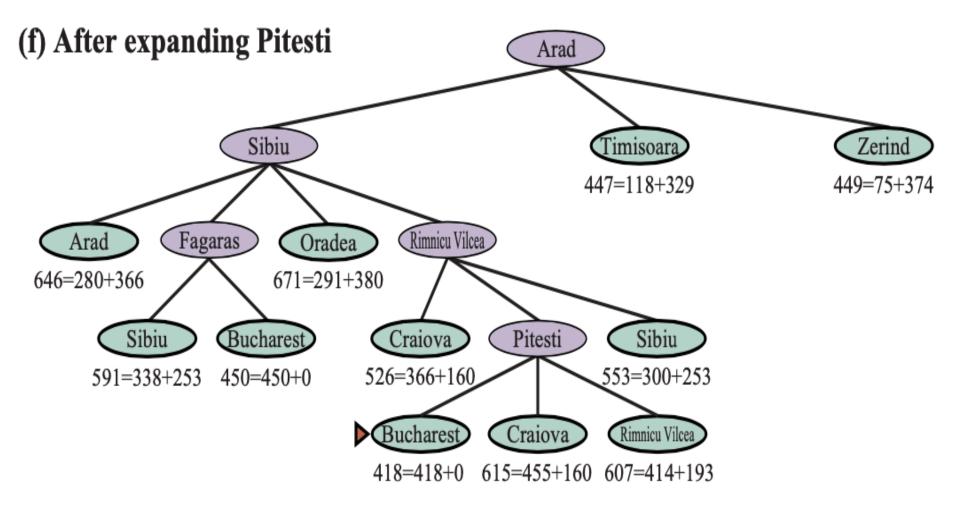
Nodes are labeled with f = g + h. The *h* values are the Straight-Line Distances heuristic h_{SLD}

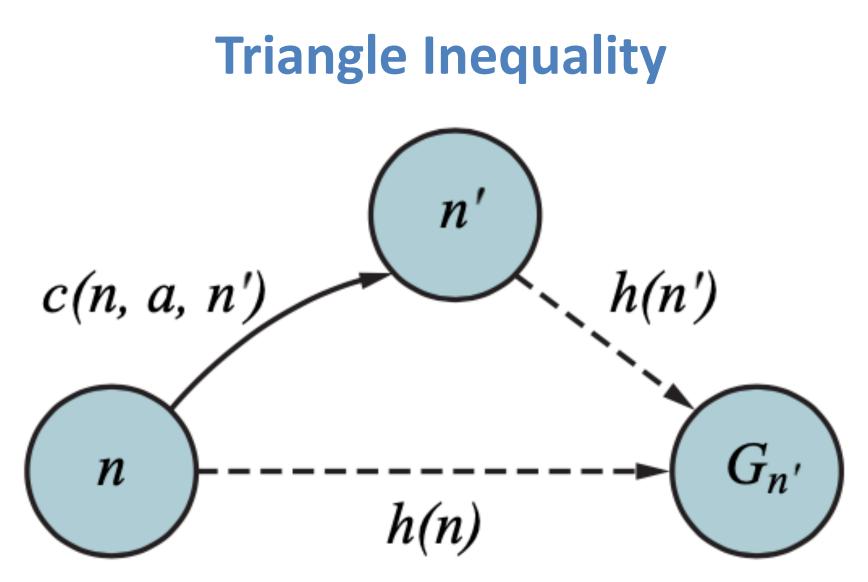




Nodes are labeled with f = g + h.

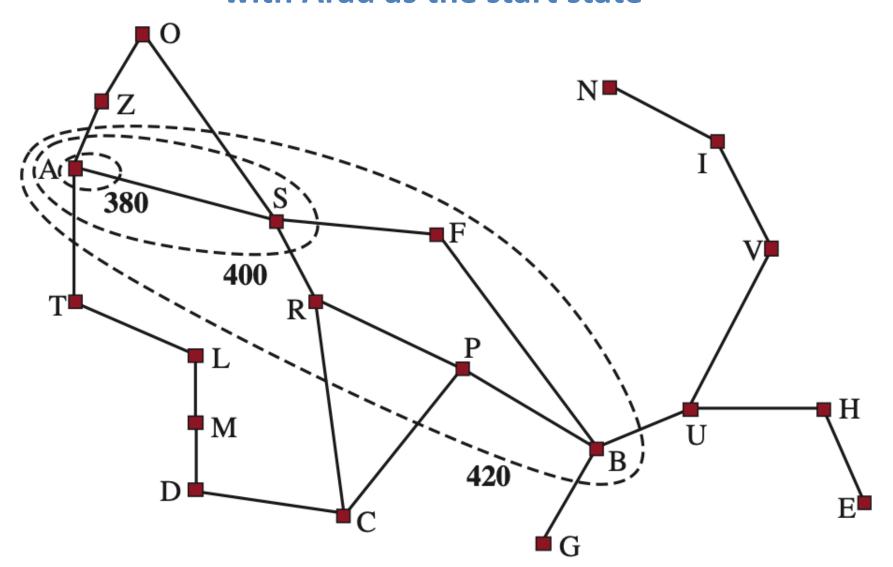
The *h* values are the Straight-Line Distances heuristic h_{SLD}



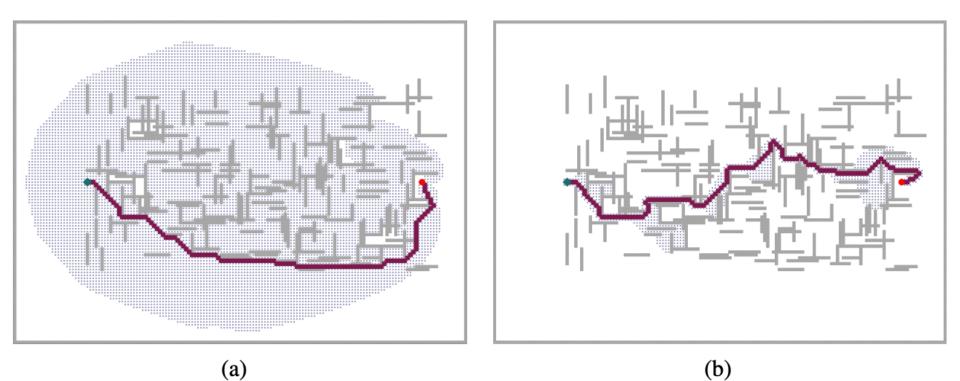


If the heuristic h is consistent, then the single number h(n) will be less than the sum of the cost c(n, a, a') of the action from n to n' plus the heuristic estimate h(n').

Map of Romania showing contours *at f* = 380, *f* = 400, and *f* = 420, with Arad as the start state



(a) A* Search(b) Weighted A* Search



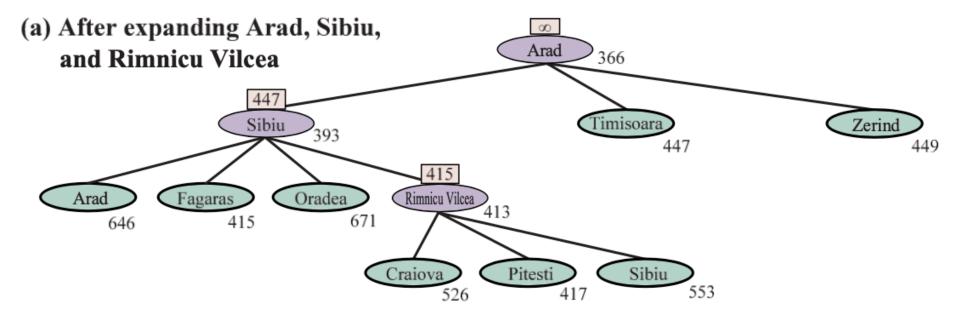
The gray bars are obstacles, the purple line is the path from the green start to red goal, and the small dots are states that were reached by each search. On this particular problem, weighted A* explores 7 times fewer states and finds a path that is 5% more costly.

Recursive Best-First Search (RBFS) Algorithm

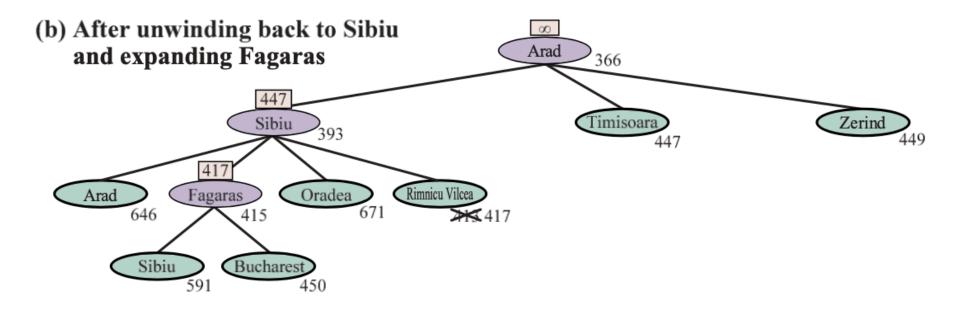
function RECURSIVE-BEST-FIRST-SEARCH(*problem*) **returns** a solution or *failure* solution, fvalue \leftarrow RBFS(*problem*, NODE(*problem*.INITIAL), ∞) **return** solution

function RBFS(problem, node, f_limit) returns a solution or failure, and a new f-cost limit if problem.IS-GOAL(node.STATE) then return node successors \leftarrow LIST(EXPAND(node)) if successors is empty then return failure, ∞ for each s in successors do // update f with value from previous search $s.f \leftarrow \max(s.PATH-COST + h(s), node.f)$) while true do best \leftarrow the node in successors with lowest f-value if best.f > f_limit then return failure, best.f alternative \leftarrow the second-lowest f-value among successors result, best.f \leftarrow RBFS(problem, best, min(f_limit, alternative)) if result \neq failure then return result, best.f

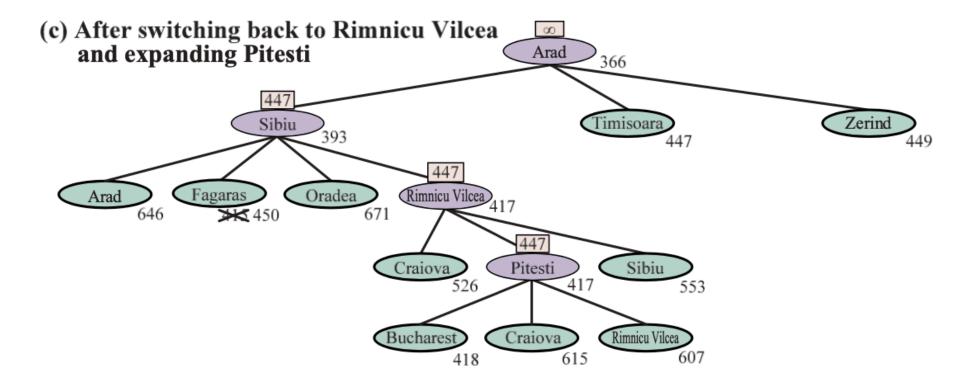
Recursive Best-First Search (RBFS)

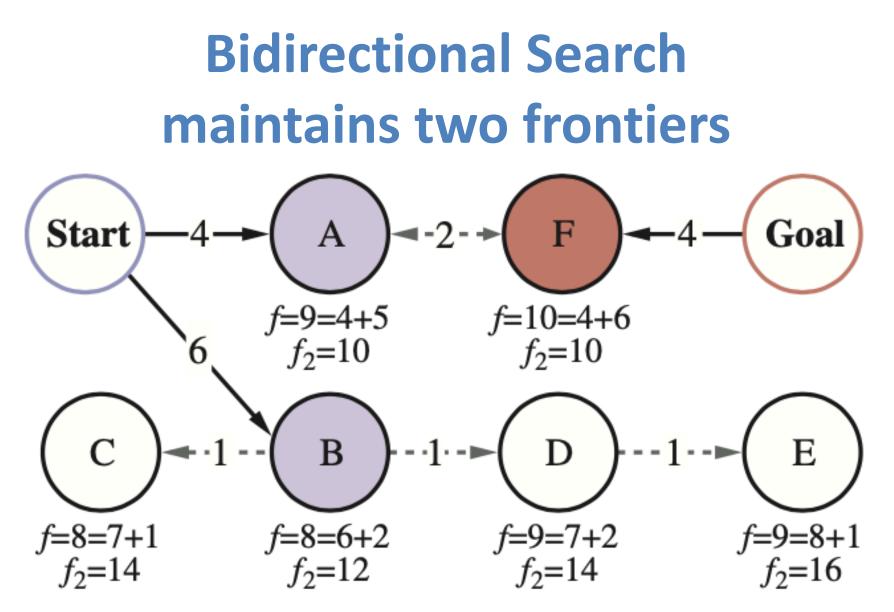


Recursive Best-First Search (RBFS)



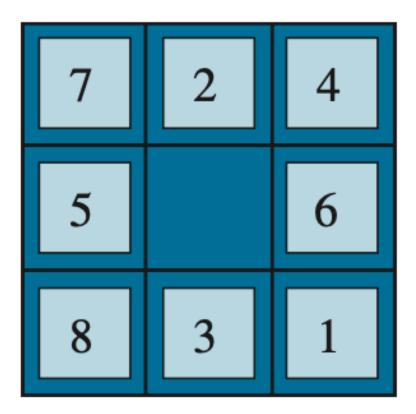
Recursive Best-First Search (RBFS)

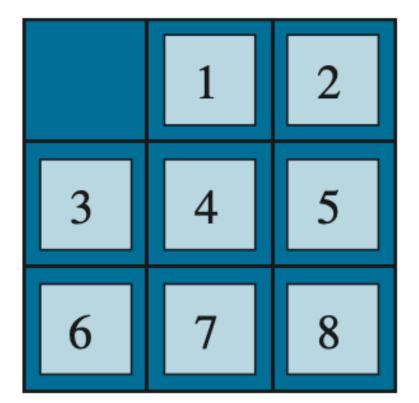




On the left, nodes A and B are successors of Start; on the right, node F is an inverse successor of Goal

A typical instance of the 8-puzzle The shortest solution is 26 actions long



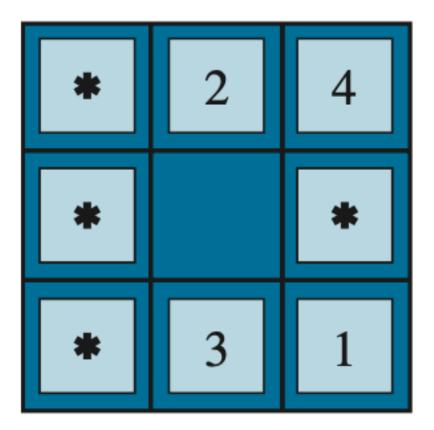


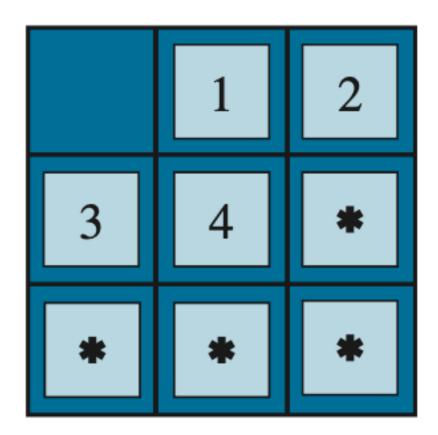
Goal State

Comparison of the search costs and effective branching factors for 8-puzzle problems

	Search Cost (nodes generated)			Effective Branching Factor			
d	BFS	$A^*(h_1)$	$A^*(h_2)$	BFS	$A^*(h_1)$	$A^*(h_2)$	
6	128	24	19	2.01	1.42	1.34	
8	368	48	31	1.91	1.40	1.30	
10	1033	116	48	1.85	1.43	1.27	
12	2672	279	84	1.80	1.45	1.28	
14	6783	678	174	1.77	1.47	1.31	
16	17270	1683	364	1.74	1.48	1.32	
18	41558	4102	751	1.72	1.49	1.34	
20	91493	9905	1318	1.69	1.50	1.34	
22	175921	22955	2548	1.66	1.50	1.34	
24	290082	53039	5733	1.62	1.50	1.36	
26	395355	110372	10080	1.58	1.50	1.35	
28	463234	202565	22055	1.53	1.49	1.36	

A subproblem of the 8-puzzle





Start State

Goal State

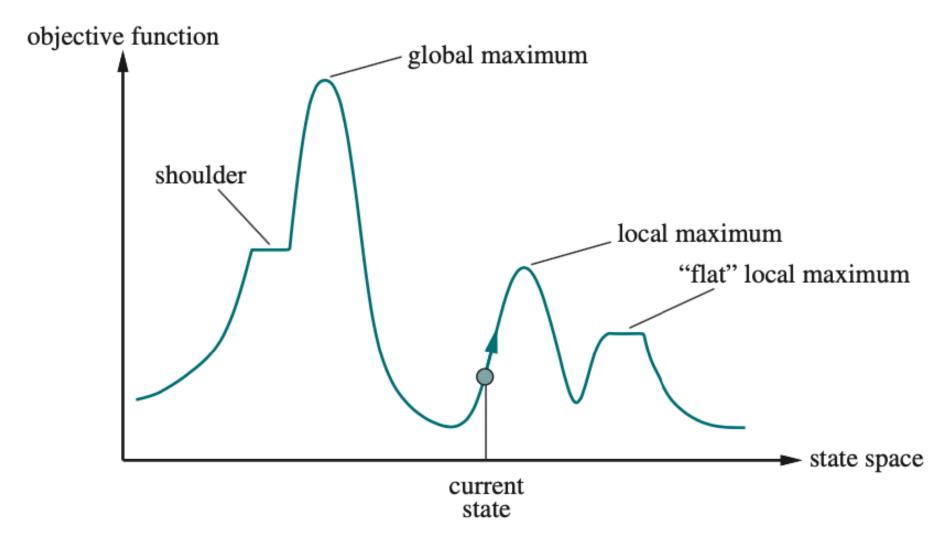
The task is to get tiles 1, 2, 3, 4, and the blank into their correct positions, without worrying about what happens to the other tiles

A Web service providing driving directions, computed by a search algorithm.



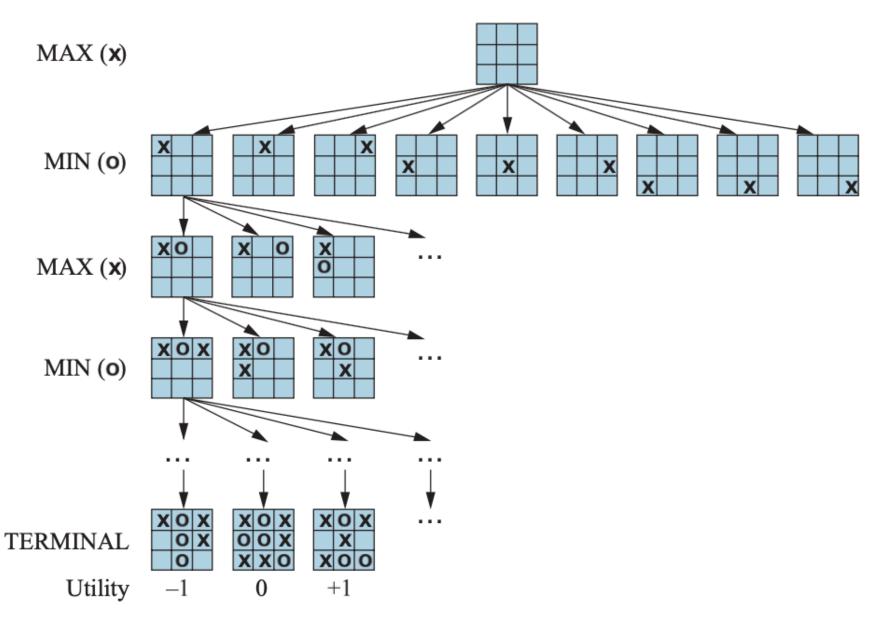
Search in Complex Environments

A one-dimensional state-space landscape



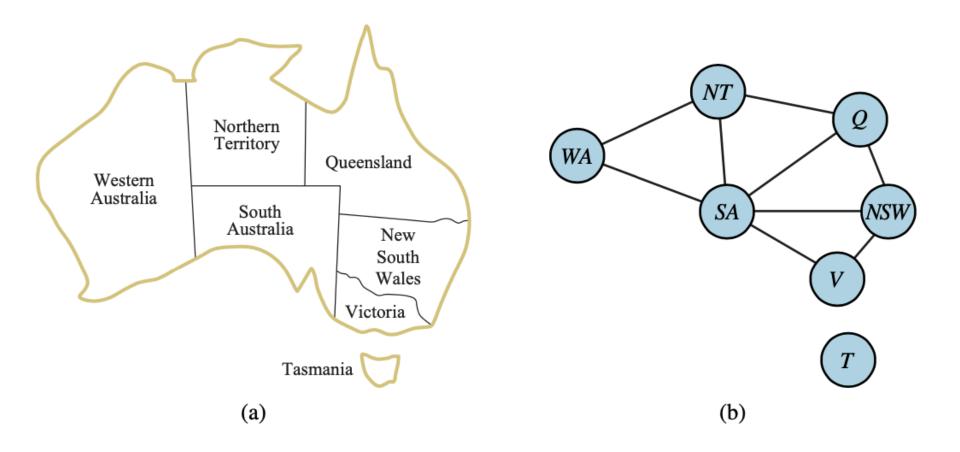
Adversarial Search and Games

Game Tree for the Game of Tic-tac-toe

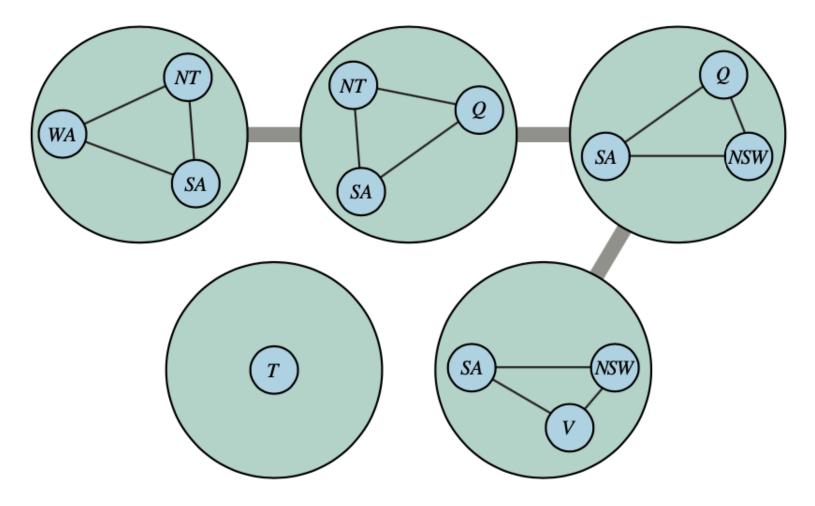


Constraint Satisfaction Problems

The Map-Coloring Problem Represented as a Constraint Graph



A Tree Decomposition of the Constraint Graph



AIMA Python

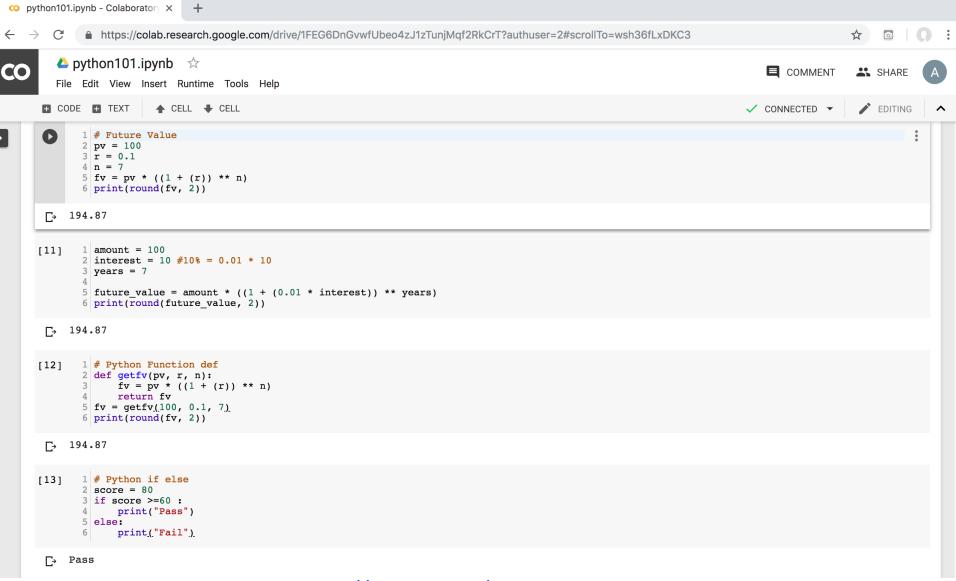
- Artificial Intelligence: A Modern Approach (AIMA)
 - <u>http://aima.cs.berkeley.edu/</u>
- AIMA Python
 - <u>http://aima.cs.berkeley.edu/python/readme.html</u>
- Search
 - <u>http://aima.cs.berkeley.edu/python/search.html</u>
- Games: Adversarial Search

http://aima.cs.berkeley.edu/python/games.html

- CSP (Constraint Satisfaction Problems)
 - <u>http://aima.cs.berkeley.edu/python/csp.html</u>

Python in Google Colab (Python101)

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT



https://tinyurl.com/aintpupython101

Summary

- Solving Problems by Searching
- Search in Complex Environments
- Adversarial Search and Games
- Constraint Satisfaction Problems

References

- Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson.
- Aurélien Géron (2019), Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems, 2nd Edition, O'Reilly Media.