

Princess Nora University
Faculty of Computer & Information Systems



جامعة الأميرة نورة بنت عبد الرحمن
Princess Nora Bint Abdul Rahman University

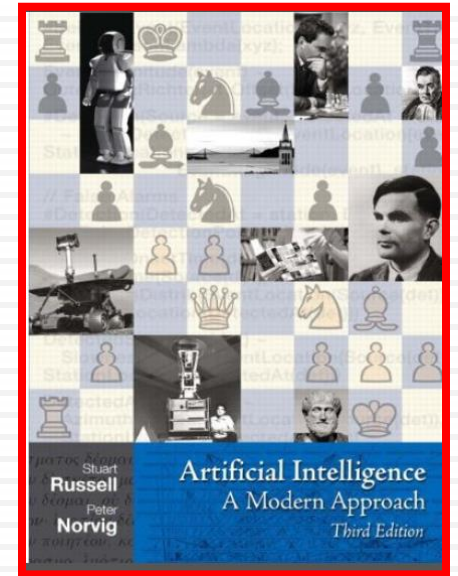


ARTIFICIAL INTELLIGENCE

(CS 370D)



جامعة الأميرة نورة بنت عبد الرحمن
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(CHAPTER-4)

BEYOND CLASSICAL SEARCH



LOCAL SEARCH STRATEGY

- Hill-Climbing Search.
- Simulated Annealing Search.
- Local Beam Search.
- Genetic Algorithms.





Classical search **versus** Local Search

Classical search

1. Find solution in a systematic exploration of search space.
2. The **path** to the goal is a **solution** to the problem.
3. Keeps one or more paths in memory.
4. Records which alternatives have been explored at each point along the path.

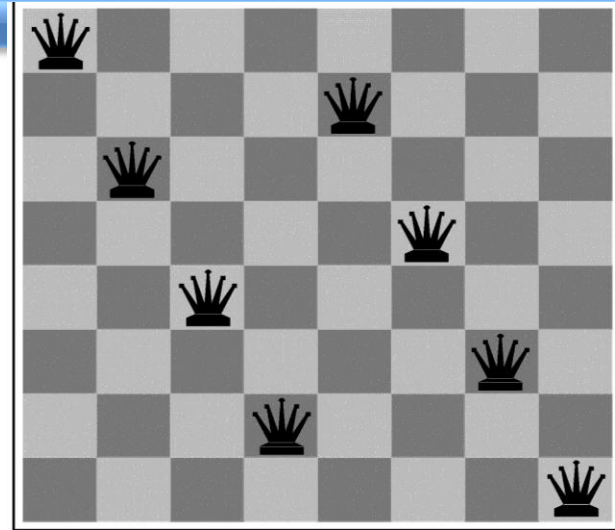
Local Search

1. Find best state according to some objective function $h(s)$.
e.g., **n-queens**, $h(s) = \#$ of attacking queens.
2. the path to the goal is irrelevant ; the goal state itself is the solution.
3. Solution **path** needs not be maintained.
4. record a single "current" state, and move to neighboring states in order to try **improve** it.



Example: n-queens

- Put n queens on an $n \times n$ board with no two queens on the same row, column, or diagonal.



- In the 8-queens problem, what matters is the final configuration of queens, not the order in which they are added.





Local Search: Key Idea

Key idea:

1. Select (**random**) initial state (generate an initial guess).
2. Make local modification to improve current state (evaluate current state and move to other states).
3. Repeat Step 2 until goal state found (or out of time).





Local Search: Key Idea

Advantages

- Use very little memory – usually a constant amount.
- Can often find reasonable solutions in large or infinite state spaces (e.g., continuous). For which systematic search is unsuitable.

Drawback:

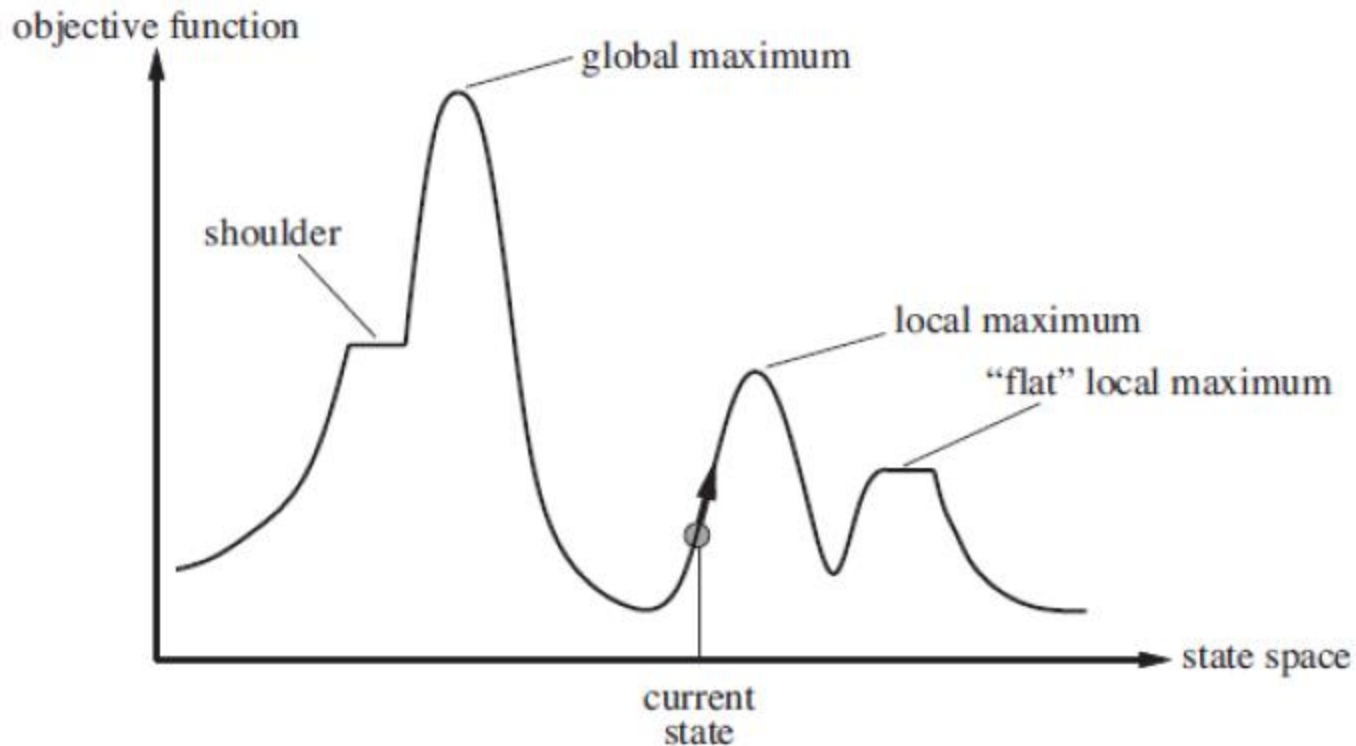
- Local Search can get stuck in local maxima and not find the optimal solution.





State Space Landscape

- A state space landscape: is a graph of states associated with their costs.





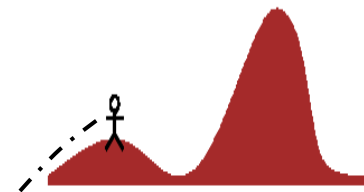
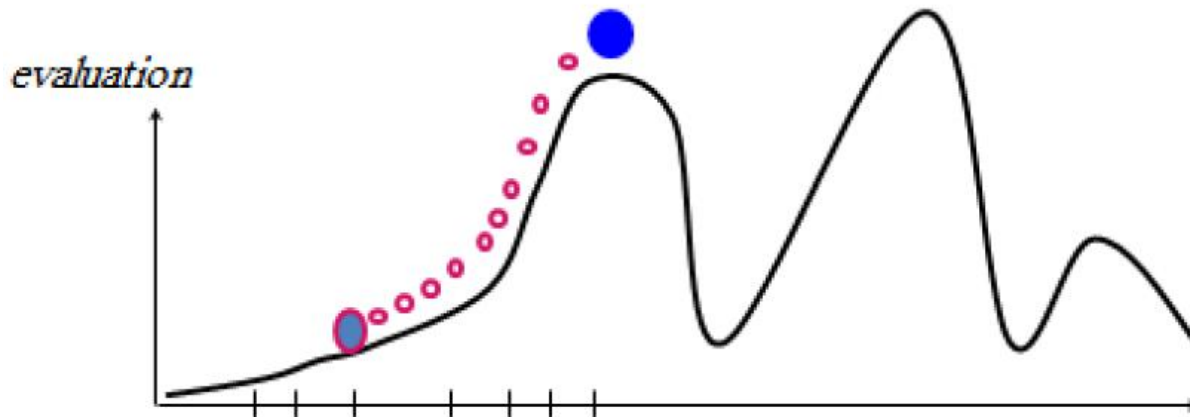
Hill-Climbing Search





Hill-Climbing Search

- **Main Idea:** Keep a single current node and move to a neighboring state to improve it.
- Uses a loop that continuously moves in the direction of increasing value (**uphill**):
- Choose the best successor, choose **randomly** if there is more than one.
- Terminate when a peak reached where no neighbor has a higher value.
- It also called greedy local search, steepest ascent/descent.





Hill-Climbing Search

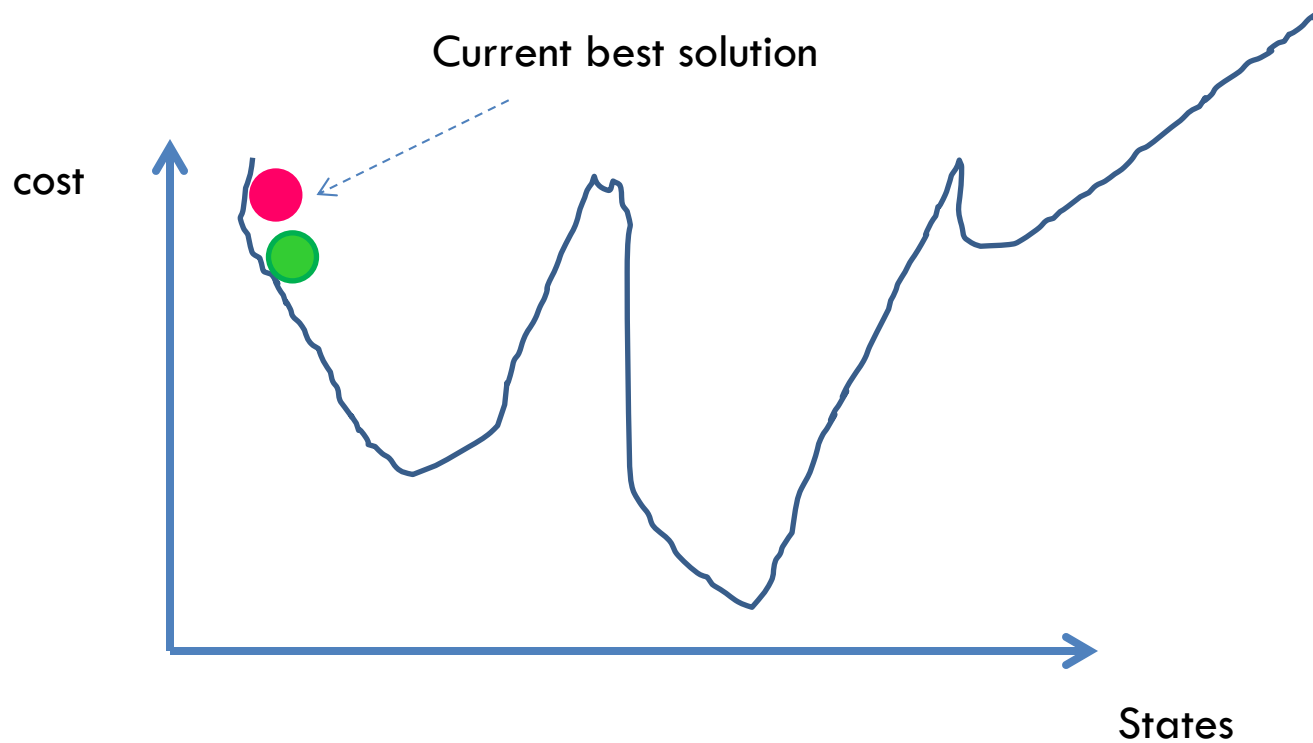
```
function HILL-CLIMBING(problem) returns a state that is a local maximum
  inputs: problem, a problem
  local variables: current, a node
                  neighbor, a node

  current ← MAKE-NODE(INITIAL-STATE[problem])
  loop do
    neighbor ← a highest-valued successor of current
    if VALUE[neighbor] ≤ VALUE[current] then return STATE[current]
    current ← neighbor
```



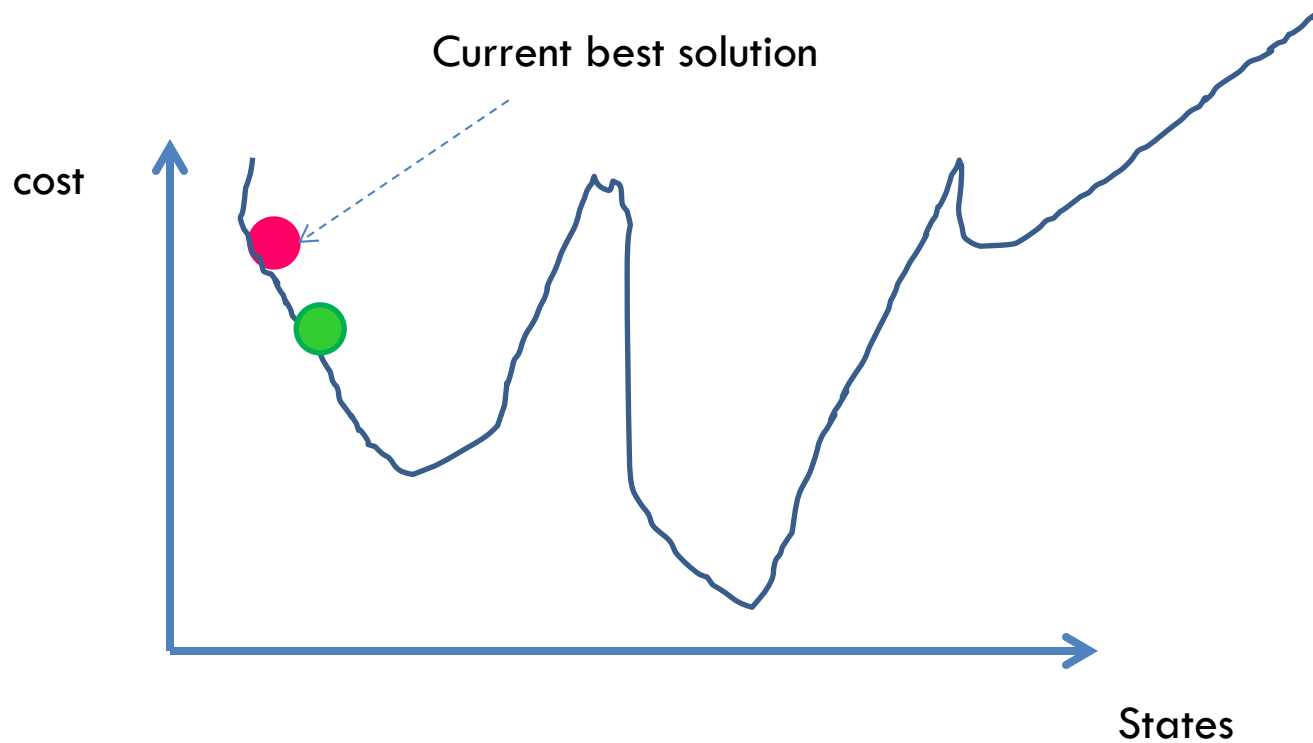


Hill-Climbing in Action ...



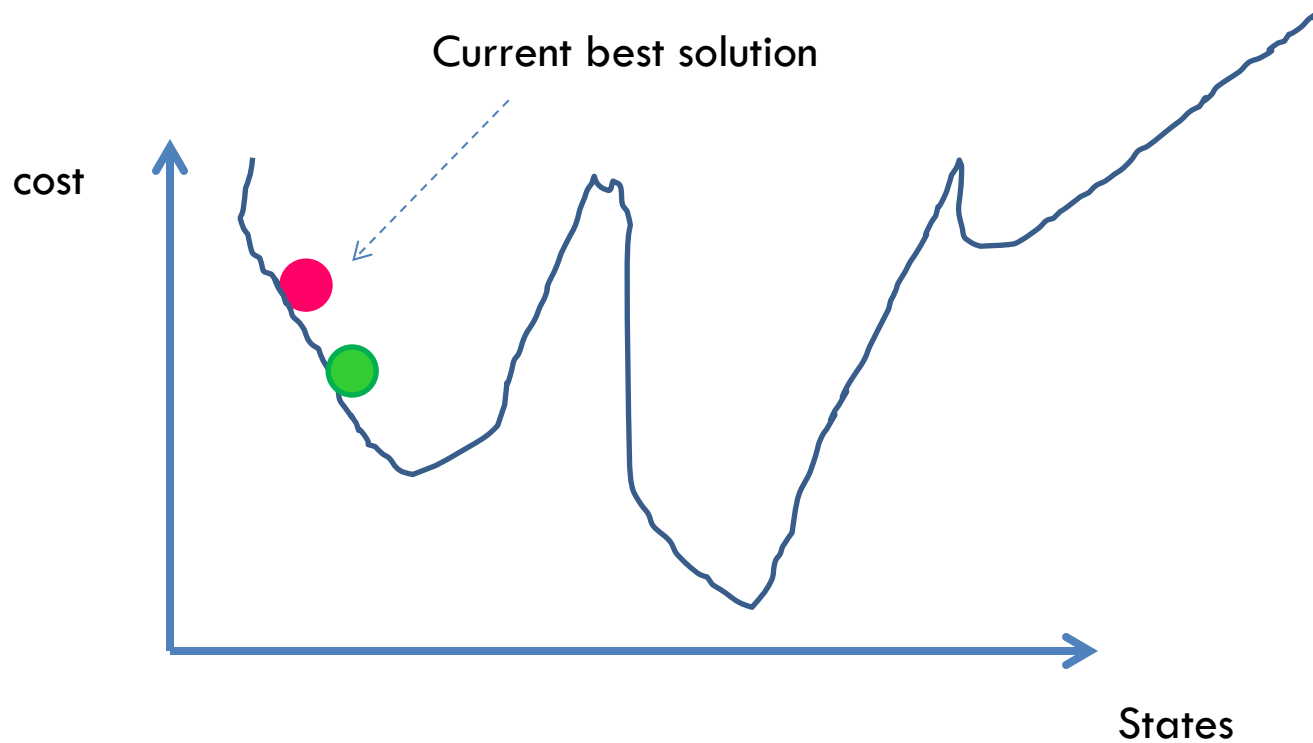


Hill-Climbing in Action ...



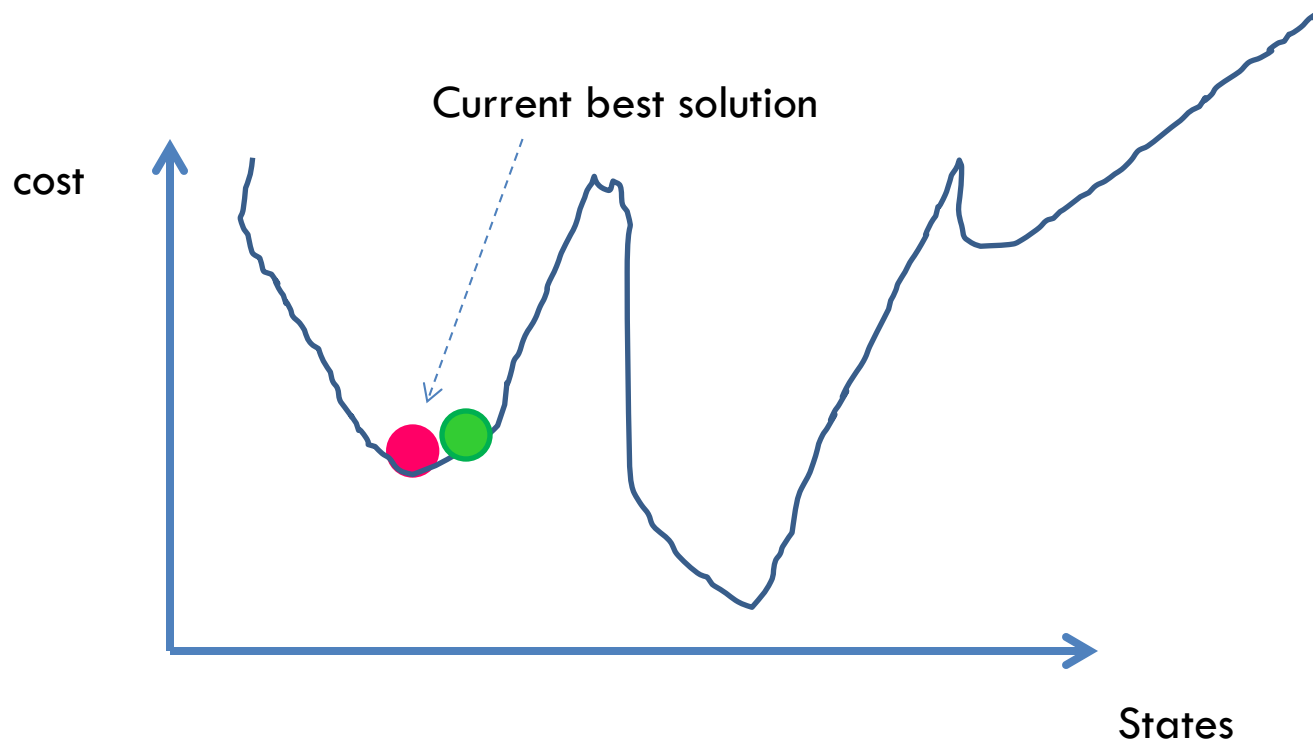


Hill-Climbing in Action ...



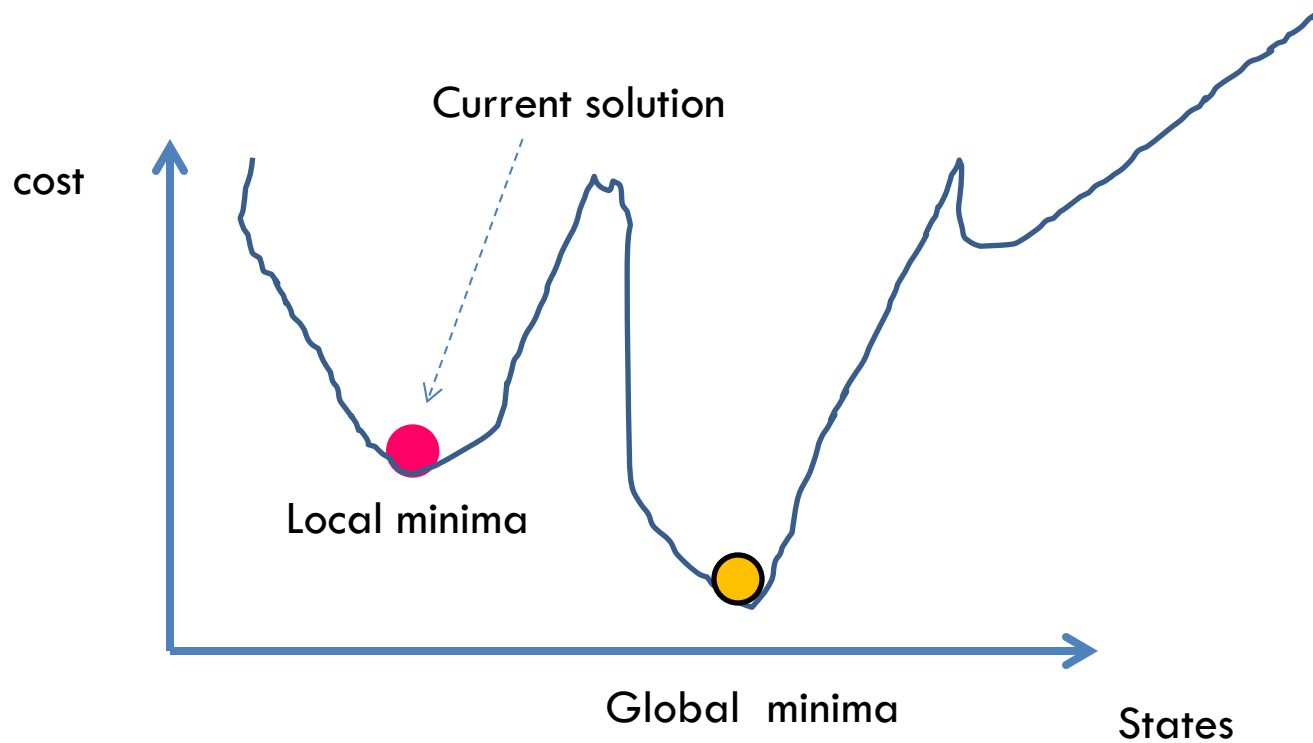


Hill-Climbing in Action ...



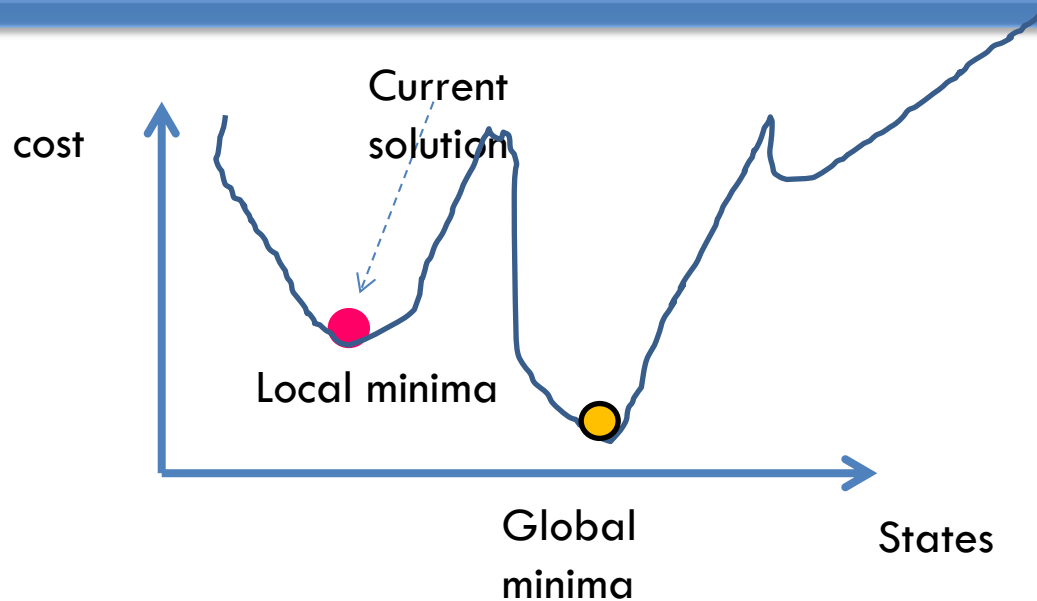


Hill-Climbing in Action ...





Hill-Climbing in Action ...



Drawback: Depending on initial state, it can get stuck in local maxima/minimum or flat local maximum and not find the solution.



Cure: Random restart.





Simulated Annealing Search



The Problem



- ❑ Most minimization strategies find the *nearest* local minimum

- ❑ **Standard strategy**
 - ✓ Generate trial point based on current estimates
 - ✓ Evaluate function at proposed location
 - ✓ Accept new value if it improves solution





The Solution

- ❑ We need a strategy to find other minima
- ❑ This means, we must sometimes select new points that do not improve solution
- ❑ How?





Annealing

- ❑ One manner in which crystals are formed

- ❑ Gradual cooling of liquid ...
 - ✓ At high temperatures, molecules move freely
 - ✓ At low temperatures, molecules are "stuck"
 - ✓ If cooling is slowLow energy, organized crystal lattice formed





Simulated annealing Search

- **Main Idea:** escape local maxima by allowing some "bad" moves but gradually decrease their frequency.
- Instead of picking the **best** move, it picks a **random** move..





Simulated annealing Search

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

inputs: *problem*, a problem

schedule, a mapping from time to “temperature”

local variables: *current*, a node

next, a node

T, a “temperature” controlling prob. of downward steps

current ← MAKE-NODE(INITIAL-STATE[*problem*])

for *t* ← 1 to ∞ **do**

T ← *schedule*[*t*]

if *T* = 0 **then return** *current*

next ← a randomly selected successor of *current*

ΔE ← VALUE[*next*] – VALUE[*current*]

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

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

Similar to hill climbing, but a random move instead of best move.

Case of improvement, make the move.

Otherwise, choose the move with probability that decreases exponentially with the “badness” of the move.

➤ say the change in objective function is δ

➤ **if** δ is **positive**, then move to that state

➤ **otherwise:**

- move to this state with probability proportional to δ

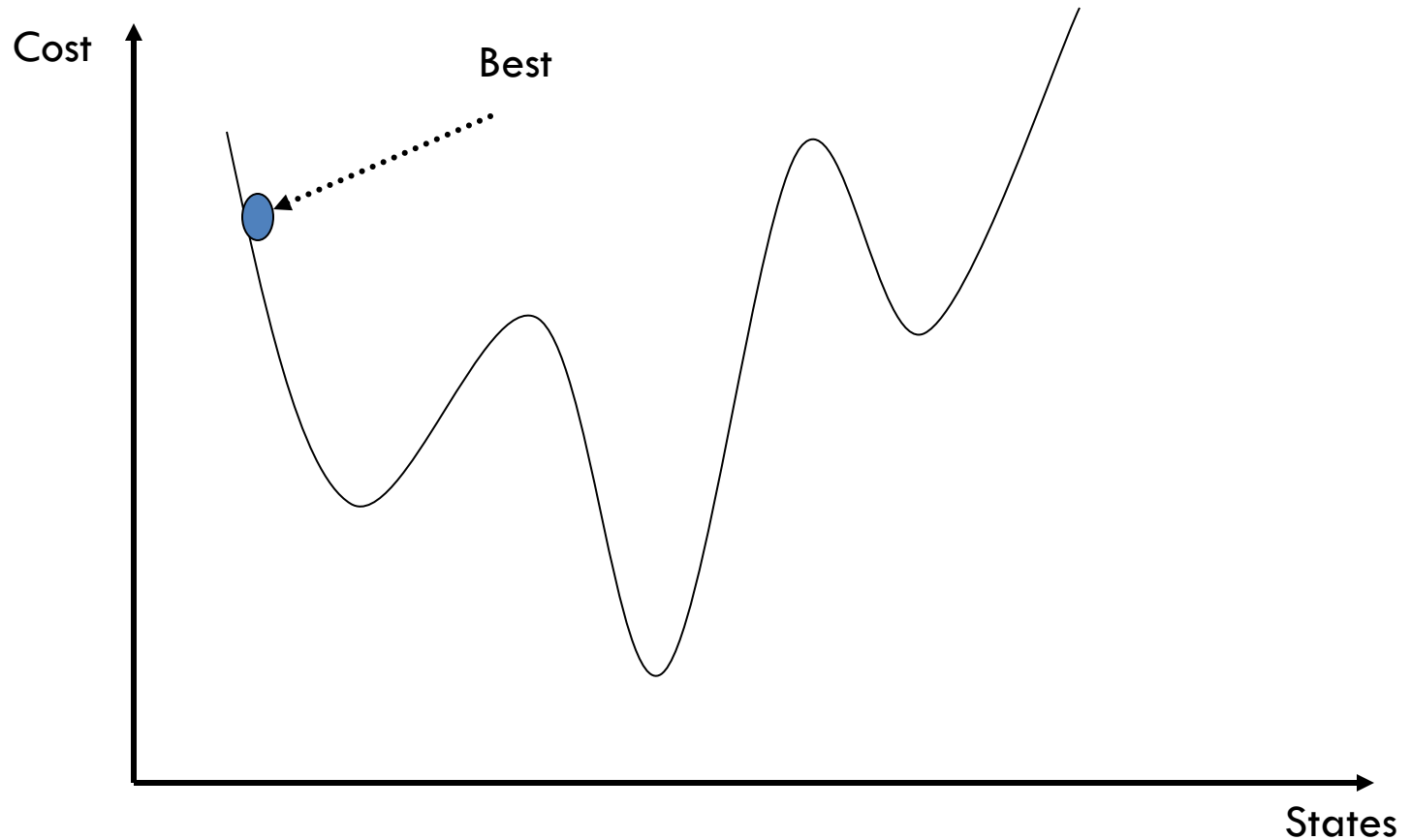
- thus: worse moves (very large negative δ) are executed less often

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(course coordinator)



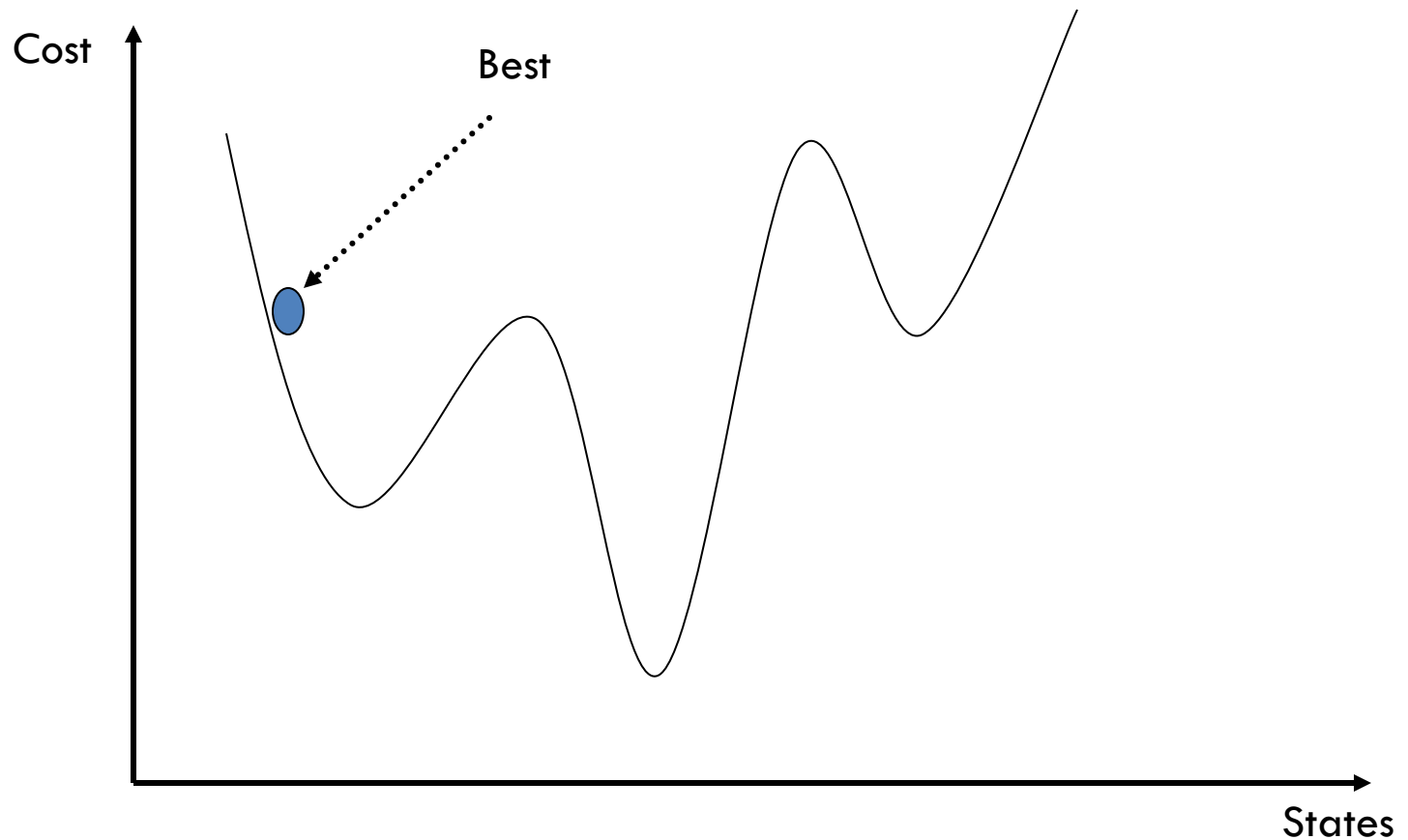


Simulated Annealing



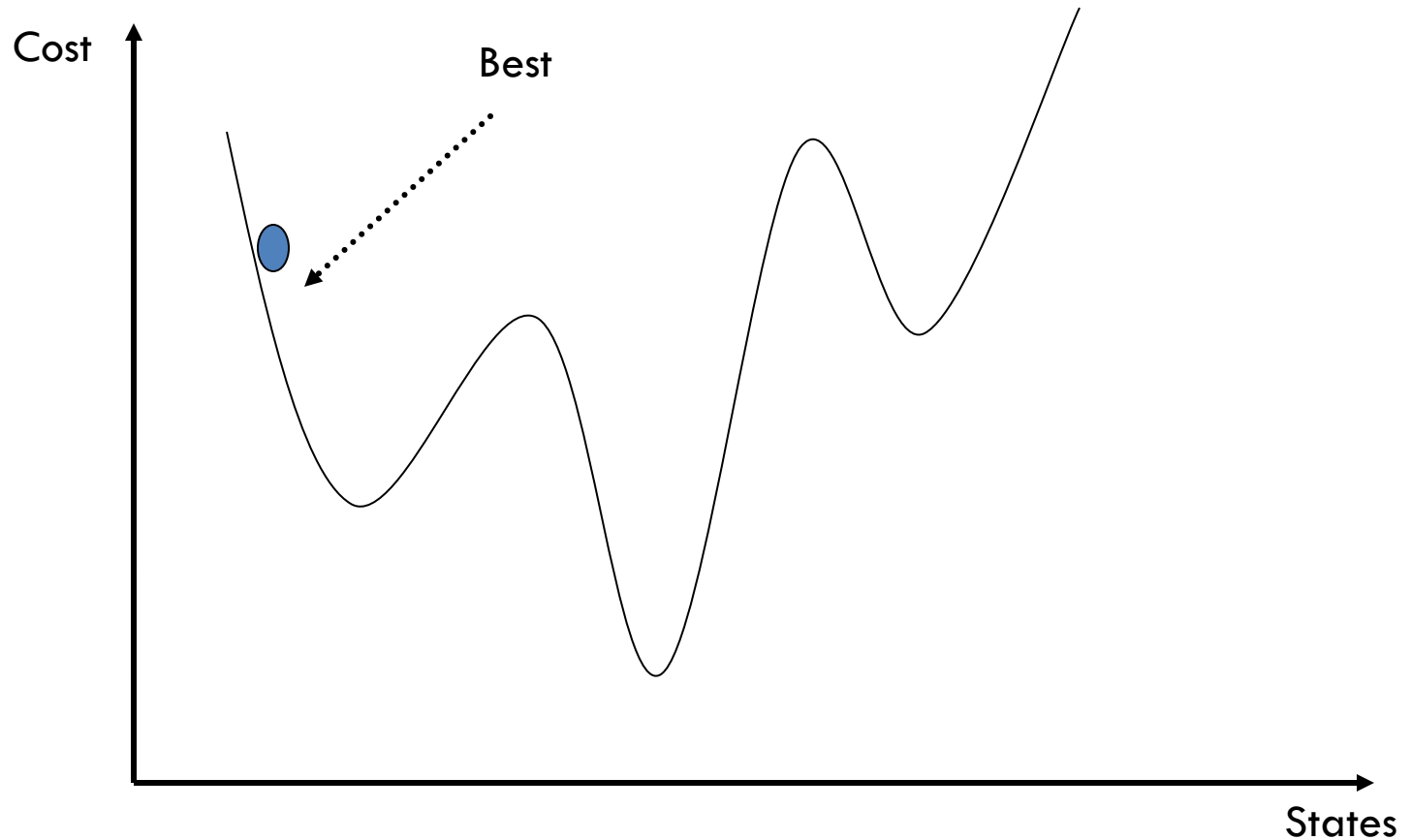


Simulated Annealing



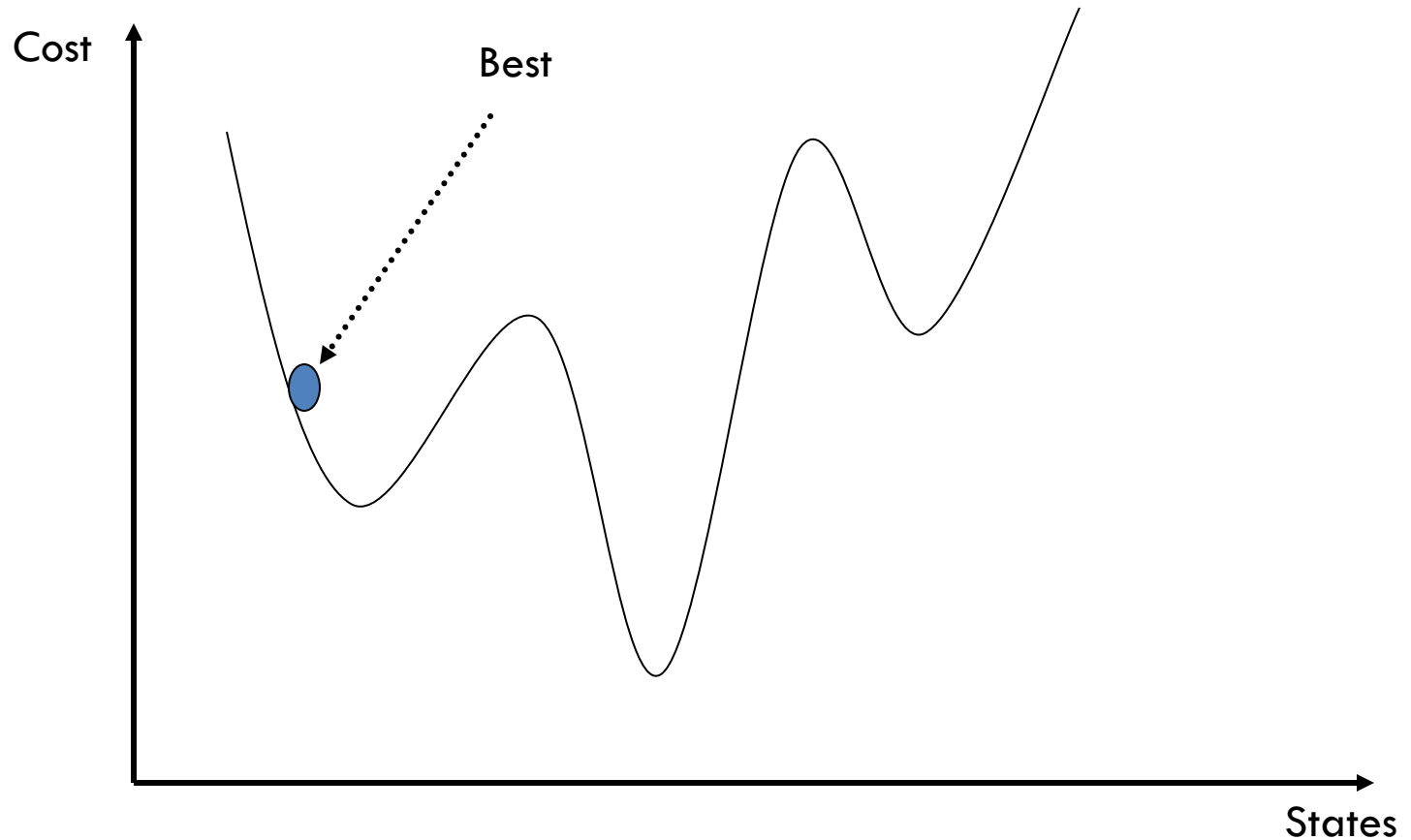


Simulated Annealing



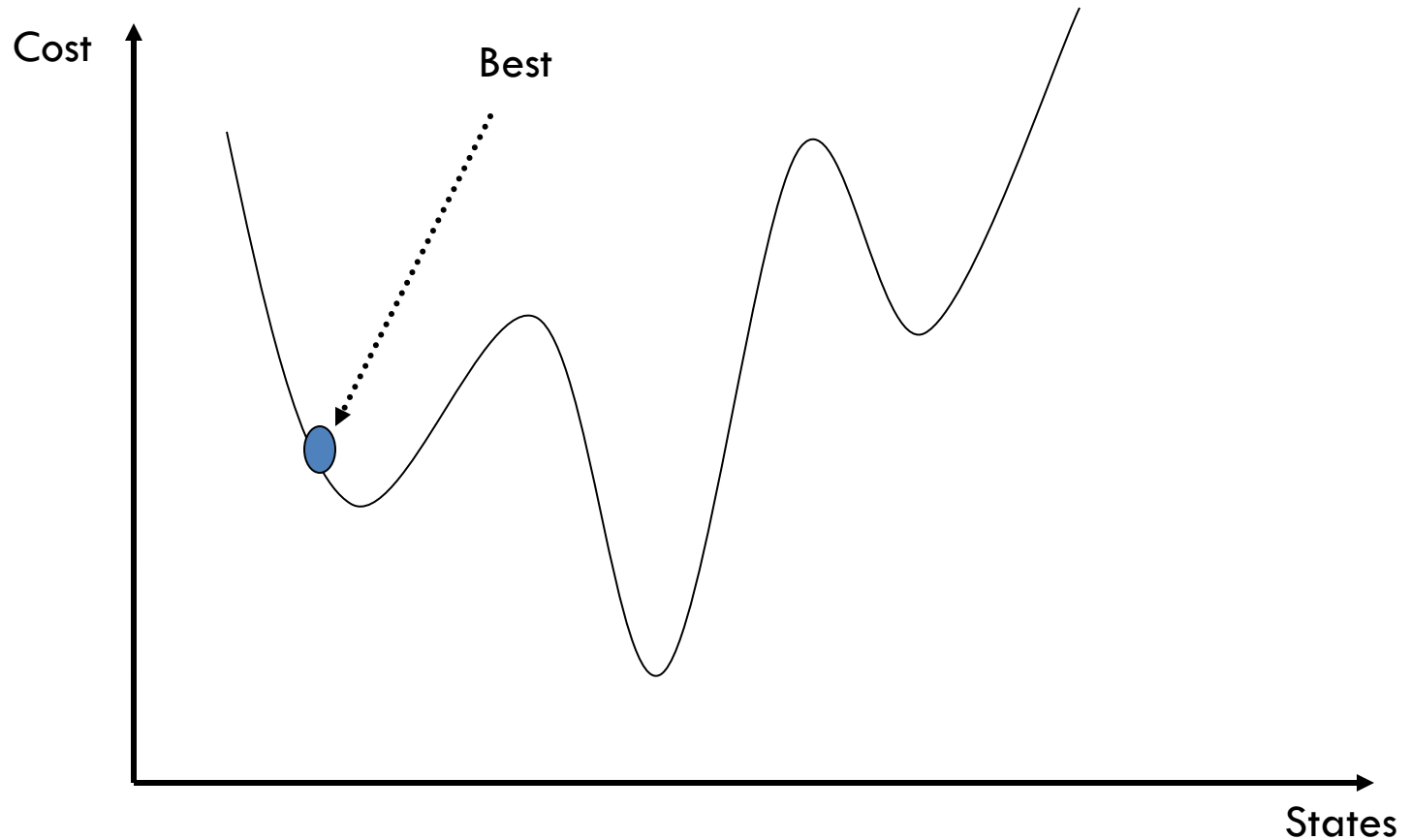


Simulated Annealing



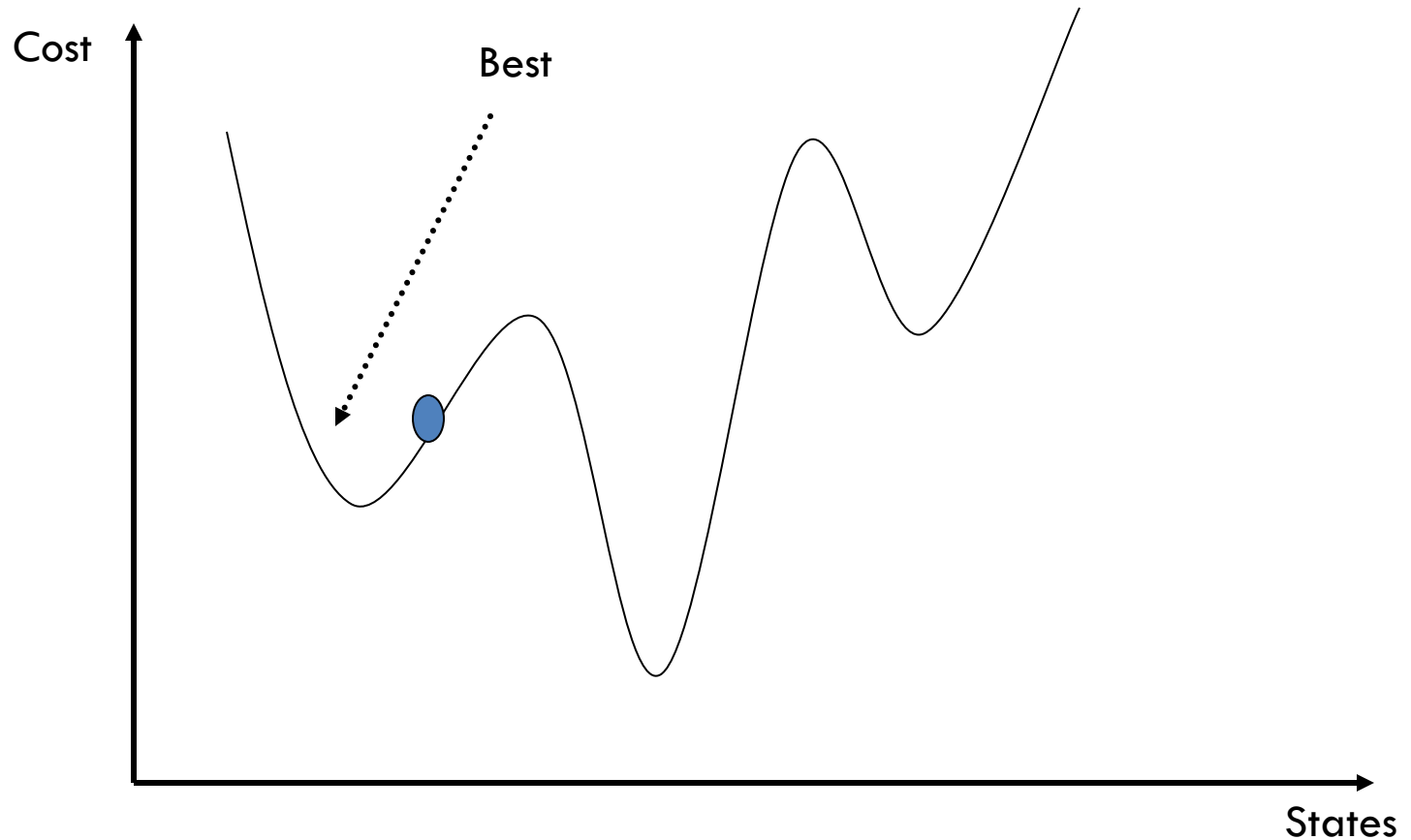


Simulated Annealing



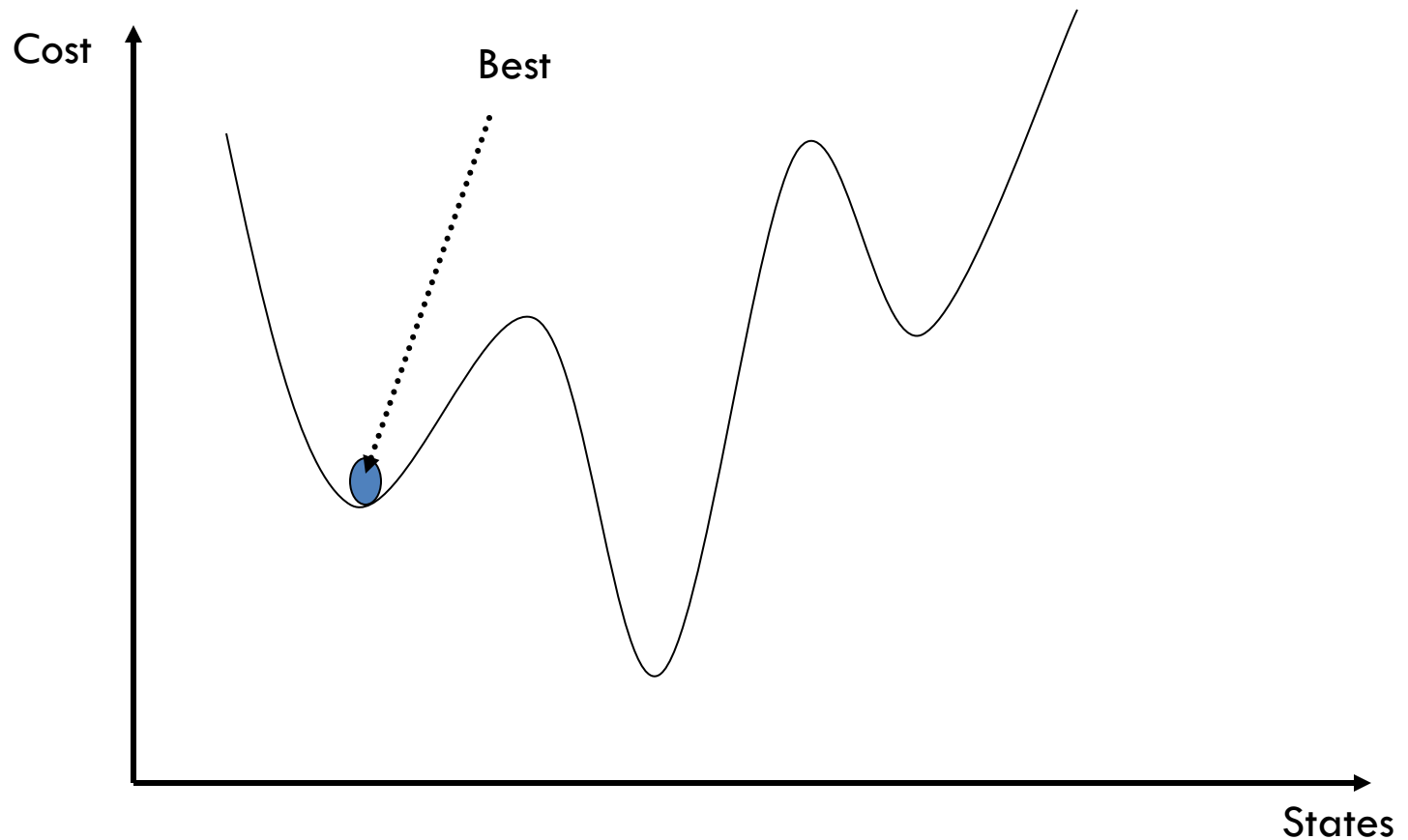


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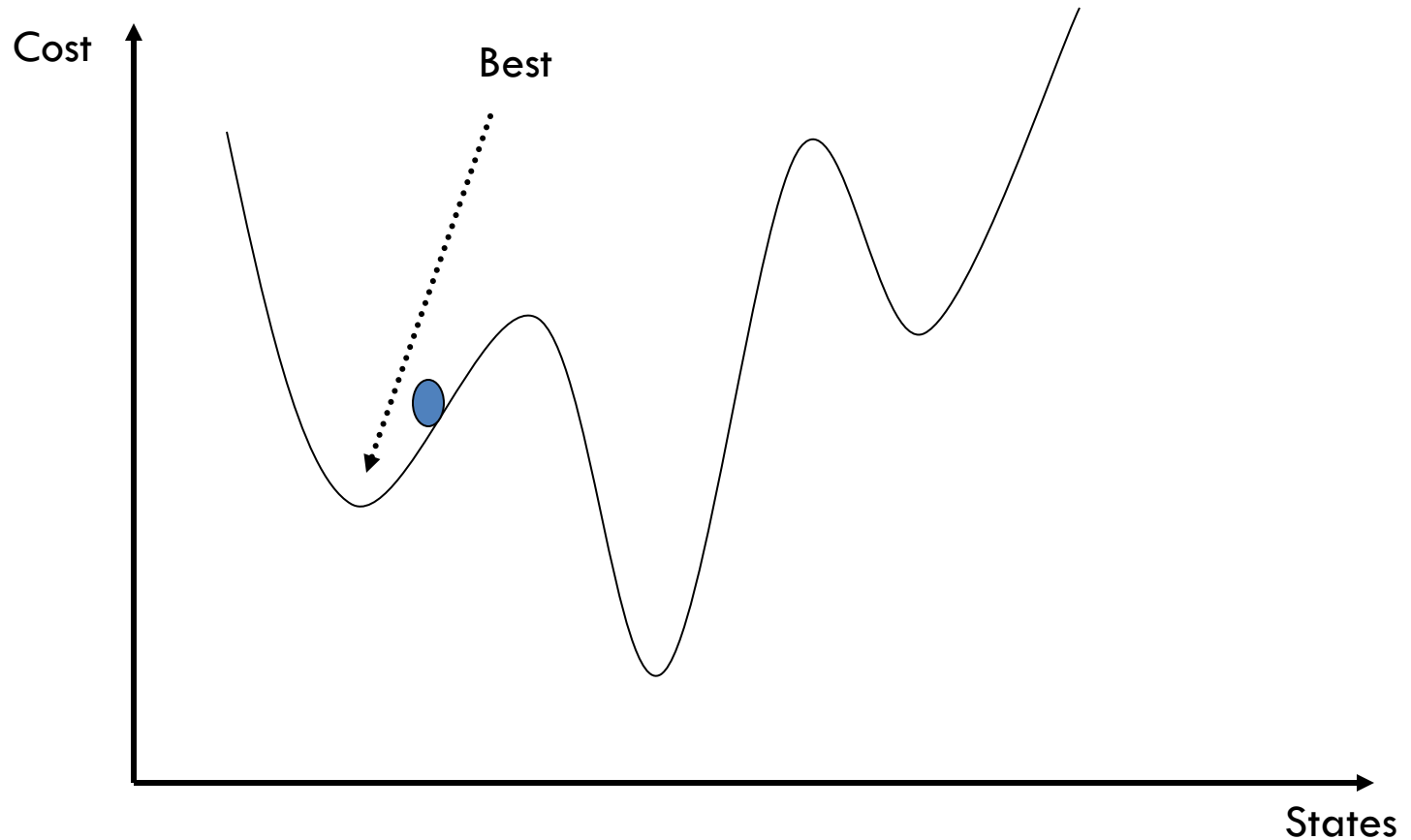


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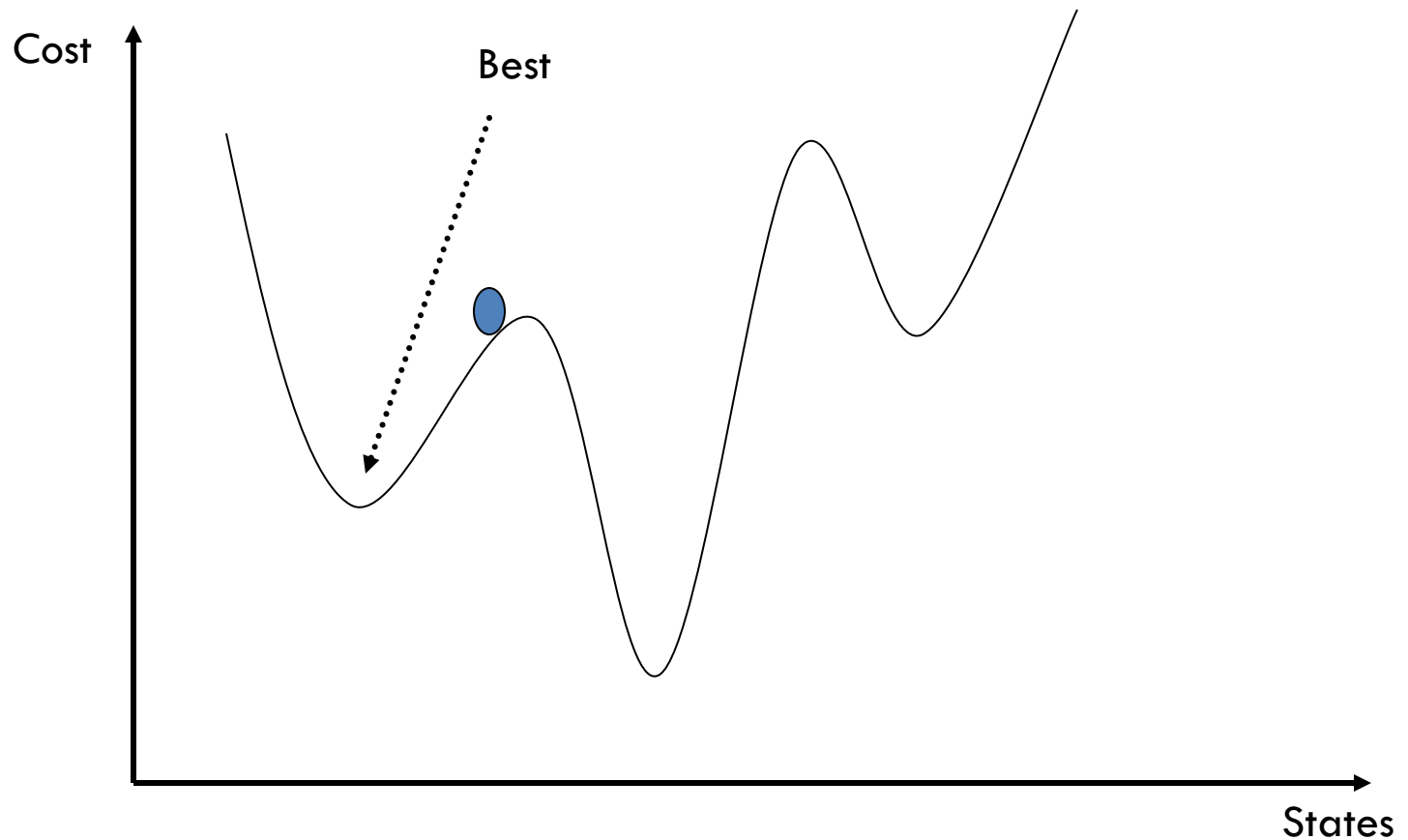


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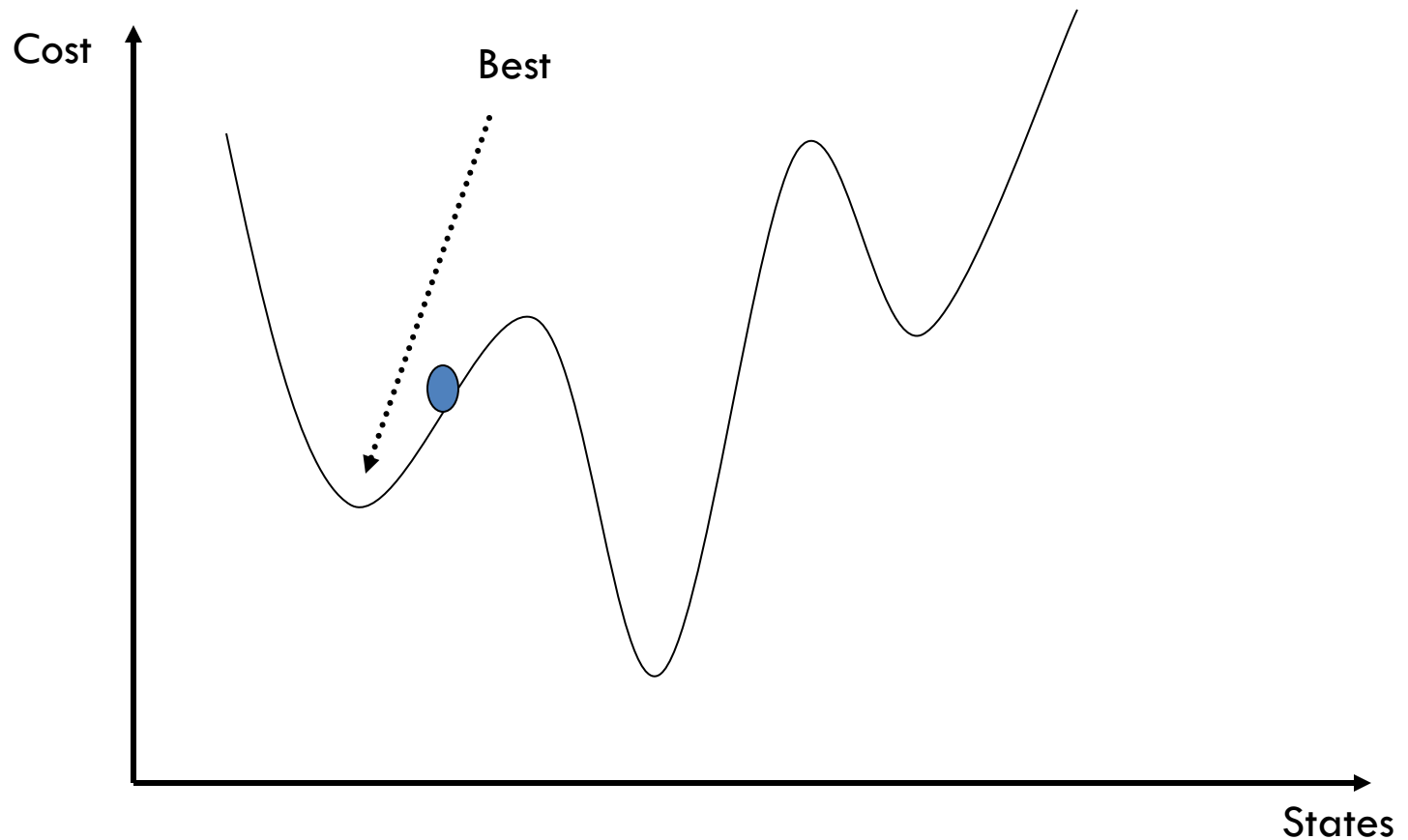


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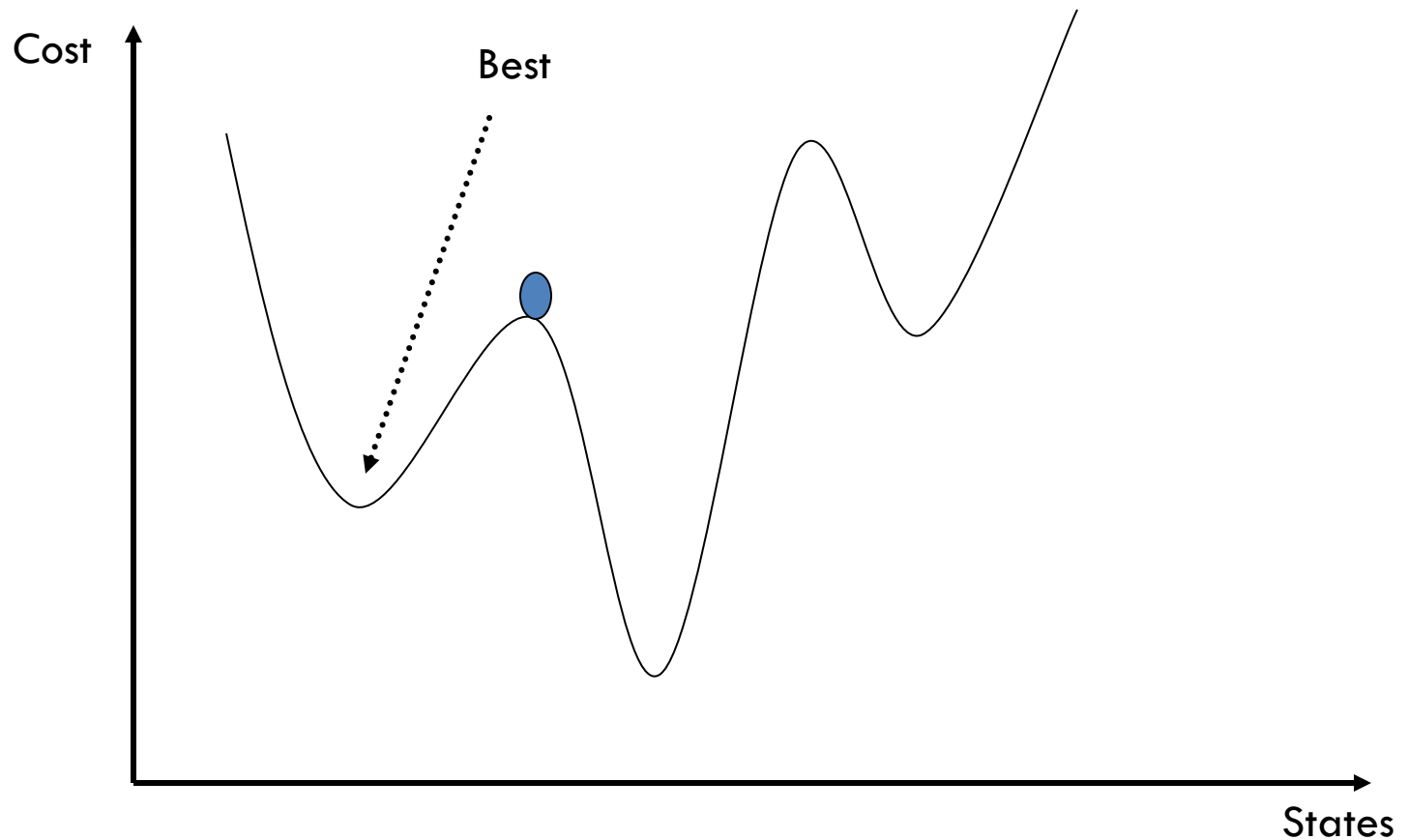


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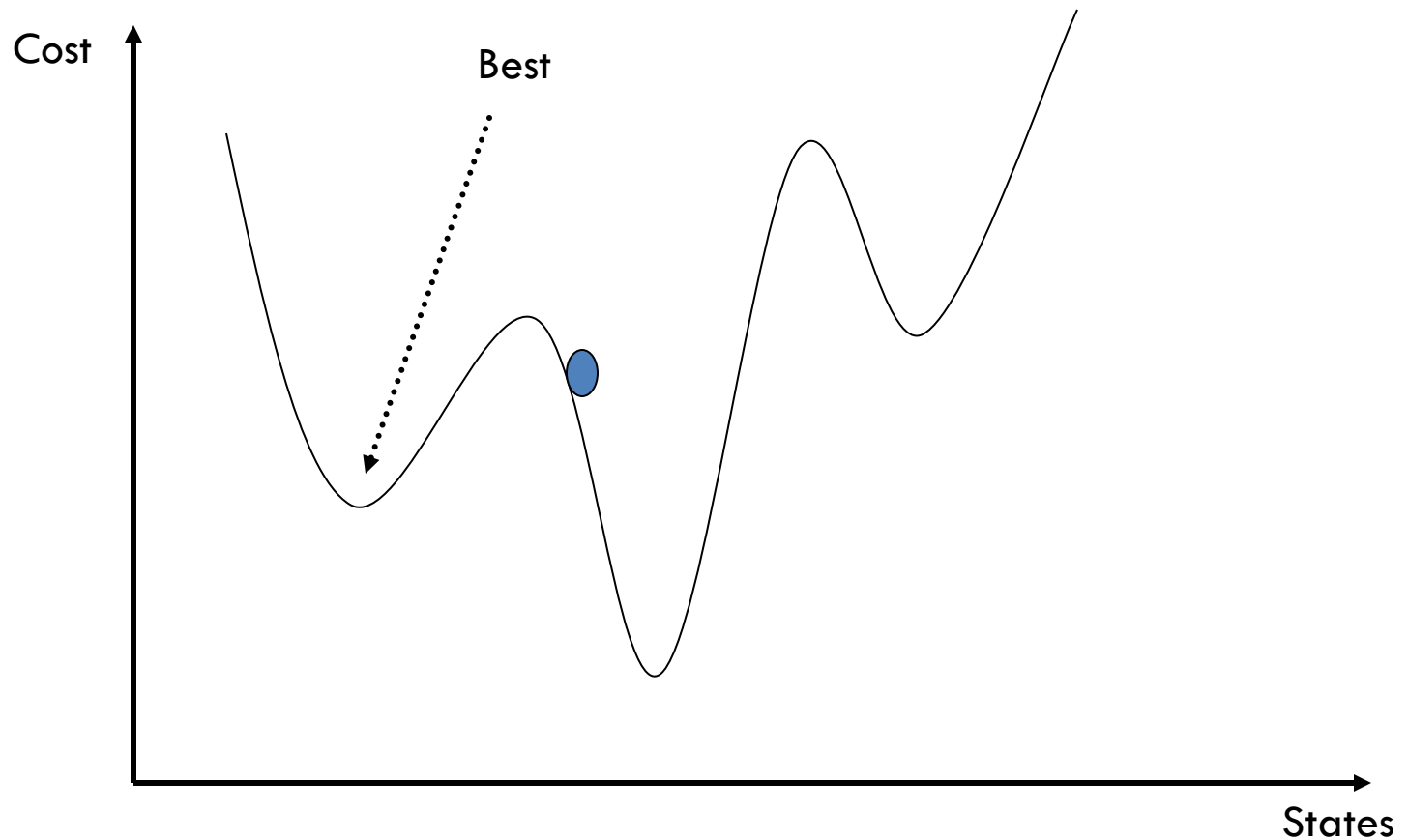


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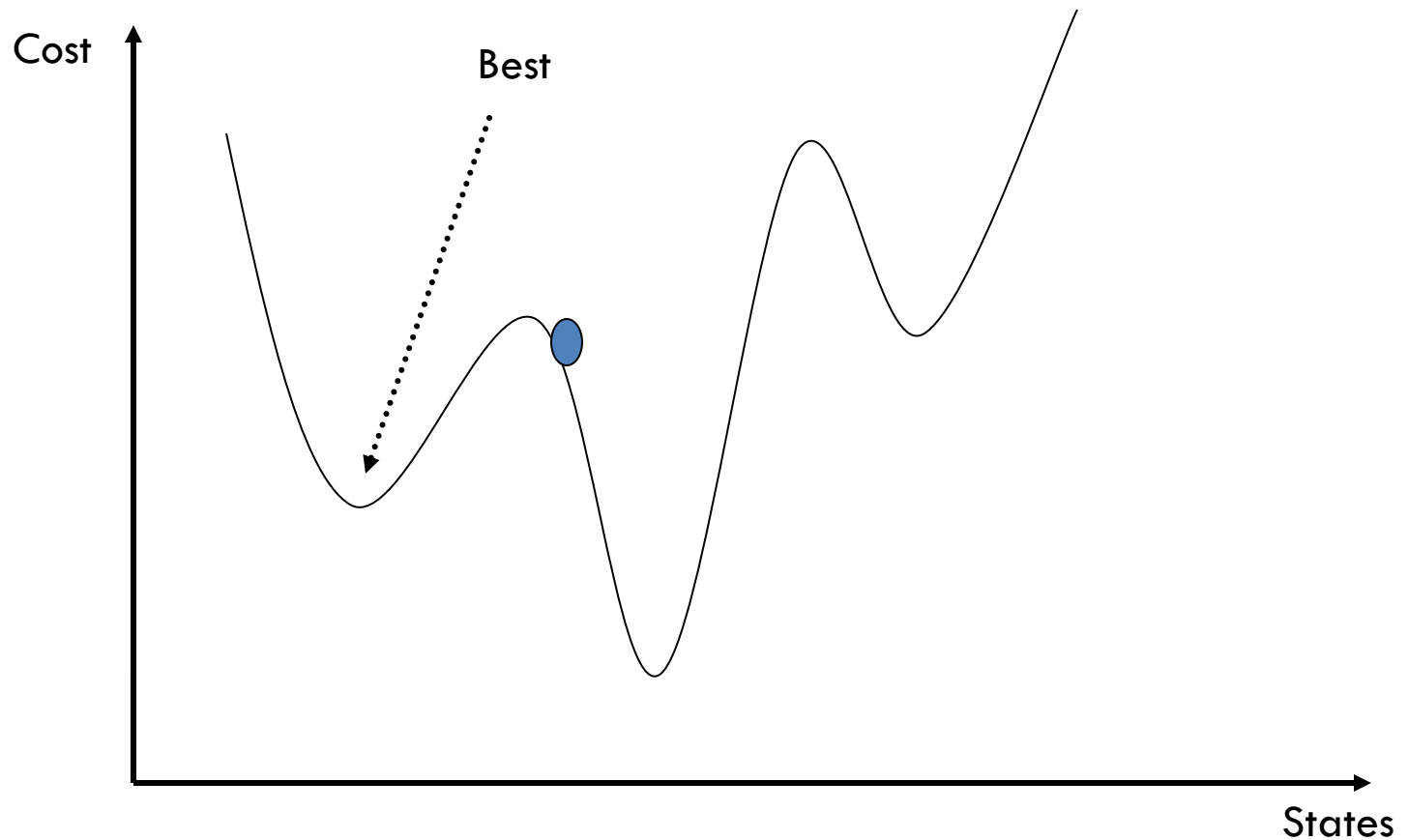


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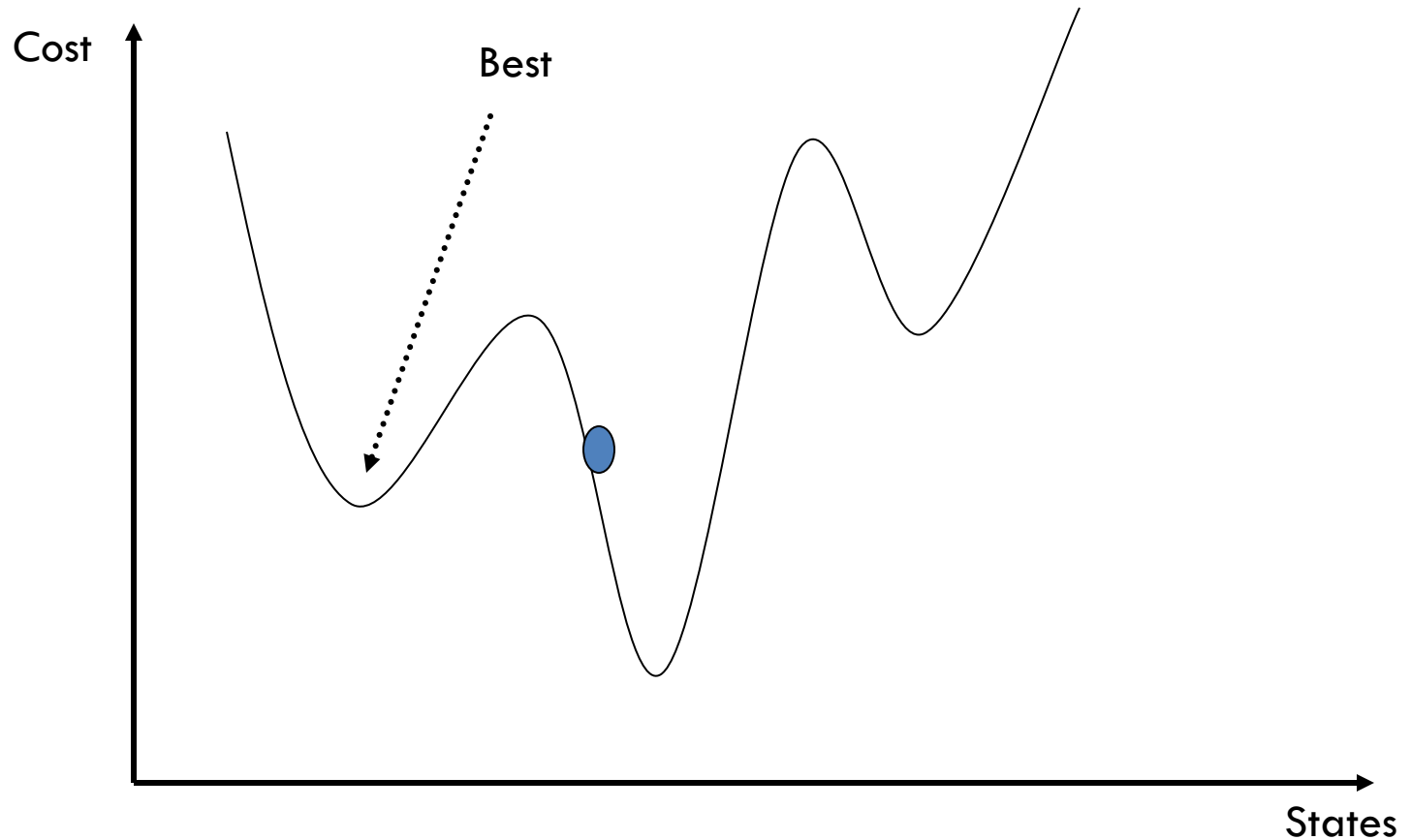


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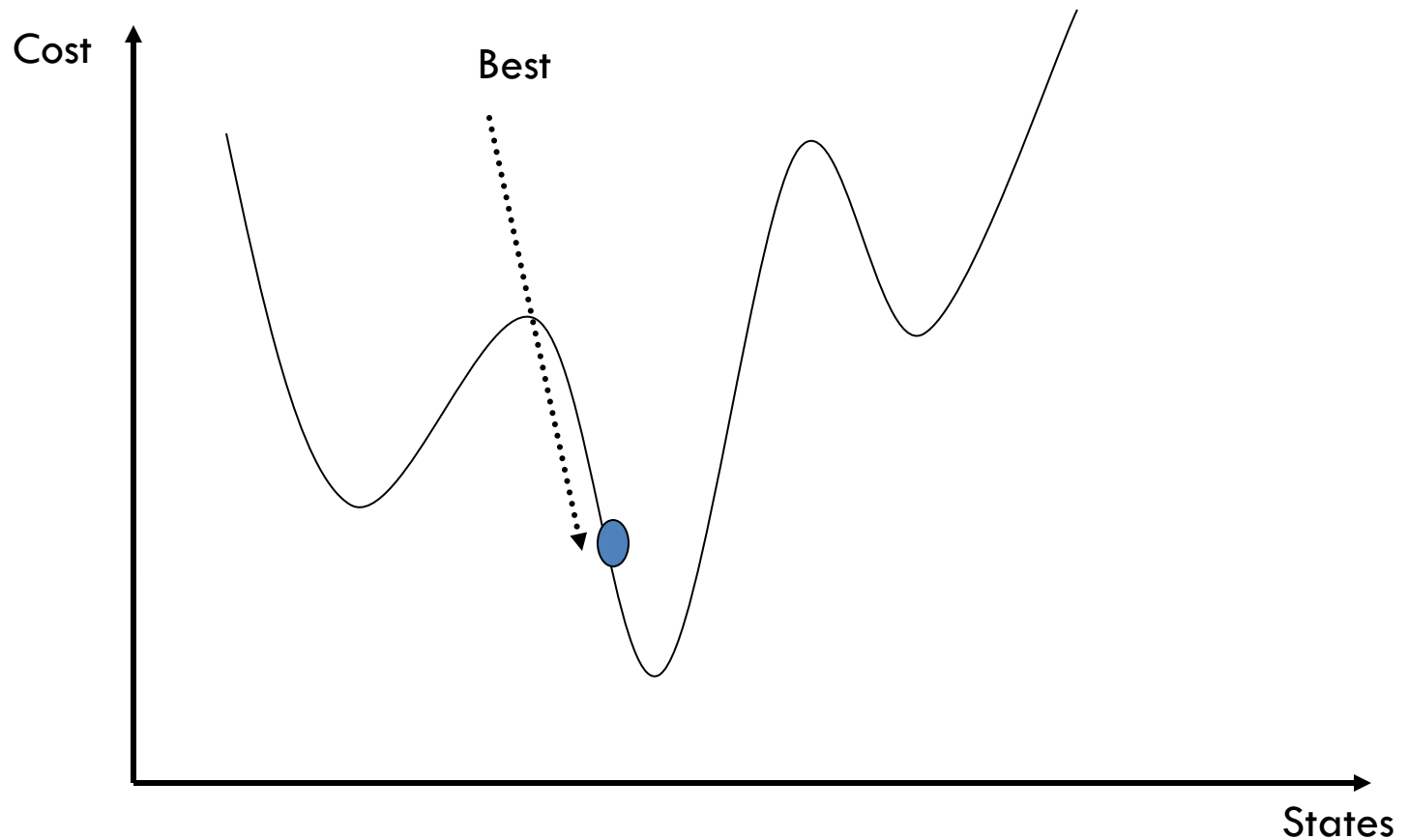


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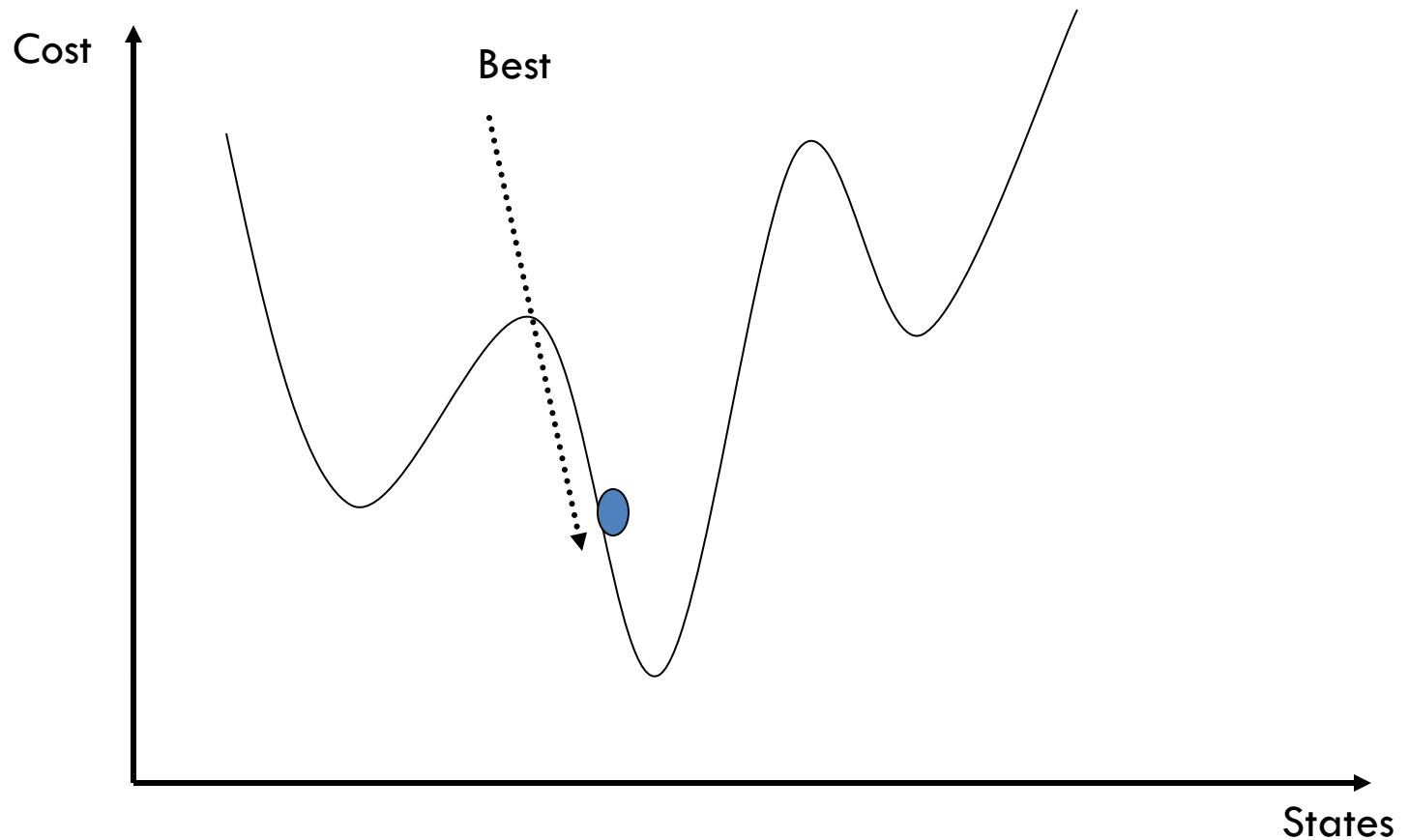


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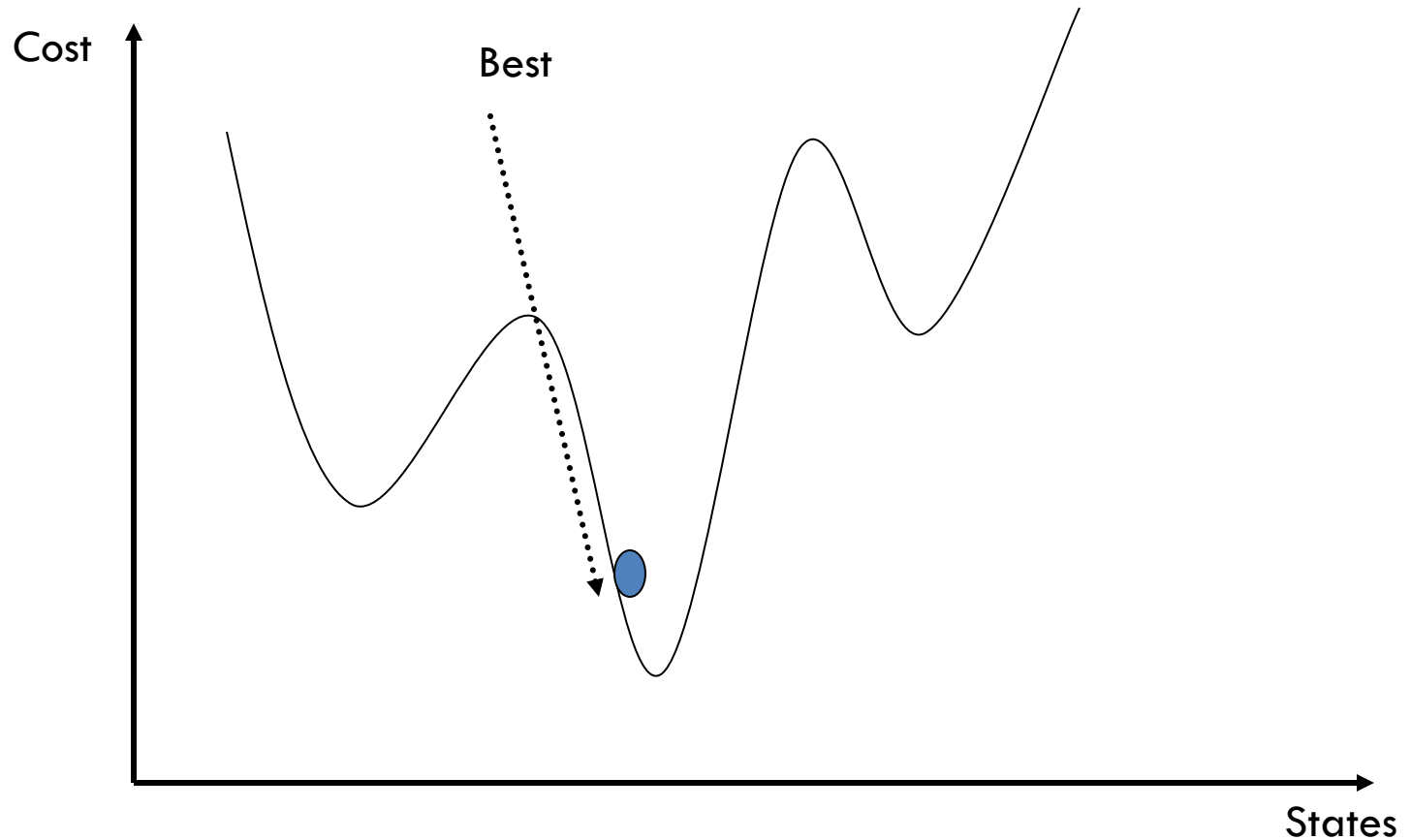


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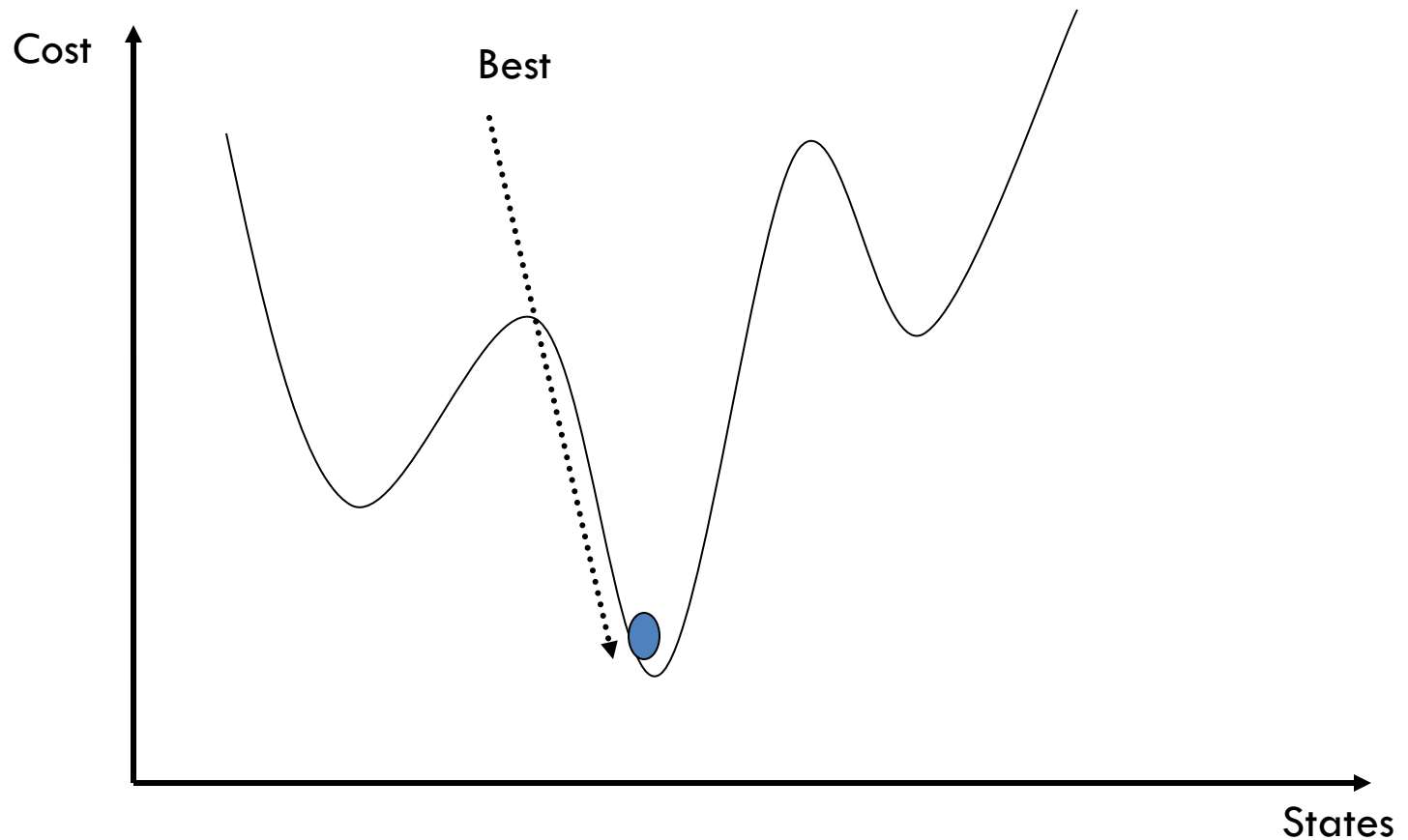


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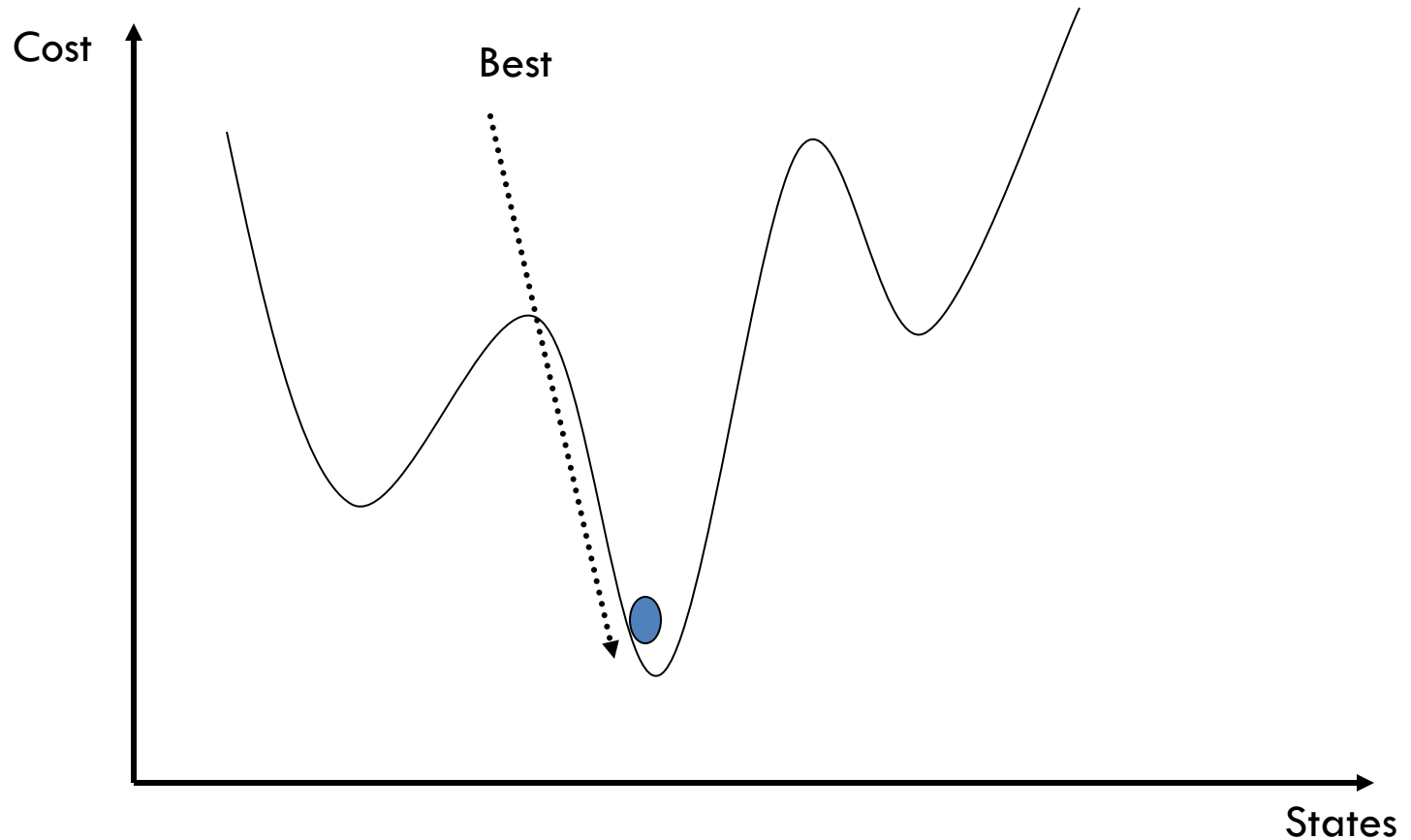


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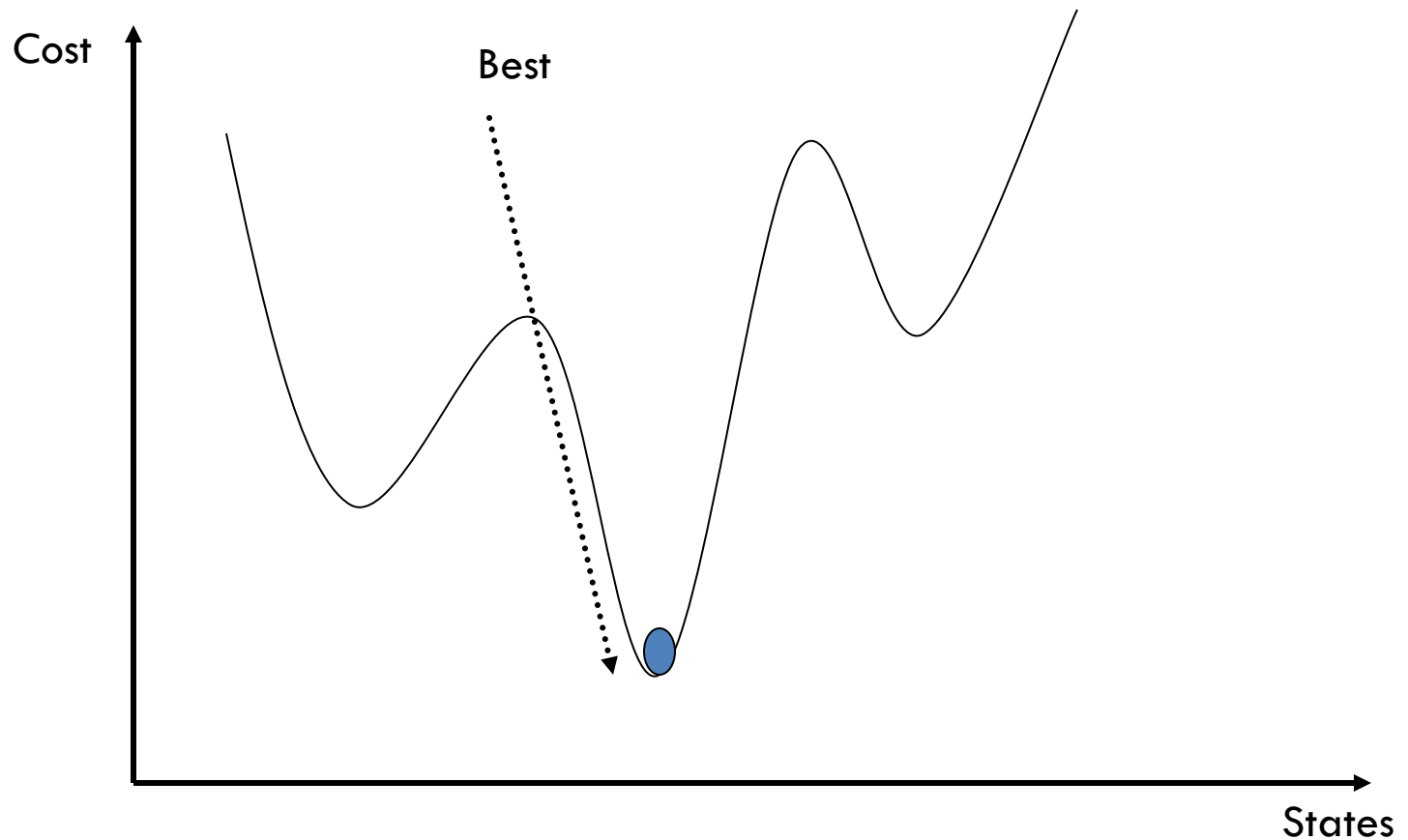


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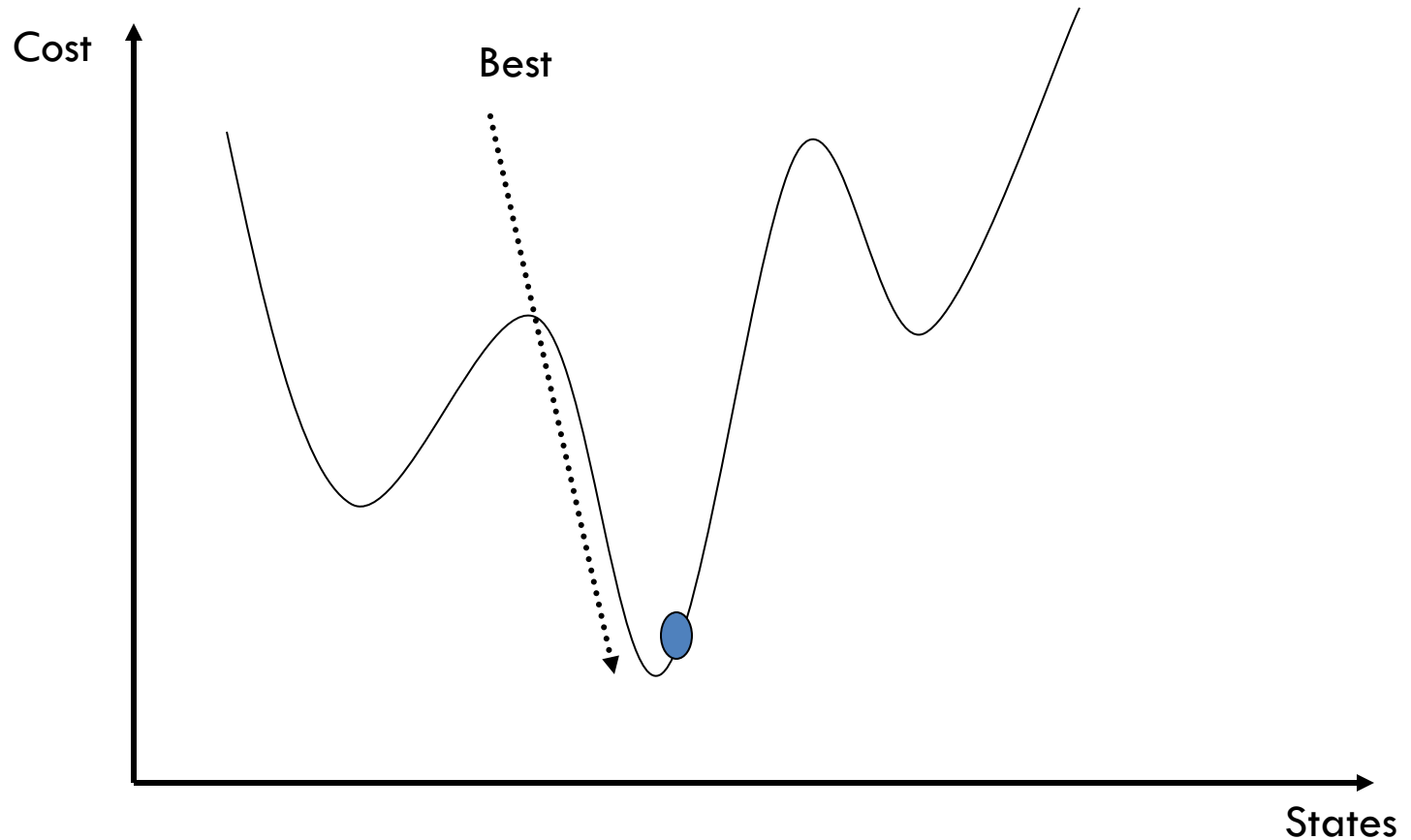


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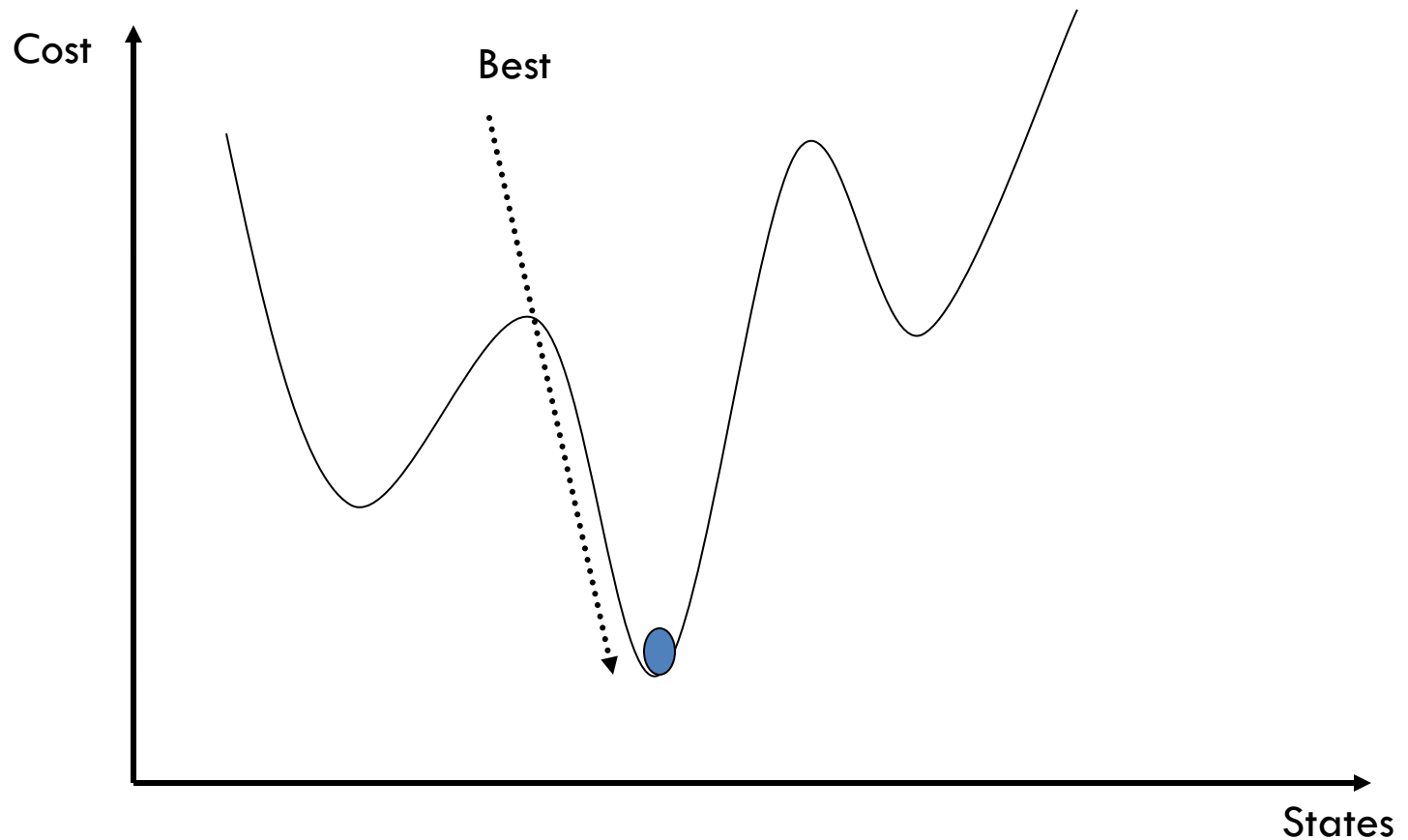


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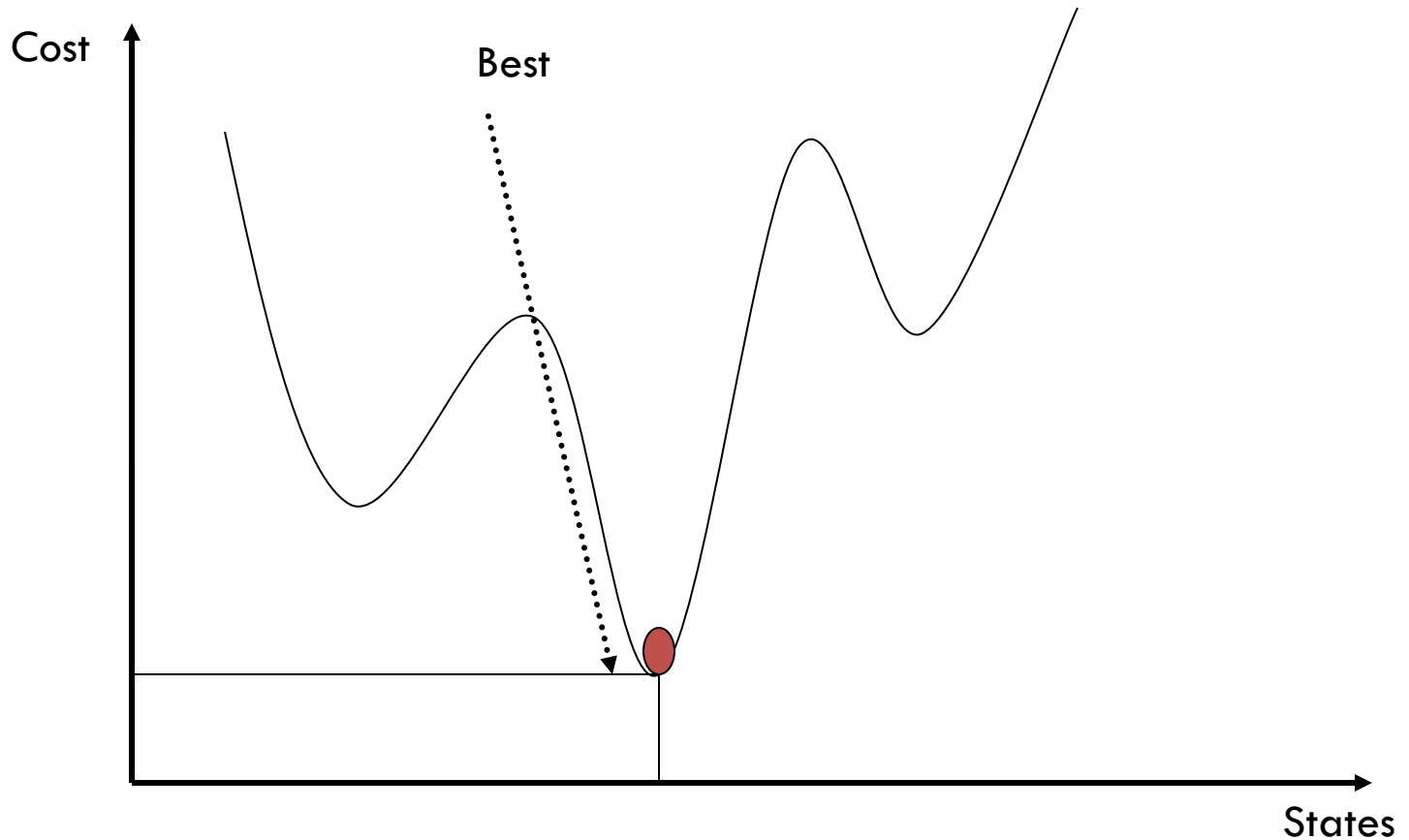


Simulated Annealing





Simulated Annealing





Simulated annealing Search

- ▣ Lets say there are 3 moves available, with changes in the objective function of $d1 = -0.1$, $d2 = 0.5$, $d3 = -5$. (Let $T = 1$).
- ▣ pick a move randomly:
 - if $d2$ is picked, move there.
 - if $d1$ or $d3$ are picked, probability of move = $\exp(d/T)$
 - move 1: $\text{prob}1 = \exp(-0.1) = 0.9$,
 - i.e., 90% of the time we will accept this move
 - move 3: $\text{prob}3 = \exp(-5) = 0.05$
 - i.e., 5% of the time we will accept this move





Properties of Simulated Annealing

- **Cooling Schedule:** determines rate at which the temperature T is lowered.





Local Beam Search





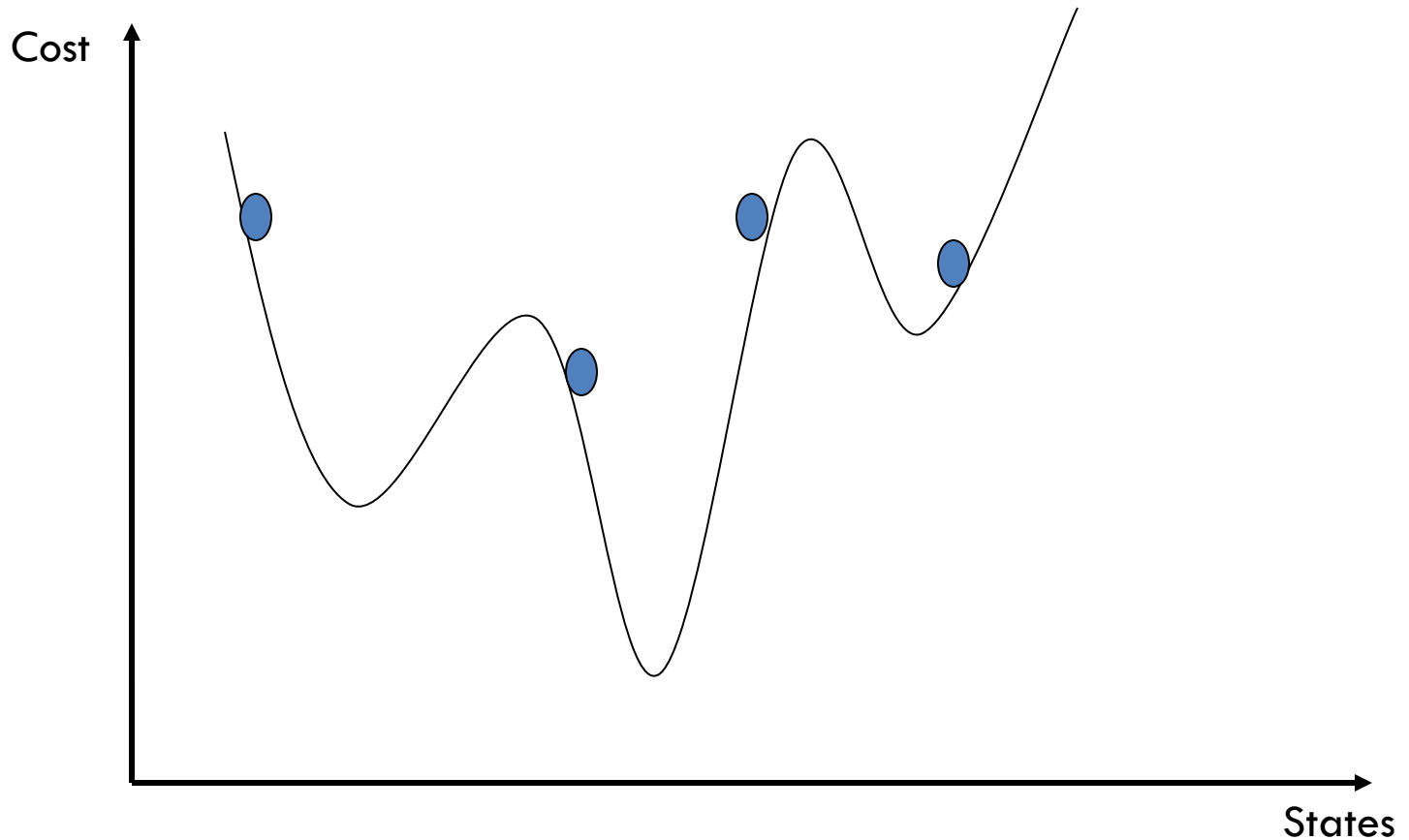
Local Beam Search

- **Main Idea:** Keep track of **k** states rather than just one.
- Start with **k** randomly generated states.
- At each iteration, all the successors of all **k** states are generated.
- If any one is a goal state, stop; else select the **k** best successors from the complete list and repeat.
- **Drawback:** the **k** states tend to regroup very quickly in the same region → lack of diversity.



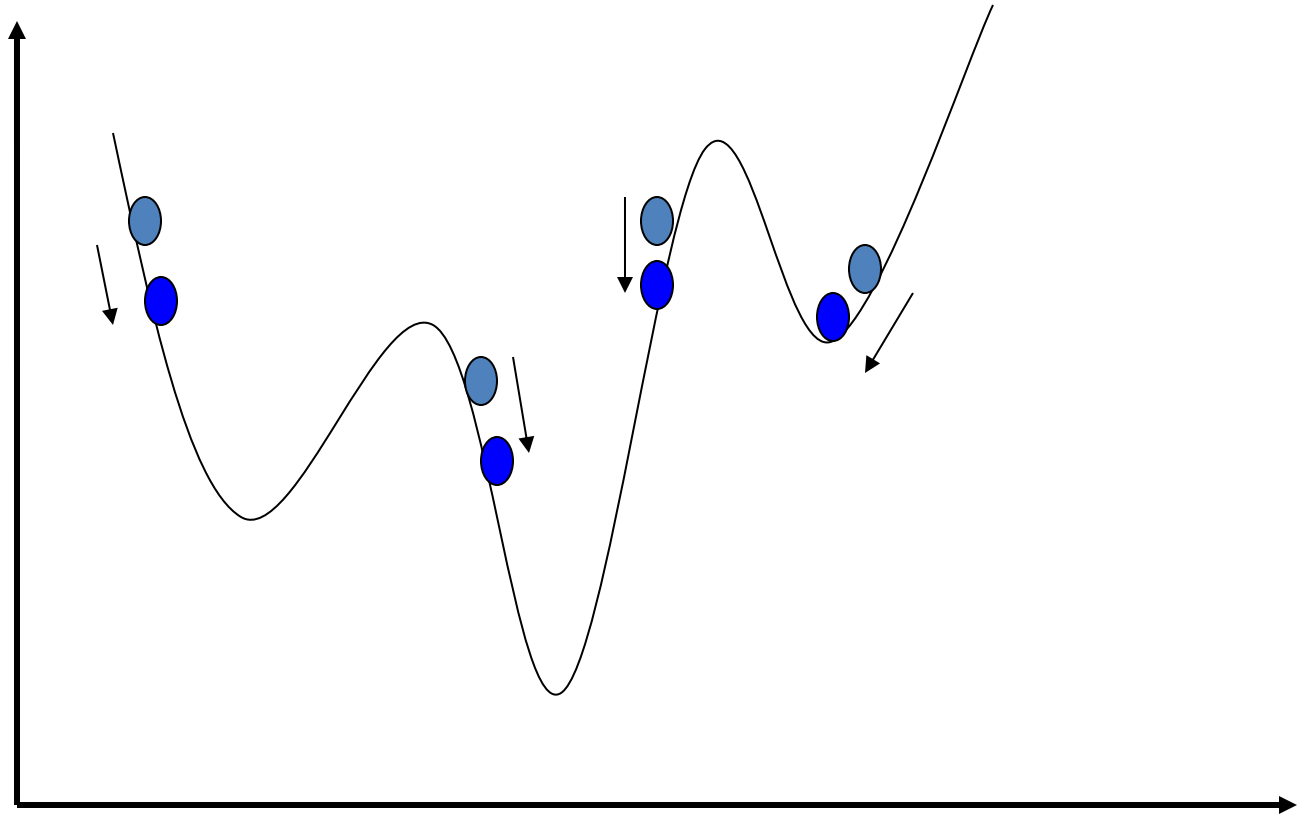


Local Beam Search



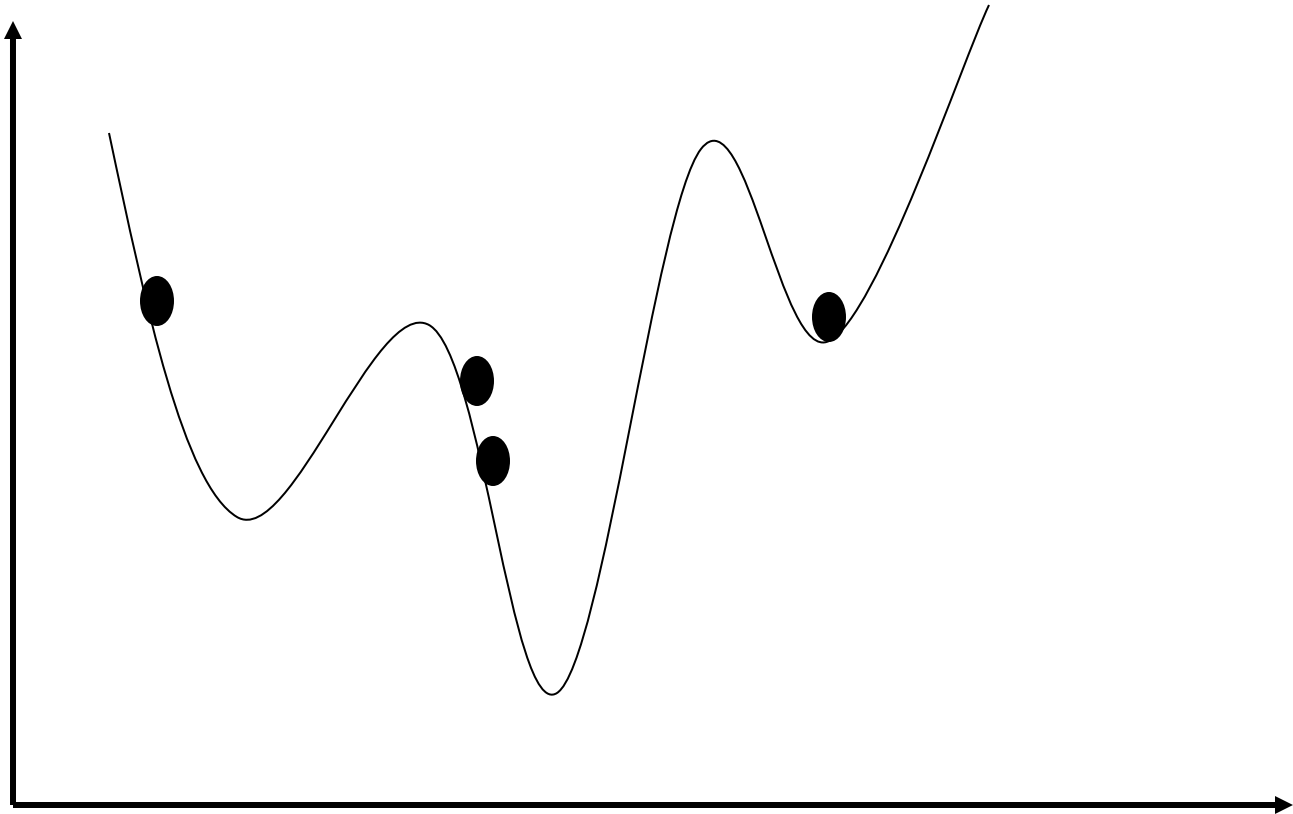


Local Beam Search



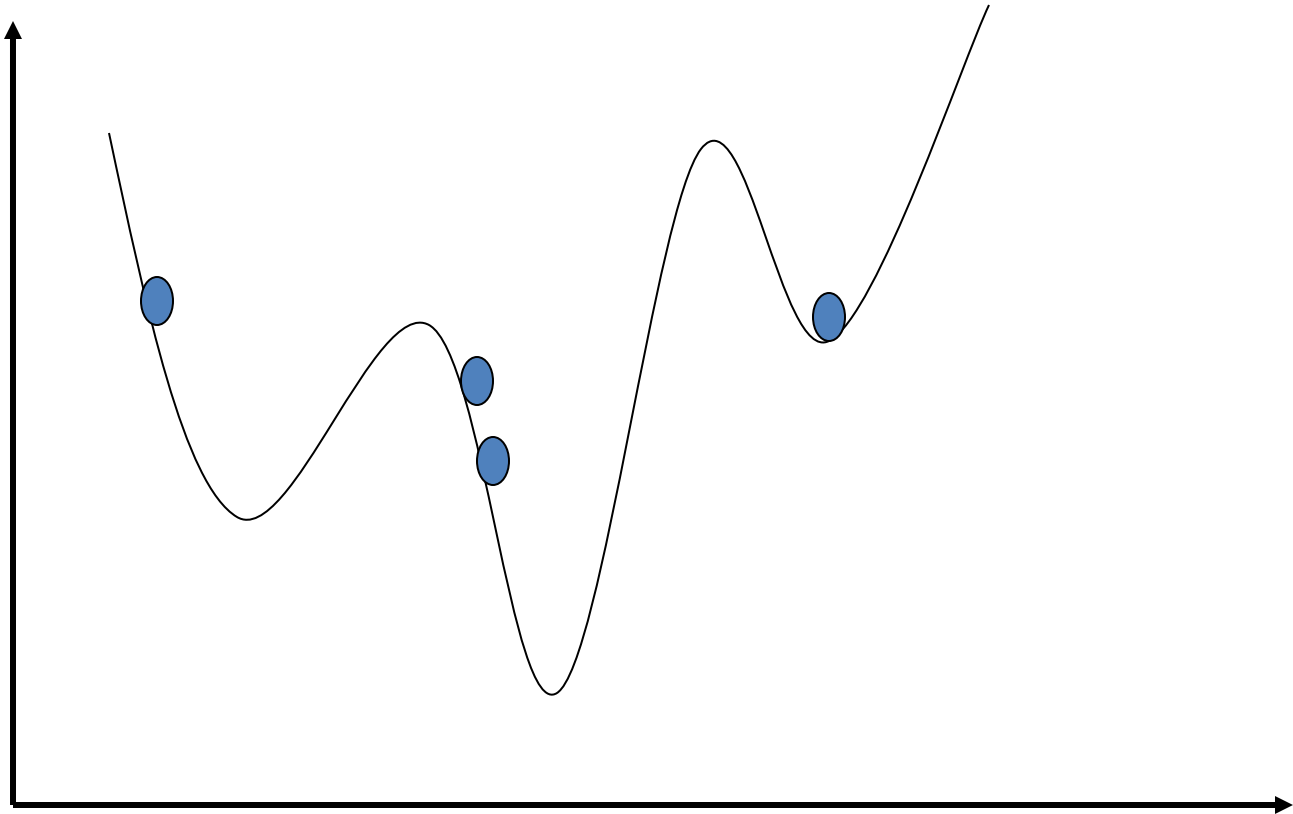


Local Beam Search



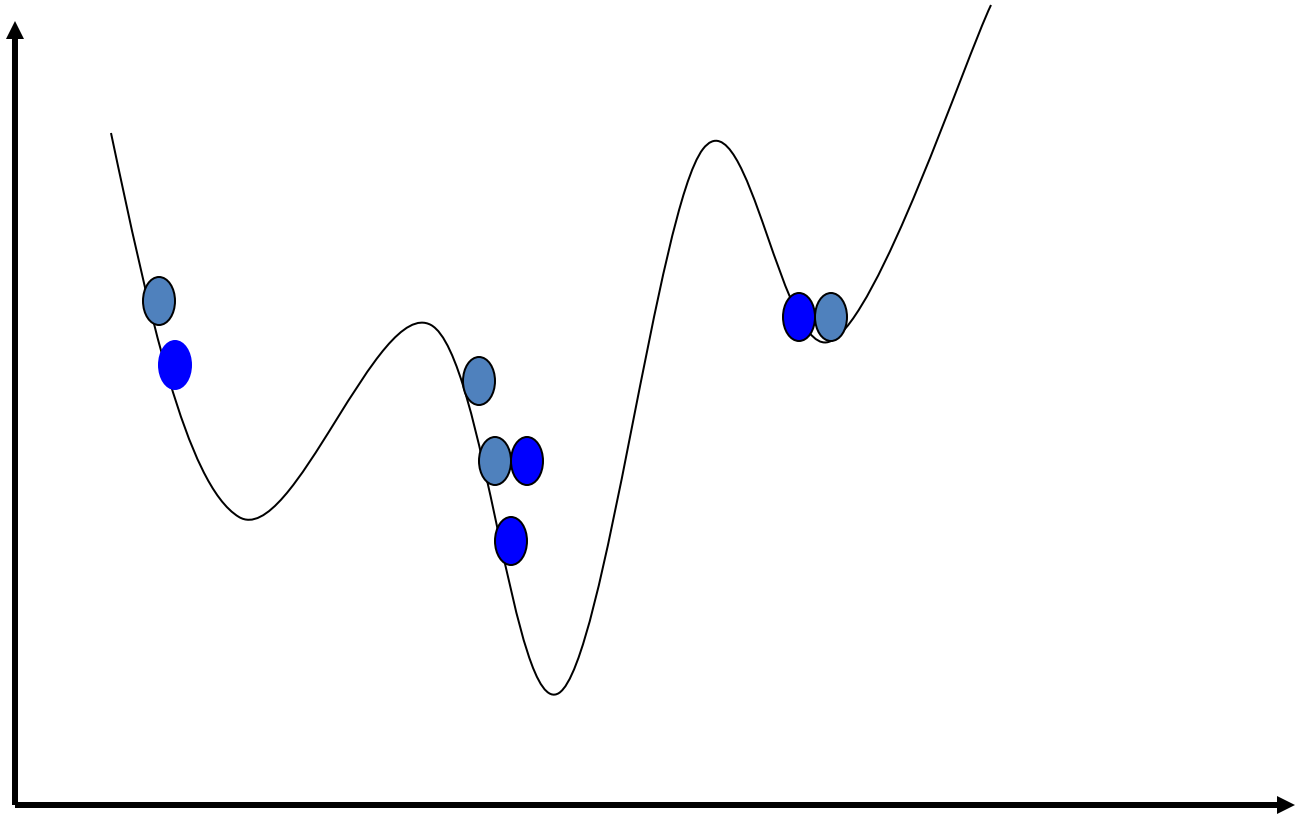


Local Beam Search



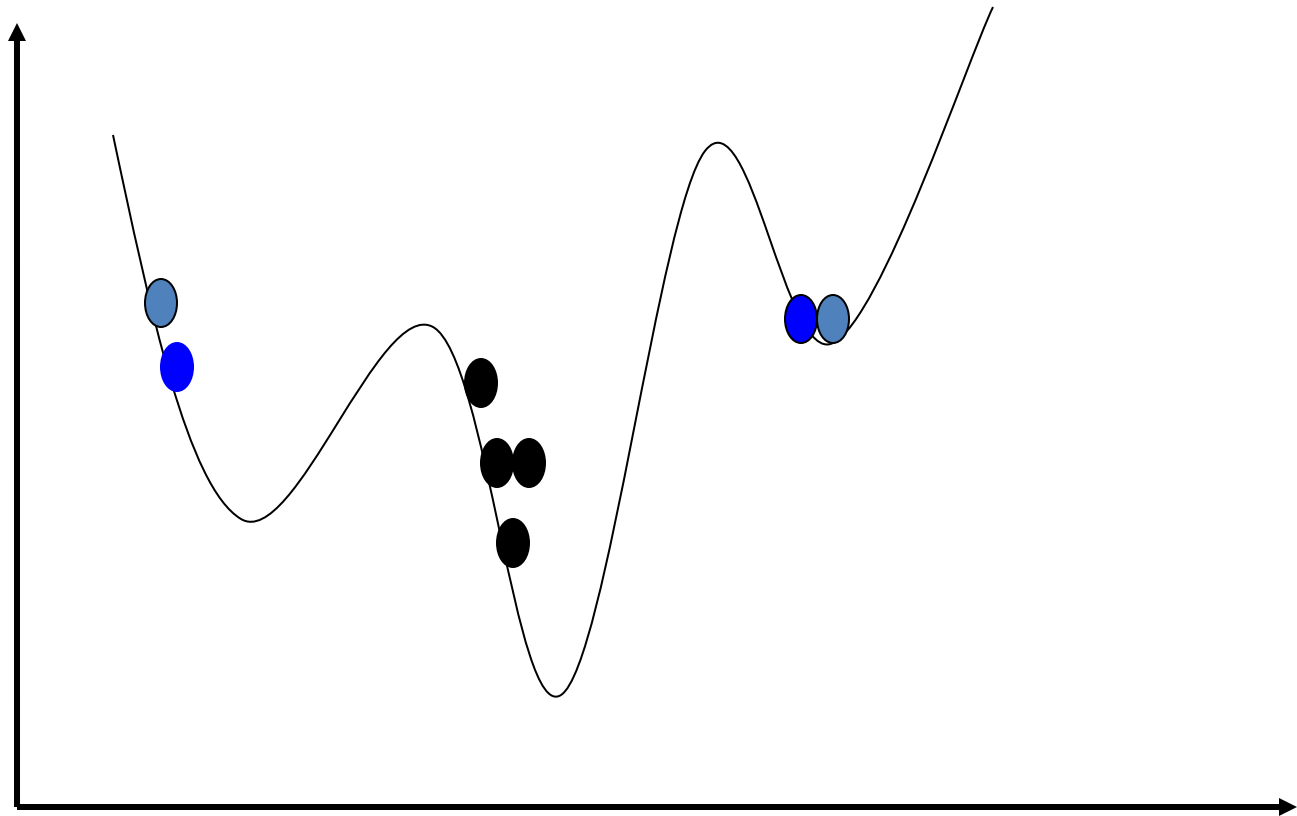


Local Beam Search



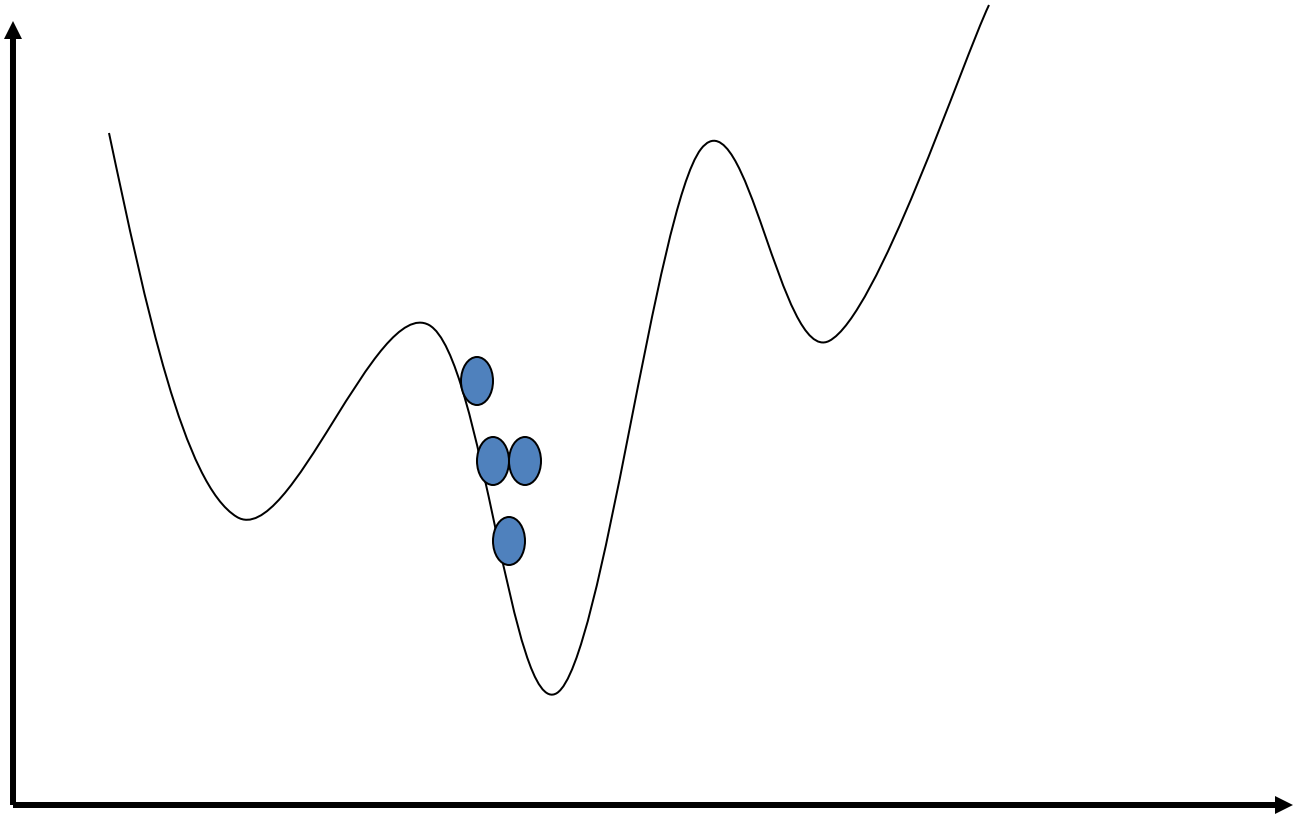


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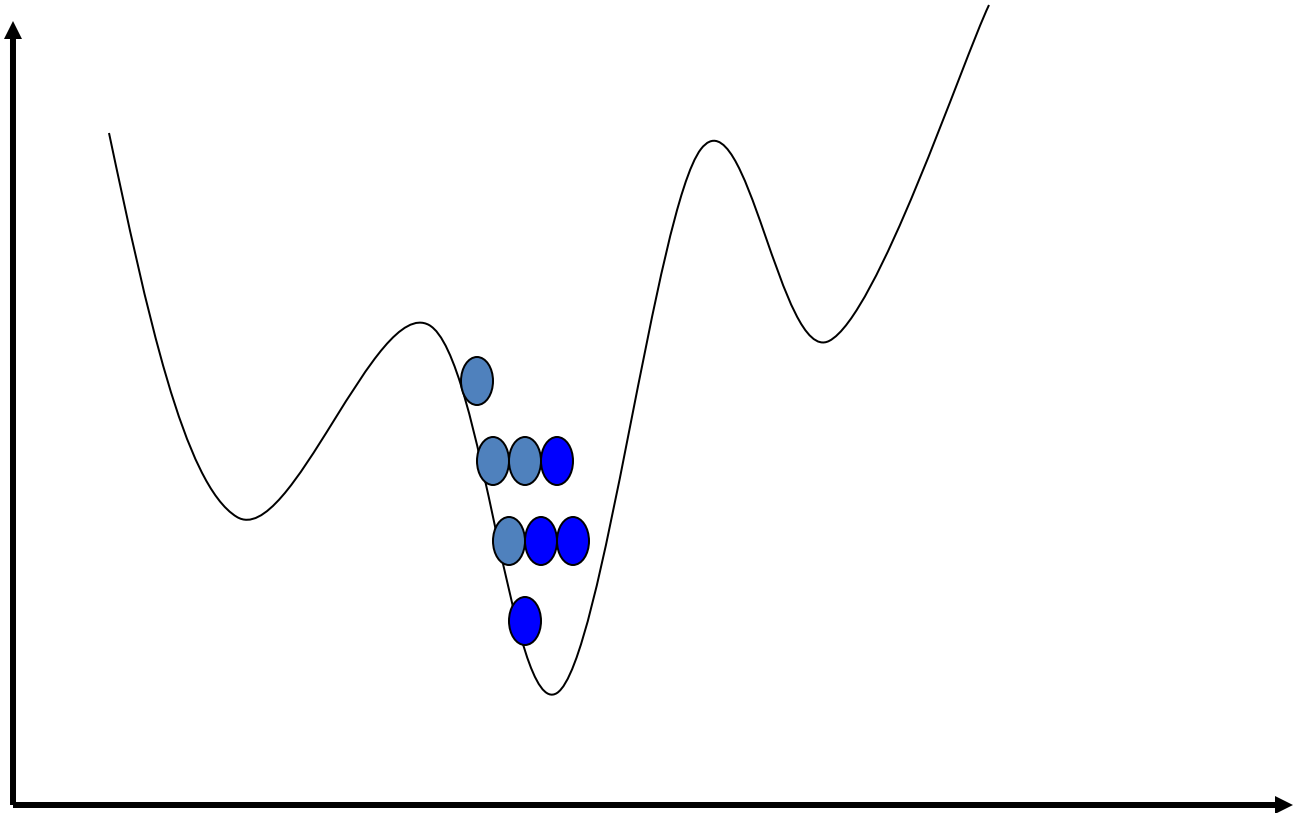


Local Beam Search



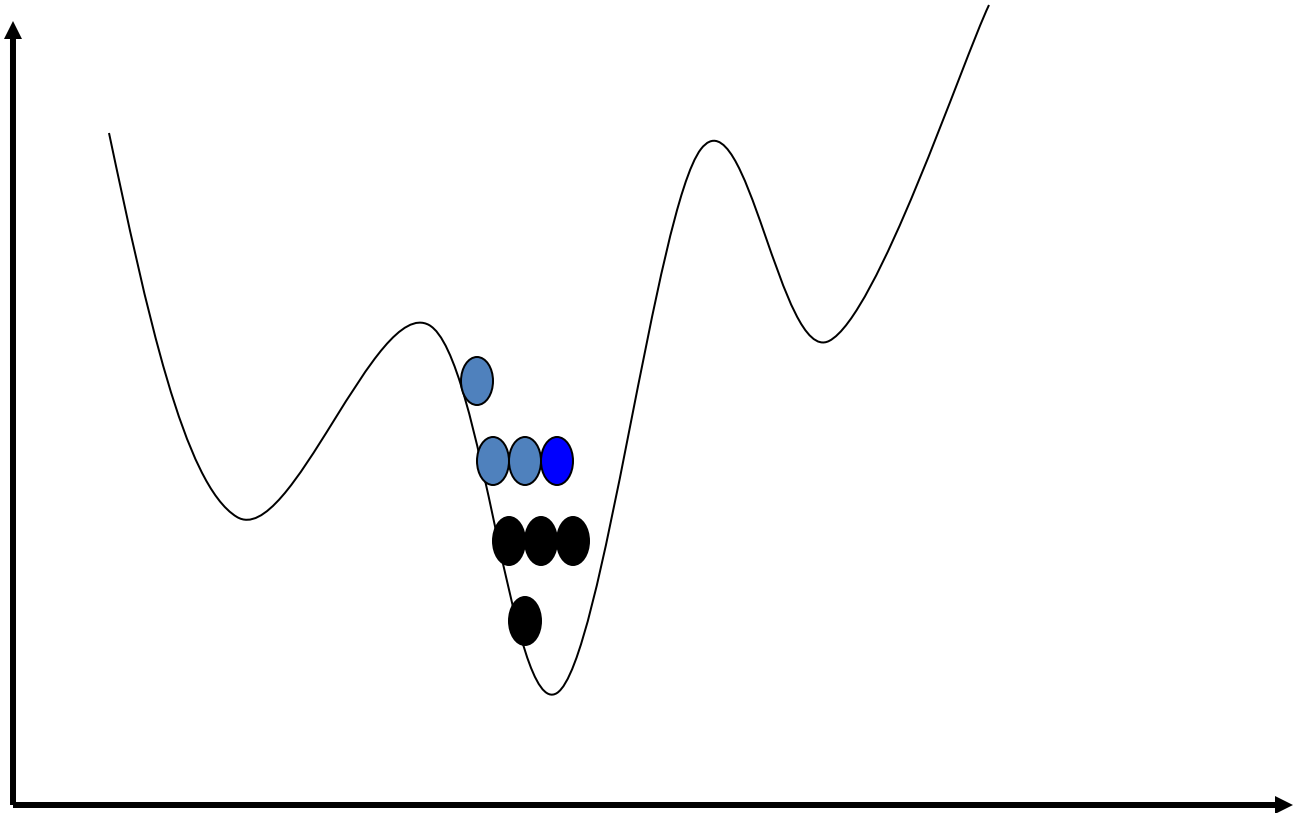


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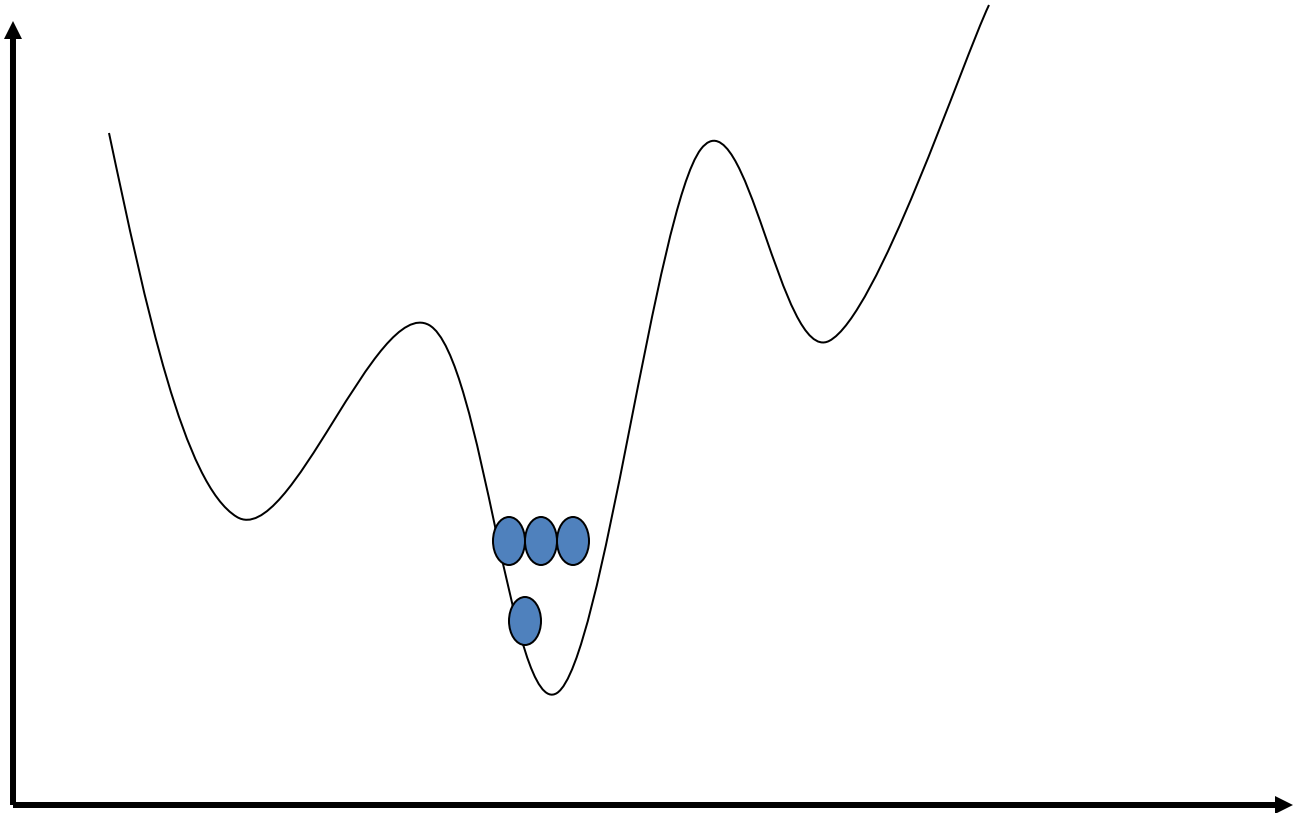


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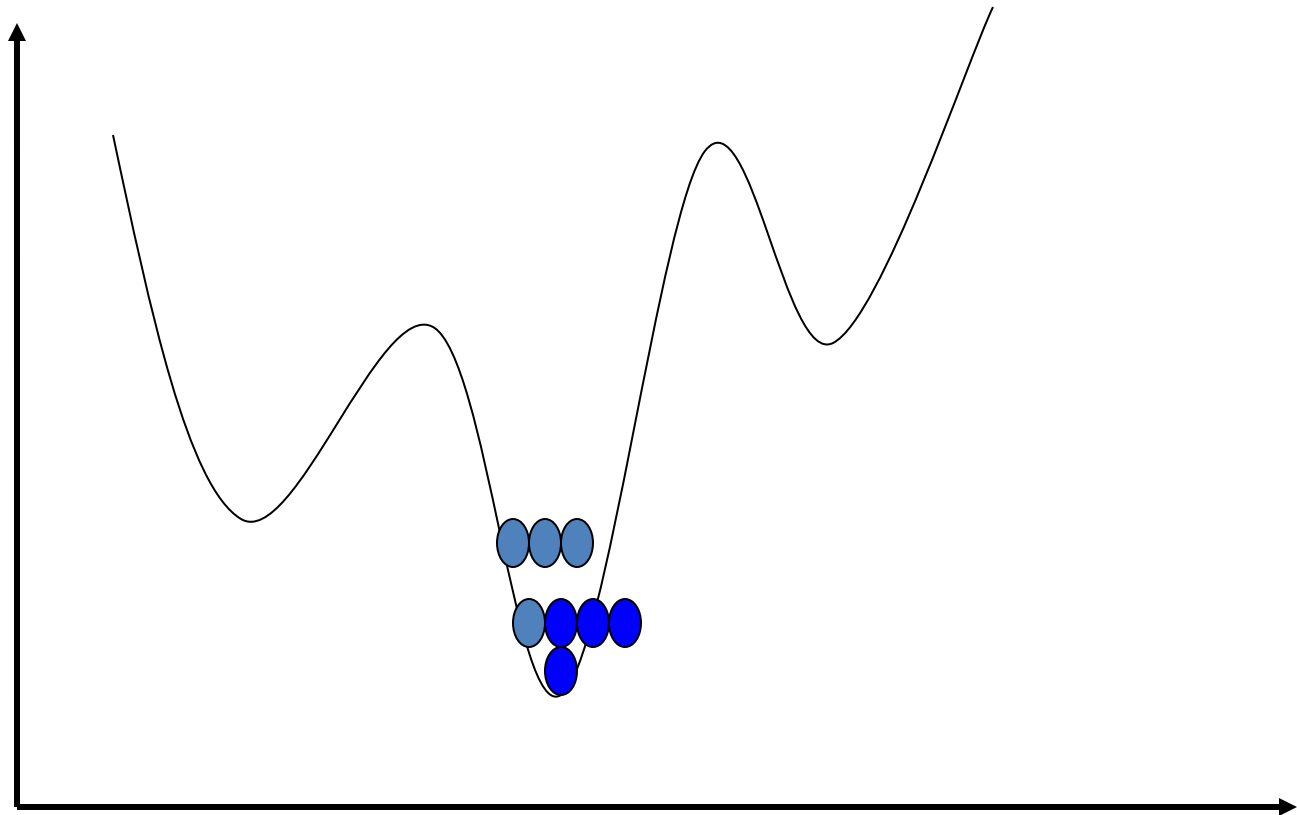


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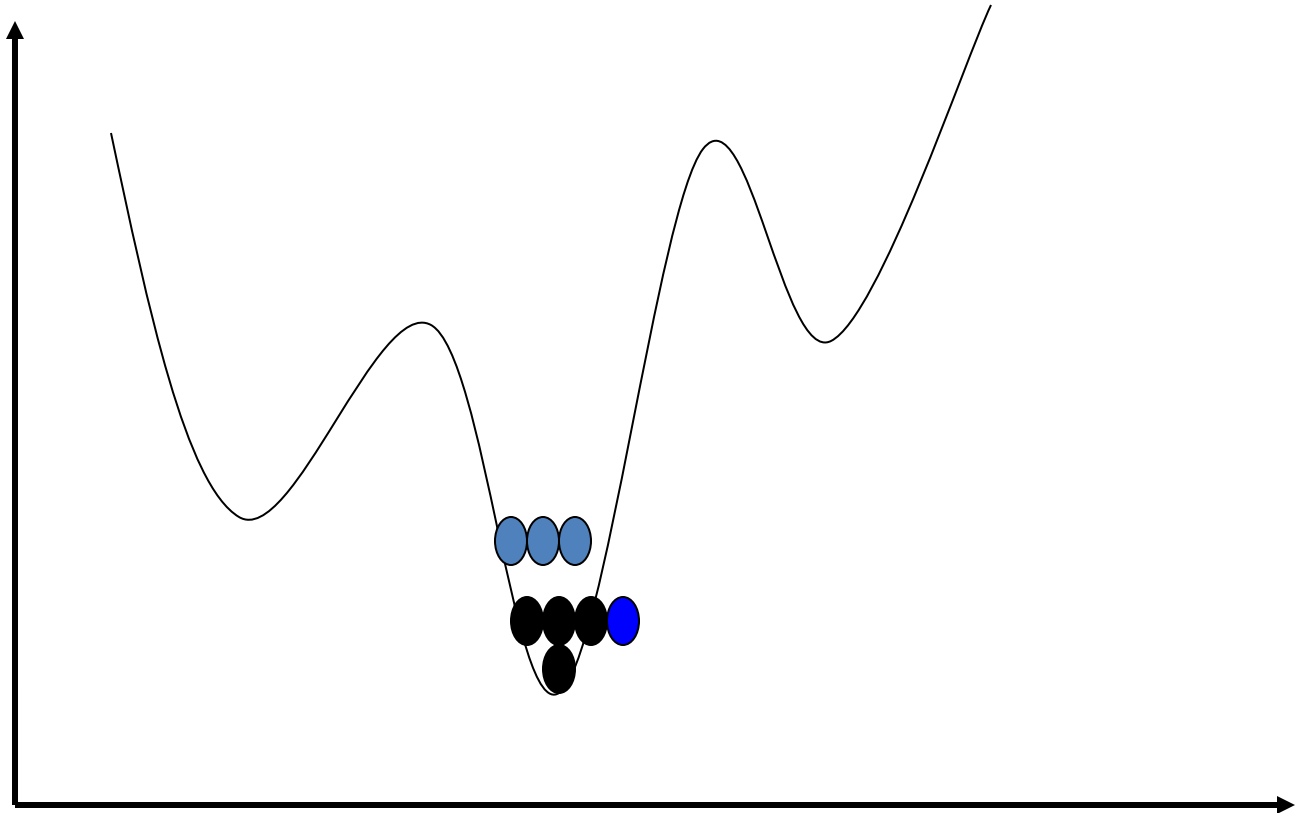


Local Beam Search



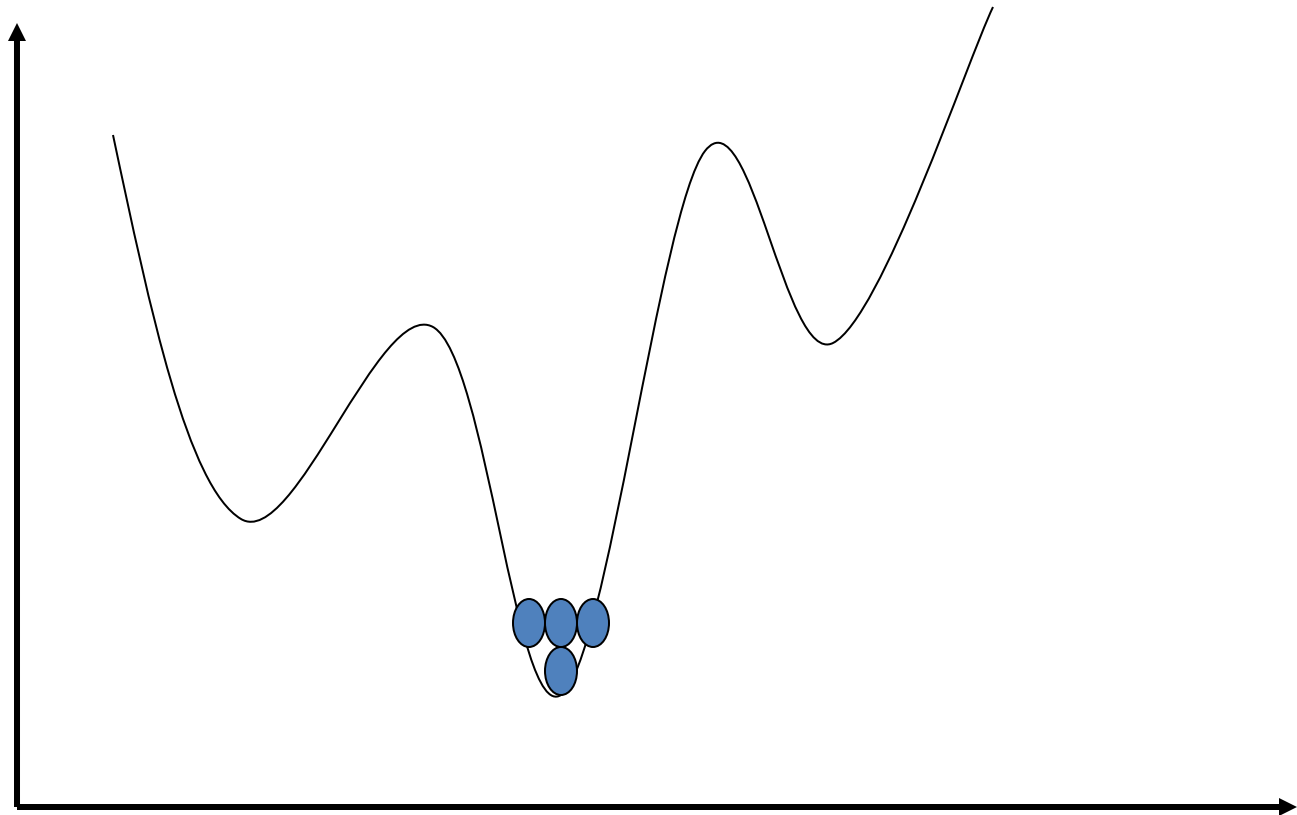


Local Beam Search



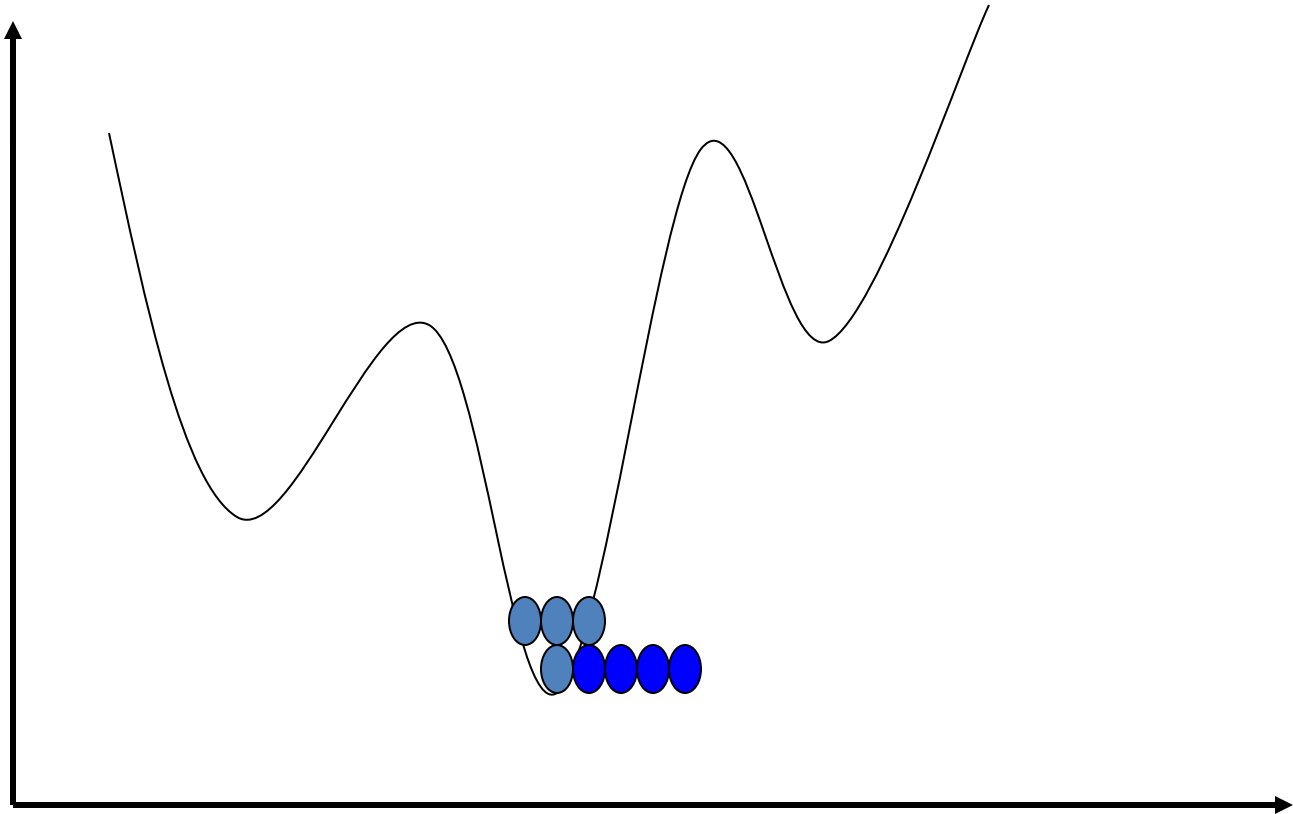


Local Beam Search



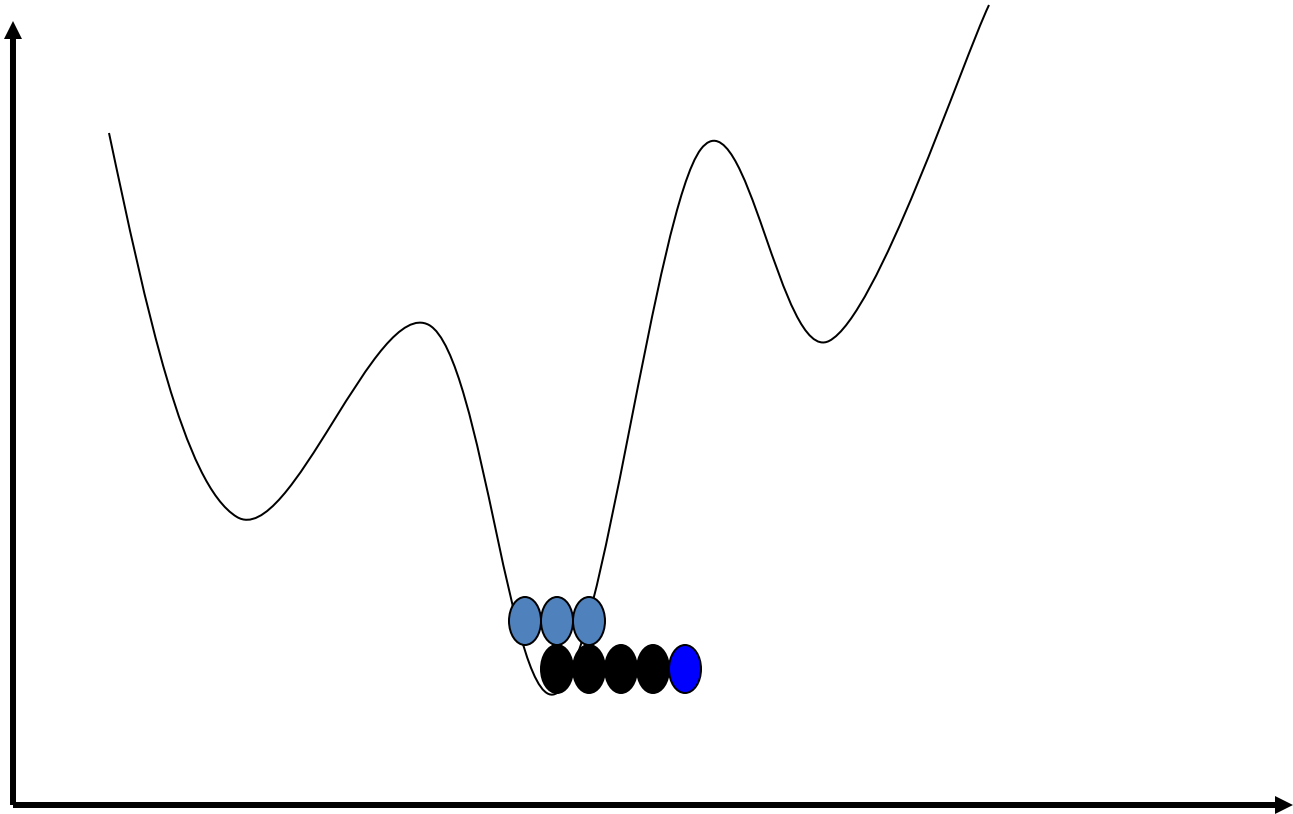


Local Beam Search



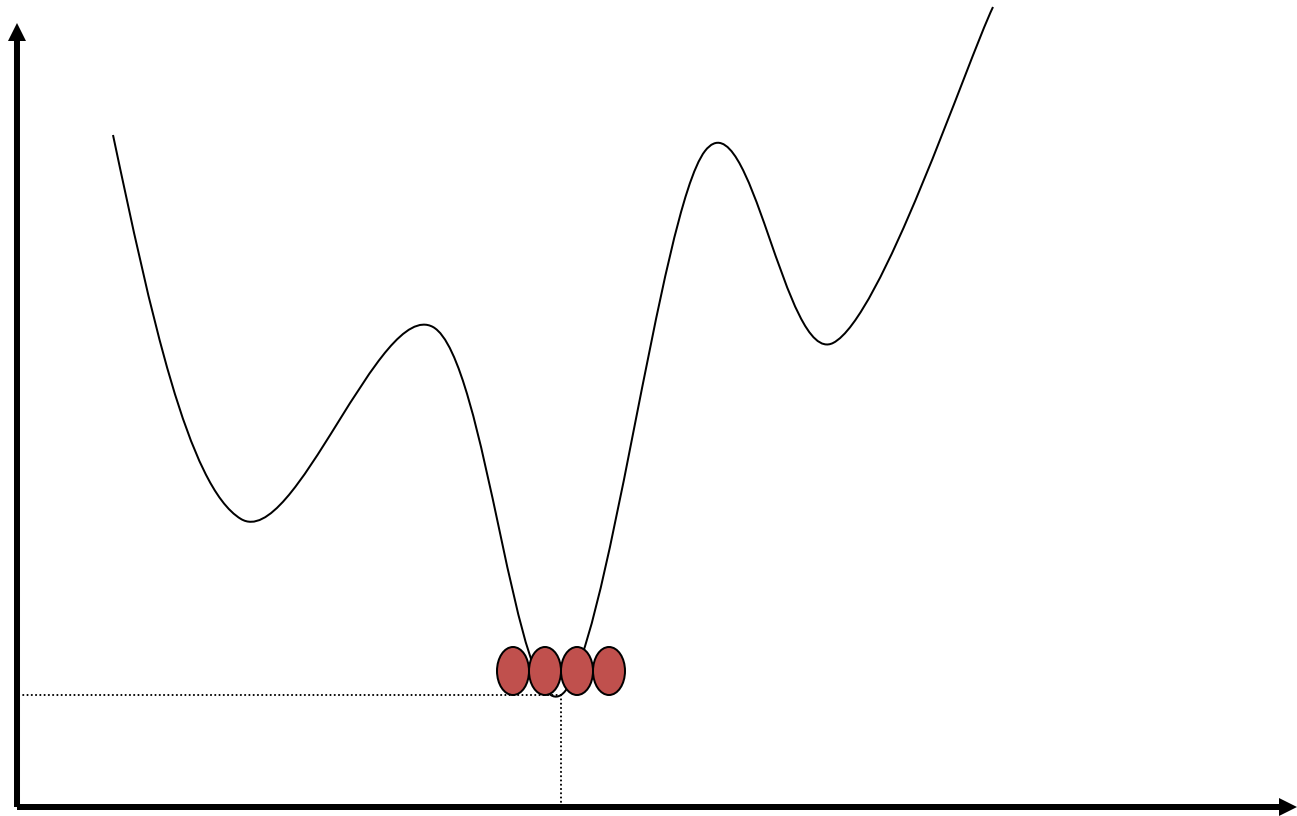


Local Beam Search





Local Beam Search





Genetic Algorithm Search





Genetic Algorithms

- Formally introduced in the US in the 70s by John Holland.
- GAs emulate **ideas** from genetics and natural selection and can search potentially large spaces.
- Before we can apply Genetic Algorithm to a problem, we need to answer:
 - How is an individual represented?
 - What is the fitness function?
 - How are individuals selected?
 - How do individuals reproduce?





Genetic Algorithms: Representation of states (solutions)

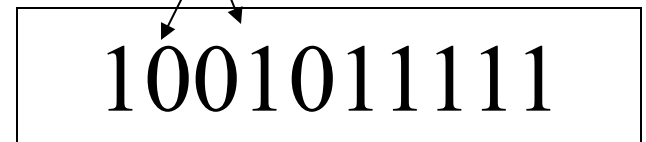
- Each state or individual is represented as a string over a finite alphabet. It is also called **chromosome** which contains **genes**.

Solution: 607



Encoding

genes



Chromosome:

Binary String



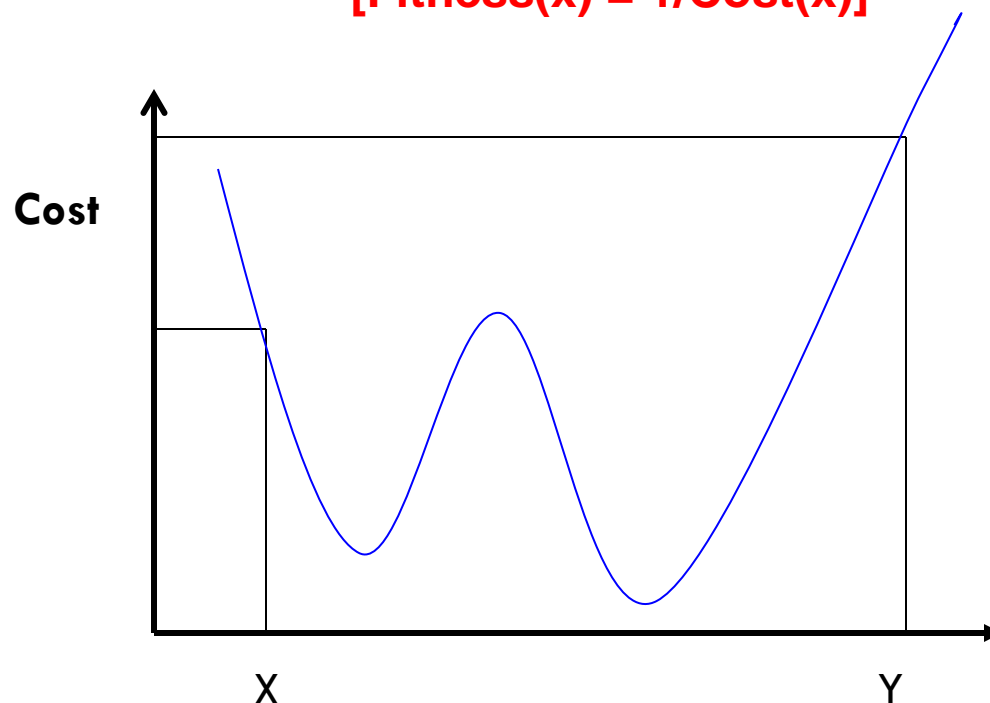


Genetic Algorithms: Fitness Function

- Each state is rated by the evaluation function called **fitness function**. Fitness function should return higher values for better states:

Fitness(X) should be greater than Fitness(Y) !!

$$[\text{Fitness}(x) = 1/\text{Cost}(x)]$$

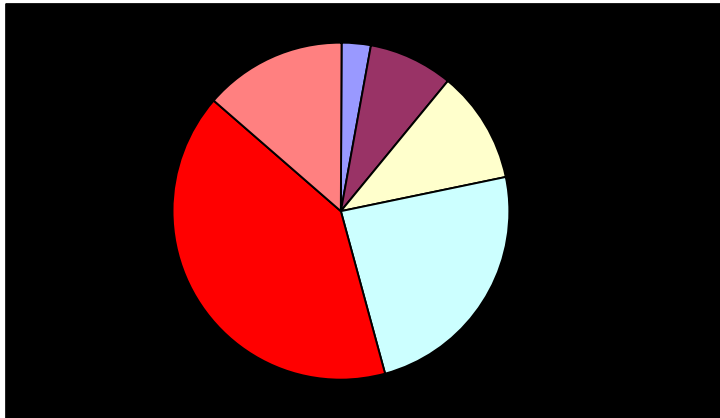


States Dr. Abeer Mahmoud
(course coordinator)





GA Parent Selection - Roulette Wheel



- Sum the fitnesses of all the population members, TF
- Generate a random number, m , between 0 and TF
- Return the **first population member** whose fitness added to the preceding population members is greater than or equal to m

Roulette Wheel Selection

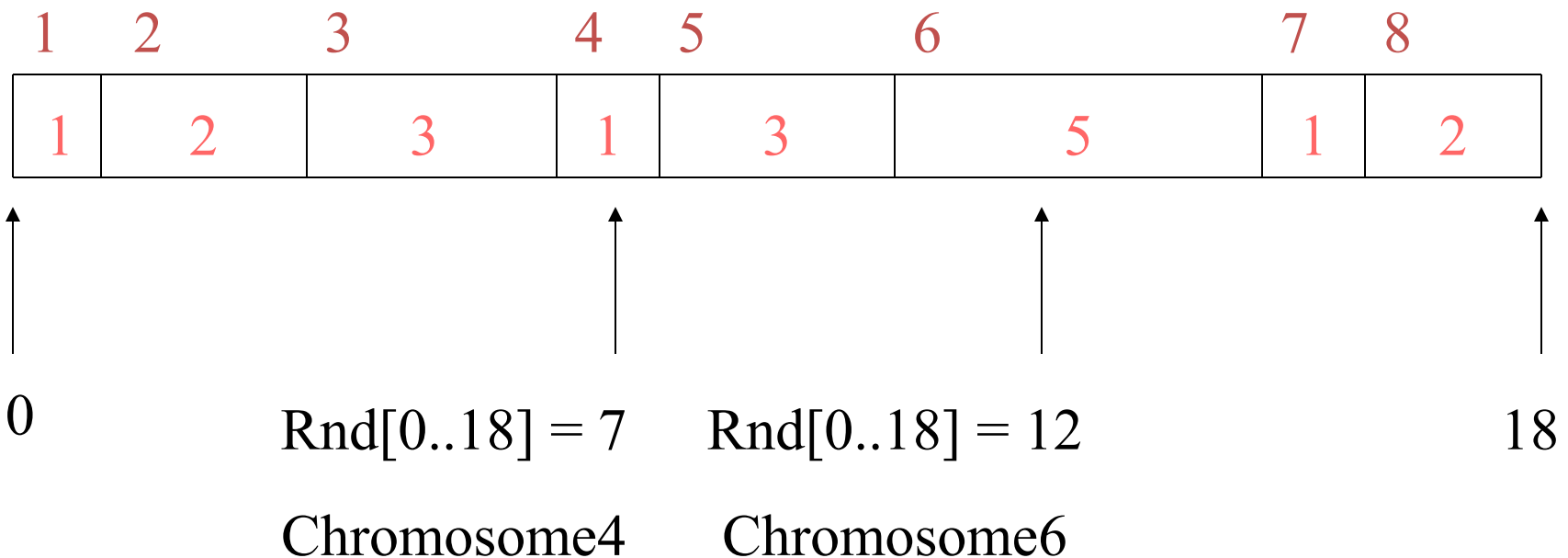




Genetic Algorithms: Selection

How are individuals selected ?

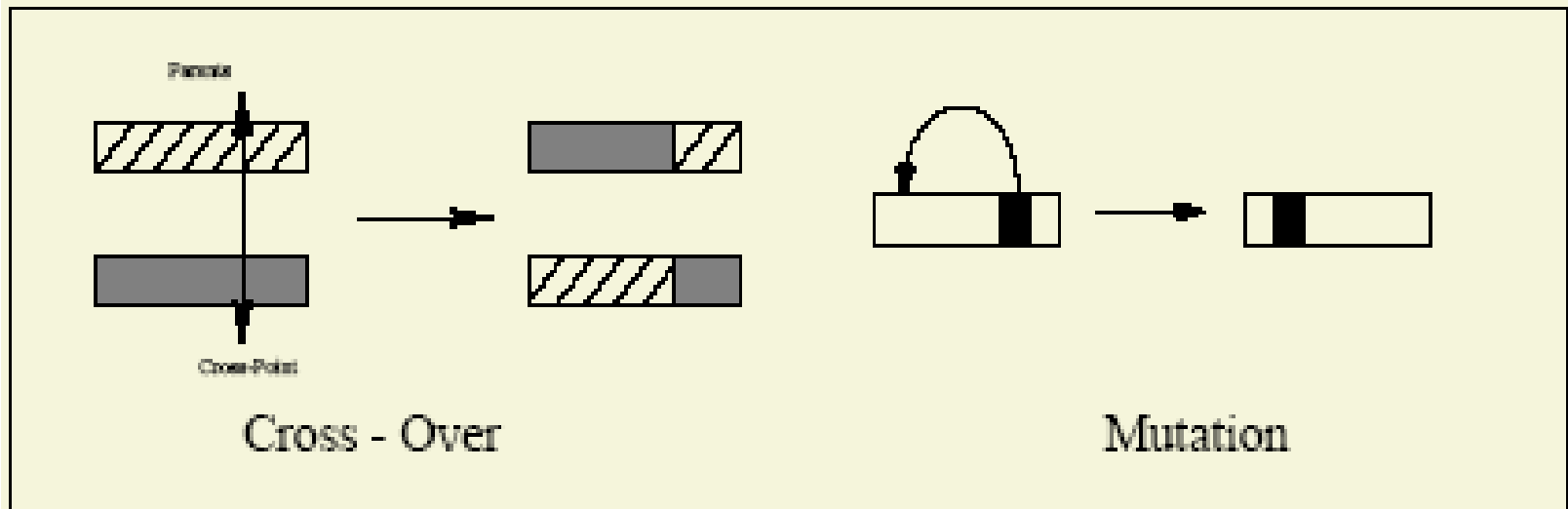
Roulette Wheel Selection





Genetic Algorithms: Cross-Over and Mutation

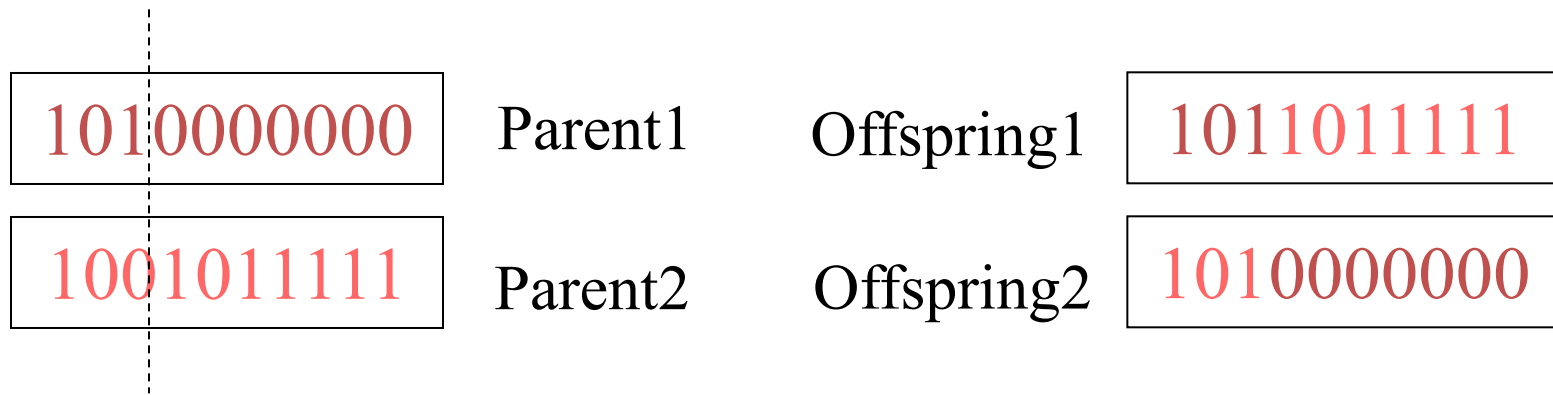
How do individuals reproduce ?





Genetic Algorithms

Crossover - Recombination



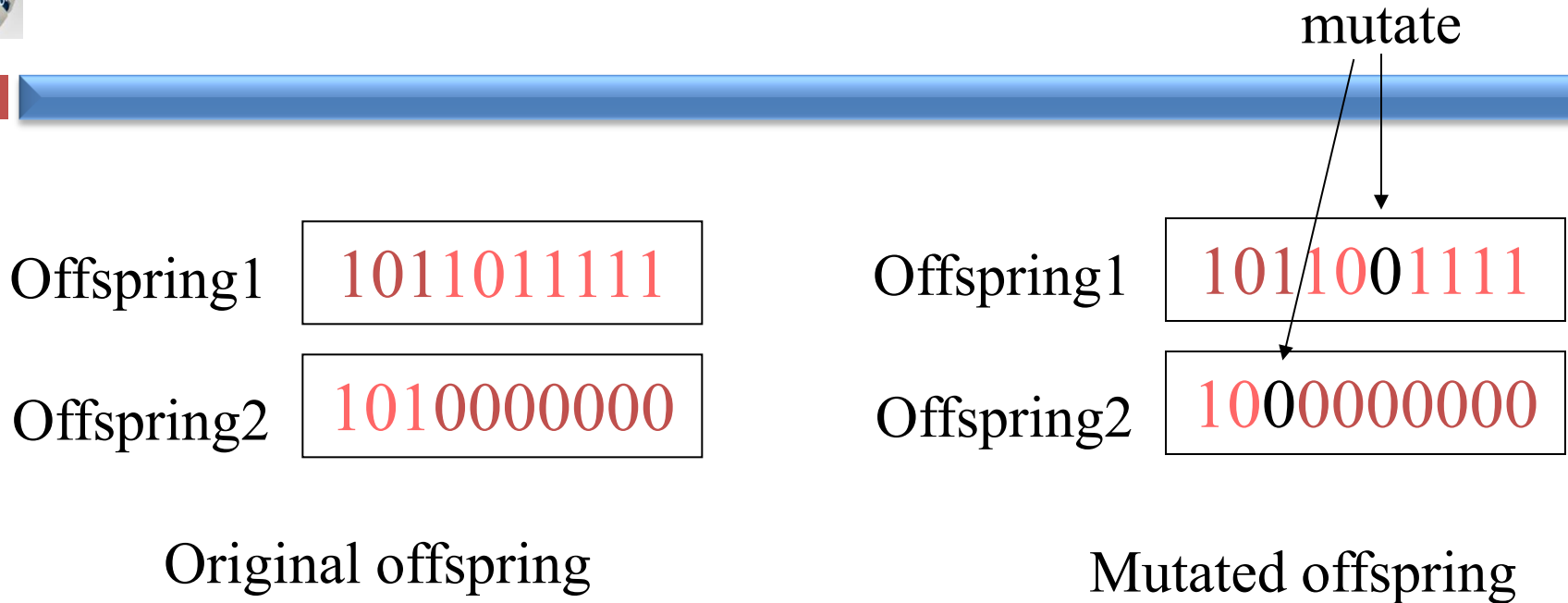
Crossover
single point -
random

With some high probability (*crossover rate*) apply crossover to the parents.
(*typical values are 0.8 to 0.95*)





Stochastic Search: Genetic Algorithms Mutation



With some small probability (the *mutation rate*) flip each bit in the offspring (*typical values between 0.1 and 0.001*)





- Given the following parents, P_1 and P_2 , and the template T
- Show how the following crossover operators work uniform crossover

P_1	A	B	C	D	E	F	G	H	I	J
P_2	E	F	J	H	B	C	I	A	D	G
T	1	0	1	1	0	0	0	1	0	1

C_1	A	F	C	D	B	C	I	H	D	J
C_2	E	B	J	H	E	F	G	A	I	G





- If P_3 and P_2 are chosen as parents and we apply one point crossover show the resulting children, C_1 and C_2 . Use a crossover point of 1 (first digit)
- Do the same using P_4 and P_2 with a crossover point of 2 (two digit) and create C_3 and C_4
- Do multiple point crossover using parent P_1 and P_3 to give C_5 and C_6 on digits 1 and 4

Chromosome	Binary String
P_1	11100
P_2	01111
P_3	10111
P_4	00100

Chromosome	Binary String
C_1	11111
C_2	00111
C_3	00111
C_4	01100

C_5	10110
C_6	11101





Genetic Algorithms

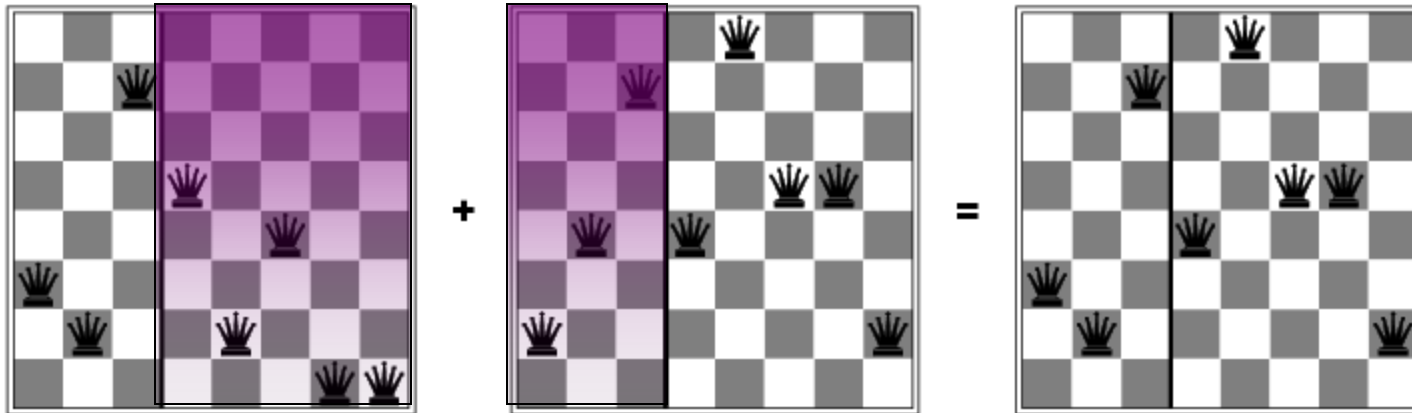
Algorithm:

1. Initialize population with p Individuals at random
2. For each Individual h compute its fitness
3. While max fitness $<$ threshold do
 Create a new generation P_s
4. Return the Individual with highest fitness





Genetic algorithms



Has the effect of “jumping” to a completely different new part of the search space (quite non-local)





Thank you



**End of
Chapter 4**

