

# Lecture 3a: Heuristic Functions

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CSCI 360

Introduction to Artificial Intelligence

USC

# Here is where we are...

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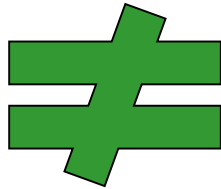


Week	30000D	30282R	Topics	Chapters
1	1/7 1/9	1/8 1/10	Intelligent Agents Problem Solving and Search	[Ch 1.1-1.4 and 2.1-2.4] [Ch 3.1-3.3]
2	1/14 1/16	1/15 1/17	Uninformed Search Heuristic Search (A*)	[Ch 3.3-3.4] [Ch 3.5]
3	1/21 <u>1/23</u>	1/22 <u>1/24</u>	Heuristic Functions Local Search	[Ch 3.6] [Ch 4.1-4.2]
	1/25		Project 1 Out	
4	1/28 1/30	1/29 1/31	Adversarial Search Knowledge Based Agents	[Ch 5.1-5.3] [Ch 7.1-7.3]
5	2/4 2/6	2/5 2/7	Propositional Logic Inference First-Order Logic	[Ch 7.4-7.5] [Ch 8.1-8.4]
	2/8 2/8		Project 1 Due Homework 1 Out	
6	2/11 2/13	2/12 2/14	Rule-Based Systems Search-Based Planning	[Ch 9.3-9.4] [Ch 10.1-10.3]
	2/15		Homework 1 Due	
7	2/18 2/20	2/19 2/21	SAT-Based Planning Knowledge Representation	[Ch 10.4] [Ch 12.1-12.5]
8	2/25 2/27	2/26 2/28	Midterm Review <b>Midterm Exam</b>	

# “One Red Paperclip”

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*It may be hard to estimate the value of...*



# “One Red Paperclip” – Real transactions made by Kyle MacDonald

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- 7/14/2005, he traded the *paperclip* for a **fish-shaped pen**.
- 7/14/2005, he traded the **pen** for a hand-sculpted **doorknob**.
- 7/25/2005, he traded the **doorknob** for a Coleman **camp stove**.
- 9/24/2005, he traded the **camp stove** for a Honda **generator**.
- 11/16/2005, he traded the **generator** for an "instant party": an empty keg, an IOU for filling the keg with any beer, and a neon Budweiser sign.
- 12/8/2005, he traded the "instant party" to for a Ski-Doo **snowmobile**.
- 12/15/05, he traded the **snowmobile** for a **two-person trip to Yahk, Canada**.
- 1/7/2006, he traded the “**second spot**” on the Yahk trip for a **box truck**.
- 2/22/2006, he traded the **truck** for a **recording contract** with Metalworks.
- 4/11/2006, he traded the **contract** for a **year's rent** in Phoenix, Arizona.
- 4/26/2006, he traded the **year's rent** for **one afternoon with Alice Cooper**.
- 5/26/2006, he traded the **afternoon with Cooper** for a motorized **snow globe**.
- 6/2/2006, he traded the **snow globe** for a **role in the film Donna on Demand**.
- 7/5/2006, he traded the **role** for a *two-story farmhouse* in Kipling, Saskatchewan.



[https://en.wikipedia.org/wiki/One\\_red\\_paperclip](https://en.wikipedia.org/wiki/One_red_paperclip)

# “One Red Paperclip”

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The world's largest paperclip, installed at Bell Park  
in Kipling in 2007



# What have we learned so far?

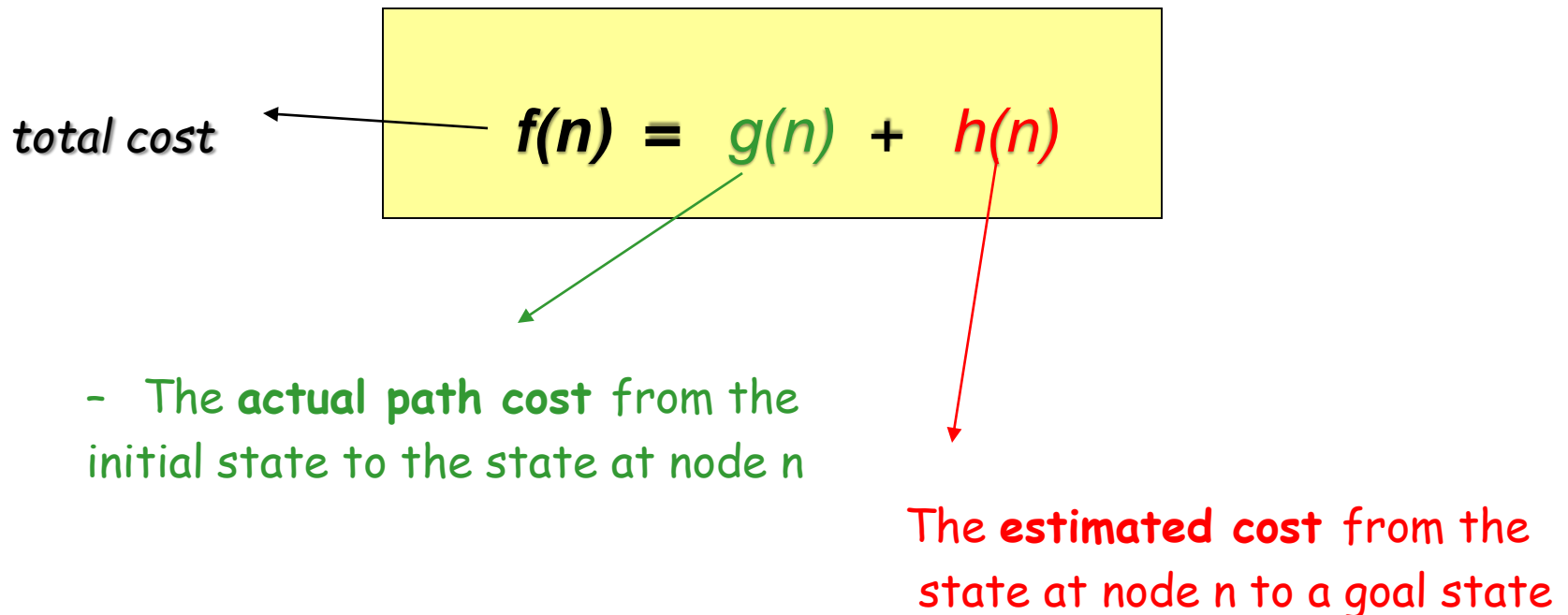
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- What is AI?
- Problem-solving agent
- Uninformed search
- Informed search ( $A^*$ )

# Recap: Cost Function $f(n)$

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- Estimated cost of best path from initial state to goal state



# Recap: Greedy Best-first Search

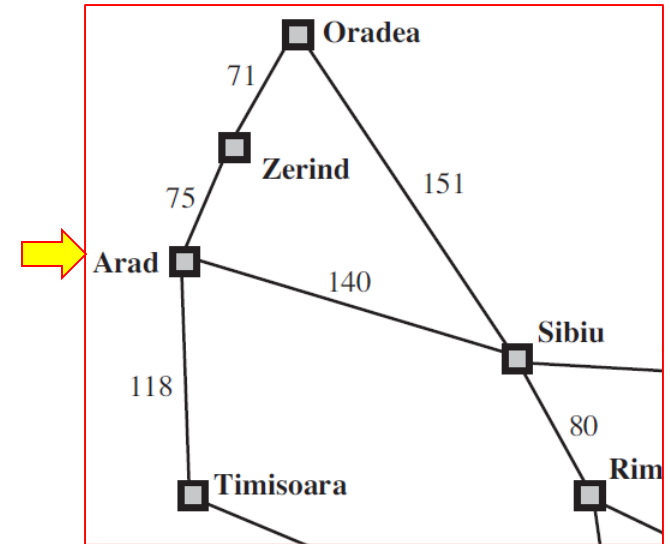
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- **Intuition:** Expands node that “appears” to be **closest to the goal** since it’s likely to lead a solution quickly
  - i.e.,  $f(n) = h(n)$
- **Example:** In Map of Romania, use “*straight-line distance to Bucharest*” as the heuristic function  $h(n)$



# Recap: Greedy Best-first Search (example run)

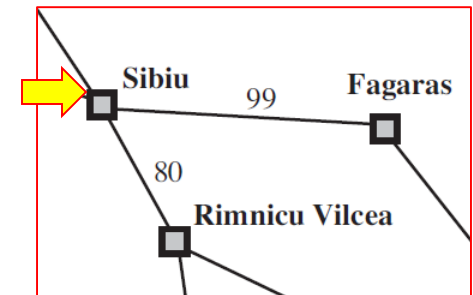
- Starting at “**Arad**”, there are three actions
  - *Go(Zerind)*
  - *Go(Sibiu)*
  - *Go(Timisoara)*
- After that, which of the new nodes should be chosen for expansion?



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

# Recap: Greedy Best-first Search (example run)

- Starting at “**Sibiu**”, there are two actions
  - Go(Fagaras)*
  - Go(Rimnicu Vilcea)*
- After that, which of these two new nodes should be expanded next?

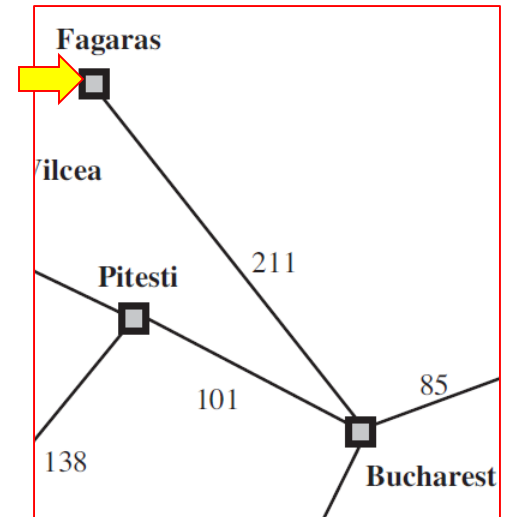


Arad	366	Mehadia	241
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# Recap: Greedy Best-first Search (example run)

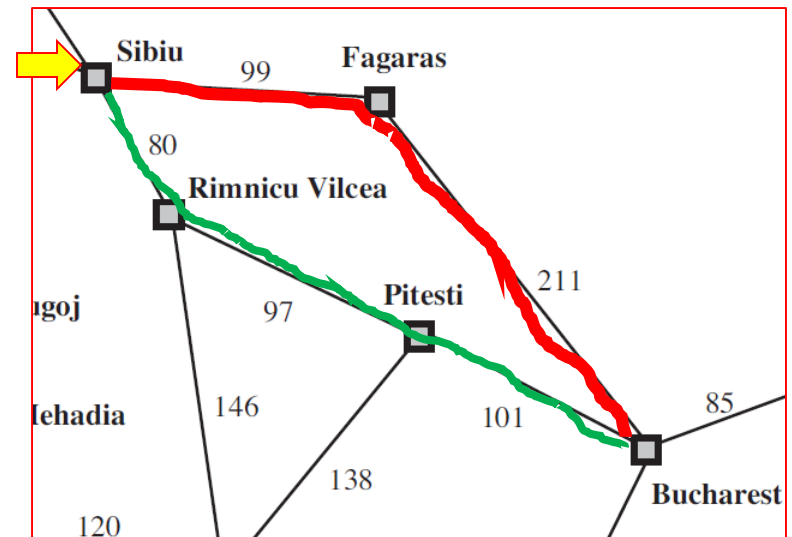
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- Starting at “**Fagaras**”, there is only one action
  - *Go(Bucharest)*
- It's a goal state!
- But, is this the **optimal** solution?



# Recap: Greedy Best-first Search (optimality)

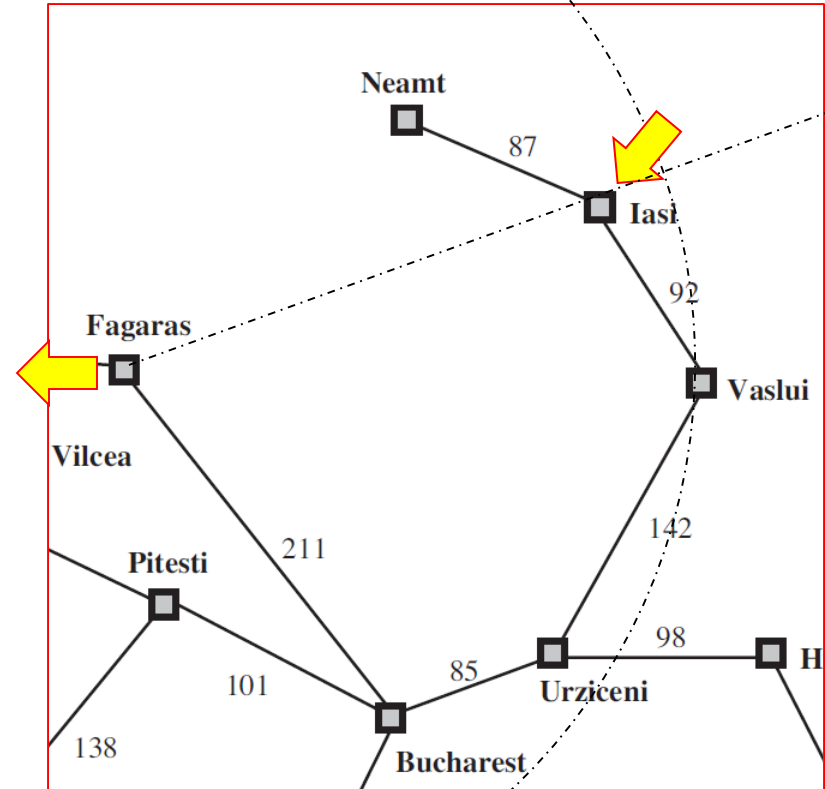
- Starting at “**Fagaras**”, there is only one action
  - *Go(Bucharest)*
- It's a goal state!
- No, it is **not optimal**



278 kilometers vs. 310 kilometers

## Recap: Greedy Best-first Search (completeness)

- Greedy Tree-Search is not complete even in a finite state space
- **Example:**
  - From “**Iasi**” to “**Fagaras**”
    - *Go(Neamt)*
    - *Go(Vaslui)*
  - Which node to expand next?
    - *Neamt*, since its “straight-line distance” to *Fagaras* is shorter
    - Will never find the solution due to infinite loop “Neamt - Iasi”



# Recap: Use A\* search, instead – minimizing total cost

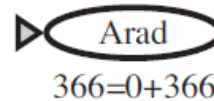
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- Most widely known form of “best-first search”
  - **Goal:** find the cheapest solution
  - **At each step:** expand node with lowest value of the total estimated solution cost:  $f(n) = g(n) + h(n)$

# Recap: A\* search (example run)

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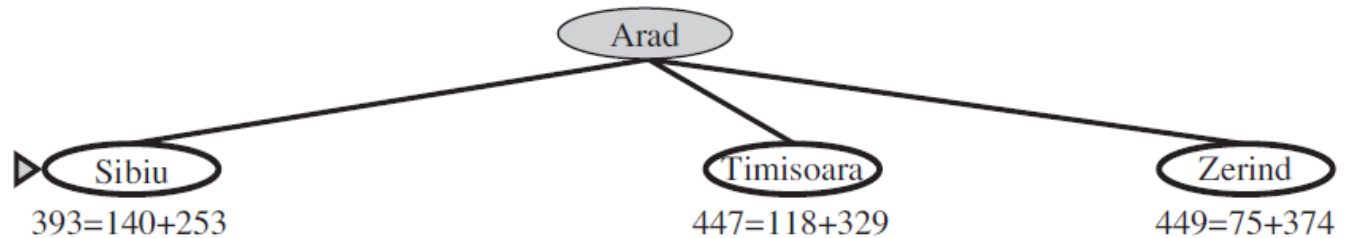
- Total estimated solution cost:  $f(n) = g(n) + h(n)$



# Recap: A\* search (example run)

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- Total estimated solution cost:  $f(n) = g(n) + h(n)$

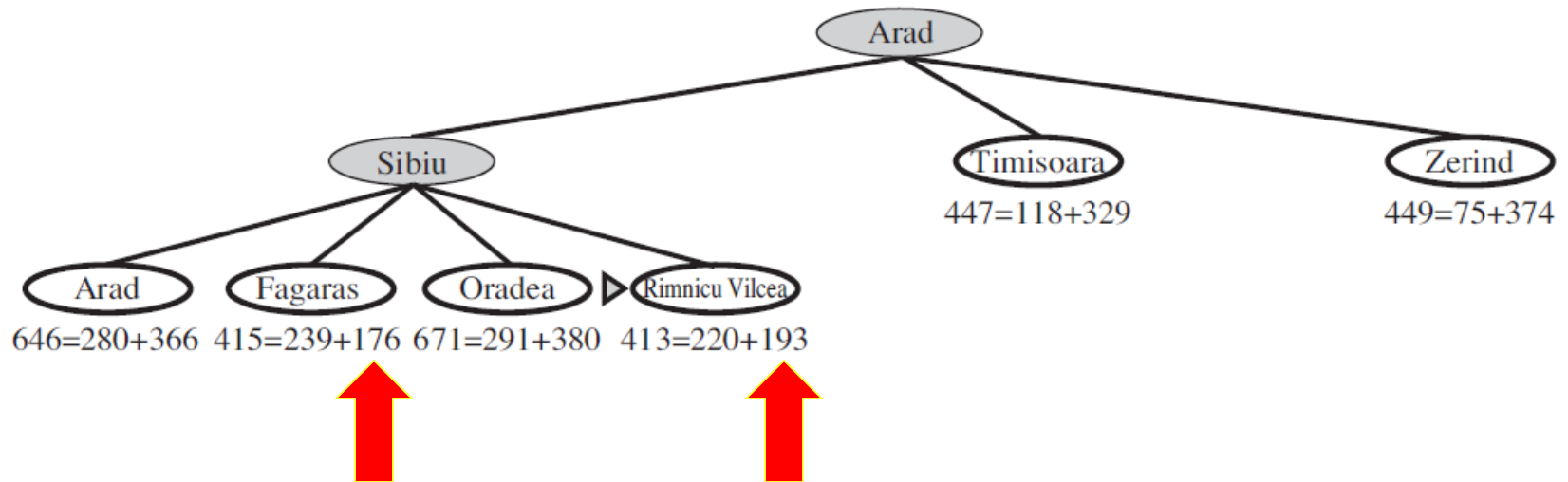




# Recap: A\* search (example run)

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- Total estimated solution cost:  $f(n) = g(n) + h(n)$

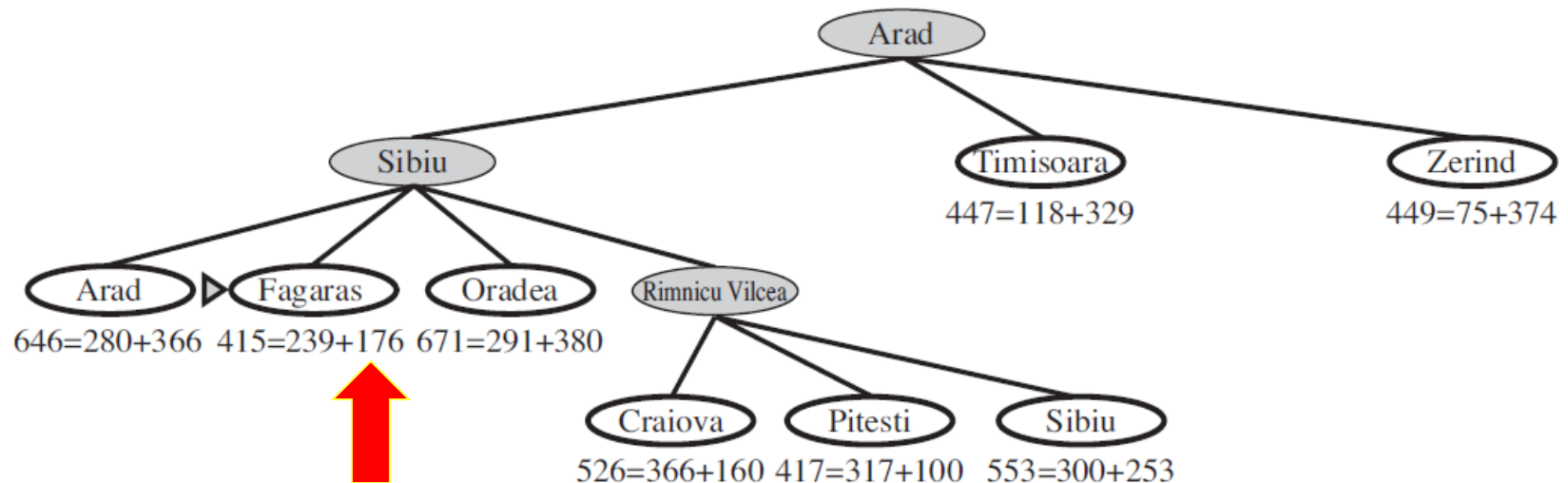


Difference between A\* search  
and Greedy best-first search

# Recap: A\* search (example run)

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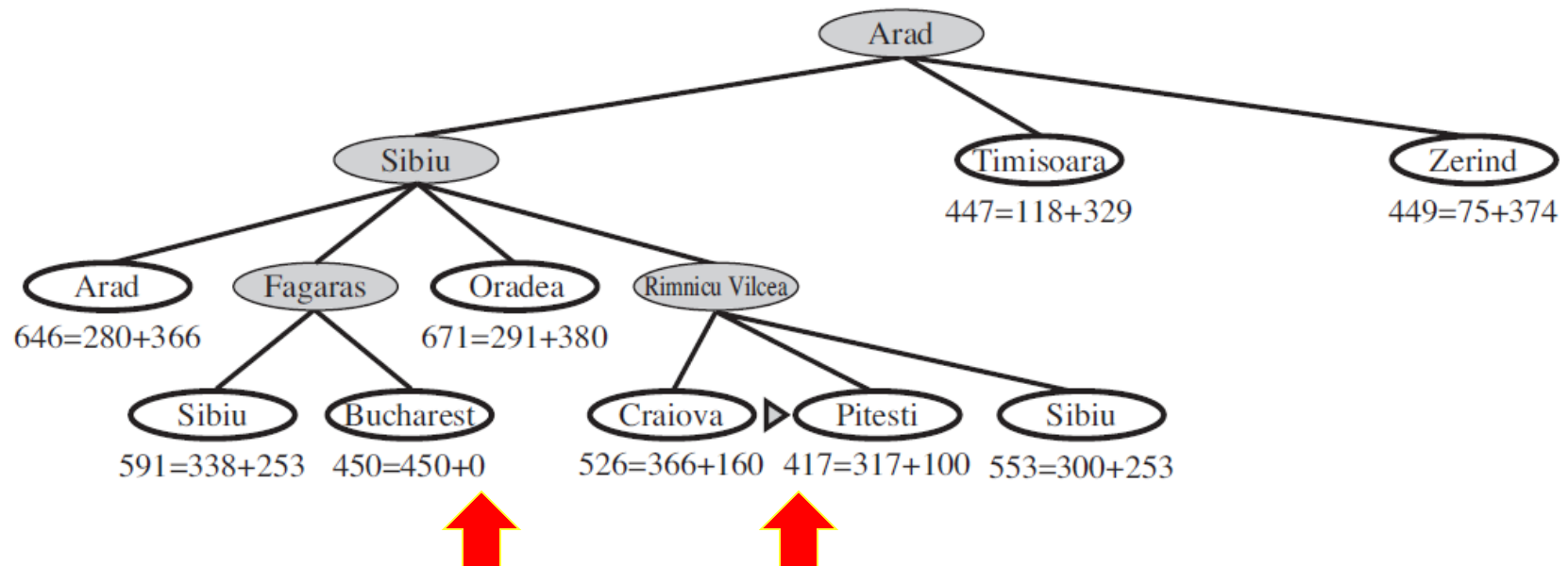
- Total estimated solution cost:  $f(n) = g(n) + h(n)$



Difference between A\* search  
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# Recap: A\* search (example run)

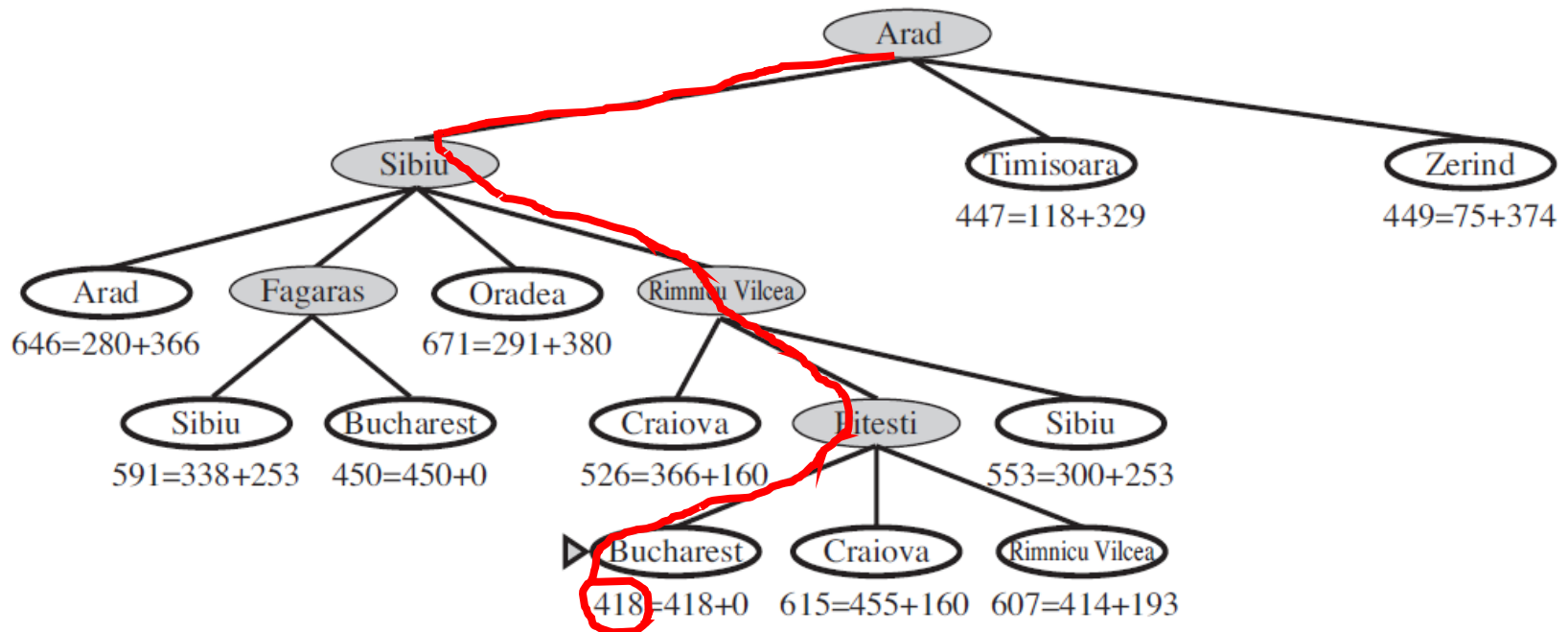
- Total estimated solution cost:  $f(n) = g(n) + h(n)$



Greedy best-first search would have stopped at this point

# Recap: A\* search (example run)

- Total estimated solution cost:  $f(n) = g(n) + h(n)$



Optimal solution

# Recap: Condition for optimality ( $A^*$ )

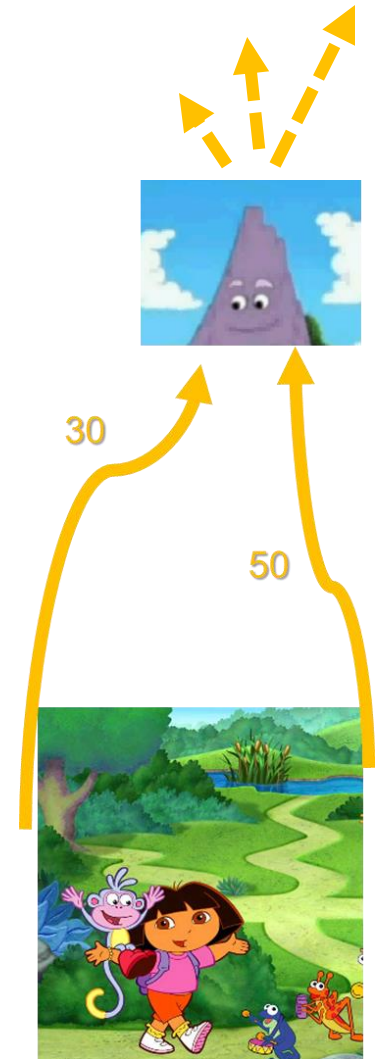
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- Heuristic function  $h(n)$  must be **admissible**
- An admissible heuristic *never overestimates* the true cost to reach the goal

Feel free to under-estimate!

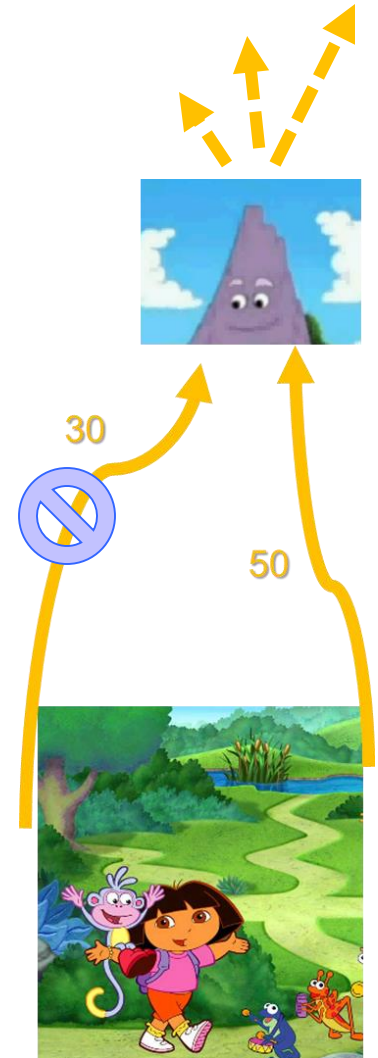
# Under-estimation is fine (and is encouraged)

- If we underestimate the distance
  - 30 → 10
  - 50 → 5
- A\* search is still “optimal”
  - Step 1. Dora and Boots travel though the path labeled “5” (50) and reach the “tall mountain”
  - Step 2. Since the actual cost is 50, they explore the other path labeled “10” (30)
  - Step 3. Only after the optimal path is found, they move forward to explore from the “tall mountain”



# Over-estimation is problematic

- If we over-estimate the distance
  - 30 → 100
  - 50 → 55
- A\* search loses the “optimality”
  - Step 1. Dora and Boots travel through the path labeled “55” (or 50) and reach the tall mountain
  - Step 2. Since the other path is labeled “100” (which is larger than 50), they will move forward from the tall mountain
  - The optimal path labeled “100” (30) is never explored, due to the over-estimated cost



# Outline for Today

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- What is AI?
- Problem-solving agent
- Uninformed search
- **Informed search ( $A^*$ )**
- **Heuristic functions**
  - How to design “admissible” heuristics



# A\* Search for 8-Puzzle

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7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

# A\* Search for 8-Puzzle

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- Branching factor < 3
- Average solution cost is 22 steps
  - Exhaustive tree search to depth 22  $\rightarrow 3^{22}$  states
  - Graph search  $\rightarrow 181,440$  distinct states



# Heuristic functions for 8-puzzle

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- Two candidates
  - $h1(n)$  = number of misplaced tiles
  - $h2(n)$  = sum of the distances of the tiles from their goal positions
    - Manhattan distance: The sum of the horizontal and vertical distances

$h1 = ??$

$h2 = ??$

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# Heuristic functions for 8-puzzle

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- Two candidates
  - $h1(n)$  = number of misplaced tiles
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    - Manhattan distance: The sum of the horizontal and vertical distances

$h1 = 8$

$h2 = 18$

How do you  
know which  
one is better?

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

# Experimental results: A\* with $h_1$ and $h_2$

---

- Solving 1200 random 8-puzzle problems

	Search Cost (nodes generated)		
$d$	IDS	$A^*(h_1)$	$A^*(h_2)$
2	10	6	6
4	112	13	12
6	680	20	18
8	6384	39	25
10	47127	93	39
12	3644035	227	73
14	–	539	113
16	–	1301	211
18	–	3056	363
20	–	7276	676
22	–	18094	1219
24	–	39135	1641

# The effect of heuristic accuracy

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- Effective branching factor  $b^*$ 
  - Assume the heuristic is perfect,  $A^*$  would explore a total of  $(N)$  nodes and the solution depth is  $d$

$N$  and  $d$  are from measurement

$$N+1 = 1 + b^* + (b^*)^2 + \dots + (b^*)^d$$

**Q:** Let ( $N=52$ ) and ( $d=5$ ), what would be the value of ( $b^*$ )?

**Answer:**  $b^*=1.92$

# Experimental results: $A^*$ with $h_1$ and $h_2$

- Solving 1200 random 8-puzzle problems

	Search Cost (nodes generated)			Effective Branching Factor		
$d$	IDS	$A^*(h_1)$	$A^*(h_2)$	IDS	$A^*(h_1)$	$A^*(h_2)$
2	10	6	6	2.45	1.79	1.79
4	112	13	12	2.87	1.48	1.45
6	680	20	18	2.73	1.34	1.30
8	6384	39	25	2.80	1.33	1.24
10	47127	93	39	2.79	1.38	1.22
12	3644035	227	73	2.78	1.42	1.24
14	—	539	113	—	1.44	1.23
16	—	1301	211	—	1.45	1.25
18	—	3056	363	—	1.46	1.26
20	—	7276	676	—	1.47	1.27
22	—	18094	1219	—	1.48	1.28
24	—	39135	1641	—	1.48	1.26

$d$

$N$

$b^*$

# Why Heuristic $h_2(n)$ is better than $h_1(n)$ ?

---

- By their definitions, for any node  $n$ , we have  $h_1(n) \leq h_2(n)$ 
  - We say that “ $h_2$  dominates  $h_1$ ”
- **Domination** translates into **efficiency**:  $A^*$  using  $h_2$  will never expand more nodes than  $A^*$  using  $h_1$

$$f(n) < C^*$$

$$g(n) + h(n) < C^*$$

$$g(n) < C^* - h(n)$$

- Two candidates
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$$f(n) < C^*$$

$$g(n) + h(n) < C^*$$

$$g(n) < C^* - h(n)$$

larger  $h(n)$   $\rightarrow$  smaller  $g(n)$

When  $h(n)=0$ , as in the Uniform-cost Search,  $g(n)$  is only bounded by  $C^*$  (i.e., no guidance from goal at all)

# How to generate heuristic functions?

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- **Admissible** heuristics can be derived from the exact solution cost of a “**relaxed**” version of the problem
- By “**relaxed**” we mean it has an “**over-approximation**” of the transition model of the original problem
  - More edges between states, to provide short cuts
  - To get “under-approximation” of the cost

# (1) Relaxed problems for 8-puzzle

---

- Original transition model

*A tile can move from square A to square B if  
A is horizontally or vertically adjacent to B, and B is blank*

- Relaxed transition model

- (a) A tile can move from square A to square B *if A is adjacent to B*
- (b) A tile can move from square A to square B *if B is blank*
- (c) A tile can move from square A to square B.

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

# Relaxed problems for 8-puzzle

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- (c) A tile can move from square A to square B.

Number of misplaced tiles

$$h1(n) = 8$$

Manhattan distance

$$h2(n) = 18$$

7	2	4
5		6
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Start State

	1	2
3	4	5
6	7	8

Goal State

# Combining heuristic functions

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- Given a **collection** of *admissible* heuristics, the **composite** heuristic (uses whichever function that is the most accurate on the node in question) is also *admissible*

$$h(n) = \max\{h_1(n), \dots, h_m(n)\}$$

- Furthermore,  **$h(n)$  dominates** all of these component heuristics



“better than”

## (2) Generating heuristics from subproblems

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- **Pattern Database:** stores exact solution cost for every possible subproblem instance
  - Every possible configuration of the first four tiles and the blank
  - Locations of the other four tiles are irrelevant (but moving them still counts toward the solution cost)
- The database can be constructed by *searching back from the goal*, and recording the cost of each pattern encountered

*	2	4
*		*
*	3	1

Start State

	1	2
3	4	*
*	*	*

Goal State

### (3) Learning heuristic functions from experience

---

- Inductive learning of a heuristic function  $h(n)$  in terms of features  $x_1(n)$  and  $x_2(n)$

$$h(n) = c_1x_1(n) + c_2x_2(n)$$

- Candidate features
  - “number of misplaced tiles”
  - “number of pairs of adjacent tiles that are not adjacent in goal state”

### (3) Learning heuristic functions from experience

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*Input:*

$(x_1=..., x_2=..., h=...)$

$(x_1=..., x_2=..., h=...)$

...

$(x_1=..., x_2=..., h=...)$



$c_1 = ??$

$c_2 = ??$



# Outline for Today

---

- What is AI?
- Problem-solving agent
- Uninformed search
- Informed search
- **Heuristic functions**
  - How to design them
  - How to evaluate them

# Summary

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- Informed search needs heuristic function,  $h(n)$ , which estimates the cost of a solution from  $n$ 
  - **Greedy best-first search** expands nodes with minimal  $h(n)$ . It is not optimal but is often fast
  - **A\* search** expands nodes with minimal  $f(n)=g(n)+h(n)$ . It is complete and optimal, provided that  $h(n)$  is admissible (or consistent). The space complexity of A\* is still high.
  - **RBFS** and **SMA\*** are robust, optimal, and use limited memory
- Performance of heuristic search depends on the quality of the heuristic function
  - Good heuristics can be constructed by (1) relaxing the problem definition, (2) storing precomputed solution costs for subproblems in a pattern database, or (3) learning from experience