

CS 460/560

Introduction to Computational Robotics
Fall 2019, Rutgers University

Lecture 10

Graph Search Algorithms

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16

Instructor: Jingjin Yu

Outline

Solving problems via search

Basic graph search algorithms

⇒ Graph

⇒ BFS

⇒ DFS

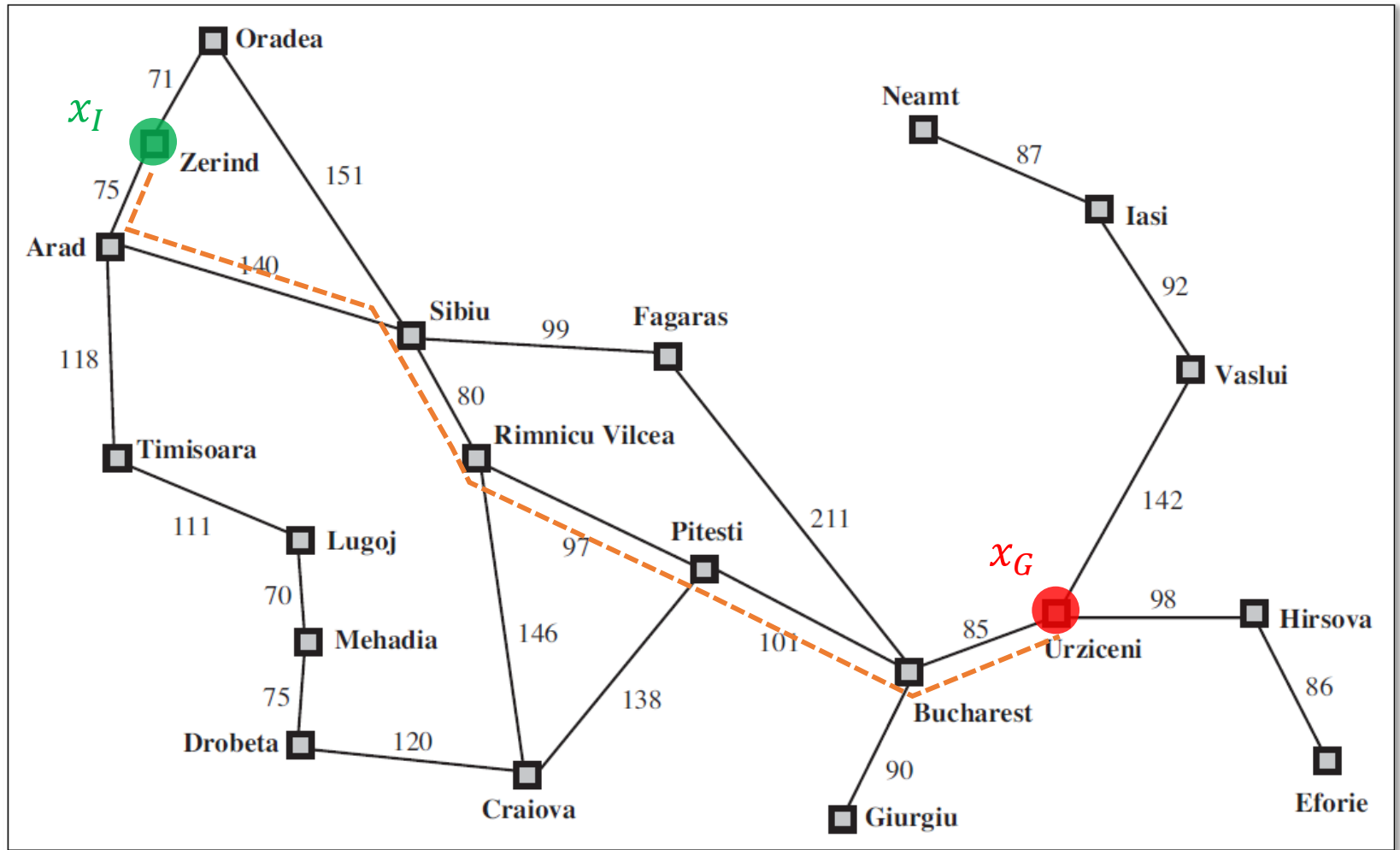
⇒ Uniform cost

⇒ A*

All pairs shortest path

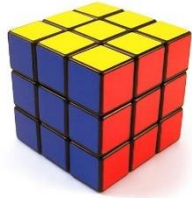
A word on the principle of dynamic programming

Solving Problems through Search: An Example



Search for a route in Romania

Components of a Search Problem



⇒ **State space** S : in this case, an edge-weighted graph

⇒ **Initial** (start) and **goal** (final) states: x_I and x_G

⇒ There can be more than one start/goal state: solve one side of a Rubik's cube

⇒ **Action**: in this case, moving from one state to a nearby state

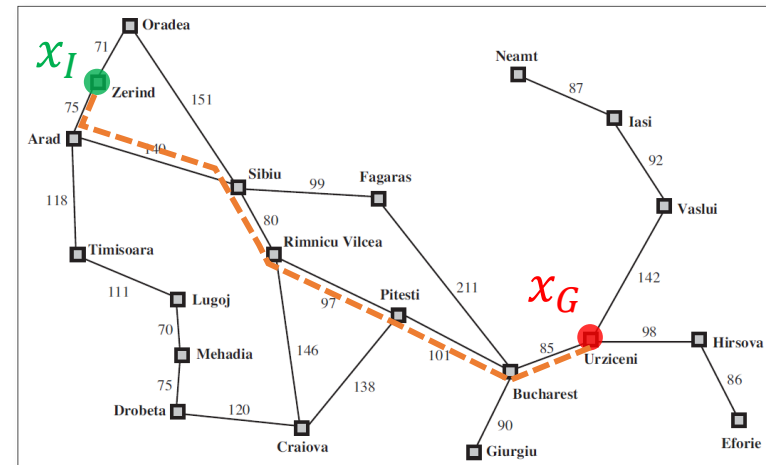
⇒ **Transition model**: tuples (s_1, a, s_2) that are valid

⇒ Sometimes written as $T(s_1, a) = s_2$

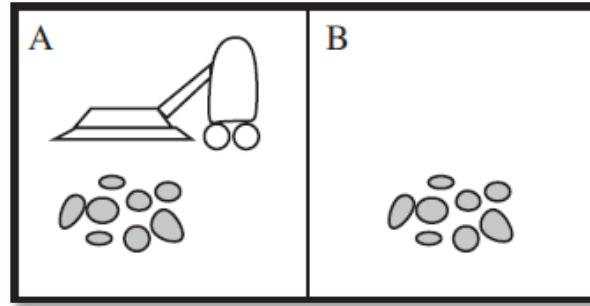
⇒ There are usually costs/rewards associated with a transition, $R(s_1, a)$

⇒ **Solution**: valid transitions connecting x_I and x_G

⇒ Optimal solution: solution with lowest cost (e.g., length of the path)



Example: Vacuum-Cleaner World



⇒ State space: $\{A, B\} \times \{A_{dirty}, A_{clean}\} \times \{B_{dirty}, B_{clean}\}$

⇒ State space size: $2 \times 2 \times 2 = 8$

⇒ Action: $\{left, right, suck\}$

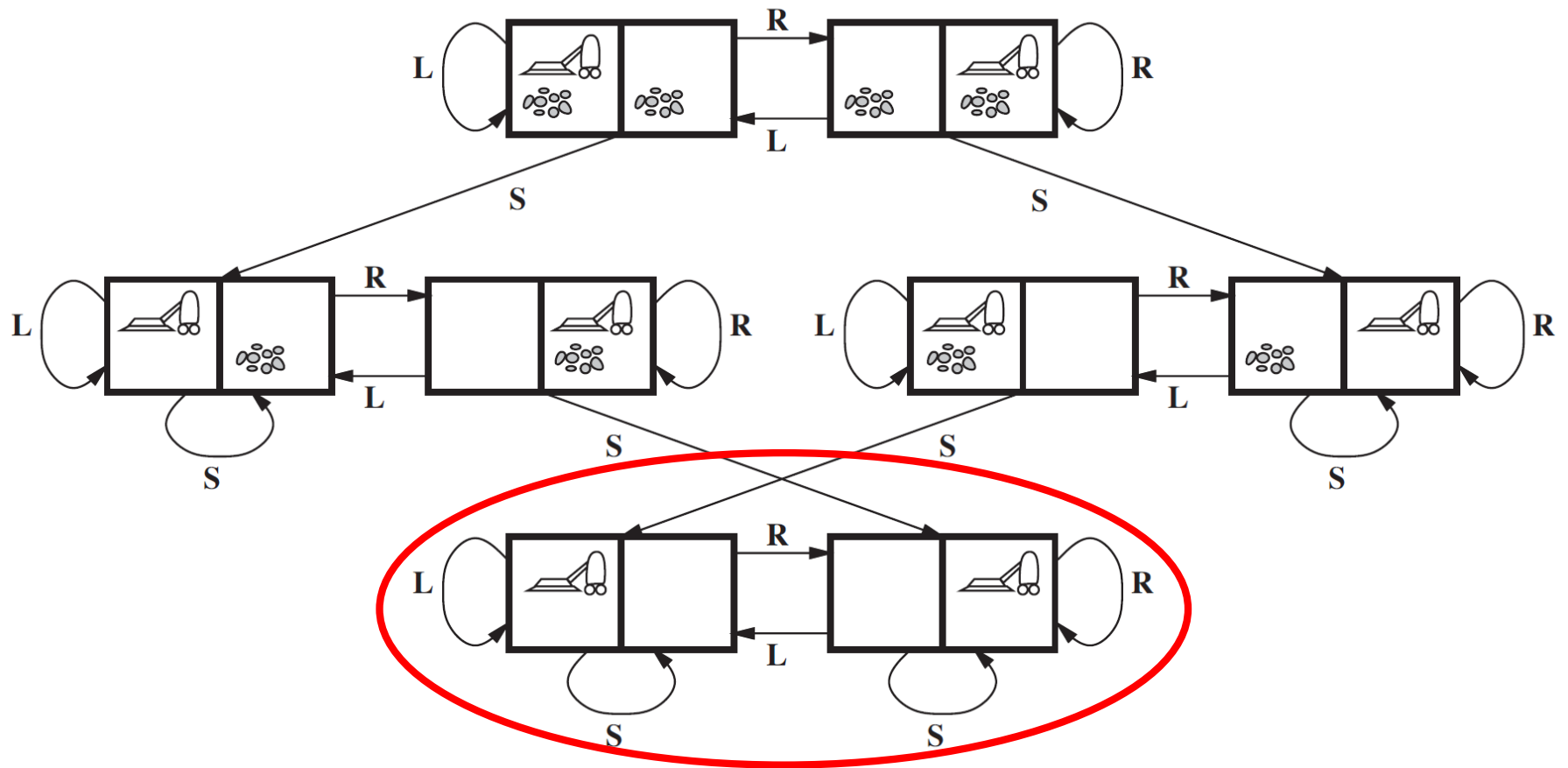
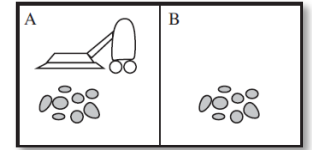
⇒ Transition example: $(A, A_{clean}, B_{dirty}) \xrightarrow{\text{right}} (B, A_{clean}, B_{dirty})$

⇒ Initial state: can be an arbitrary state

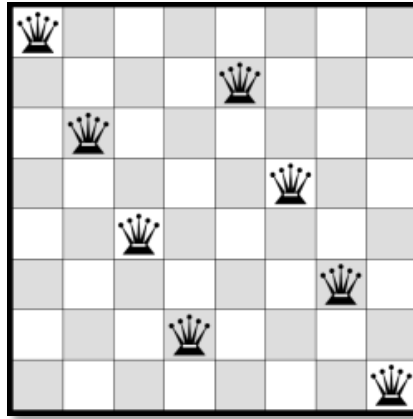
⇒ Goal states: $\{A, B\} \times \{A_{clean}\} \times \{B_{clean}\}$

⇒ Cost: can be the number of actions in a solution

State Space of the Vacuum-Cleaner World



Example: 8-Queens



⇒ State space: possible locations of 8 queens

⇒ State space size: $C(64, 8) = \frac{64 \times 63 \times \dots \times 57}{8!} \approx 4 \times 10^9$

⇒ Action/transition: place or move a queen

⇒ Initial state: can be an arbitrary state

⇒ Goal states: a placement of queens in which no two queens attacking

⇒ Cost: no clear cost

Example: 8-puzzle

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

⇒ State space: arrangements of the 8 pieces

⇒ State space size: $9! = 362880$

⇒ Action/transition: shifting a piece to the empty cell

⇒ Initial state: an arbitrary state

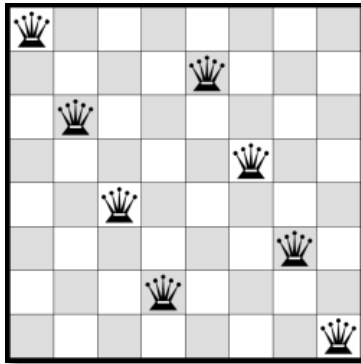
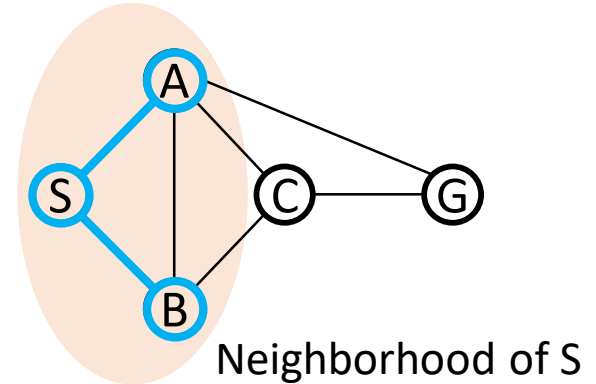
⇒ Goal state: an arbitrary fixed state

⇒ Cost: number of actions (moves)

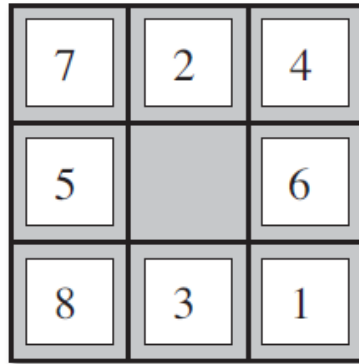
Discrete Search Algorithms

What are discrete search algorithms?

- ⇒ An algorithm whose **data structure** is a graph
- ⇒ That is, a set of “nodes” with “neighborhoods”
- ⇒ The graph may be explicit
- ⇒ Or it may be implicit
 - ⇒ What are the nodes here?
 - ⇒ And neighborhoods?
- ⇒ And even not fully known!



8 Queens

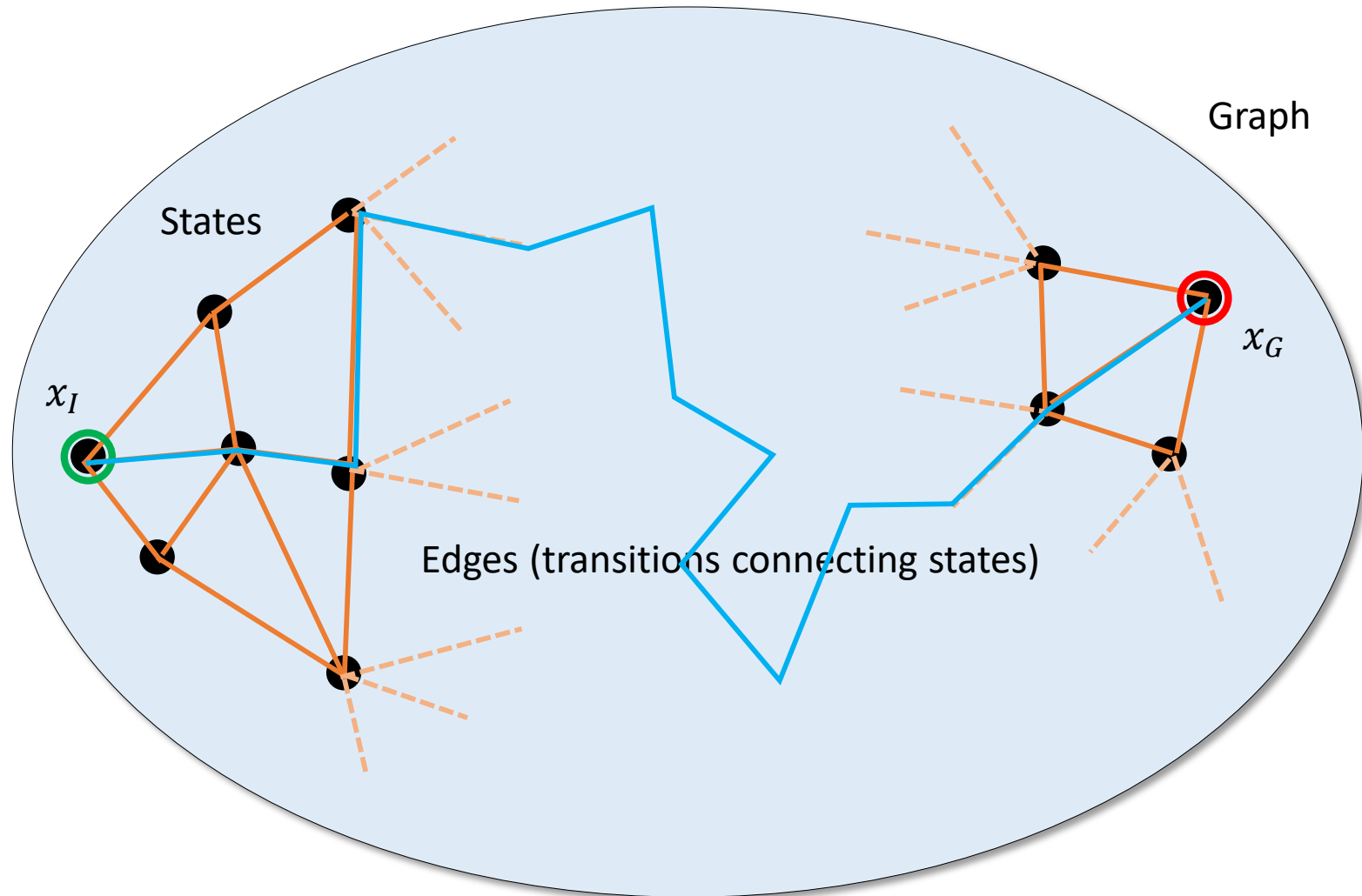


8-puzzle

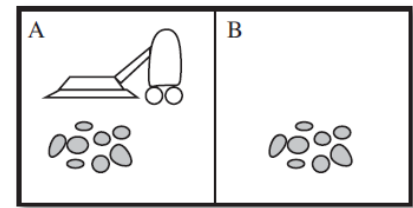


C&C: Red alert (Electronic Arts)

Graph View of Search: A Recap

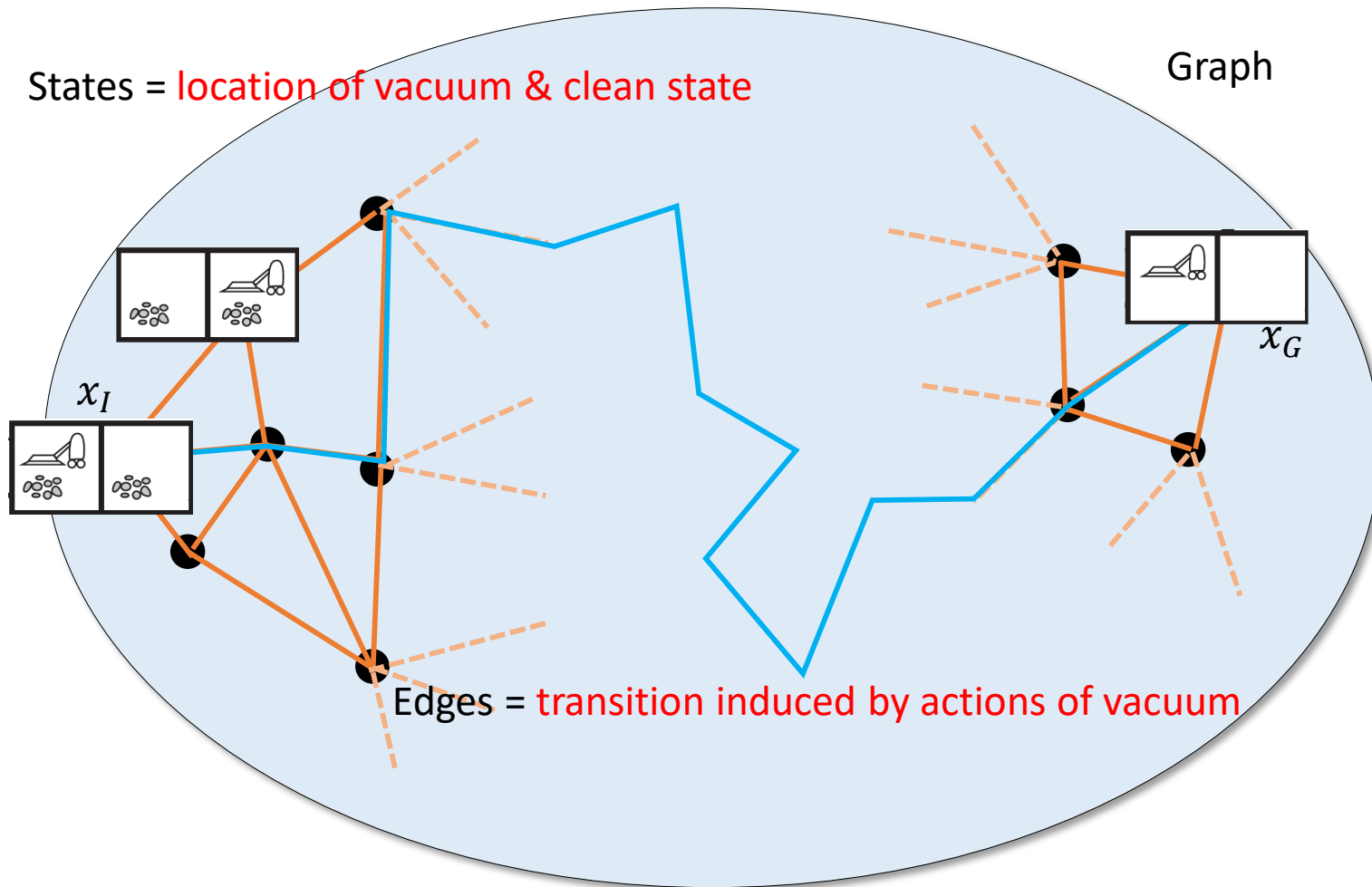


Examples Revisited: Vacuum World



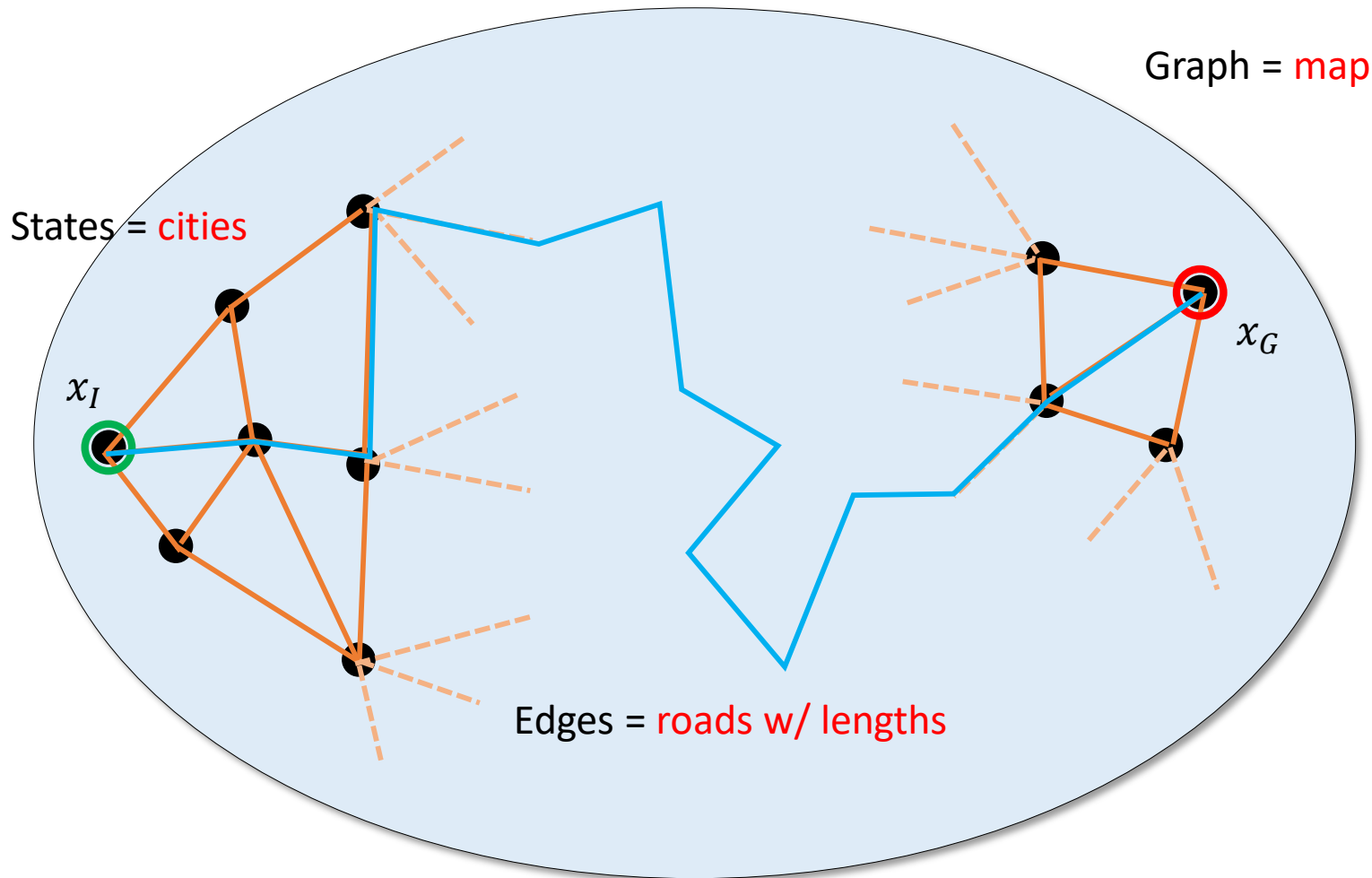
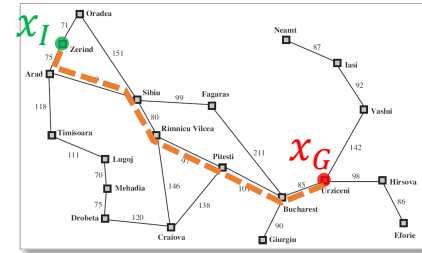
States = location of vacuum & clean state

Graph

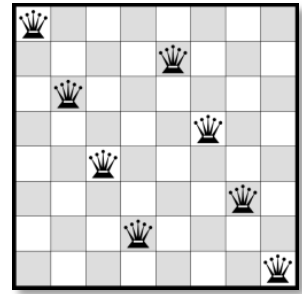


Edges = transition induced by actions of vacuum

Examples Revisited: Navigation



Examples Revisited: Eight Queens



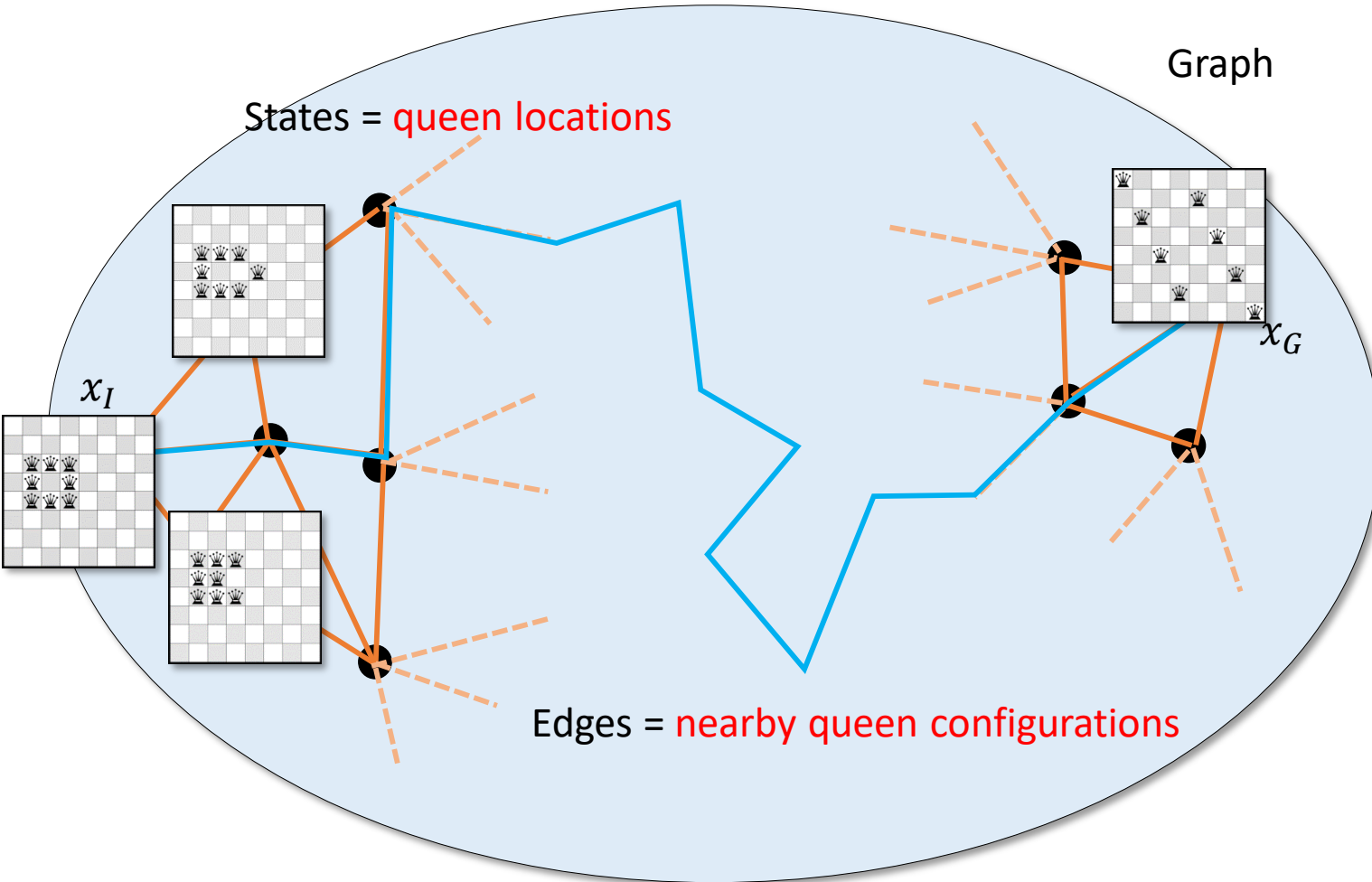
Graph

States = queen locations

x_I

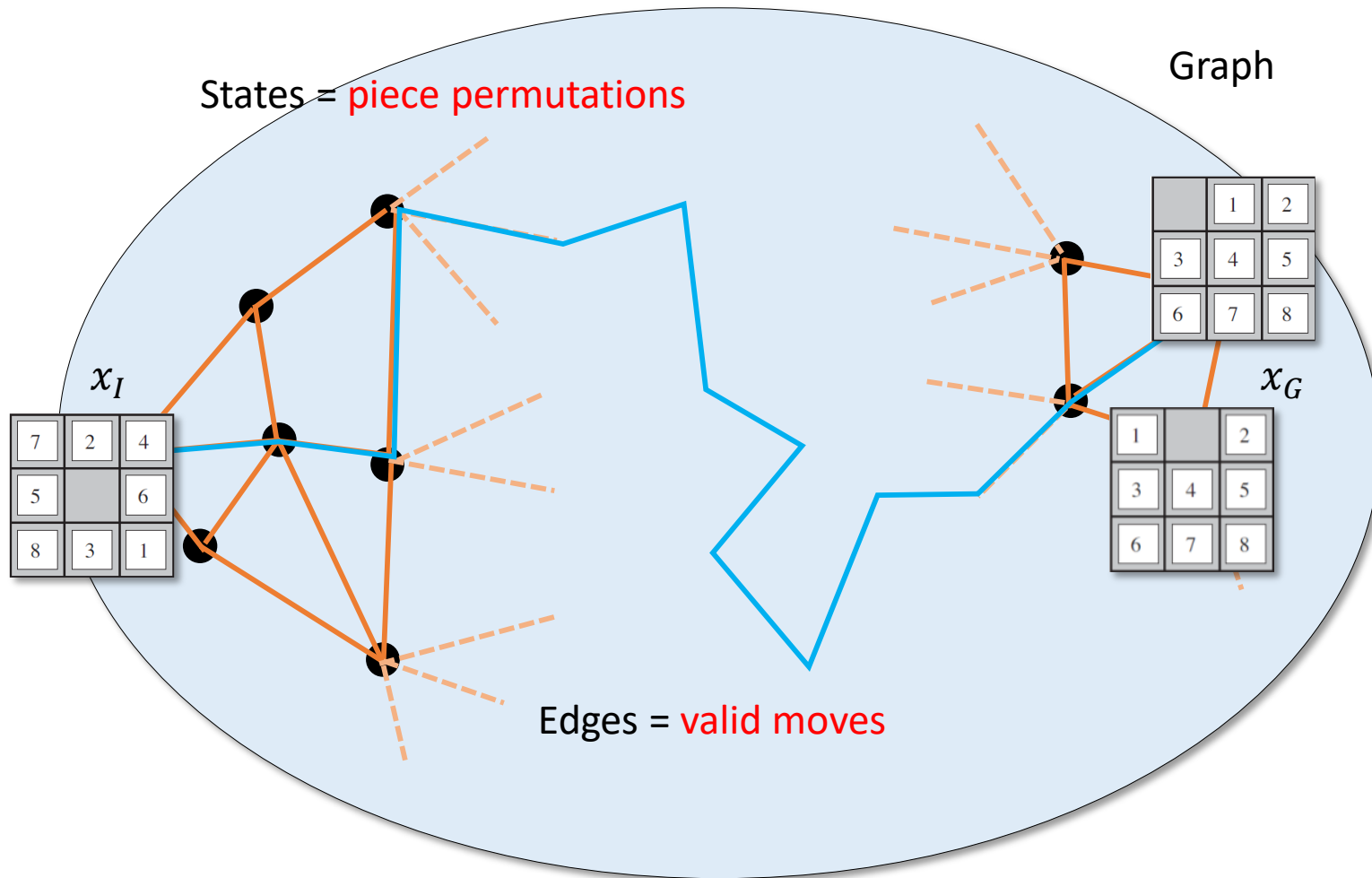
x_G

Edges = nearby queen configurations

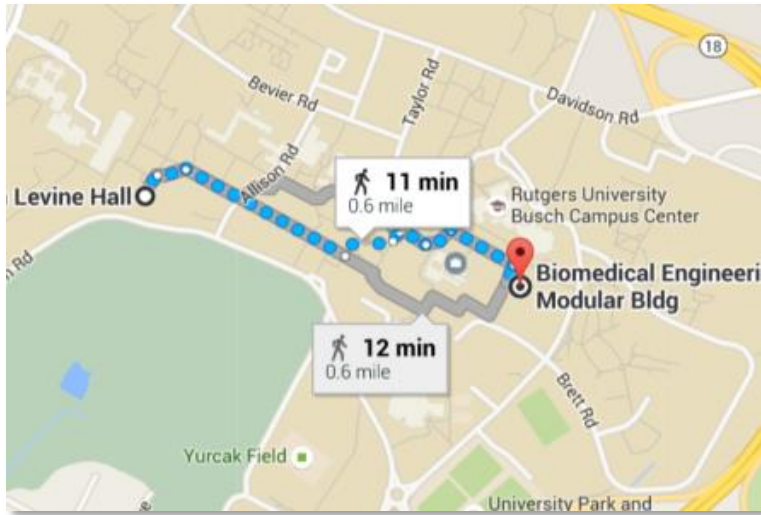


Examples Revisited: Eight Puzzle

7	2	4
5		6
8	3	1



Applications of Discrete Search Algorithms



Navigation



Robot motion planning



Competitive chess and go



Game AI

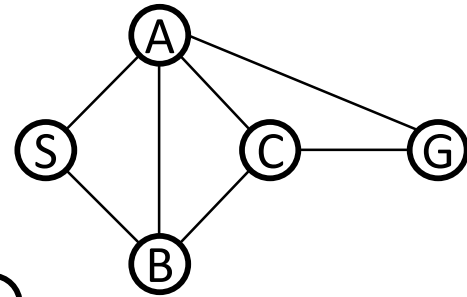
Graph Basics

A graph $G = (V, E)$ is a set of vertices V and a set of edges E

⇒ Example

⇒ $V = \{A, B, C, G, S\}$

⇒ $E = \{(A, B), (A, C), (A, G), (A, S), (B, S), (B, C), (C, G)\}$



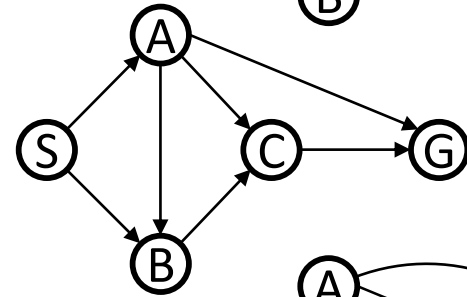
Variations

⇒ A graph may be **directed**

⇒ There can be **multi-edges** between two vertices

⇒ This is called a **multi-graph**

⇒ We will not consider multi-graphs in our course



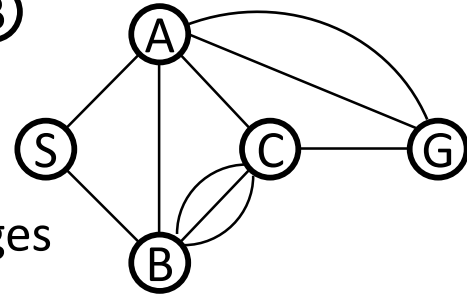
Basic properties

⇒ An undirected graph with n vertices has at most $\frac{n^2 - n}{2}$ edges

⇒ When this happens, the graph is a **complete** graph

⇒ A graph is **connected** if there is a path between any two vertices

⇒ A connected graph with $n - 1$ edges is a **tree**



A Generic Graph Search Algorithm

```
input:  $G = (V, E)$ ,  $x_I$ ,  $x_G$ 
AddToQueue( $x_I$ ,  $Queue$ ) ; // Add  $x_I$  to a queue of nodes to be expanded
while (!IsEmpty( $Queue$ ))
     $x \leftarrow$  Front( $Queue$ ) ; // Retrieve the front of the queue
    if( $x.expanded == \text{true}$ ) continue; // Do not expand a node twice
     $x.expanded = \text{true}$ ; // Mark  $x$  as expanded
    if( $x == x_G$ ) return solution; // Return if goal is reached
    for each neighbor  $n_i$  of  $x$  // Add all neighbors of to the queue
        if( $n_i.expanded == \text{false}$ ) AddToQueue( $n_i$ ,  $Queue$ )
return failure;
```

Different graph search algorithms (breadth first, depth-first, uniform-cost, ...) differ at the function AddToQueue

To retrieve the actual path, use **back pointers**

Classical Search Algorithms

⇒ Breadth-first search (BFS)

⇒ Always add new nodes at the **end** of the queue

⇒ Depth-first search (DFS)

⇒ Always add new nodes in the **front** of the queue

⇒ Uniform-cost (Dijkstra's)

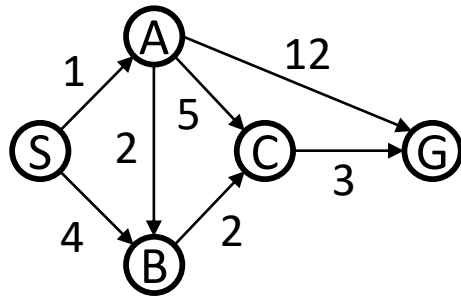
⇒ Always keep the node with the **best cost** in the front of the queue

⇒ A*

⇒ Similar to uniform-cost, but also uses a **guess** of distance to goal

Breadth First search

Problem graph (a weighted directed graph)



=

Neighbor list

S: A, B

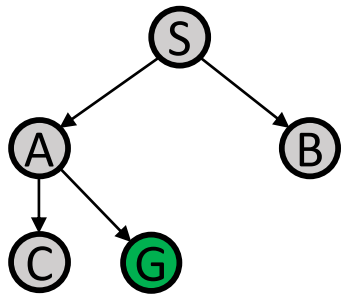
A: B, C, G

B: C

C: G

G:

Running BFS graph search (we do not use weights here)



Q: S

Q: A, B

Q: B, C, G

Q: C, G

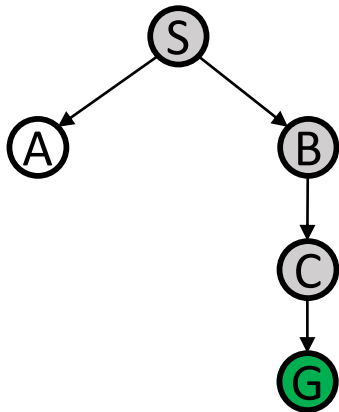
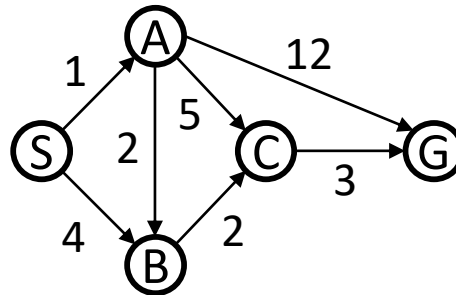
Q: G

Q:

Path can be retrieved by storing S in A and A in G as back pointers.

Depth First search

Running DFS graph search (again we do not use weights here)



Q: S

Q: B, A

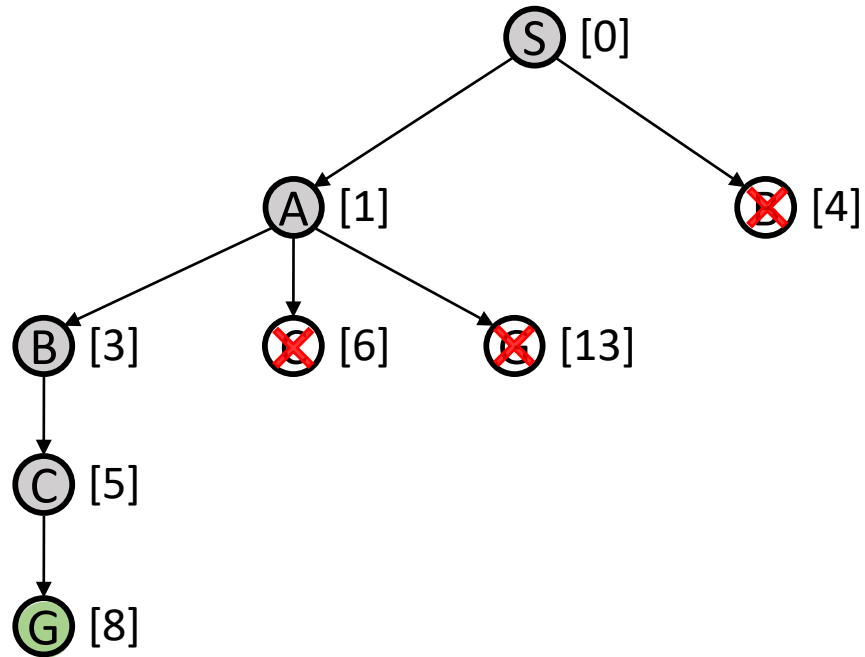
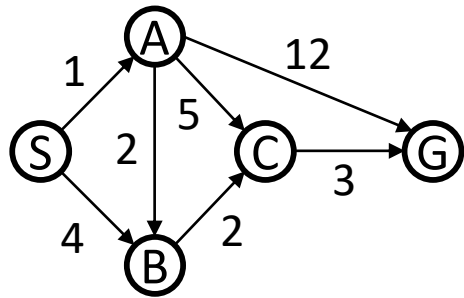
Q: C, A

Q: G, A

Q: A

Uniform-Cost Search

Maintain queue order based on current cost



⇒ Produces **optimal** path!

⇒ This is basically the Dijkstra's algorithm

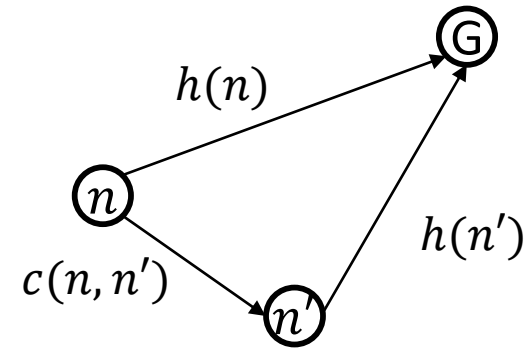
Admissible and Consistent Heuristic

⇒ Assume the cheapest path from x to a goal is $c(x)$, an **admissible heuristic** satisfies

$$h(x) \leq c(x)$$

⇒ A **consistent** heuristic is defined as

$$h(n) \leq c(n, n') + h(n')$$



⇒ A form of triangle inequality

⇒ A **consistent** heuristic is **always admissible**

⇒ The reverse is not always true

⇒ Example of heuristic functions

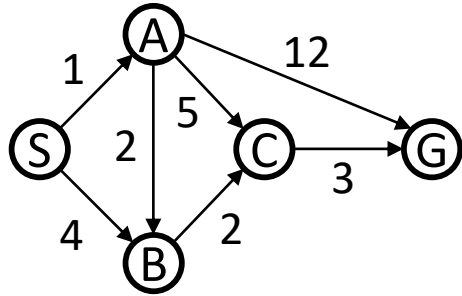
⇒ Manhattan distance

⇒ Straight-line distance

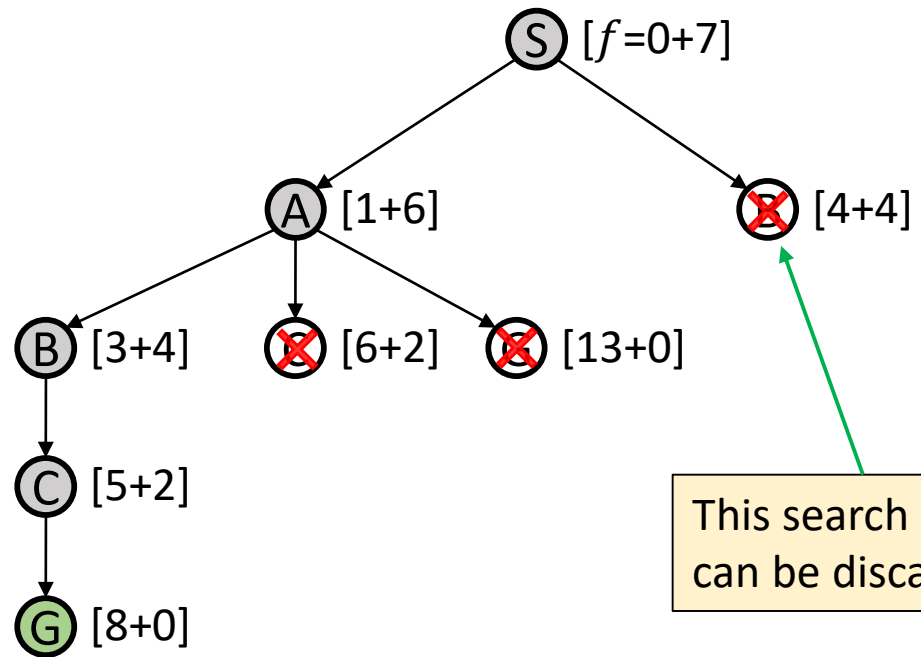
⇒ Consistent



A* Search w/ a Consistent Heuristic

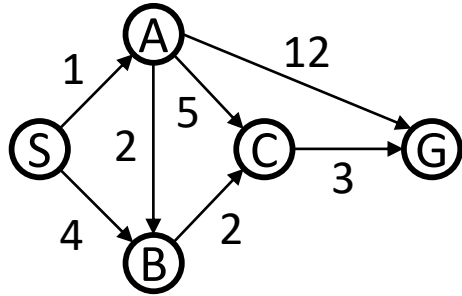


State	$h(x)$
S	7
A	6
B	4
C	2
G	0

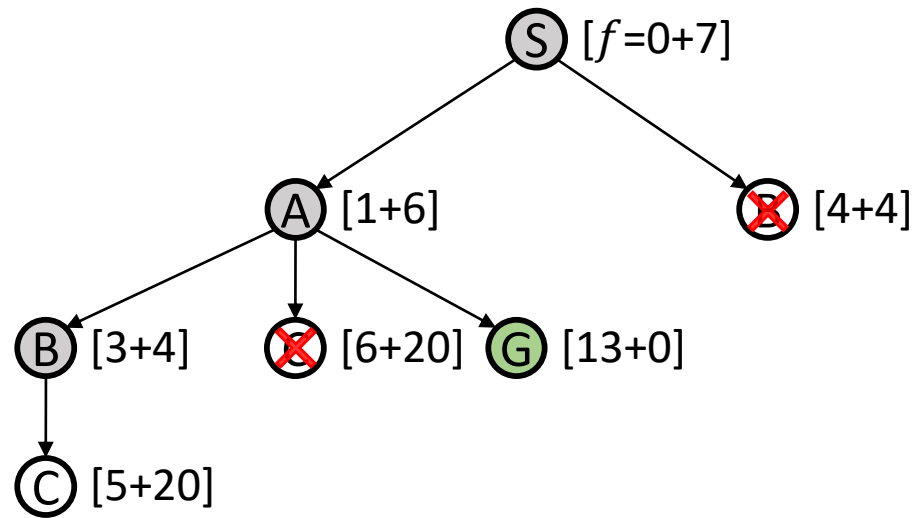


This search node
can be discarded

A* Search w/ an Inadmissible Heuristic



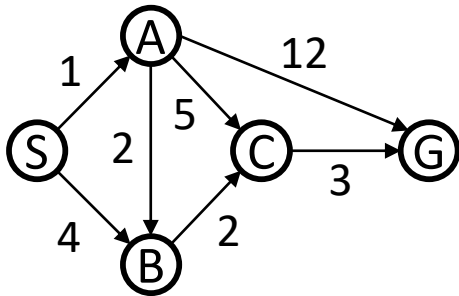
State	$h(x)$
S	7
A	6
B	4
C	20
G	0



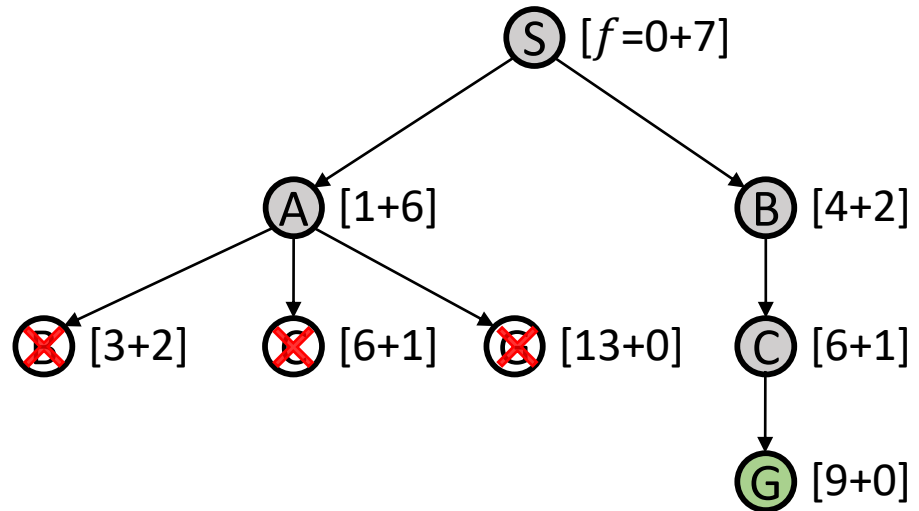
Not optimal!

$h(x)$ is **inadmissible**, e.g., $h(C) = 20 > 3 = c(C)$, the actual cost from C to G

A* Search w/ an Inconsistent Heuristic



State	$h(x)$
S	7
A	6
B	2
C	1
G	0



Not optimal!

$h(x)$ is **inconsistent**, e.g., $h(S) > c(S, B) + h(B)$, $h(A) > c(A, B) + h(B)$

Heuristic Function Design

For route finding problems, Euclidean distance is consistent

⇒ Also very efficient!

Designing heuristic functions can be **non-trivial**

Consider two heuristics for the 8-puzzle

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

⇒ h_1 : number of misplaced pieces

⇒ h_2 : sum of Manhattan distances to goal for all pieces

Heuristic Function Design

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

h_1 : #misplaced game pieces = 8

h_2 : sum Manhattan distances = $3 + 1 + 2 + 2 + 2 + 3 + 3 + 2 = 18$

Both heuristics are admissible and consistent

⇒ How to choose?

⇒ Generally, using the largest h is preferred: closer to the actual cost

⇒ Because h are **underestimates**

⇒ In this case, we can use h_2 or simply $h = \max\{h_1, h_2\}$

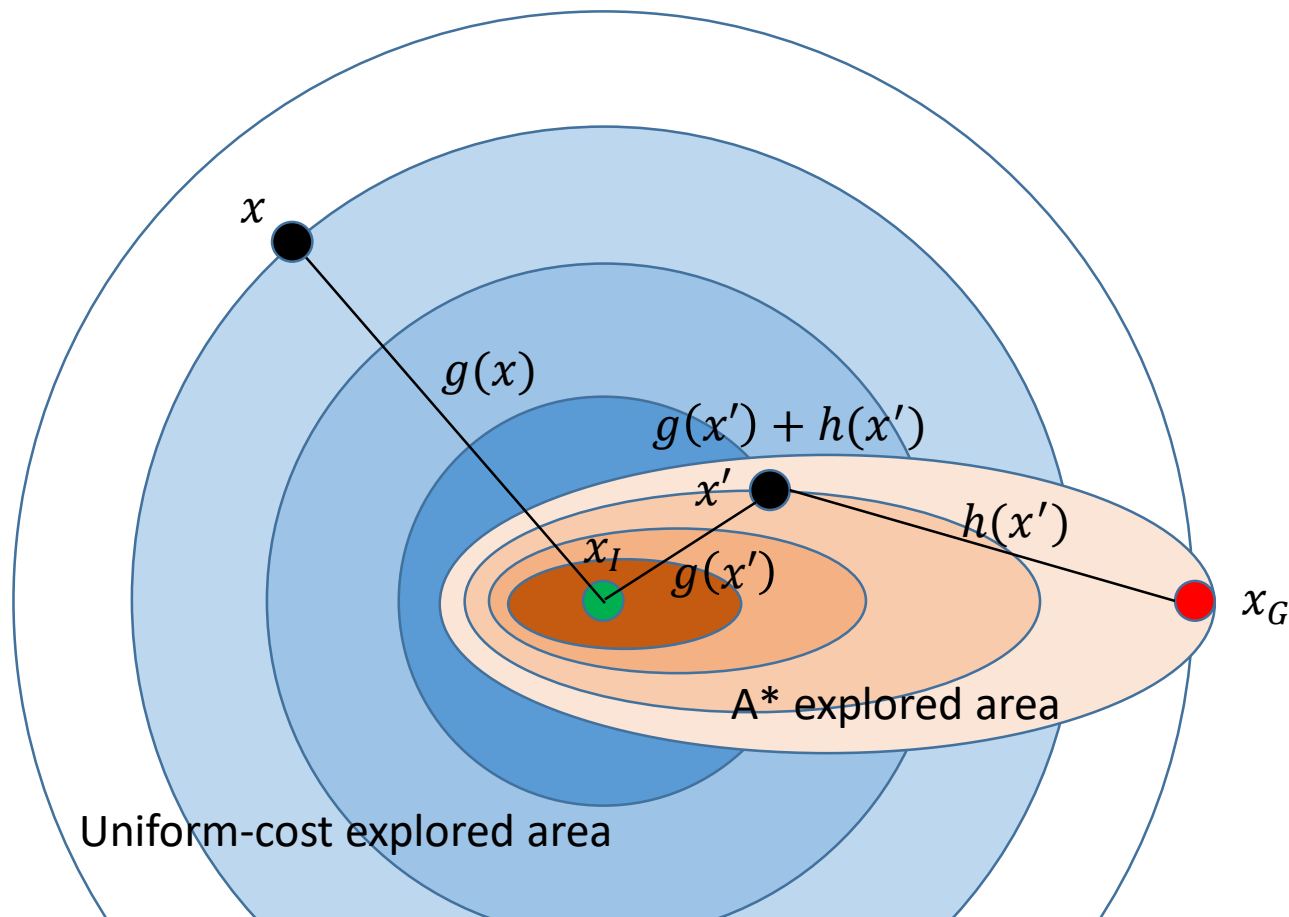
Advantage of A* Search

Both A* and uniform-cost (i.e., Dijkstra's) are optimal. Why A*?

⇒ Because A* biases the search toward the goal

⇒ A* may visit much fewer nodes

⇒ Similarly, better heuristic → smaller explored area



All Pairs Shortest Paths (Floyd-Warshall)

Floyd-Warshall is a type of dynamic programming

⇒ So are most other optimal search algorithms (e.g., Dijkstra, A*)

⇒ Pseudo-code

```
1 let dist be a  $|V| \times |V|$  array of minimum distances initialized to  $\infty$ 
2 for each vertex  $v$ 
3    $\text{dist}[v][v] \leftarrow 0$ 
4 for each edge  $(u, v)$ 
5    $\text{dist}[u][v] \leftarrow w(u, v)$  // the weight of the edge  $(u, v)$ 
6 for  $k$  from 1 to  $|V|$ 
7   for  $i$  from 1 to  $|V|$ 
8     for  $j$  from 1 to  $|V|$ 
9       if  $\text{dist}[i][j] > \text{dist}[i][k] + \text{dist}[k][j]$  then
10          $\text{dist}[i][j] \leftarrow \text{dist}[i][k] + \text{dist}[k][j]$ 
11 end if
```

⇒ Does not directly produce paths

⇒ A path tree from any vertex can be constructed by adding back pointers

⇒ Runs in time $O(|V|^3)$

The Principle of Dynamic Programming

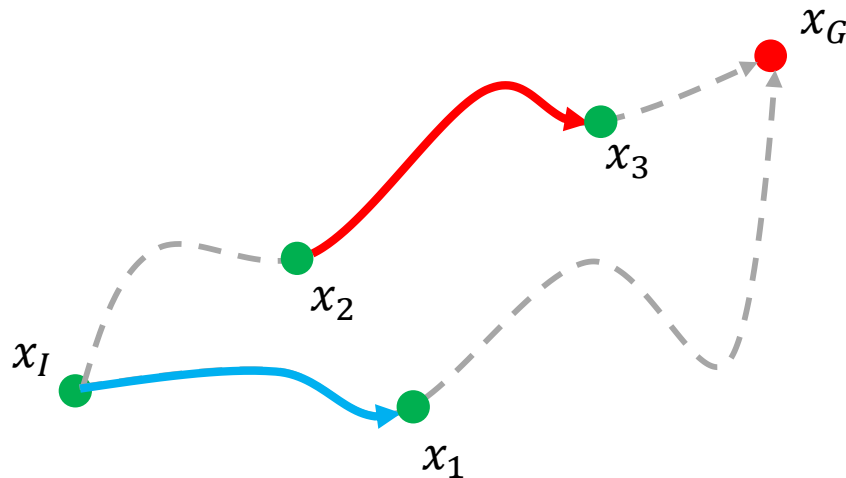
Dynamic programming is a type of recursion

⇒ It breaks a big problem into smaller pieces

⇒ E.g., $P(n) = P(n_1) + P(n_2)$ with $n = n_1 + n_2$

⇒ The problem must have structures that allow computation to be reused

⇒ E.g., for path optimality, any segment of an optimal path must also be optimal



⇒ Divide-and-conquer search algorithms, e.g., merge-sort, are special cases

⇒ $P(n) = P(n_1) + P(n_2)$ for $n_1 = n_2 = \frac{n}{2}$

⇒ Dijkstra's and A* are also types of dynamic programming

Dynamic Programming in Search

Recall `AddToQueue` is the crucial step of graph search

- ⇒ BFS and DFS do not care about edge costs
- ⇒ Uniform cost and A* do
- ⇒ This is in fact dynamic programming!
- ⇒ Priority of unvisited = cost-to-come + estimated cost-to-go
- ⇒ I.e., $f = g + h$
 - ⇒ g , cost-to-come, is fixed
 - ⇒ h , estimated cost-to-go, determines algorithm behavior
 - ⇒ Uniform cost: $h = 0$
 - ⇒ A*: h is consistent
 - ⇒ Other behaviors are possible by changing h

D* Algorithm Brief Intro

D* and D*-lite stand for “dynamic” A*



- ⇒ Supports previously unknown obstacles
- ⇒ Initially, for parts of the environment that is unknown, assume no obstacle
- ⇒ Runs A* backwards to find an initial optimal solution
- ⇒ Then, execute the path
- ⇒ If we hit an obstacle along the way
 - ⇒ Update the node itself to be unavailable
 - ⇒ Put all its descendent nodes on the queue for search again
 - ⇒ Do the above step recursively
 - ⇒ Restart the A* search to find an optimal path
- ⇒ Repeat the previous two steps
- ⇒ One may view D* as running many A* searches
- ⇒ A new A* search will be run as a previously unknown obstacle is met
- ⇒ More details: https://www.cs.cmu.edu/~motionplanning/lecture/AppH-astar-dstar_howie.pdf