

Lecture 3b: Local Search

CSCI 360

Introduction to Artificial Intelligence

USC

Here is where we are...



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 Midterm Exam	

Outline

- What is AI?
- Problem-solving agent
- Uninformed search
- Informed search (A^*)
- **Local search**
 - Hill-climbing search
 - Simulated annealing
 - Local beam search
 - Genetic algorithm

Goal state vs. Path to goal

- Previously, solution to the search problem is a “sequence of actions” leading to a goal state

- Example: 8-puzzle

7	2	4
5		6
8	3	1

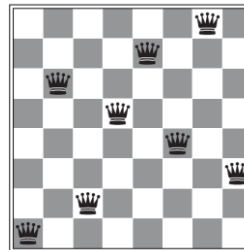
Start State

	1	2
3	4	5
6	7	8

Goal State

- What if you just want the “goal state”, not the “path to goal state”?

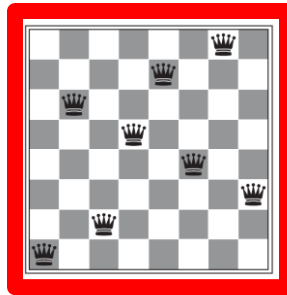
- Example: 8-queens



- In such cases, you may use “**Local Search**”

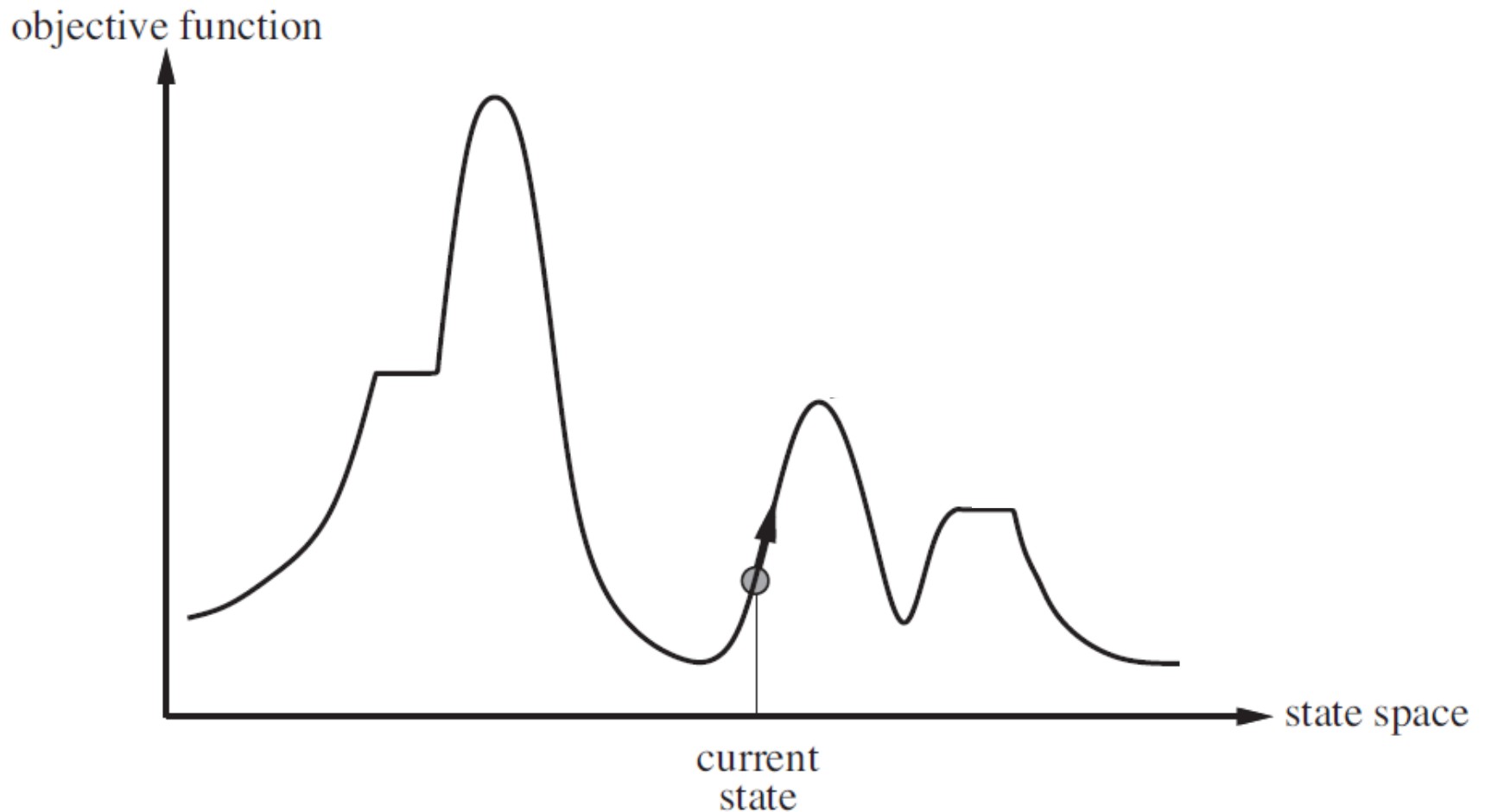
Local Search: *the idea*

- Operate using a **single, current node** (rather than paths) and move only to **neighbors** of that node



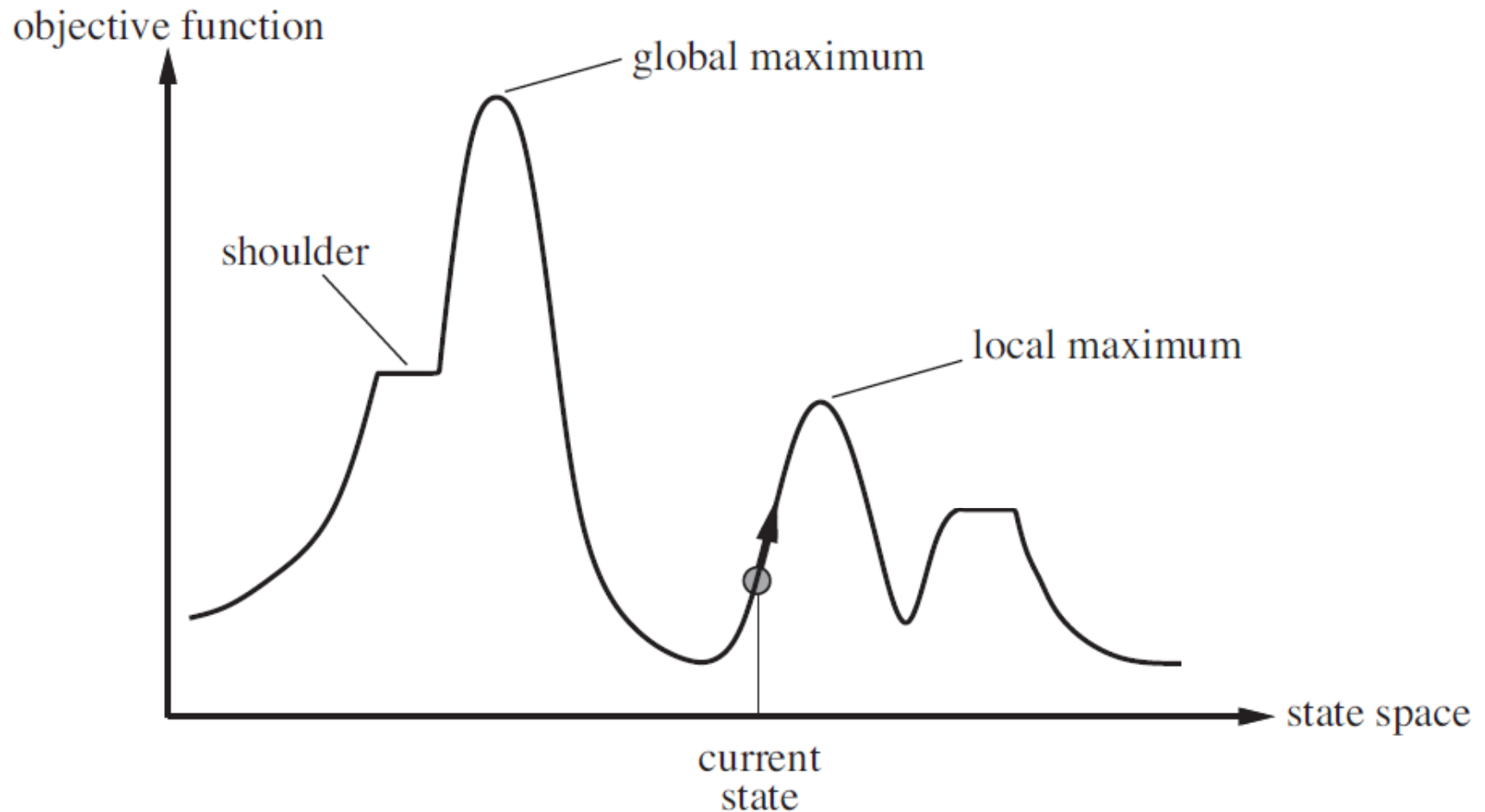
- Advantages
 - Use very little memory
 - Often find reasonable solutions in large and infinite spaces

Local Search: *the state space landscape*



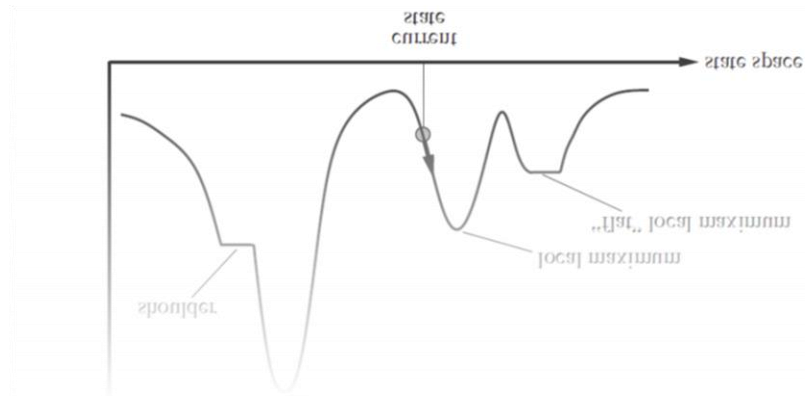
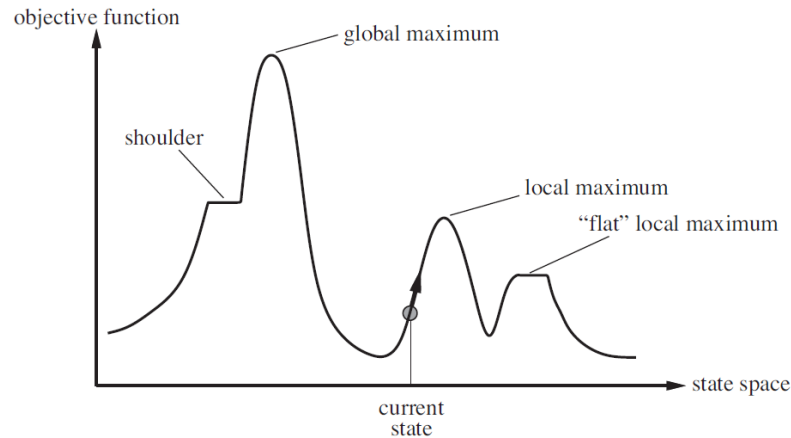
Local Search: *the state space landscape*

- *Local optimal vs. global optimal*



Local Search: state space landscape

- *Maximal vs. Minimal*



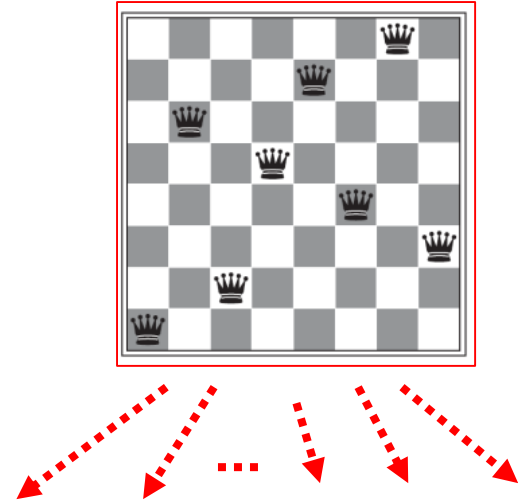
Hill-climbing search

- Continually moves in the direction of increasing value (***steepest-ascent*** version)

```
function HILL-CLIMBING(problem) returns a state that is a local maximum  
    current  $\leftarrow$  MAKE-NODE(problem.INITIAL-STATE)  
    loop do  
        neighbor  $\leftarrow$  a highest-valued successor of current  
        if neighbor.VALUE  $\leq$  current.VALUE then return current.STATE  
        current  $\leftarrow$  neighbor
```

Hill-climbing search: 8-queens example

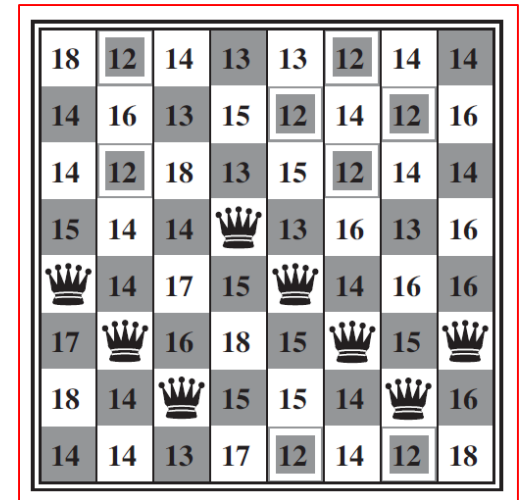
- Successors of a state are generated by moving a single queen to another square
 - How many?
 - $8 \times 7 = 56$ successors



Hill-climbing search: 8-queens example

- Successors of a state are generated by moving a single queen to another square
 - How many?
 - $8 \times 7 = 56$ successors
- Heuristic **cost** function
 - the number of “non-attacking” pairs

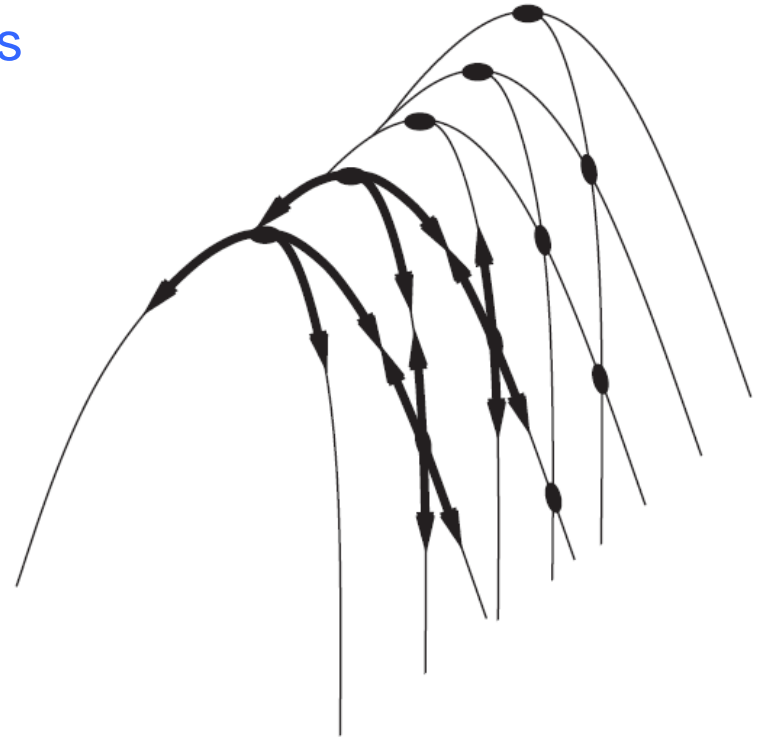
- It's a “**Greedy** Local Search”



18	12	14	13	13	12	14	14
14	16	13	15	12	14	12	16
14	12	18	13	15	12	14	14
15	14	14	♙	13	16	13	16
♙	14	17	15	♙	14	16	16
17	♙	16	18	15	♙	15	♙
18	14	♙	15	15	14	♙	16
14	14	13	17	12	14	12	18

Difficulties for hill-climbing search

- Local maxima
 - A peak that is higher than each of its neighboring states, but lower than the global maximum
- Ridges
 - A sequence of local maxima
- Plateaux
 - A flat area of the state-space landscape



Variants of hill-climbing search

- Stochastic hill climbing
 - Choose **at random** among the “uphill” moves, with probability varying with the steepness of the uphill move
- First-choice hill climbing
 - Same as “stochastic hill climbing” but choose the **first successor** that is better than the current state
- Random-restart hill climbing
 - Conduct a series of hill-climbing search from randomly generated initial states



Look like a
desperate move...

Success rate of “random-restart”

- If each “restart” has a **probability (p)** of success, the expected number of “restarts” would be ($1/p$)
 - **Example:** for 8-queens, normal hill-climbing has 14% success rate

$$p=0.14$$

$$(1/p = 7.14285) \text{ is roughly } 7 \text{ restarts}$$

Outline

- What is AI?
- Problem-solving agent
- Uninformed search
- Informed search (A^*)
- **Local search**
 - Hill-climbing search
 - **Simulated annealing**
 - Local beam search
 - Genetic algorithm

Simulated annealing

- Combines “**hill climbing**” with “**random walk**” in a way that yields both efficiency and completeness

Simulated annealing

- Combines “**hill climbing**” with “**random walk**” in a way that yields both efficiency and completeness

function SIMULATED-ANNEALING(*problem*, *schedule*) **returns** a solution state

inputs: *problem*, a problem

schedule, a mapping from time to “temperature”

current \leftarrow MAKE-NODE(*problem*.INITIAL-STATE)

for $t = 1$ **to** ∞ **do**

next \leftarrow a randomly selected successor of *current*

$\Delta E \leftarrow next.VALUE - current.VALUE$

if $\Delta E > 0$ **then** *current* \leftarrow *next*

Simulated annealing

- Combines “**hill climbing**” with “**random walk**” in a way that yields both efficiency and completeness

function SIMULATED-ANNEALING(*problem*, *schedule*) **returns** a solution state

inputs: *problem*, a problem

schedule, a mapping from time to “temperature”

current \leftarrow MAKE-NODE(*problem*.INITIAL-STATE)

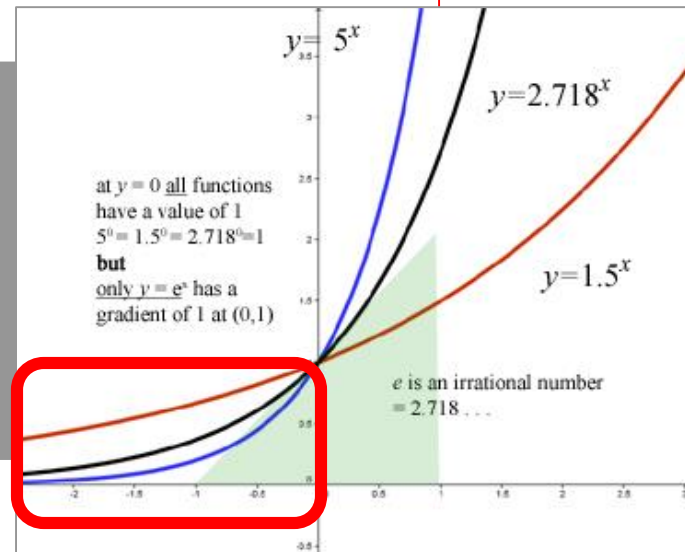
for $t = 1$ **to** ∞ **do**

next \leftarrow a randomly selected successor of *current*

$\Delta E \leftarrow next.VALUE - current.VALUE$

if $\Delta E > 0$ **then** *current* \leftarrow *next*

else *current* \leftarrow *next* only with probability $e^{\Delta E/T}$



Simulated annealing

- Combines “**hill climbing**” with “**random walk**” in a way that yields both efficiency and completeness

```
function SIMULATED-ANNEALING(problem, schedule) returns a solution state
  inputs: problem, a problem
           schedule, a mapping from time to “temperature”

  current  $\leftarrow$  MAKE-NODE(problem.INITIAL-STATE)
  for  $t = 1$  to  $\infty$  do
     $T \leftarrow \text{schedule}(t)$ 
    if  $T = 0$  then return current
    next  $\leftarrow$  a randomly selected successor of current
     $\Delta E \leftarrow \text{next.VALUE} - \text{current.VALUE}$ 
    if  $\Delta E > 0$  then current  $\leftarrow$  next
    else current  $\leftarrow$  next only with probability  $e^{\Delta E/T}$ 
```

T decreases over time

Outline

- What is AI?
- Problem-solving agent
- Uninformed search
- Informed search (A^*)
- **Local search**
 - Hill-climbing search
 - Simulated annealing
 - **Local beam search**
 - Genetic algorithm

Local beam search

- Keep track of (k) states rather than just one
 - It begins with (k) randomly generated states
 - At each step, all successors of (k) states are generated
 - Select (k) best successors from complete list
 - Repeat
- It differs from (k) random-restart searches
 - Random restarts are independent from each other
 - Local beam search passes information among (k) threads
 - Potential disadvantage: Lack of diversity

18	12	14	13	13	12	14	14
14	16	13	15	12	14	12	16
14	12	18	13	15	12	14	14
15	14	14	♙	13	16	13	16
♙	14	17	15	♙	14	16	16
17	♙	16	18	15	♙	15	♙
18	14	♙	15	15	14	♙	16
14	14	13	17	12	14	12	18

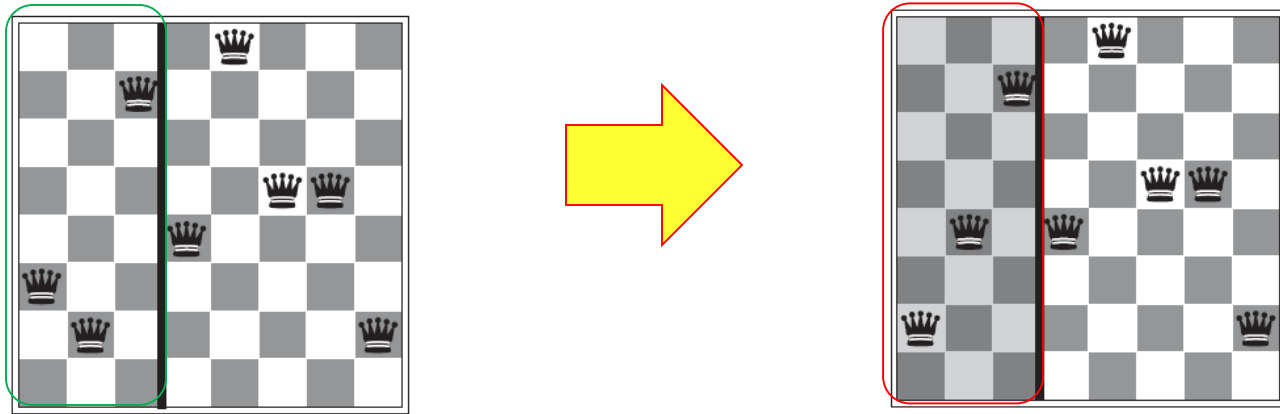


Outline

- What is AI?
- Problem-solving agent
- Uninformed search
- Informed search (A^*)
- **Local search**
 - Hill-climbing search
 - Simulated annealing
 - Local beam search
 - **Genetic algorithm**

Raising the granularity of search

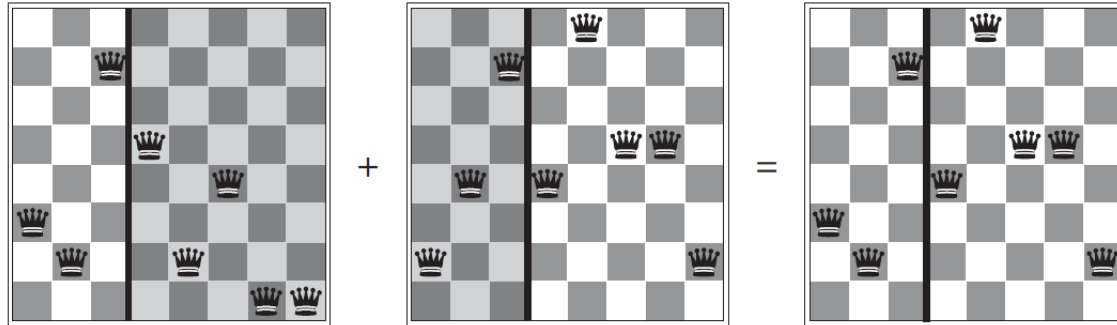
- Move “**3 queens per step**” instead of “**1 queen per step**”
 - **Why?** The block can be a meaningful component of a solution



Question: How to achieve this?

Cross-over

- Create a state by combining components of two states

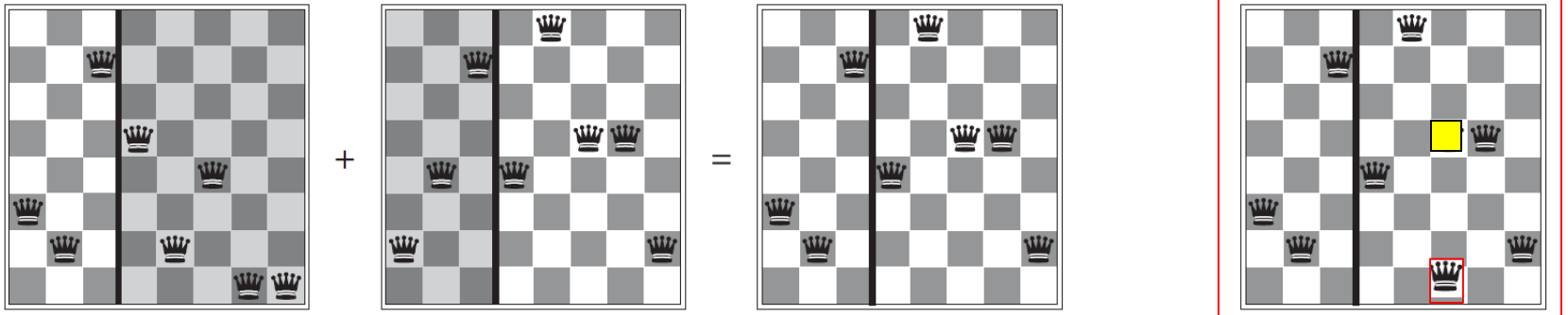


$$32752411 + 24748552 = 32748552$$

Problem: Lack of **diversity** (new components)?

Mutation

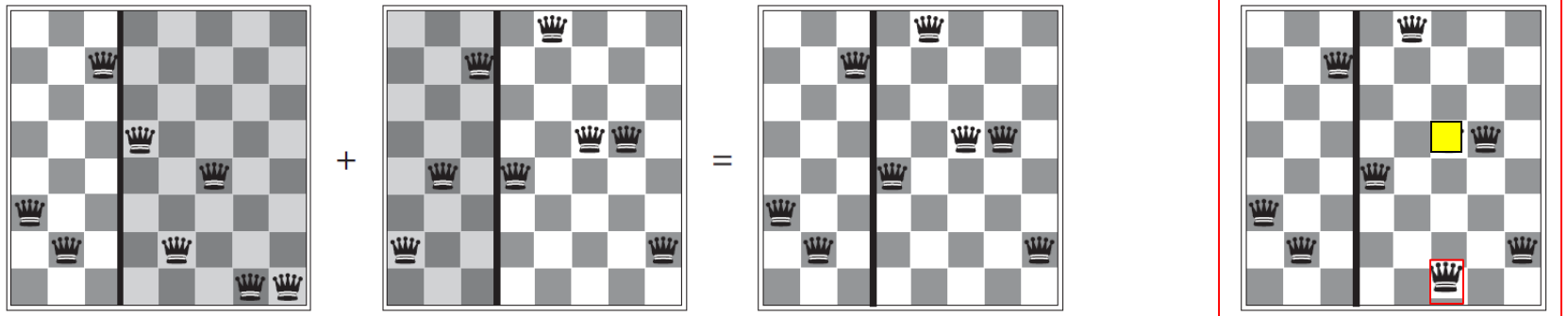
- Randomly change the position of a queen



$$32752411 + 24748552 = 32748552$$

Mutation

- Randomly change the position of a queen



$$32752411 + 24748552 = 32748552 \rightarrow 32748152$$

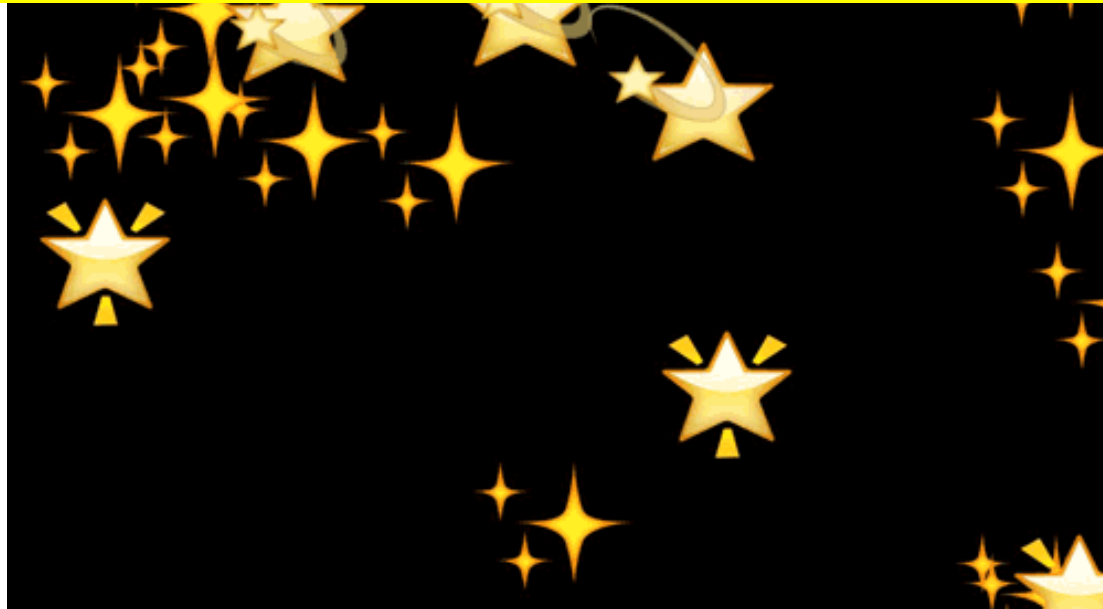
A red dashed arrow indicates the mutation of the 8th queen from position 1 to position 5 in the sequence.

Putting them together

Cross-over + Mutation + Selection

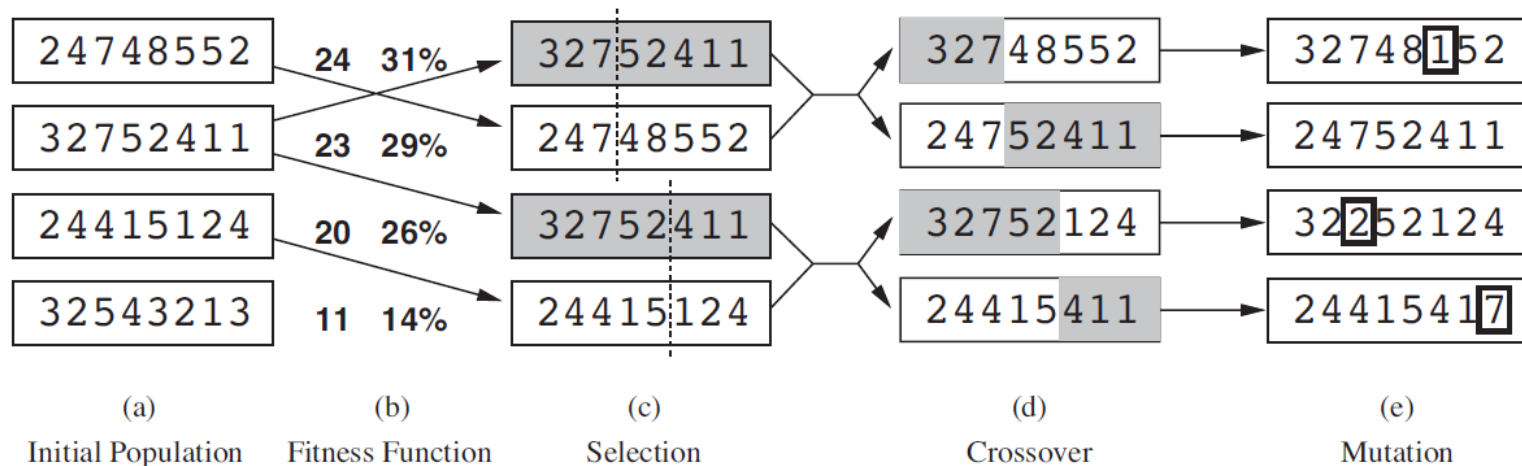
=

Genetic Algorithm



Fitness of states → Selection

- Use **most promising** states for “cross-over” and “mutation”
-- they form a **population**



For 8-queens: 24, 23, 20, and 11 are numbers of non-attacking pairs

$$\text{SUM}(24, 23, 20, 11) = 78$$

$$(24/78) = 31\% \quad (23/78) = 29\% \quad (20/78) = 26\% \quad (11/78) = 14\%$$

Genetic algorithm

function GENETIC-ALGORITHM(*population*, FITNESS-FN) **returns** an individual

inputs: *population*, a set of individuals

FITNESS-FN, a function that measures the fitness of an individual

repeat

new_population \leftarrow empty set

for $i = 1$ **to** SIZE(*population*) **do**

$x \leftarrow$ RANDOM-SELECTION(*population*, FITNESS-FN)

$y \leftarrow$ RANDOM-SELECTION(*population*, FITNESS-FN)

$child \leftarrow$ REPRODUCE(x, y)

if (small random probability) **then** $child \leftarrow$ MUTATE($child$)

add $child$ to *new_population*

population \leftarrow *new_population*

until some individual is fit enough, or enough time has elapsed

return the best individual in *population*, according to FITNESS-FN

Selection

Cross-over

Mutation

Outline

- What is AI?
- Problem-solving agent
- Uninformed search
- Informed search (A^*)
- **Local search**
 - Hill-climbing search
 - Simulated annealing
 - Local beam search
 - Genetic algorithm