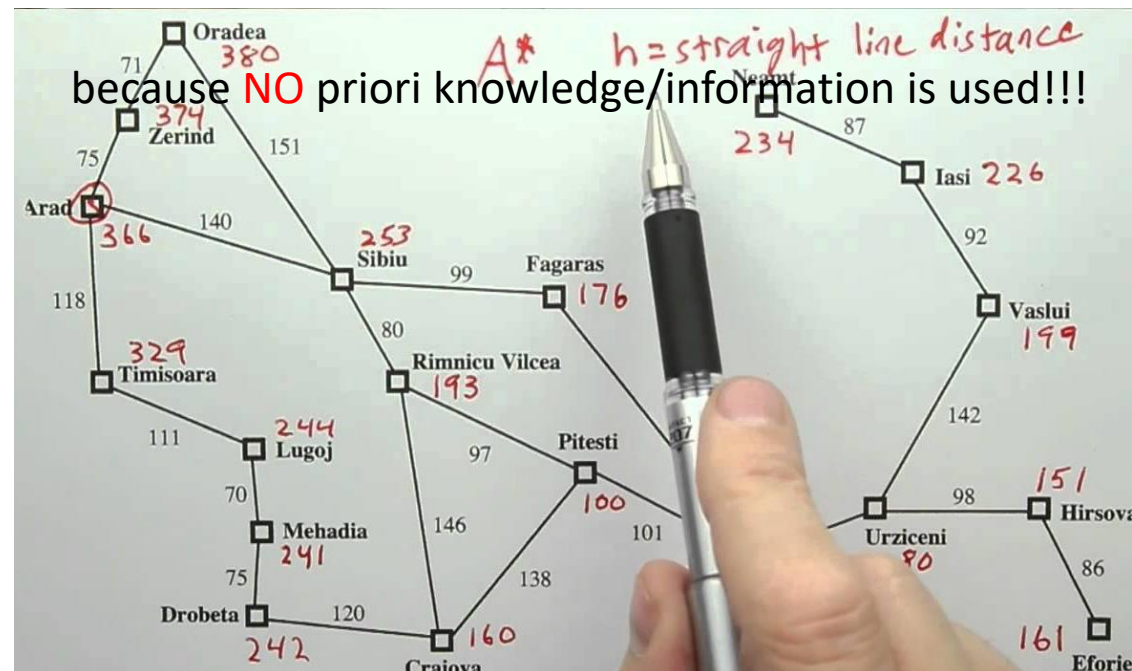


Heuristic Search



Last week: Basic Search

- We have seen how to formalise a problem (state, action, transition)
- We have seen some basic search methods
 - Do you remember what are the methods?
 - How they differ from each other?
- Basic search methods
 - Sometimes powerful (see the reading materials of last lecture)
 - Sometimes stupid (video BFS v.s. DFS of last lecture)
- When branching factor is high...
 - Chess: 35
 - Game Go: 250

Uninformed Search -> Informed Search

- Basic search methods
 - Sometimes powerful (see the reading materials of last lecture)
 - Sometimes stupid (video BFS v.s. DFS of last lecture)
 - I want to spend less time to travel to the airport, but DFS does not care 😞
 - I want to spend get a higher score in my game (collecting items before ending the game), but BFS does not understand 😞
 - Why? Because **NO** priori knowledge/information is used!!! -> **Uninformed**
- **Question:** Can I make use of the problem-specific knowledge?

YES!!! A little AI now 😊

Outline

- Heuristic Functions
- Heuristic Search Methods
- Further Studies on Heuristics

I. Heuristic Functions

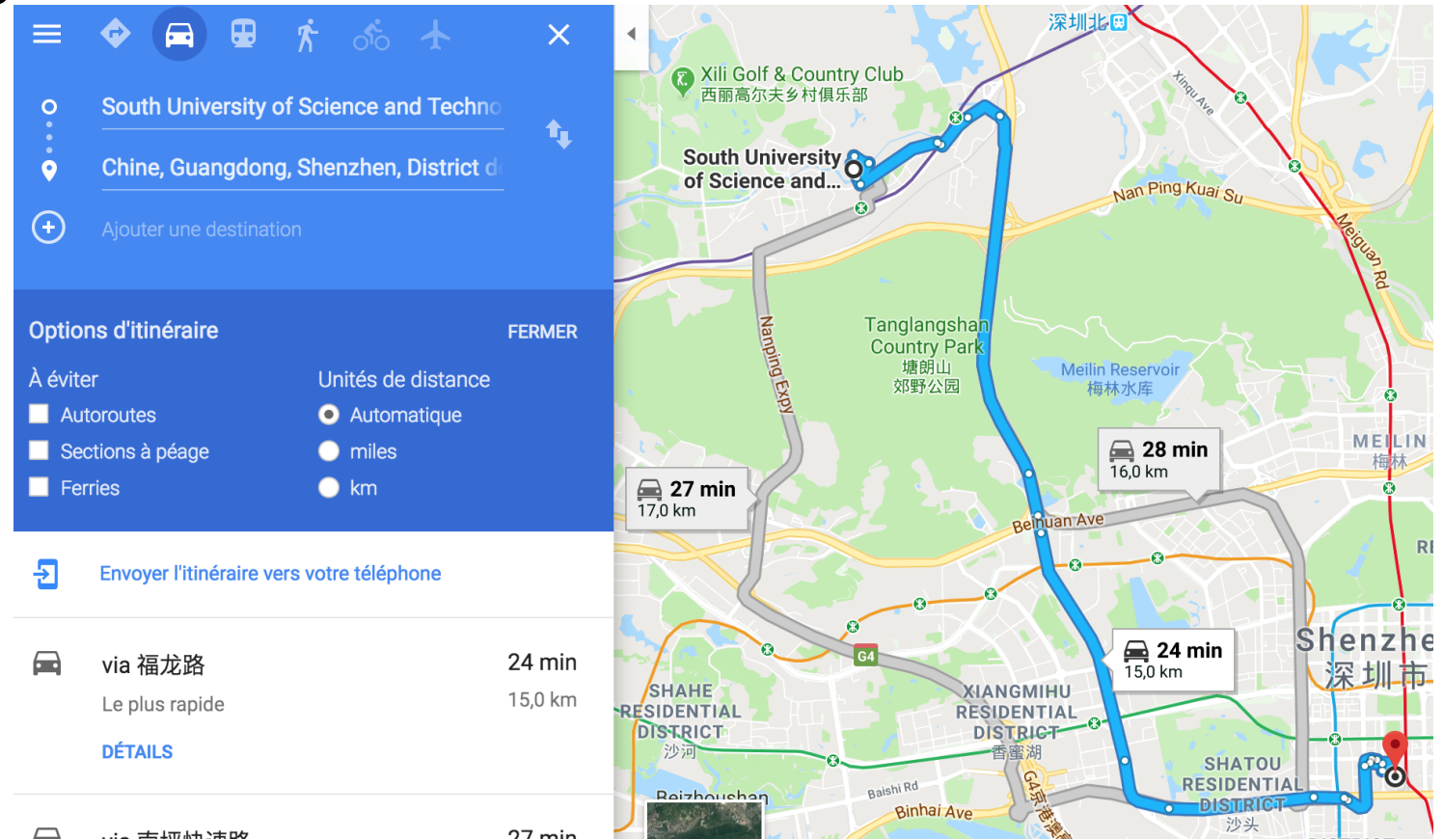
- Evaluation Function & Heuristic Function
- Admissible Heuristics

From Basic Search to Heuristic Search

- Basic search (uninformed): **use NO** domain knowledge.
 - Have **no bias** in the search space & have to **look everywhere** to find the answer.
 - Time complexity is intractable for complex tasks.
- Heuristic search (informed): **use** domain knowledge.
 - **Question**: What is 'domain knowledge'?
 - **Answer**: Help direct/bias the search & which part of the search space to explore.
 - Can lead to drastic speed up.

Example: Route Planning

- What do you care more?
 - Faster?
 - Shorter distance?
 - Cheaper?
- Can you use some information (distance, cost, traffic, reward, etc.) to bias the search?



Evaluation Function

- Example: **Best-First Search**, by name, visit the “**best**” node first.
- To determine “best” or not, an **evaluation function** is needed.
 - The evaluation function, $f(s)$, estimates the cost at node s (**state**).
 - Several evaluation function can be designed for one single problem.
 - Best-First Search expands the node with **lowest** cost first.
- The meaning of **cost** is generalised.
 - In the route planning example, the “cost” can refer to the total distance, total time, or total expenses for traveling. -> *Decided by the customers!*
 - The “cost” can be a combination of different types of cost. People are greedy, we always want to travel faster while spending less money! -> *Trade-off!*

[Question] Difference(s) between Best-First Search and Uniform Cost Search?

[Answer] Not given right now. We will see the answer later in this lecture!

Heuristic Function

- **Question**: How to encode/represent domain knowledge into search?
- **Answer**: Heuristic function $h(s)$ at node s (**state**).

➤ Heuristic function $h(s)$ estimates the lowest cost from s to *Goal*.

➤ In this part, we consider a narrow case:

- (1) $h(s) = 0$ if s is the goal node;
- (2) nonnegative;
- (3) **problem-specific / application-dependent**.

- Good h equips search methods with some **intelligence** → A little AI now.

[Question] What is the difference between an evaluation function and a heuristic function?

[Answer] Heuristic is a component of an evaluation function. / Evaluation function consists of heuristic(s).

Evaluation Function and Heuristic Search

- Evaluation function $f(s)$: a cost estimate & node s with the lowest $f(s)$ is expanded first.
- Heuristic methods have $h(s)$ as a component of $f(s)$.
- The choice of f determines the search strategy.
 - Example: shortest V.S. fastest route from SUSTech to Shekou

Example: Route planning

- $h_0(s) = 0$.
 - $h^*(s)$ = the true cost from s to the goal.
 - $h_{SLD}(s)$ = straight-line distance from node s to the goal.
 - $h_{SLD}(s) + 20\%$: usually better than $h_{SLD}(s)$.
- Find a 'good' h : **problem-specific** & **a serious research problem**.

Example: 8-puzzle

- Possible heuristics:
 - $h_1(s)$ = the number of misplaced tiles
 - $h_2(s)$ = the sum of the distances of the tiles from their goal positions -> also called *city block distance* or *Manhattan distance*

- **[Question]** Can you tell the

- $h_1(\text{StartState})$ -> 8
- $h_2(\text{StartState})$ -> 18
- and true solution cost? -> 26

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

'Good' Heuristics

- A heuristic can be powerful only if it is of a 'good' quality.
- A 'good' heuristic should be **admissible**.

Admissible Heuristics

- Admissible heuristic: $h(s)$ **never overestimates** the cheapest (optimal) cost from s to the goal:
 - $\forall s \rightarrow h(s) \leq h^*(s)$, where $h^*(s)$ is the true cost from s to the goal.
- Admissible heuristics are **optimistic**.

Admissible Heuristics: Examples

Two extreme cases:

1. The **trivial** $h_0(s) = 0$: No help for searching.
2. The **perfect** $h^*(s)$ = the true cost from s to the goal: lead directly to the best path, but unknown in practice.

Admissible Heuristics: Examples

For route planning:

- $h_{SLD}(s)$: Admissible, since a straight line is the shortest distance between two points.
- $h_{SLD}(s) + 20\%$: Not always admissible, since some may surpass the true distance to the goal.

Admissible Heuristics: Examples

For 8-puzzle:

- $h_{mis}(s) = \# \text{misplaced tiles} \in [0,8]$: Admissible.
- $h_{1stp}(s) = \#(1\text{-step move})$ to reach the goal: Admissible.

➤ **Fact:** $h_{1stp}(s) \geq h_{mis}(s)$

- **Question:** which is 'better'?
- **Guess:** $h_{1stp}(s)$ is 'better'.
- **But:** what does 'better' point to? and Why?

Exercise 1:
 $h_{mis}(s) = ?$
 $h_{1stp}(s) = ?$

7	2	4
5		6
8	3	1

	1	2
3	4	5
6	7	8

Recap: Heuristic Search and Heuristics

- Basic search uses no domain knowledge.
- Heuristic search uses domain knowledge by a heuristic function.
- Good heuristics
 - can drastically reduce search cost;
 - should be admissible.

II. Heuristic Search Methods

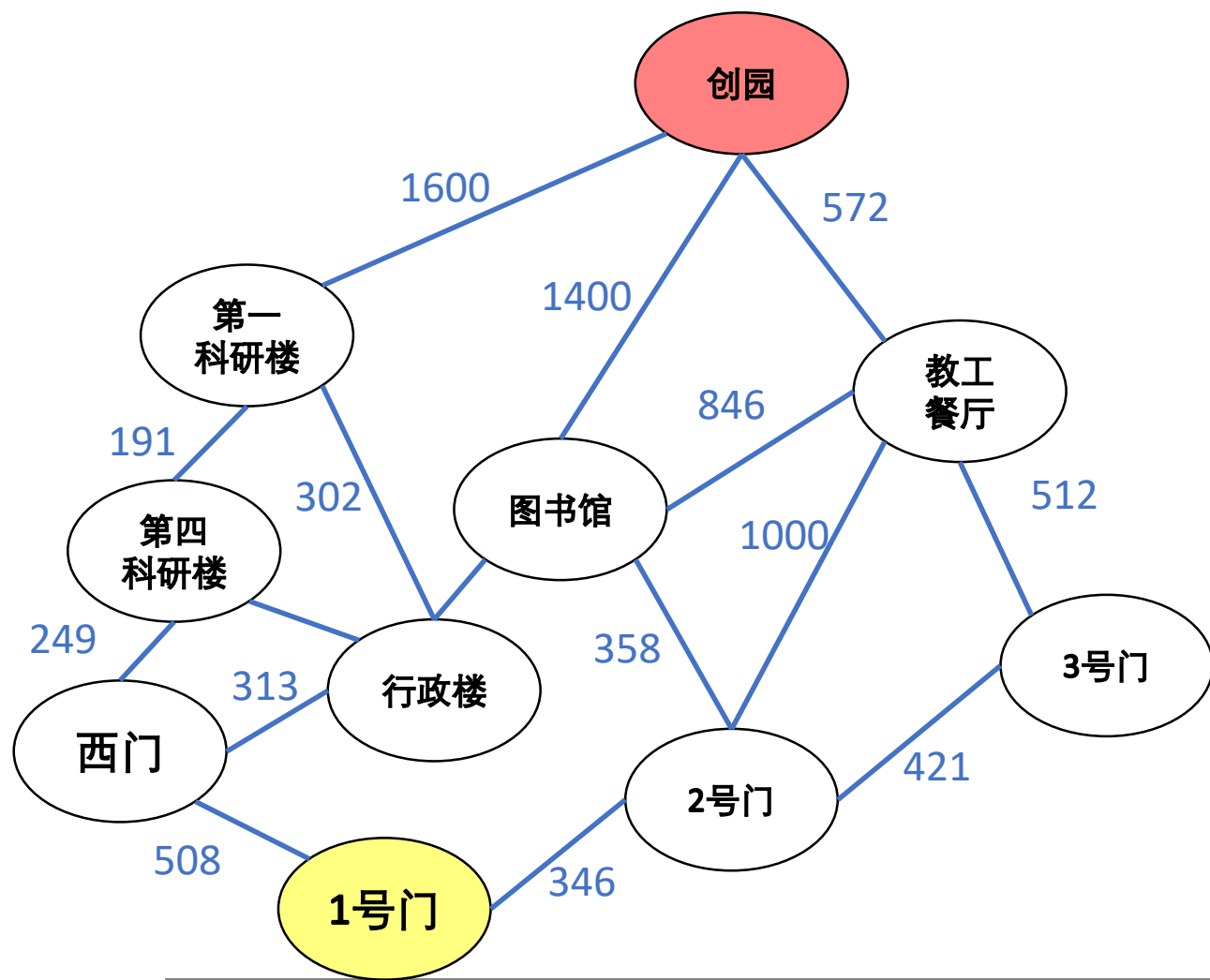
- Greedy Best-First Search
- A* Search

Greedy Best-first Search

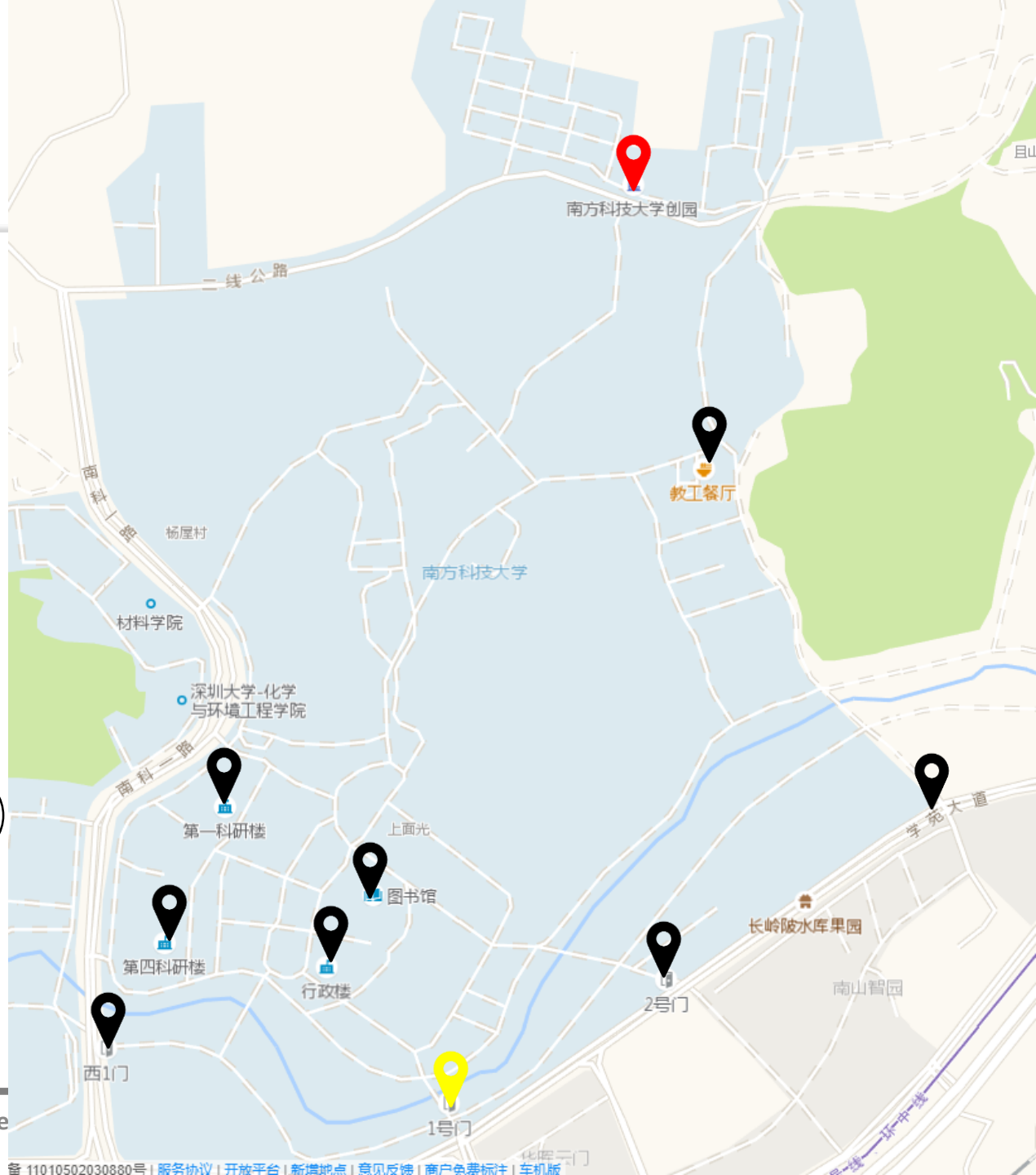
Core Idea

- Idea: Expand the node that seems closest to the Goal.
- Expand node s that has the minimal $f(s) = h(s)$.
- **Recall**: what guide the search order of uniform-cost search?

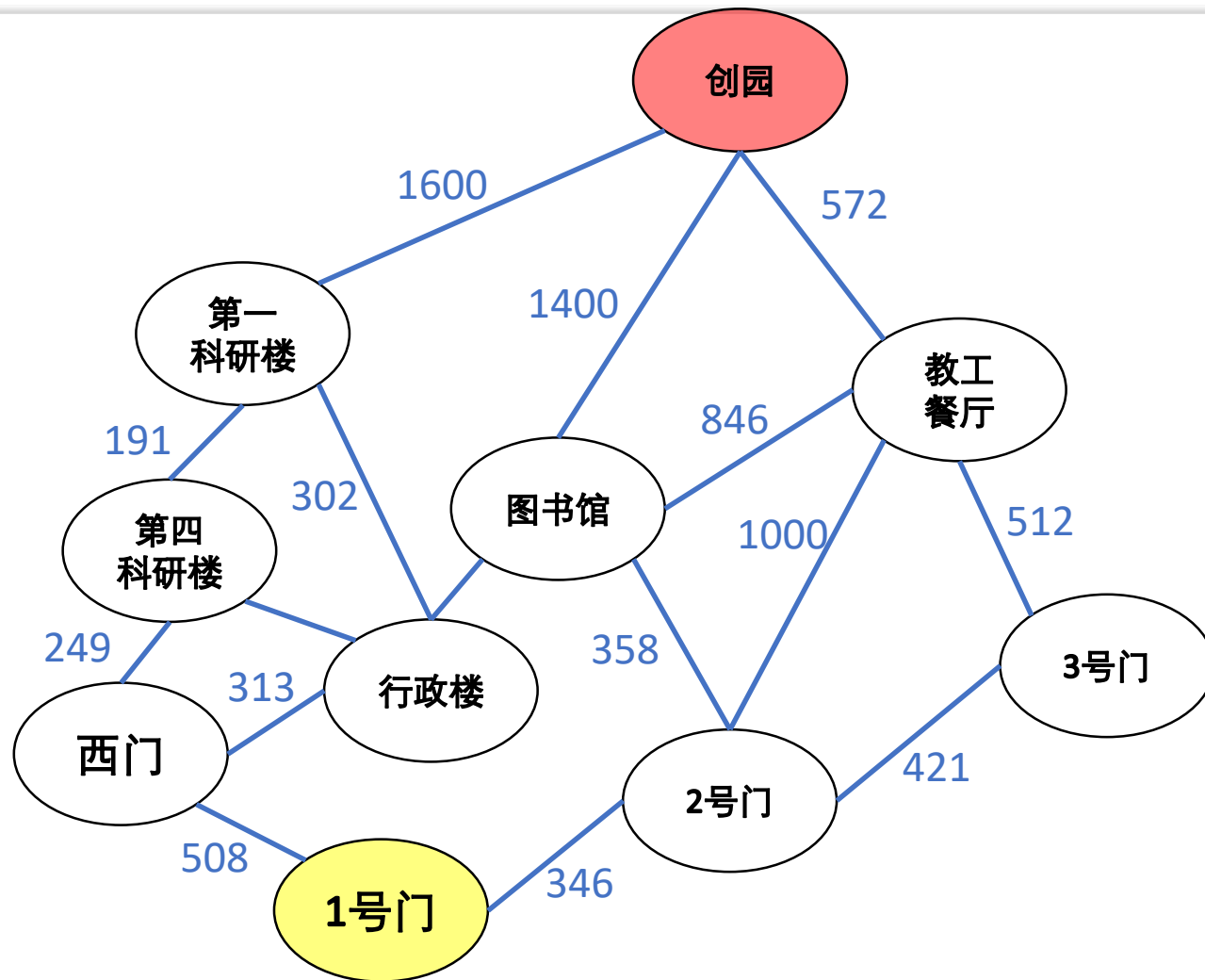
Greedy Search: Illustration 1



Artificial Intelligence



Greedy Search: Illustration 1



Node	SLD to 创园
创园	0
第一科研楼	962
第四科研楼	1080
西门	1300
1号门	1200
图书馆	960
行政楼	1100
教工餐厅	374
二号门	1000
三号门	888

**Heuristics:
domain-
knowledge**

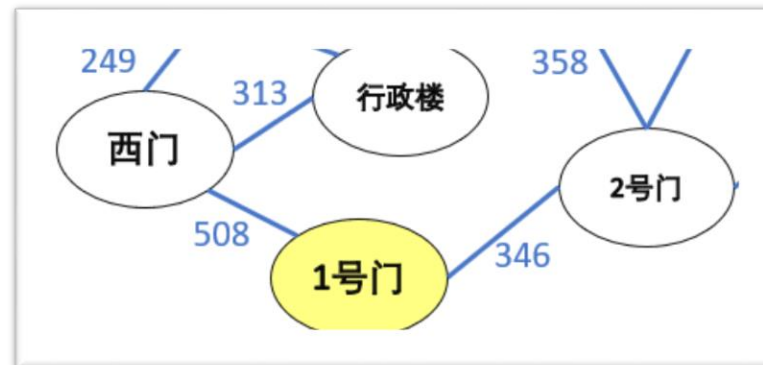
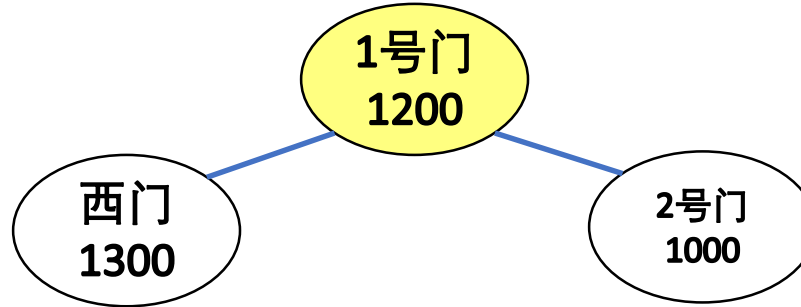
Greedy Search: Illustration 1

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1号门
1200

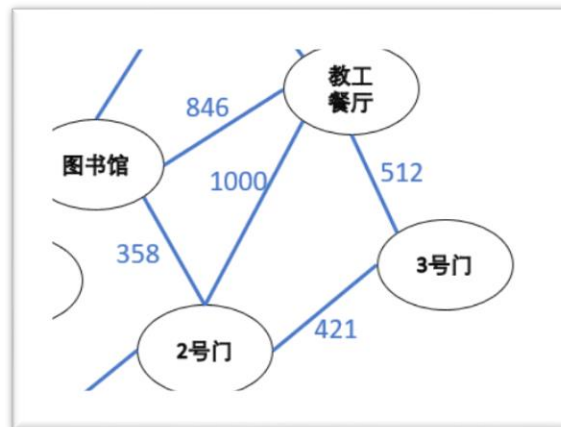
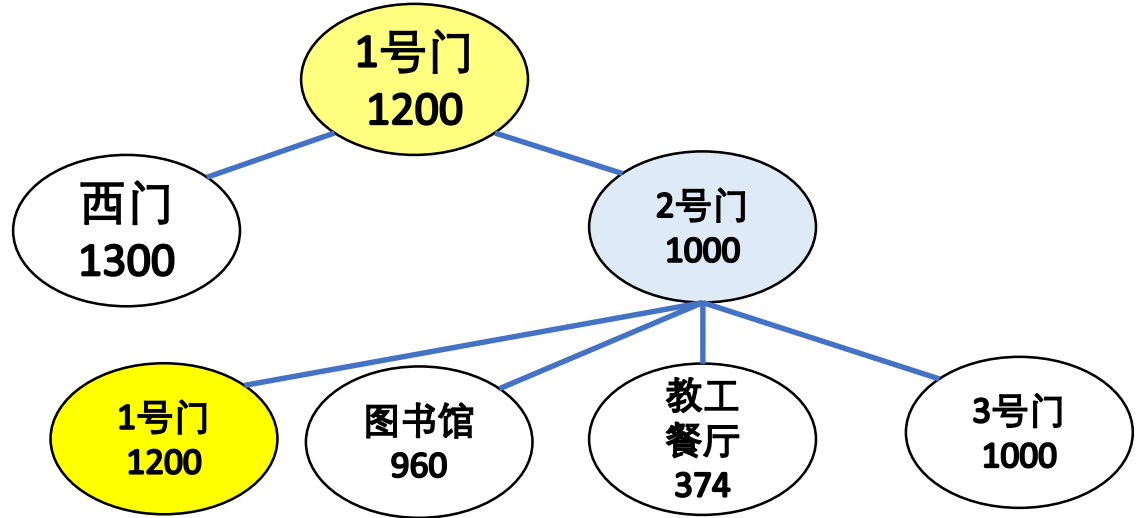
Greedy Search: Illustration 1

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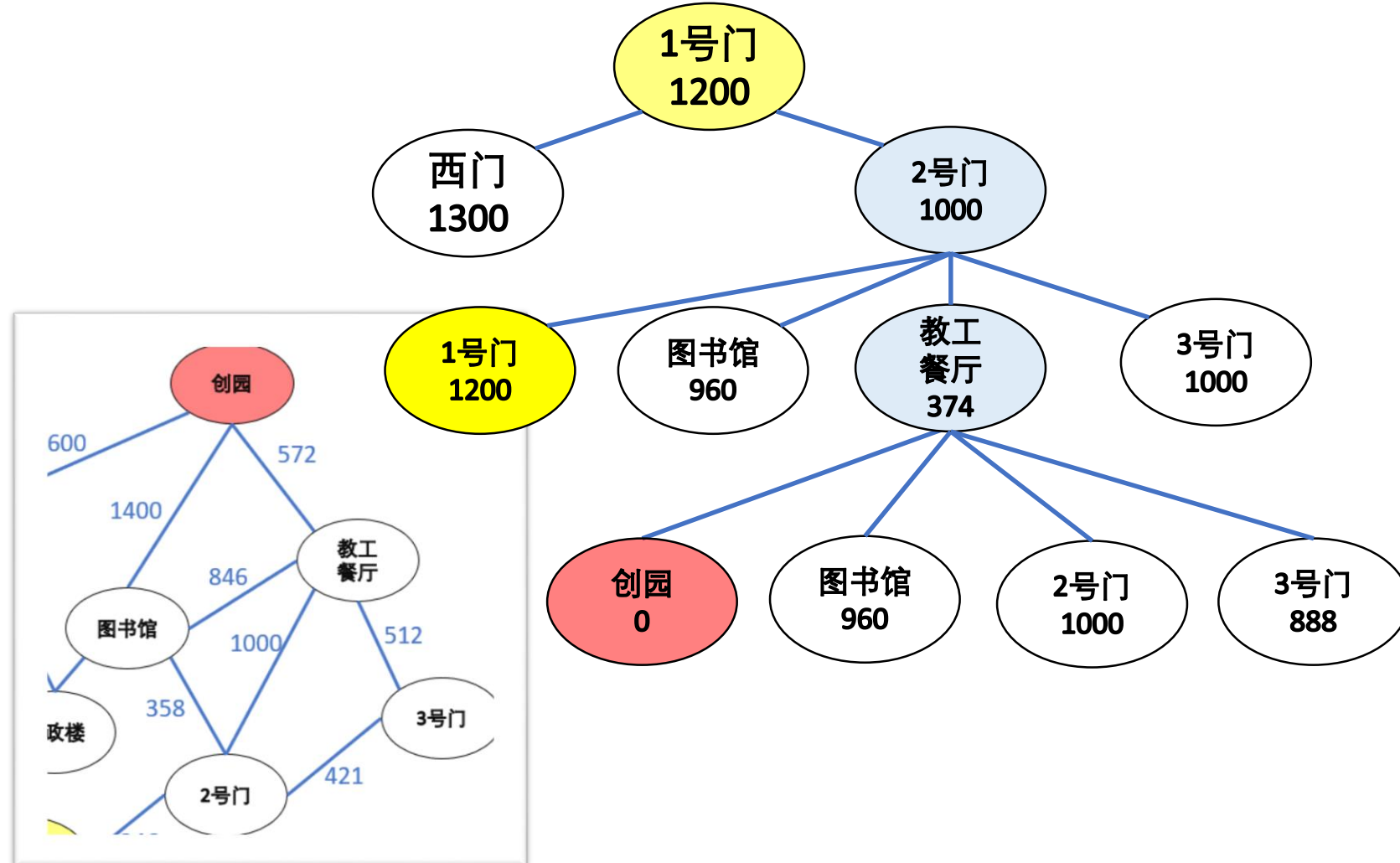
Greedy Search: Illustration 1

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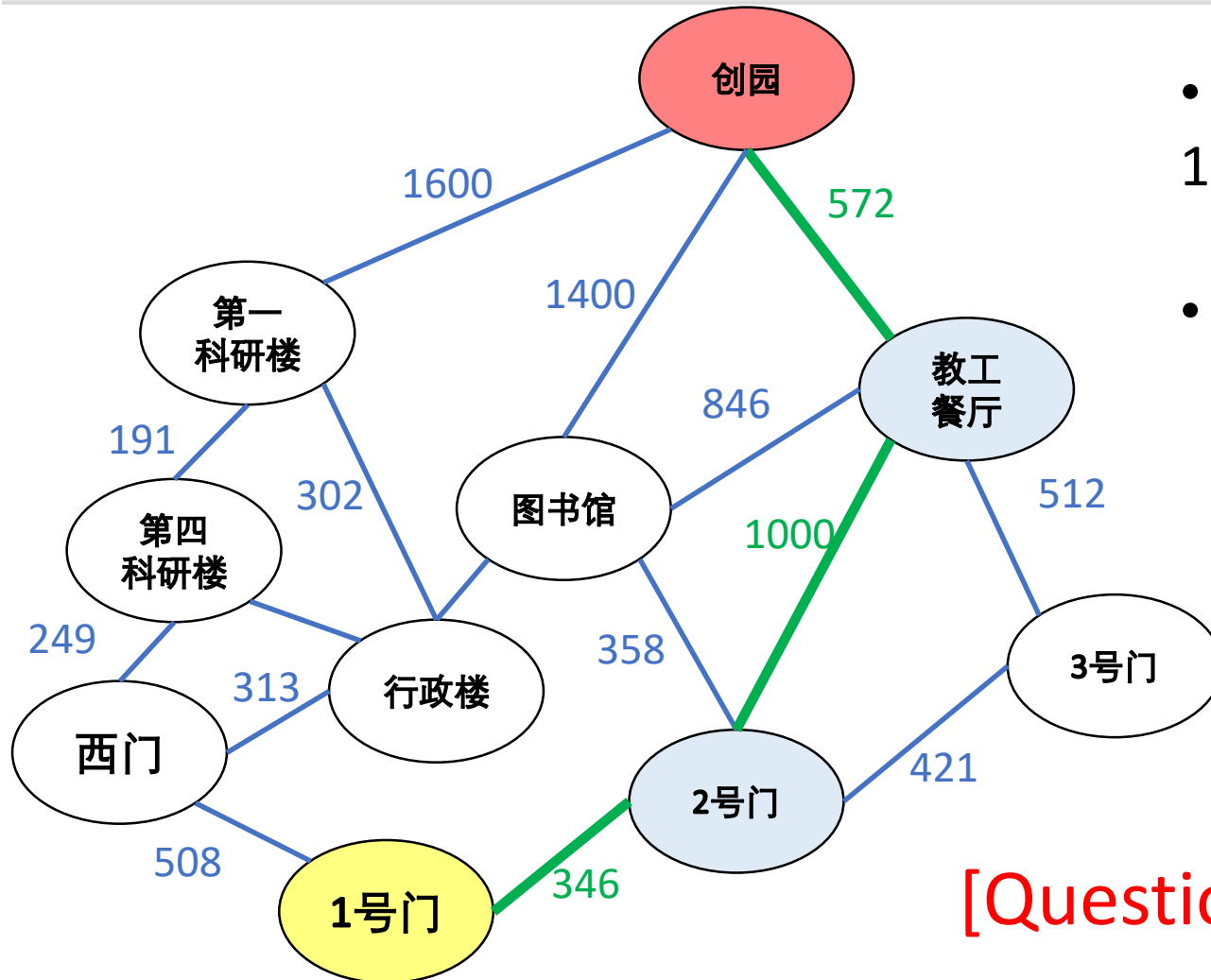


Greedy Search: Illustration 1

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Greedy Search: Illustration 1



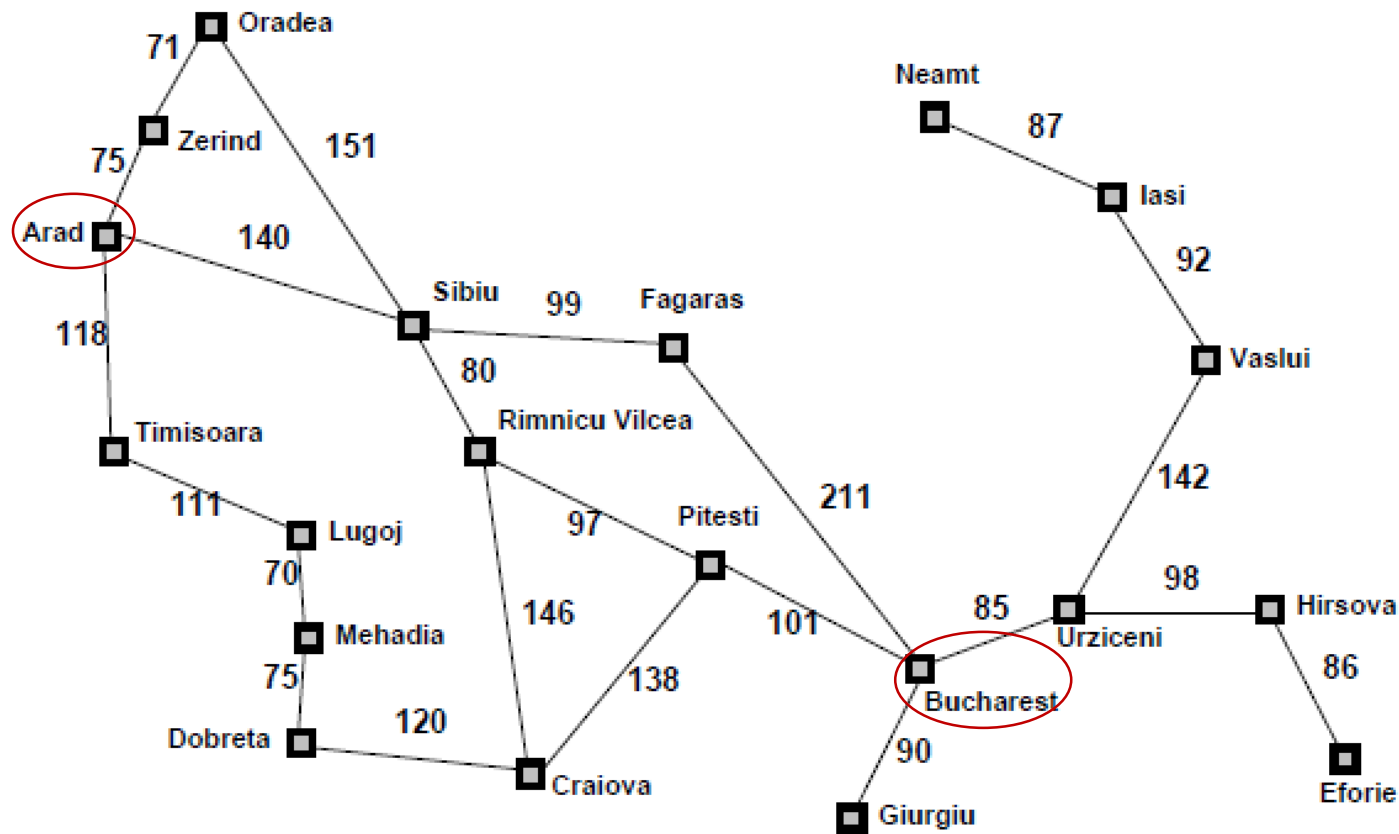
- **Solution:**

1号门->2号门 ->教工餐厅->创园

- ***Distance*** = $346 + 1000 + 572 = 1918m$

[Question] Is it an optimal solution?

Greedy Search: Illustration 2



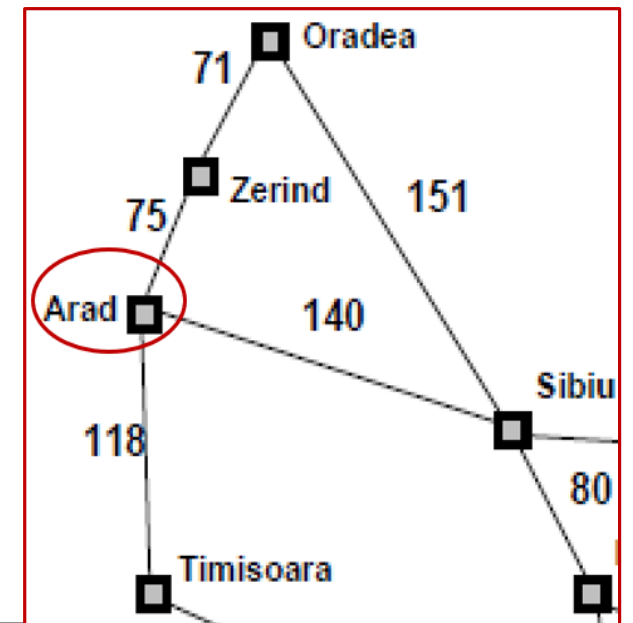
Straight-line distance to Bucharest	
Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
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Oradea	380
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Rimnicu Vilcea	193
Sibiu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

**Heuristics:
domain-
knowledge**

Greedy Search: Illustration 2

Straight-line distance
to Bucharest

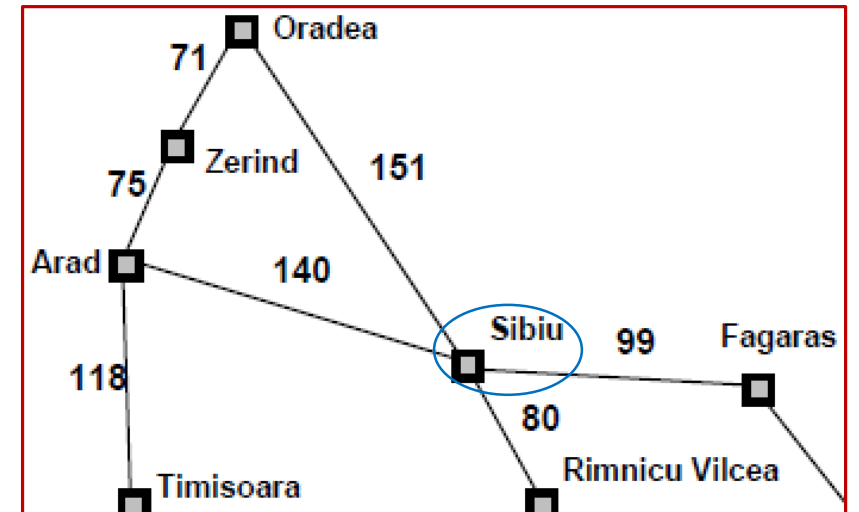
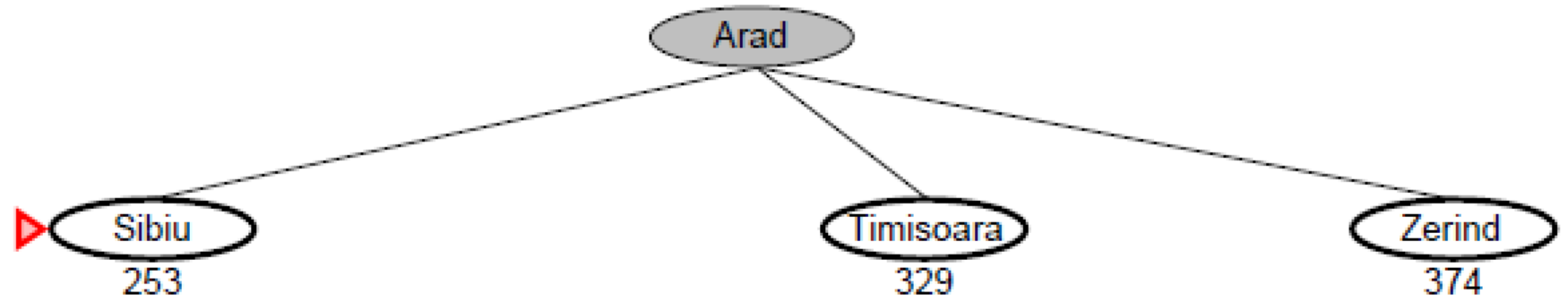
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Greedy Search: Illustration 2

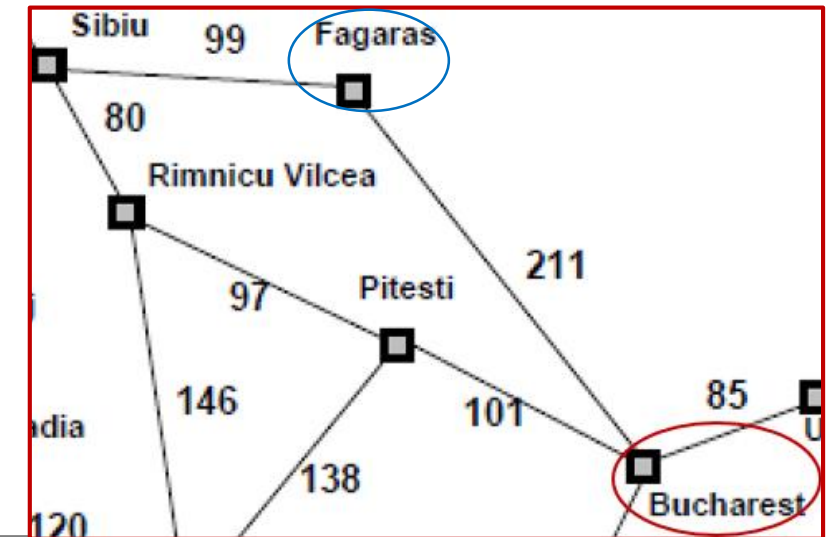
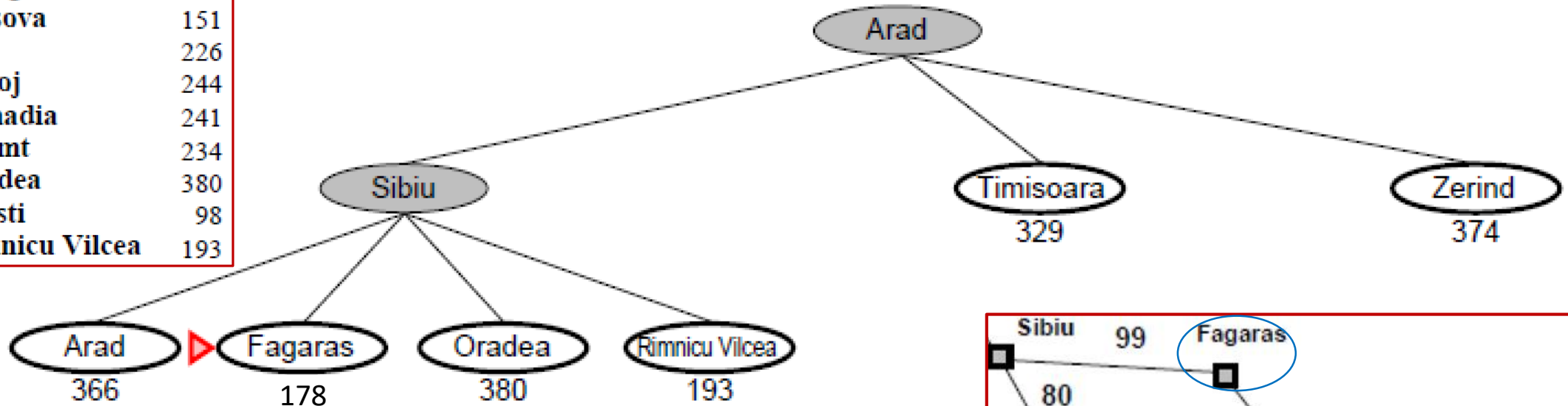
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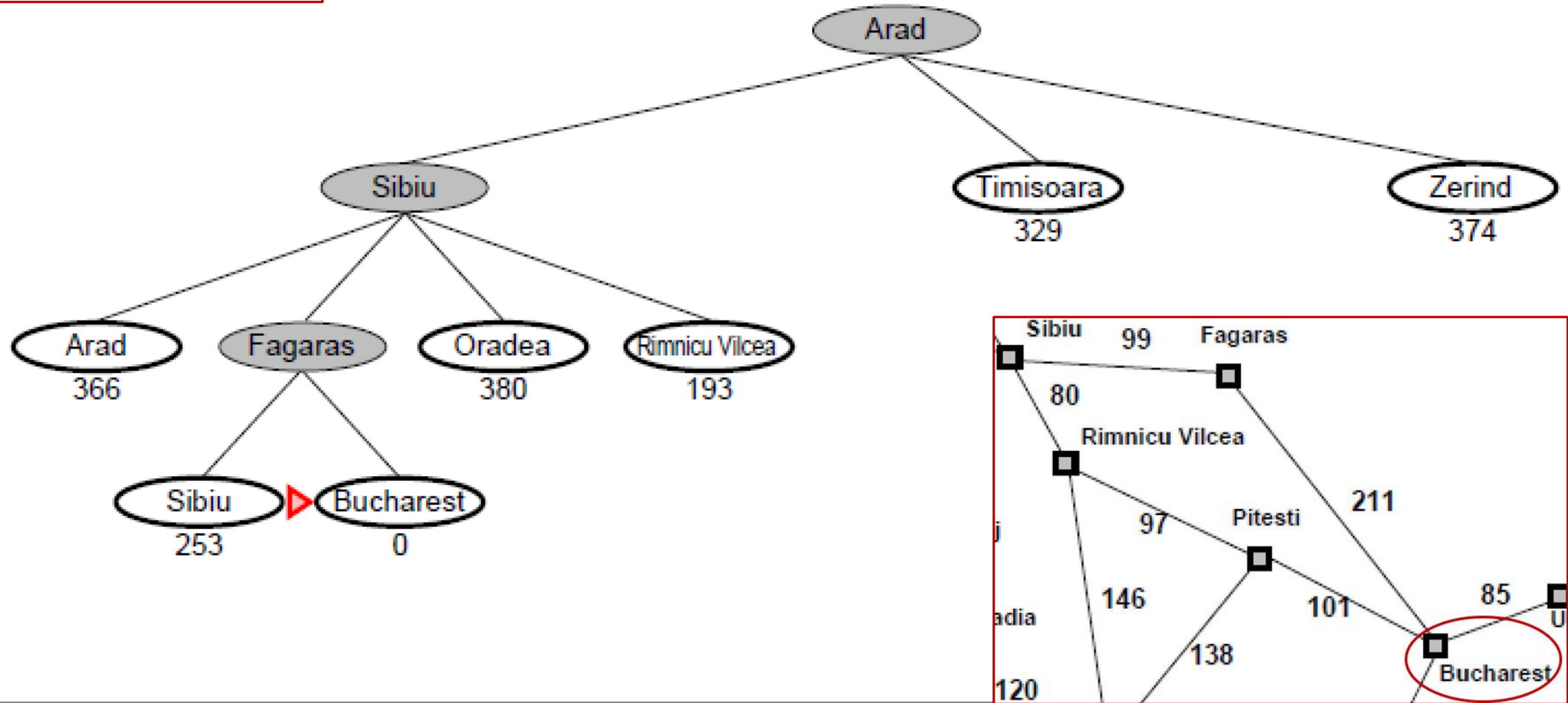
Greedy Search: Illustration 2

Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
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Rimnicu Vilcea	193



Greedy Search: Illustration 2

Sibiu 253



Core Idea Revisit

- Idea: Expand the node that seems closest to the Goal.
- Expand node s that has the minimal $f(s) = h(s)$.

Greedy Search: Performance Metrics

b – maximum # successors of any node in search tree.
 d – depth of the least-cost solution.
 m – maximum length of any path in the state space.

- **Complete?** No, can stuck in loops.
 - E.g. Oradea as the goal, Iasi → Neamt → Iasi → Neamt → ...
 - Complete in the finite space with repeated-state checking.
- **Optimal?** No.
- **Time?** $O(b^m)$, but good heuristics can give drastic improvement.
- **Space?** $O(b^m)$, keep all nodes in memory.

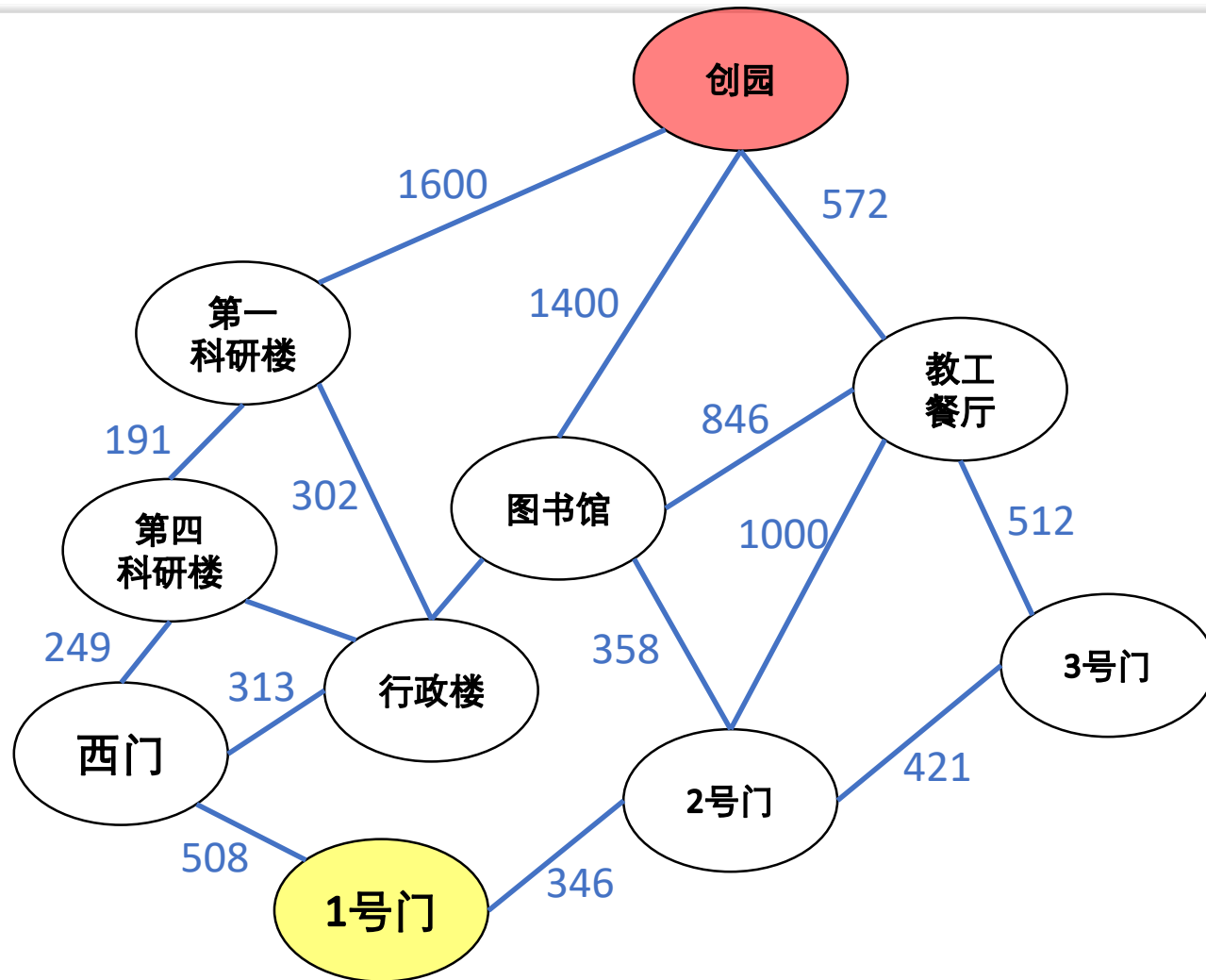
➤ Memory requirement is the biggest handicaps.

A* Search

Core Idea

- Idea: **avoid** expanding paths that are **already expensive**.
- Expand the node s that has the minimal $f(s) = h(s) + g(s)$
 - $g(s)$: cost from *Start* to s .
 - $h(s)$: estimated cost from s to *Goal*.
 - $f(s)$: estimated total cost of path from *Start* through s to *Goal*.
- **Recall**: what guide the search order of uniform-cost search?

A*: Illustration 1



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**Heuristics:
domain-
knowledge**

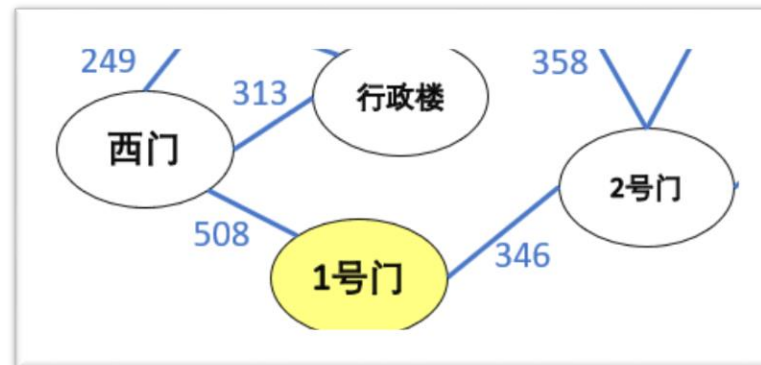
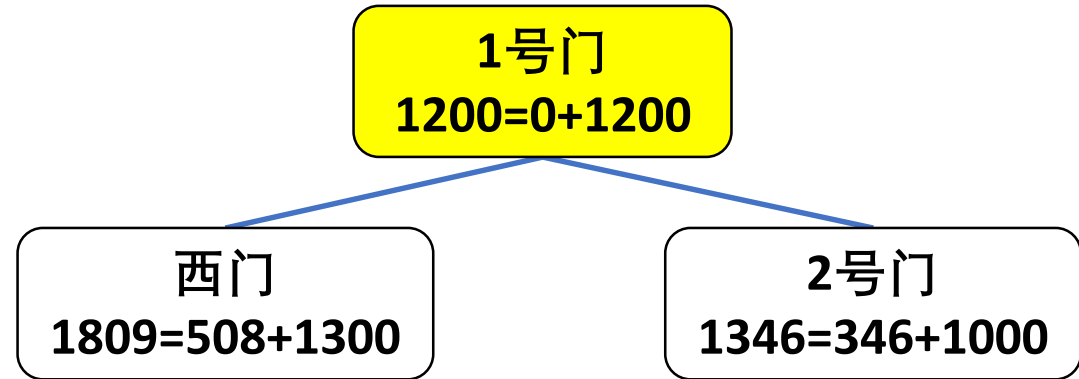
A*: Illustration 1

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1号门
 $1200=0+1200$

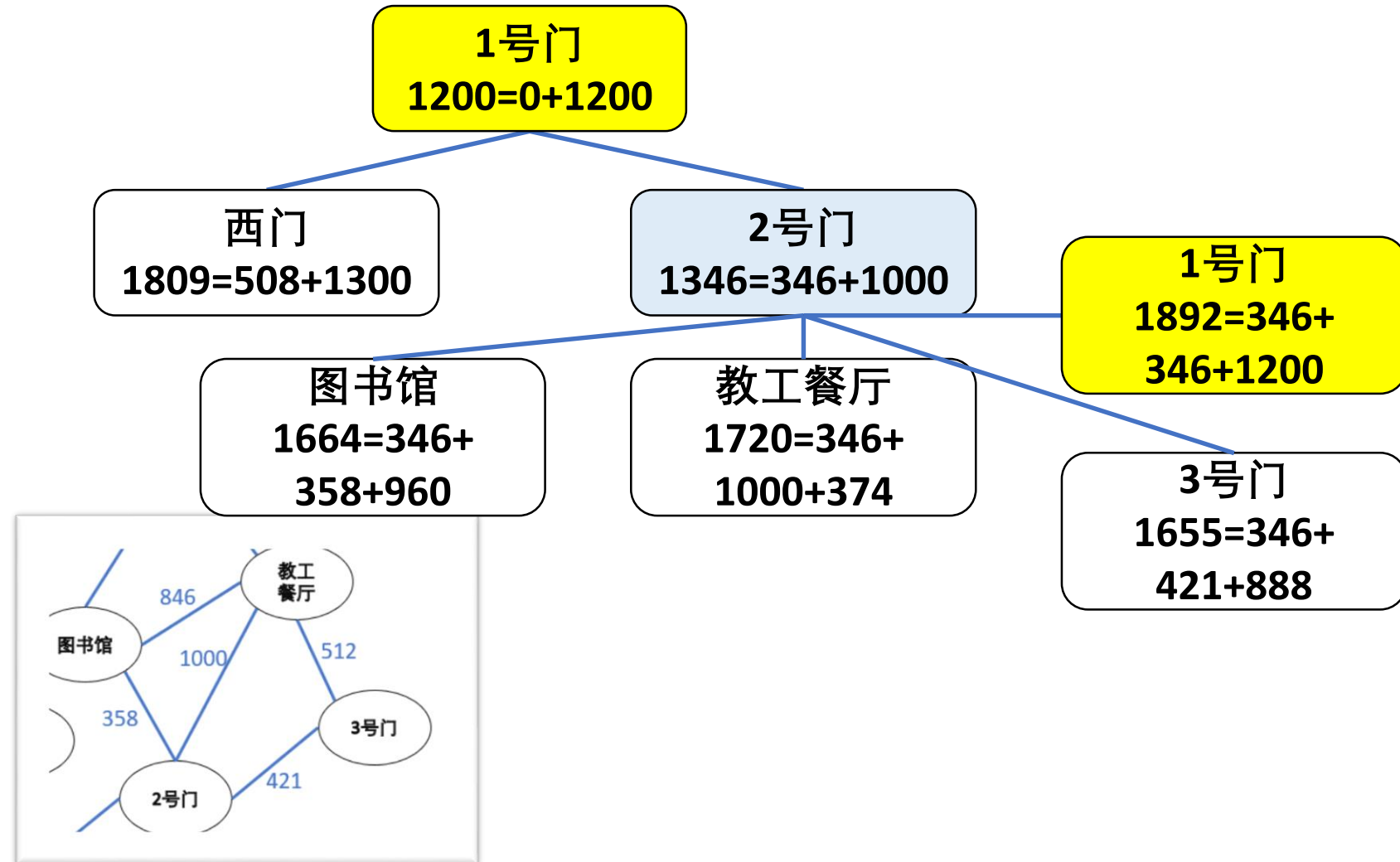
A*: Illustration 1

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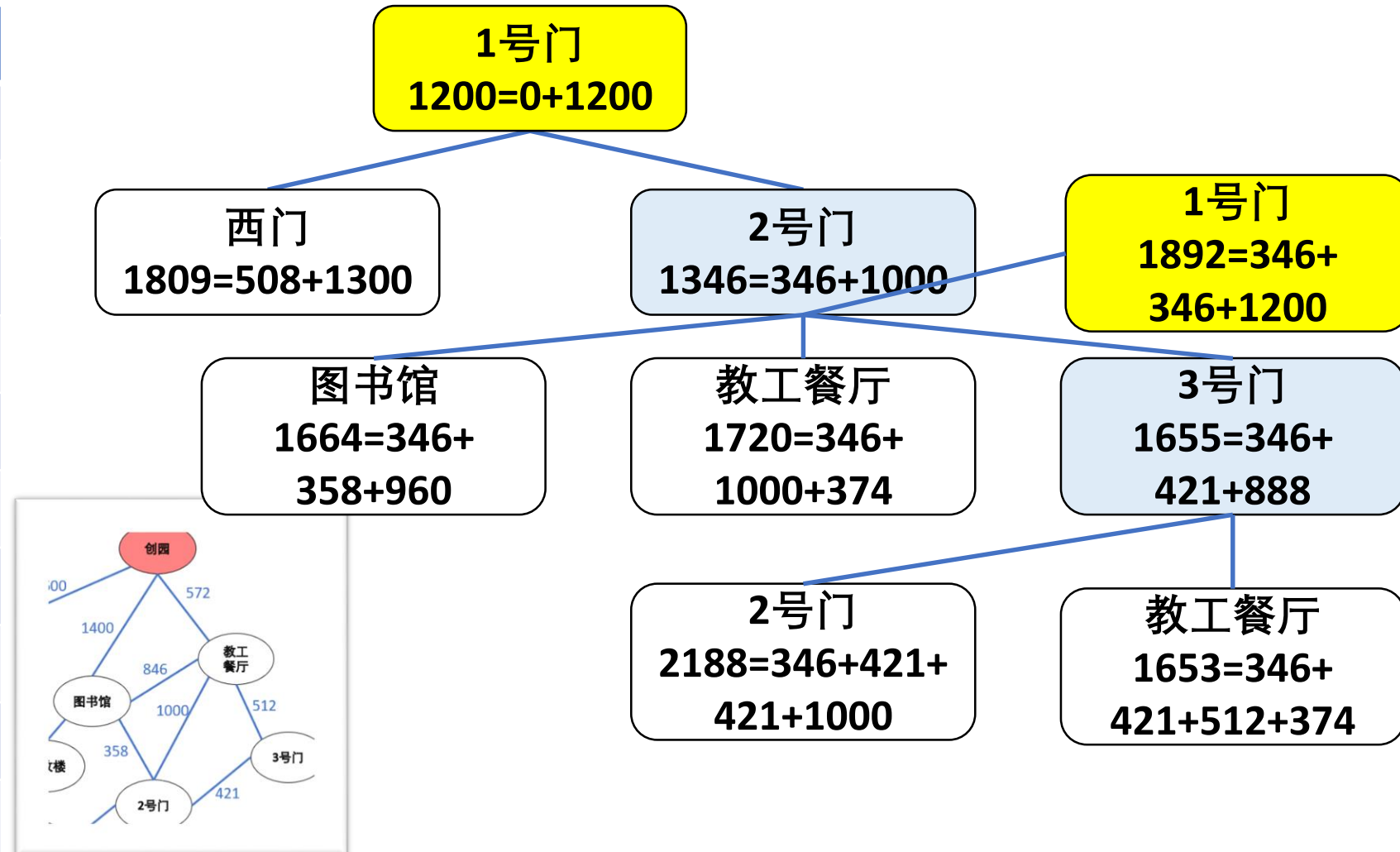
A*: Illustration 1

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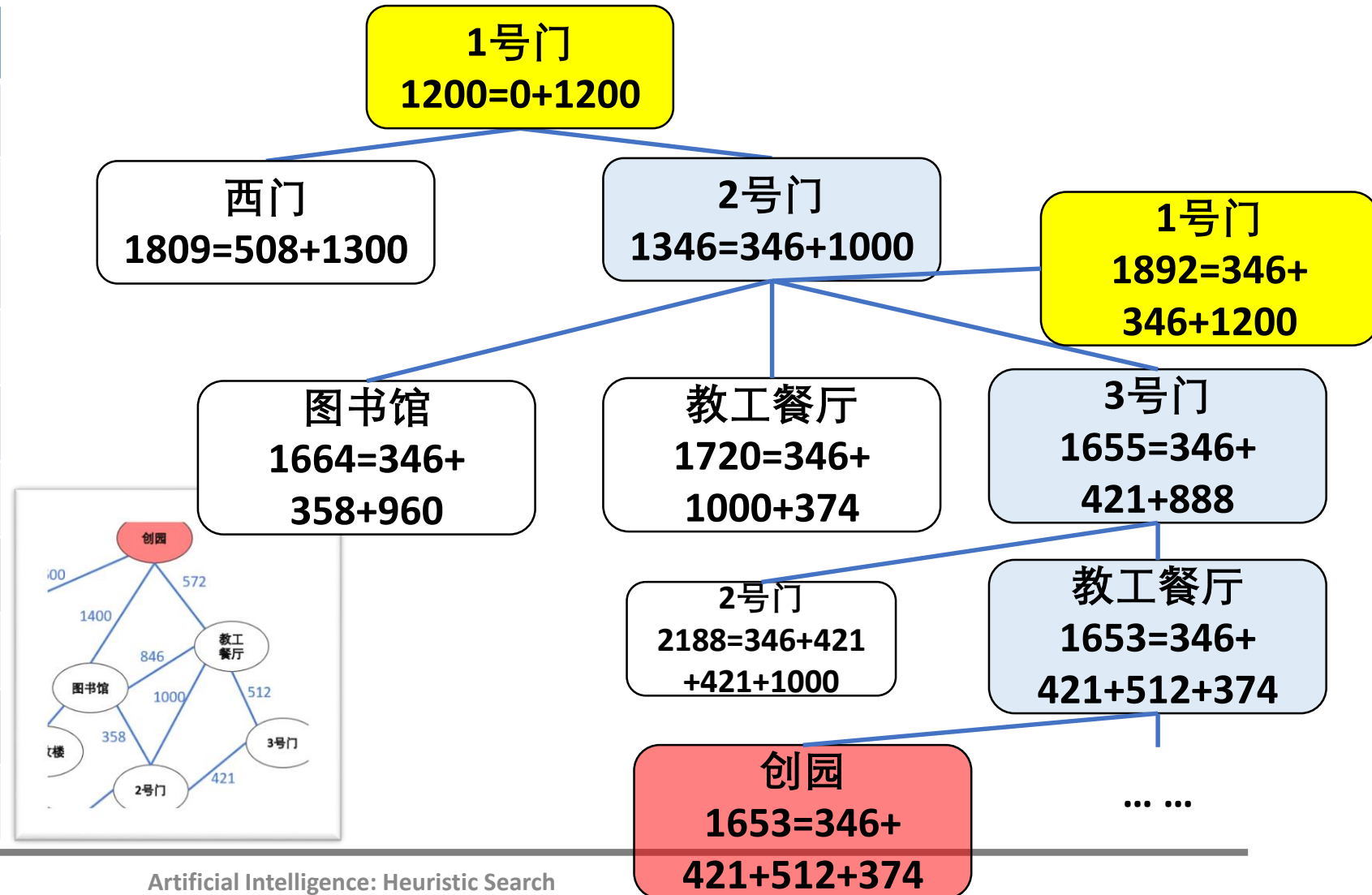
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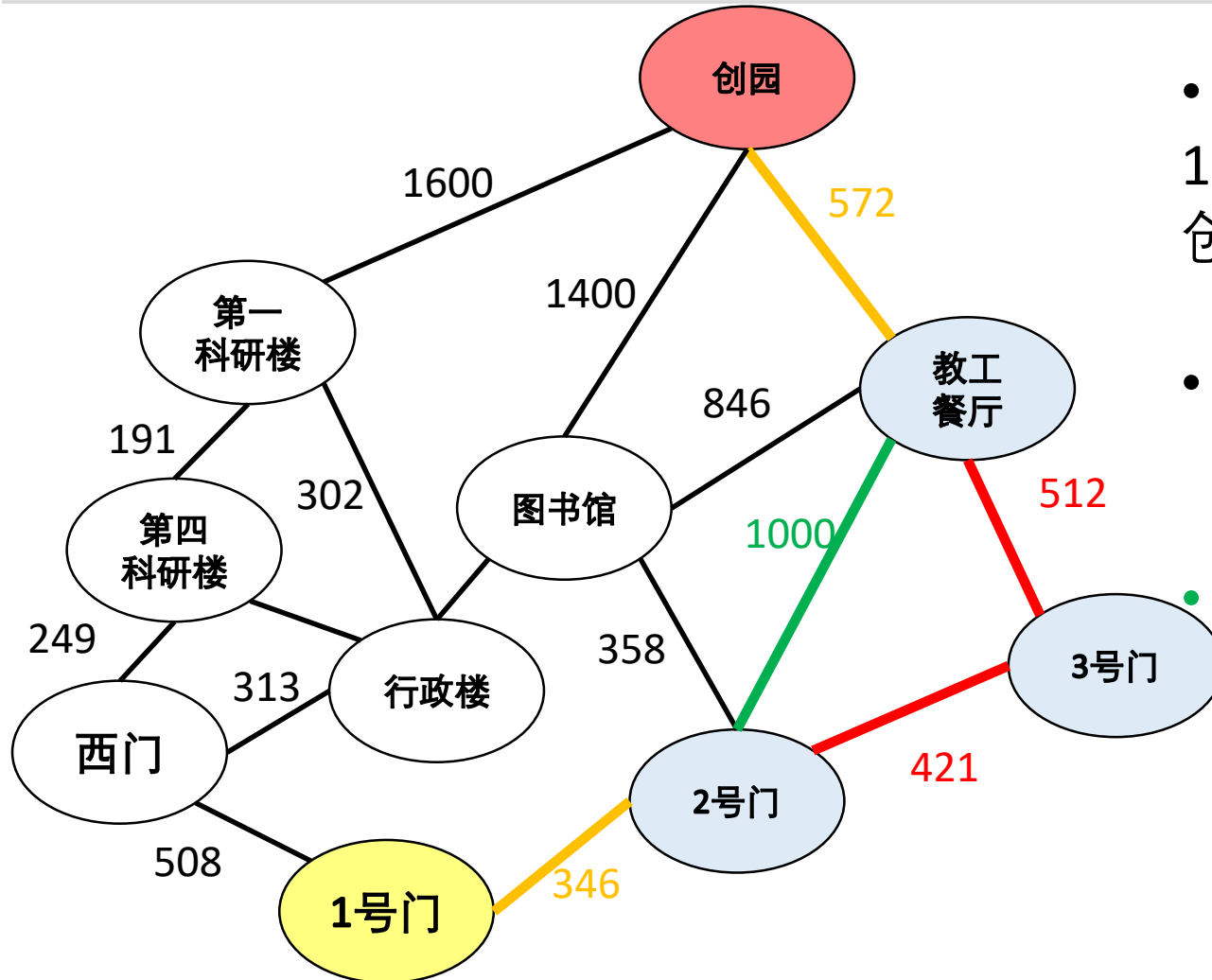


A*: Illustration 1

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A*: Illustration 1



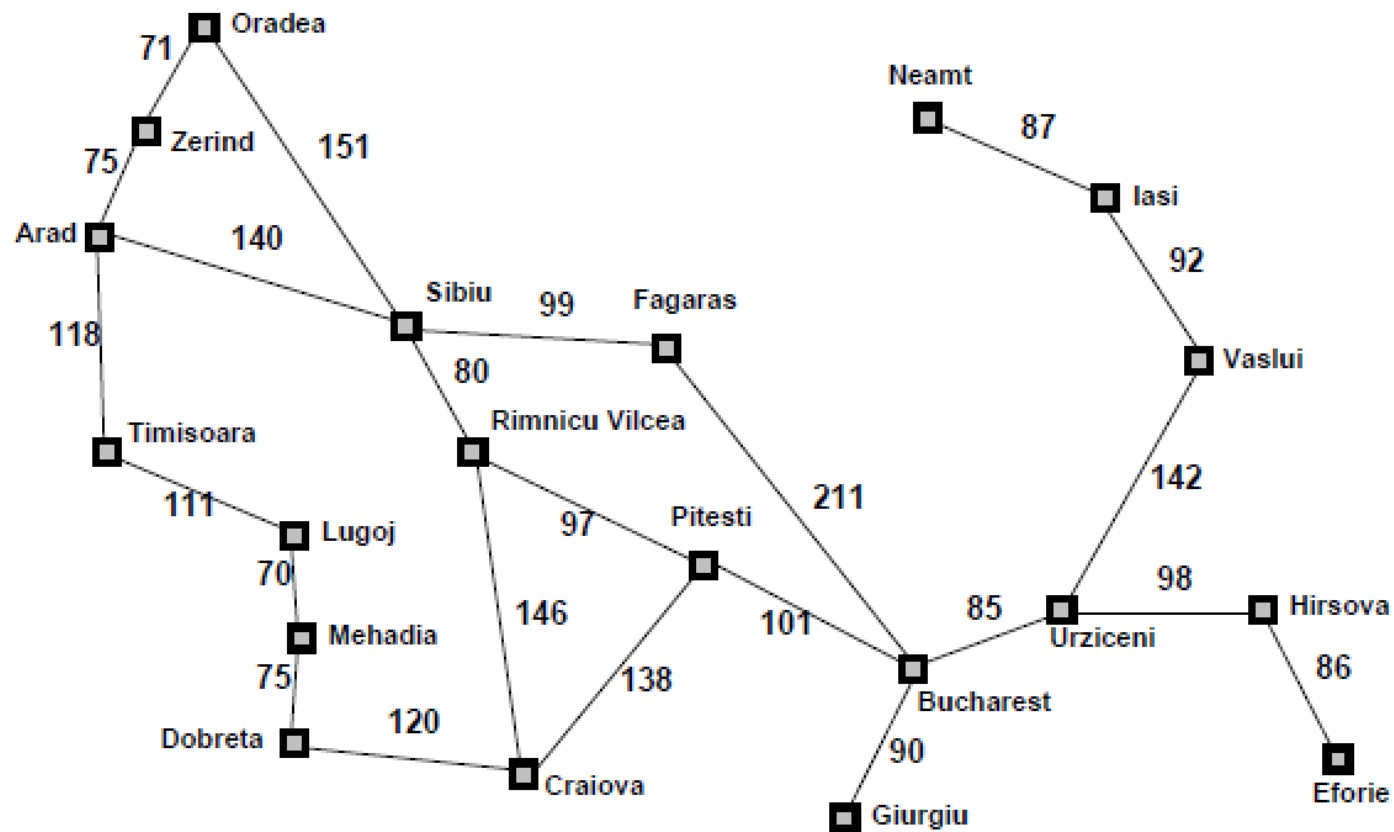
- **Solution:**

1号门->2号门->3号门->教工餐厅->创园

- ***Distance*** = $346 + 421 + 512 + 572 = 1851m$

- **Solution by Greedy Search:** 1918m

A*: Illustration 2



Straight-line distance to Bucharest	
Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
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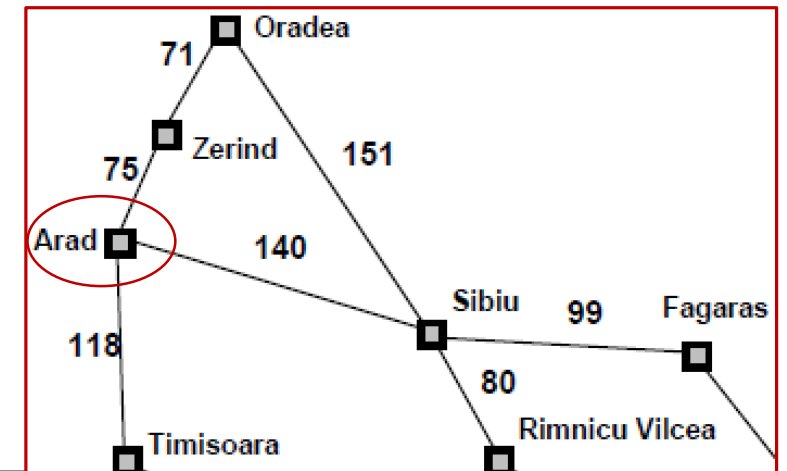
**Heuristics:
domain-
knowledge**

A*: Illustration 2

Straight-line distance
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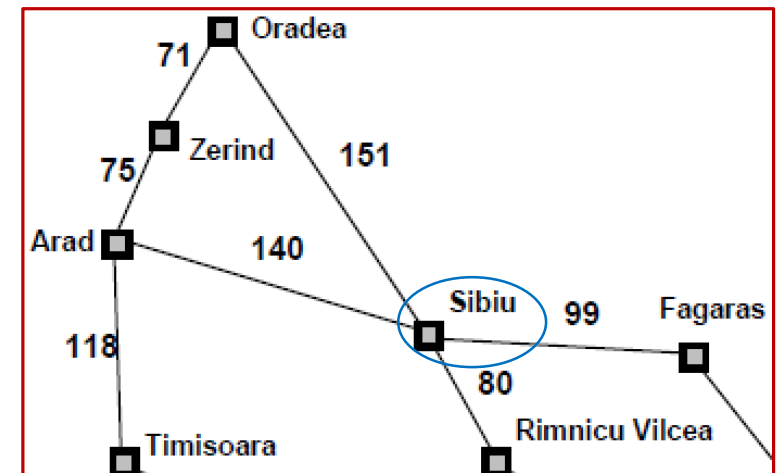
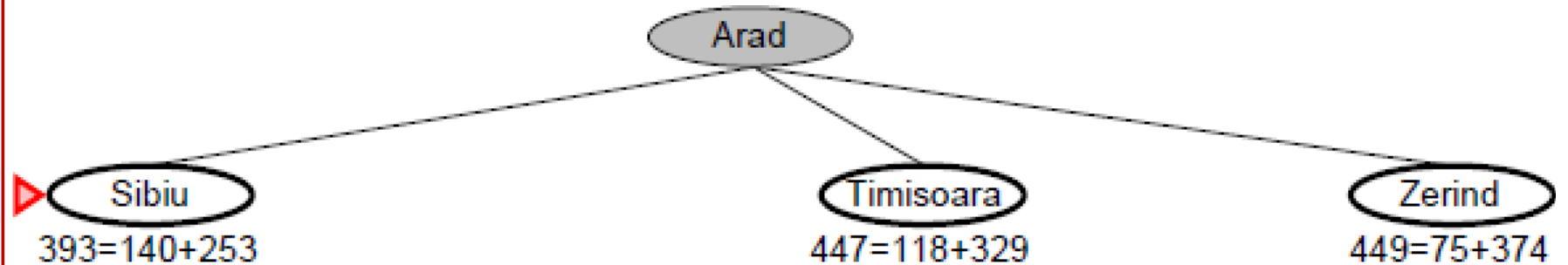
▶ Arad
 $366 = 0 + 366$



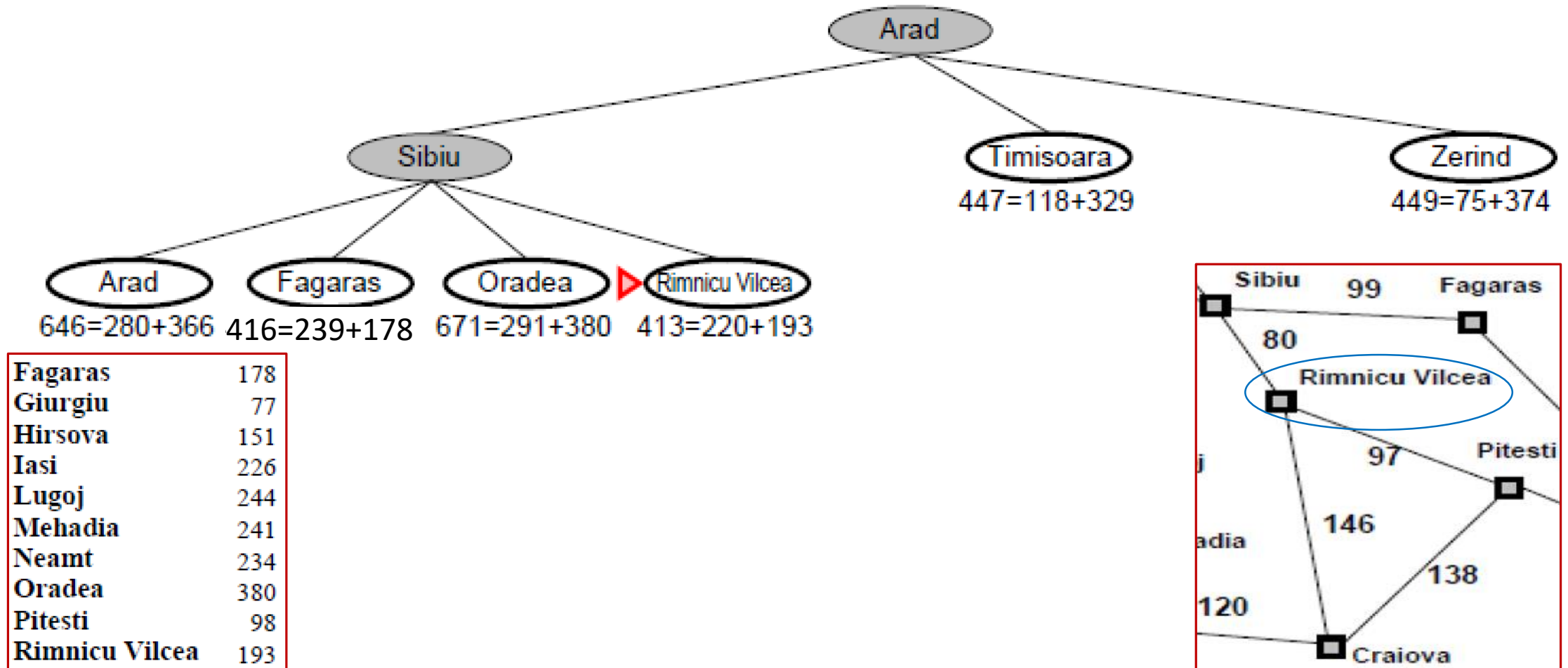
A*: Illustration 2

Straight-line distance
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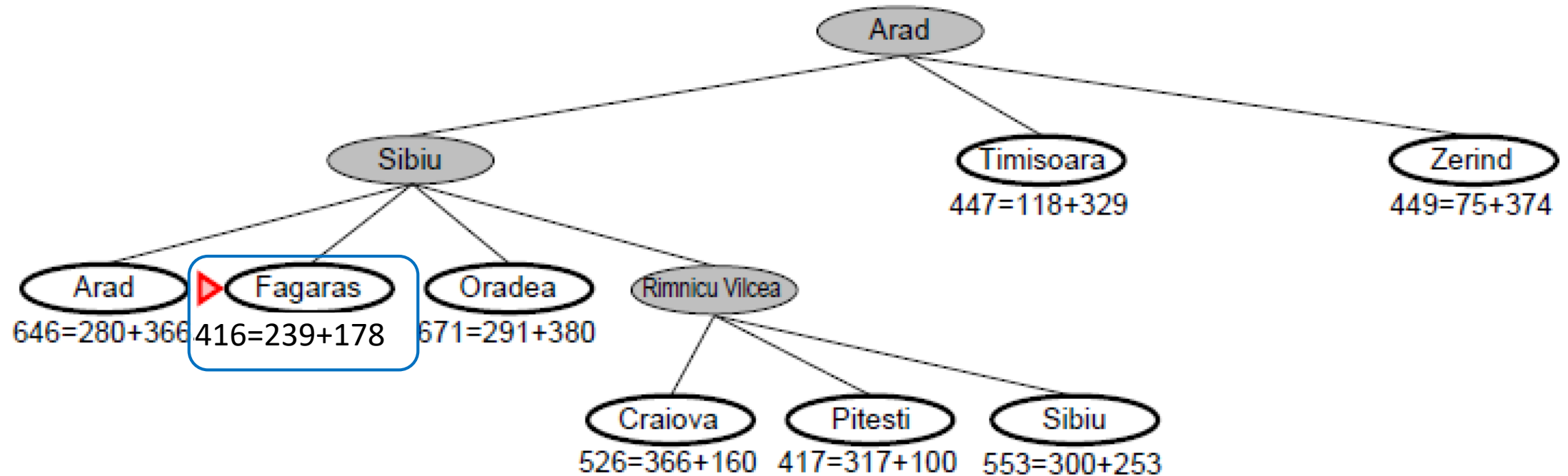
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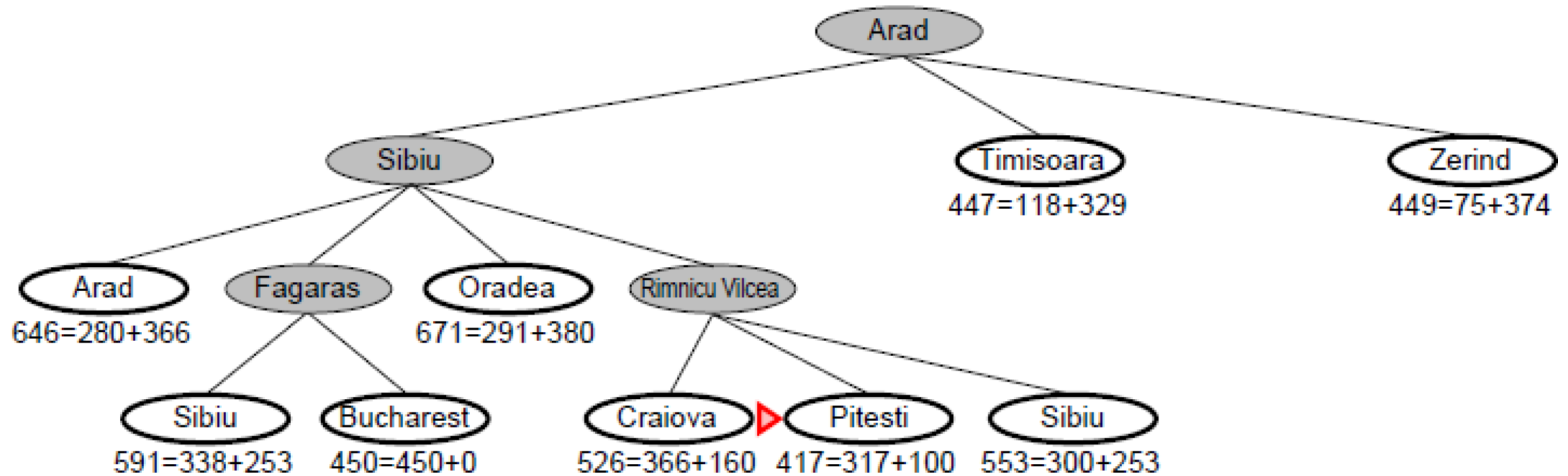
A*: Illustration 2



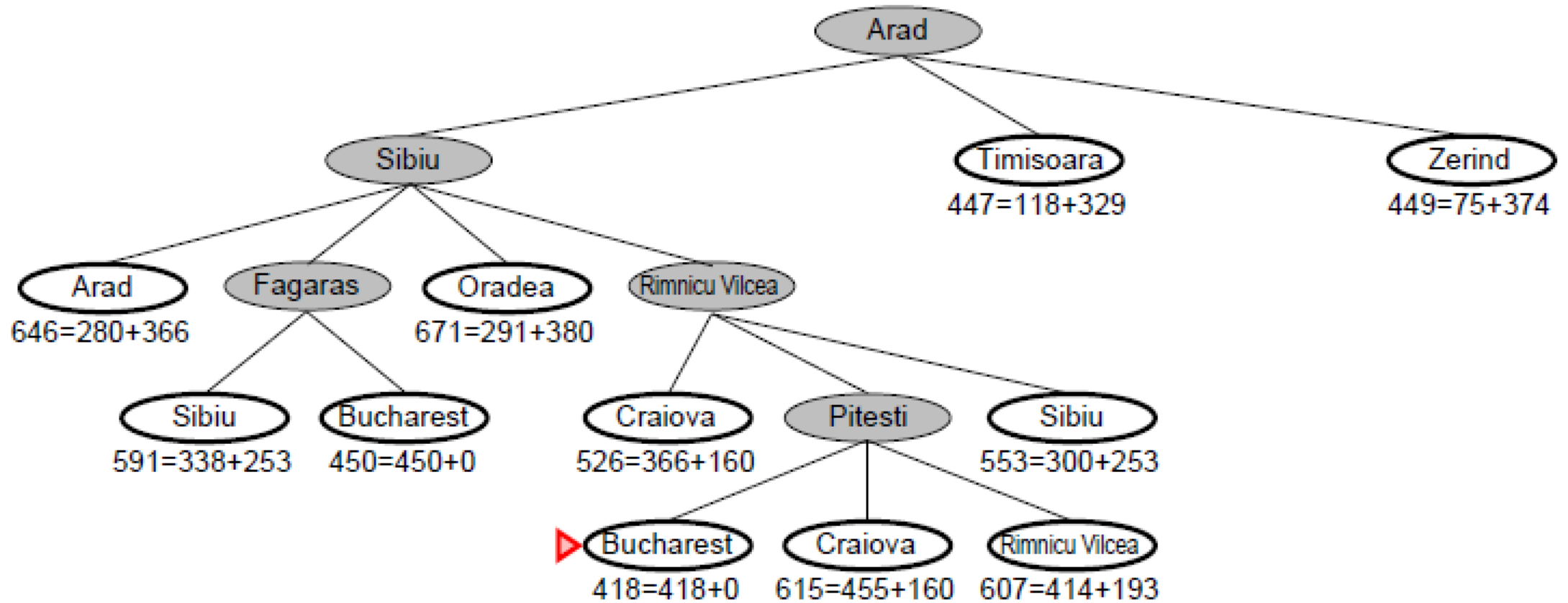
A*: Illustration 2



A*: Illustration 2



A*: Illustration 2



A*: Pseudo-code

```
function A-STAR-SEARCH(initialState, goalTest)
    returns SUCCESS or FAILURE : /* Cost  $f(n) = g(n) + h(n)$  */

    frontier = Heap.new(initialState)
    explored = Set.new()

    while not frontier.isEmpty():
        state = frontier.deleteMin()
        explored.add(state)

        if goalTest(state):
            return SUCCESS(state)

        for neighbor in state.neighbors():
            if neighbor not in frontier  $\cup$  explored:
                frontier.insert(neighbor)
            else if neighbor in frontier:
                frontier.decreaseKey(neighbor)

    return FAILURE
```

Recap: Core Idea

- Idea: **avoid** expanding paths that are **already expensive**.
- Expand the node s that has the minimal $f(s) = h(s) + g(s)$
 - $g(s)$: cost from Start to s .
 - $h(s)$: estimated cost from s to Goal.
 - $f(s)$: estimated total cost of path from Start through s to Goal.

Optimality of A*

- **Theorem:** A* with h is optimal if h is admissible.
- **Proof:**
 - **Notation:** S – start, G – goal, s – a node on optimal path, s' – non-optimal goal, c^* – cost of optimal path.
 - **To show:** A* always pick s over $s' \Leftrightarrow f(s) < f(s')$.
 - **Known:** h is admissible $\Rightarrow h(s) < c^*(s, G)$.
 - **Deduce:**
 - 1) $f(s') = g(s') + h(s') = g(s') + 0 > c^*$ (s' is the goal node & c^* the smallest).
 - 2) $f(s) = g(s) + h(s) < g(s) + c^*(s, G) = c^*(S, s) + c^*(s, G) = c^*$.
 - **Conclude:** combine (1)&(2) $\Rightarrow f(s) < f(s') \quad \square$

A*: Performance Metrics

b – maximum # successors of any node in search tree.
 d – depth of the least-cost solution.
 m – maximum length of any path in the state space.

- Complete? Yes.
- Optimal? Yes*, if h is admissible.
- Time? $O(b^d)$.
- Space? $O(b^d)$, keep every node in memory.

- If a solution exists, A* will find the best.
- Memory is the major problem for A*.

A*: Example



- Super Mario played by a path-finding algorithm A*. The bot won the Mario AI competitions in 2009 (<https://youtu.be/DIkMs4ZHHr8>).

Brief Summary

Summary: Heuristic Search

- **Core idea**: expand the path that seems most **promising**.
- Node s with lowest $f(s)$ \rightarrow the most **promising**.
- Usually $f(s) = h(s) + ?$.

- Greedy: Incomplete & Not always optimal
- A*: Complete & Optimal

Summary: Search Methods with $f(s)$

- The choice of f determines the search methods.

- Uniform-cost search: $f(s) = g(s)$.
- Greedy best-first search: $f(s) = h(s)$.
- A* search: $f(s) = g(s) + h(s)$.

-
- $g(s)$: the path cost from Start to node s .
 - $h(s)$: the estimated cost from node s to Goal.

III. Further Studies on Heuristics

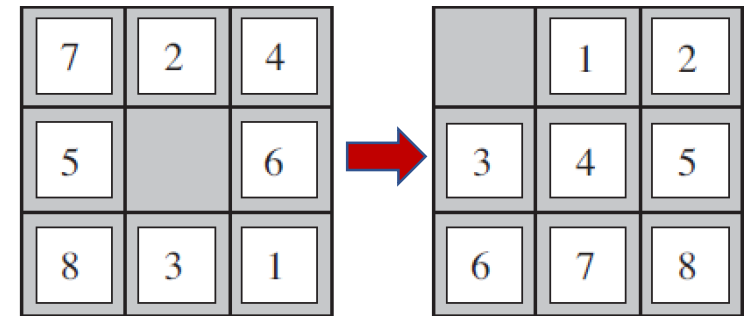
- Search Efficiency of Heuristics
- Generate Admissible Heuristics

III.1 Search Efficiency of Heuristics

Recall: Heuristics for 8-puzzle Problem

- $h_{mis}(s) = \# \text{misplaced tiles} \in [0,8]$: **Admissible**.
 - $h_{1stp}(s) = \#(1\text{-step move})$ to reach the goal configuration: **Admissible**.
- $h_{1stp}(s) \geq h_{mis}(s) \Rightarrow h_{1stp}(s)$ is '**better**' than $h_{mis}(s)$.

What does 'better' mean?



Dominance

- For **admissible** h_1 and h_2 , if $h_1(s) \geq h_2(s)$ for $\forall s$
 $\Rightarrow h_1$ **dominates** h_2 and is **more efficient** for search.
 - **Theorem**: For any admissible heuristics h_1 and h_2 , define
$$h(s) = \max\{h_1(s), h_2(s)\}$$
 $h(s)$ is admissible and dominates both h_1 and h_2 .
- 'Better' heuristic = dominance = better search efficiency.

Even Better Dominance

- **Question:** Which one to choose from a collection of admissible heuristics h_1, \dots, h_m & none dominates any other?
- **Answer:** $h(s) = \max\{h_1(s), \dots, h_m(s)\}$ dominates all the others.

Effect of Heuristic Accuracy on Performance

- Quality indicator of an heuristic:
 - Effective branching factor b^*
 - N = total number of nodes
 - d = solution depth
 - Then, $N + 1 = 1 + b^* + (b^*)^2 + \dots + (b^*)^d$
 - A well designed heuristic would have a b^* close to 1, allowing to solve a large problem at reasonable cost.

Quantify Search Efficiency

- **Effective Branching Factor b^*** : For a solution from A*, calculate b^* satisfying:
$$N = b^* + (b^*)^2 + \dots + (b^*)^d$$
 - N : #nodes of the solution,
 - d : depth of the solution tree.
- E.g., A* finds a solution at depth 5 using 52 nodes $\Rightarrow b^* = 1.92$.
- Good heuristics have b^* close to 1 \rightarrow large problems solved at reasonable computational cost.
- b^* quantifies search efficiency of heuristics.

Empirical: Factor b^* for Search Efficiency

- **Aim:** Compare h_1 and h_2 regarding the search efficiency.
- **Setting:** Generate 1200 random problems with $d = \{2, \dots, 24\}$ and solve them with IDS and A* with h_1 & h_2 .
- **Note:** IDS – a baseline.

Empirical: Factor b^* for Search Efficiency

	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

Empirical: Factor b^* for Search Efficiency

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4	—	—	—	—	—	—
6	—	—	—	—	—	—
8	—	—	—	—	—	—
10	—	—	—	—	—	—
12	—	—	—	—	—	—
14	—	—	—	—	—	—
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- h_2 is 'better' than h_1 regarding search efficiency.
- This goodness is reflected by b^* being closer to 1.
- A^* with h_2 performs much better than IDS.

III.2 Generate Admissible Heuristics

We Know about Heuristics ...

- We know:
 - How to judge their admissibility.
 - How to compare their goodness regarding searching efficiency.
- **Question:** How to produce such 'good' heuristics?

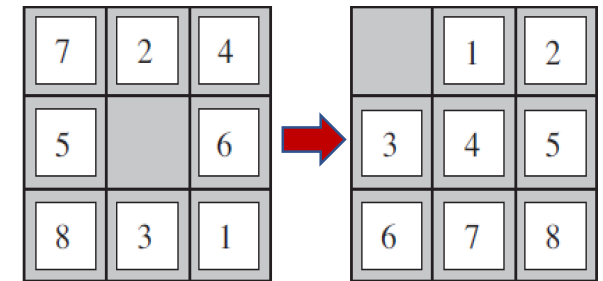
(1) Generate from Relaxed Problems

Where are h_{mis} & h_{1stp} from?

For 8-puzzle problem:

- **Real Rule:** A tile can only move to the **adjacent empty** square.
- **Relaxed rules:** h_{mis} and h_{1stp} are admissible
 - R1: A tile can move **anywhere** $\Rightarrow h_{mis}(s) = \#(\text{misplaced tiles})$.
 - R2: A tile can move one step in **any direction** regardless of an occupied neighbour $\Rightarrow h_{1stp}(s) = \#(1\text{-step move})$ to reach goal.

➤ Optimal solutions to problems with R1, R2 are easier to find.



Relaxed Problem

- **Relaxed problem**: a problem with **relaxed rules** on the action.
- E.g. 8-puzzle problems with R1 and R2.
- **Theorem**: The cost of an optimal solution to **a relaxed problem** is an **admissible heuristic** for the original problem.
- No wonder h_{mis} and h_{1stp} are admissible.

(2) Generate from Sub-problems

Subproblem

- Subproblem
 - Task: get tiles 1, 2, 3 and 4 into their correct positions.
 - Relaxation: move them disregarding the others.
- Theory: $\text{cost}^*(\text{subproblem}) < \text{cost}^*(\text{original})$.
 - $\text{cost}^*(\text{subproblem})$: the cost of the optimal solution of this subproblem.

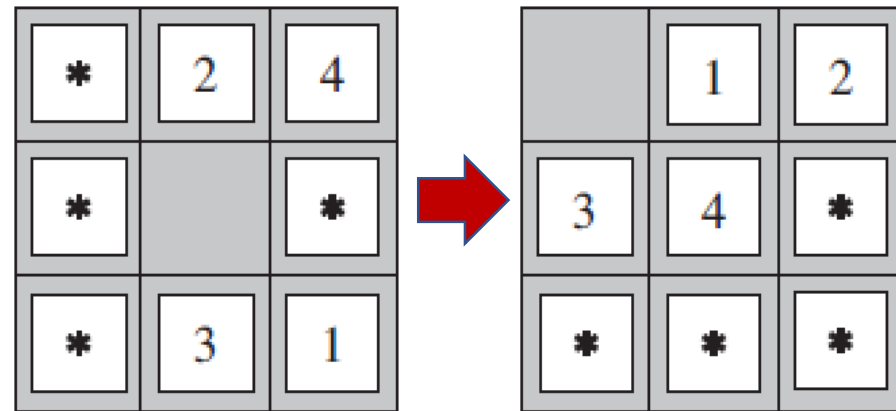


Fig.1. A subproblem of 8-puzzle.

Subproblem and Admissible Heuristics

- **Admissible $h_{sub}^*(s)$** : estimate the cost from s to the subproblem goal.
 - E.g. $h_{sub}^{(1,2,3,4)}$ is the cost to solve the 1-2-3-4 subproblem.
- $h_{sub}(s)$ dominates $h_{1stp}(s)$
 - $h_{sub}(s) = \max\{h_{sub}^{(1,2,3,4)}(s), h_{sub}^{(2,3,4,5)}(s), \dots\}$.

Disjoint Subproblems

- **Question:** Will the **addition of heuristics** from subproblem (1-2-3-4) and (5-6-7-8) give an **admissible heuristic**, considering the two subproblems are not overlapped?
- **Answer:** No, since they always **share some moves**.
- **Question:** What if **not count** those shared moves?
- **Answer:** $h_{sub}^{(1,2,3,4)}(s) + h_{sub}^{(5,6,7,8)}(s) \leq c^*(s) \Rightarrow$ admissible.
 - Disjoint pattern database

(3) Generate from Experiences

'Experience' Formulation

For 8-puzzle problem:

- Solve many 8-puzzles to obtain many examples.
- Each example consists of a state from the solution path and the actual cost of the solution from that point.
- These examples are our 'experience' for this problem.
- **Question:** How to learn $h(s)$ from these experience?

Learn Heuristics from Experience

- **Question:** What are the **good experience features**?
- **Answer:** **Relevant** to predicting the states' cost to Goal, e.g.
 - $x_1(s)$: #(displaced tiles).
 - $x_2(s)$: #(pairs of adjacent tiles) that are not adjacent in Goal state.
- **Question:** How to learn h from those **relevant experience features**?
- **Answer:** (e.g.) Construct model as

$$h(s) = w_1 x_1(s) + w_2 x_2(s),$$

where w_1, w_2 are model parameters to learn from training data by a learning method such as neural networks and decision trees.

Brief Summary

Summary: Search Methods

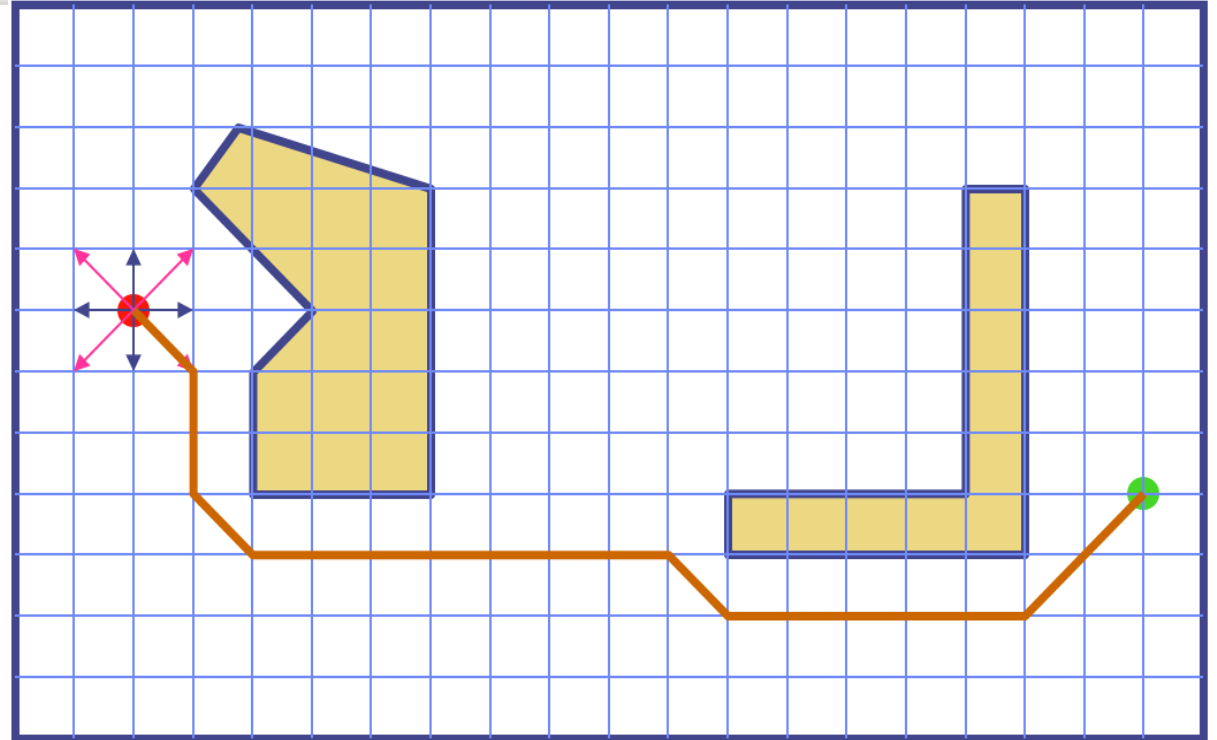
- **Uninformed Search:** Use no domain knowledge.
 - Other names: basic search, blind search
 - BFS, UCS, DFS, DLS and IDS
- **Informed Search:** Use heuristics to encode domain knowledge.
 - Other name: heuristic search
 - Greedy search and A* search.

Summary: Heuristics

- Heuristic $h(s)$: estimate the cost from s to Goal.
 - (1) $h(s) = 0$ if s is Goal. (2) nonnegative. (3) problem-specific.
- Admissibility: $h(s)$ never overestimates cheapest cost from s to Goal.
- Effective branching factor b^* : quantify the search efficiency of $h(\cdot)$.
- Generate admissible heuristics:
 - (1) from relaxed problems.
 - (2) from sub-problem.
 - (3) from experience.

Example: Robot Navigation

- Move along the line or diagonal.
- $h_{SLD}(s)$: straight-line distance from n to the goal.
- cost of a horizontal/vertical move = 1
- cost of one diagonal move = $\sqrt{2}$.



Question: find the optimal path from Red to Green by (1) greedy search and (2) A* search.

Reading Materials for This Lecture

- AI textbook (3rd edition)
 - Chapter II.3: Solving Problems by Searching (pages 92-108)
 - AI-book codes: <https://github.com/aimacode>
- Algorithms textbook
 - 24: Single-Source Shortest Paths (pages 644-683)
- Articles
 - [1] Seet, B. C., Liu, G., Lee, B. S., Foh, C. H., Wong, K. J., & Lee, K. K. (2004, May). A-STAR: A mobile ad hoc routing strategy for metropolis vehicular communications. In *International Conference on Research in Networking* (pp. 989-999). Springer, Berlin, Heidelberg.
 - [2] Duchoň, F., Babinec, A., Kajan, M., Beňo, P., Florek, M., Fico, T., & Jurišica, L. (2014). *Path planning with modified a star algorithm for a mobile robot*. Procedia Engineering, 96, 59-69.
- Demos:
 - <http://www.cnblogs.com/0zcl/p/6242790.html>
 - <http://ashblue.github.io/javascript-pathfinding/>
 - <https://github.com/bgrins/javascript-astar>
 - <https://www.mathworks.com/matlabcentral/fileexchange/66461-astar-demo>