

SWARM INTELLIGENCE

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WHY?



WHAT KIND OF PROBLEMS?

WHAT KIND OF PROBLEMS?

Optimization

WHAT KIND OF PROBLEMS?

Optimization

Modeling

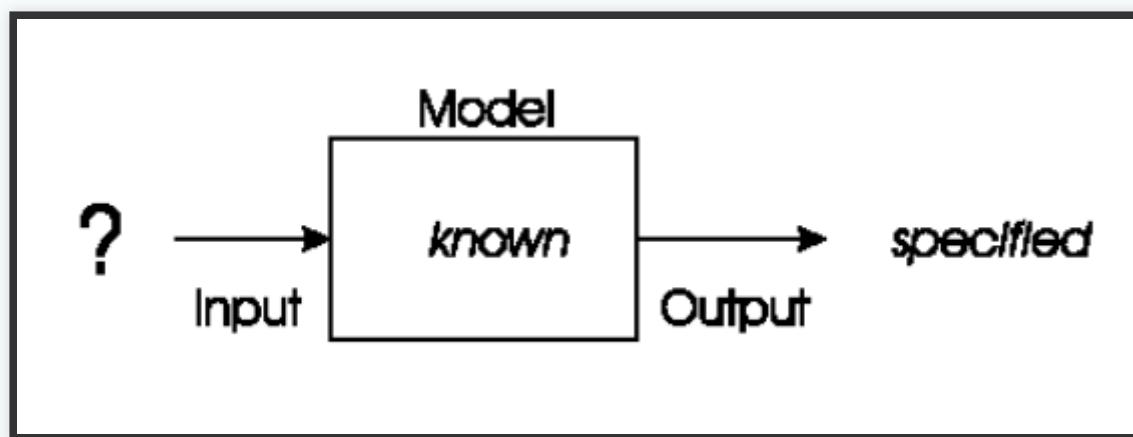
WHAT KIND OF PROBLEMS?

Optimization

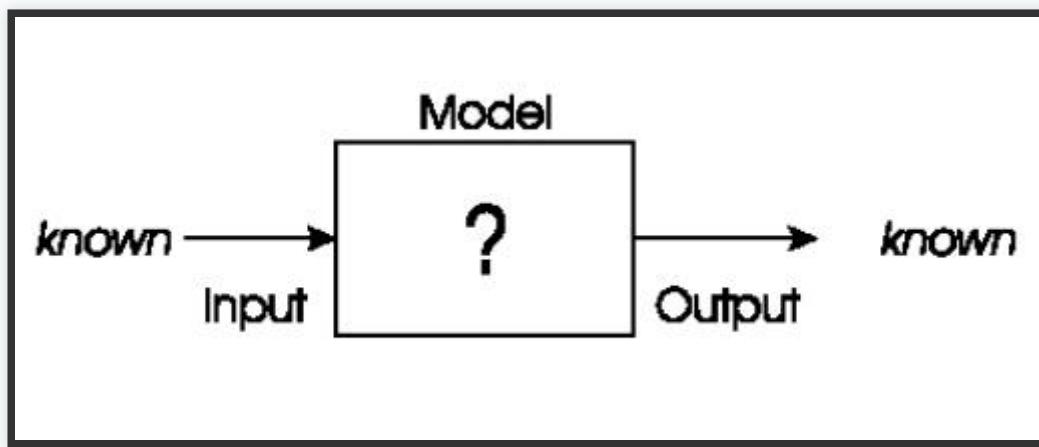
Modeling

Simulation

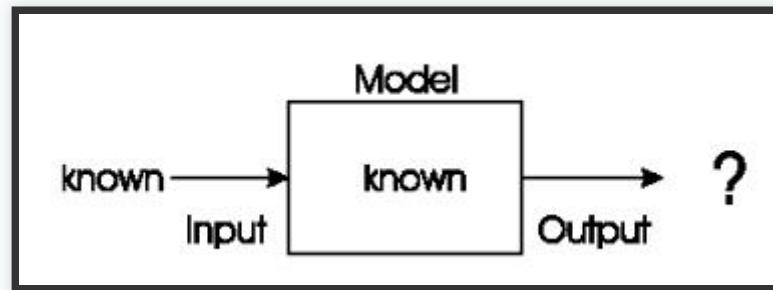
OPTIMIZATION



MODELING



SIMULATION



OPTIMIZATION



EXHAUSTIVE SEARCH



OTHER METHODS

OTHER METHODS

Analytical

OTHER METHODS

Analytical
Uninformed

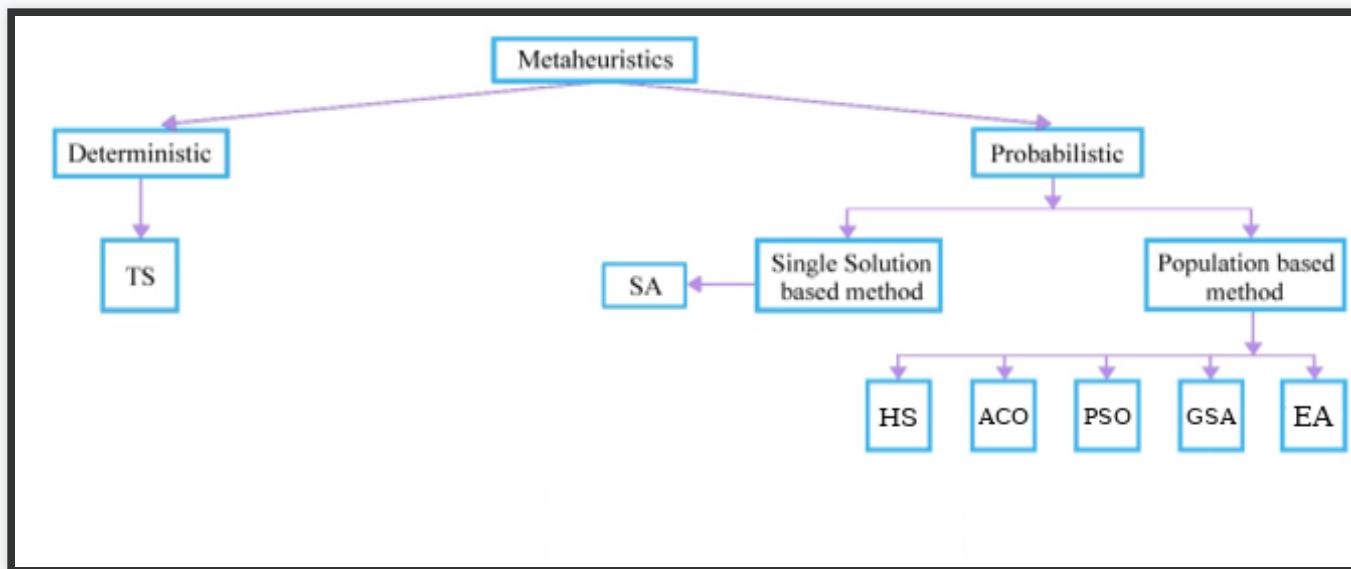
OTHER METHODS

Analytical

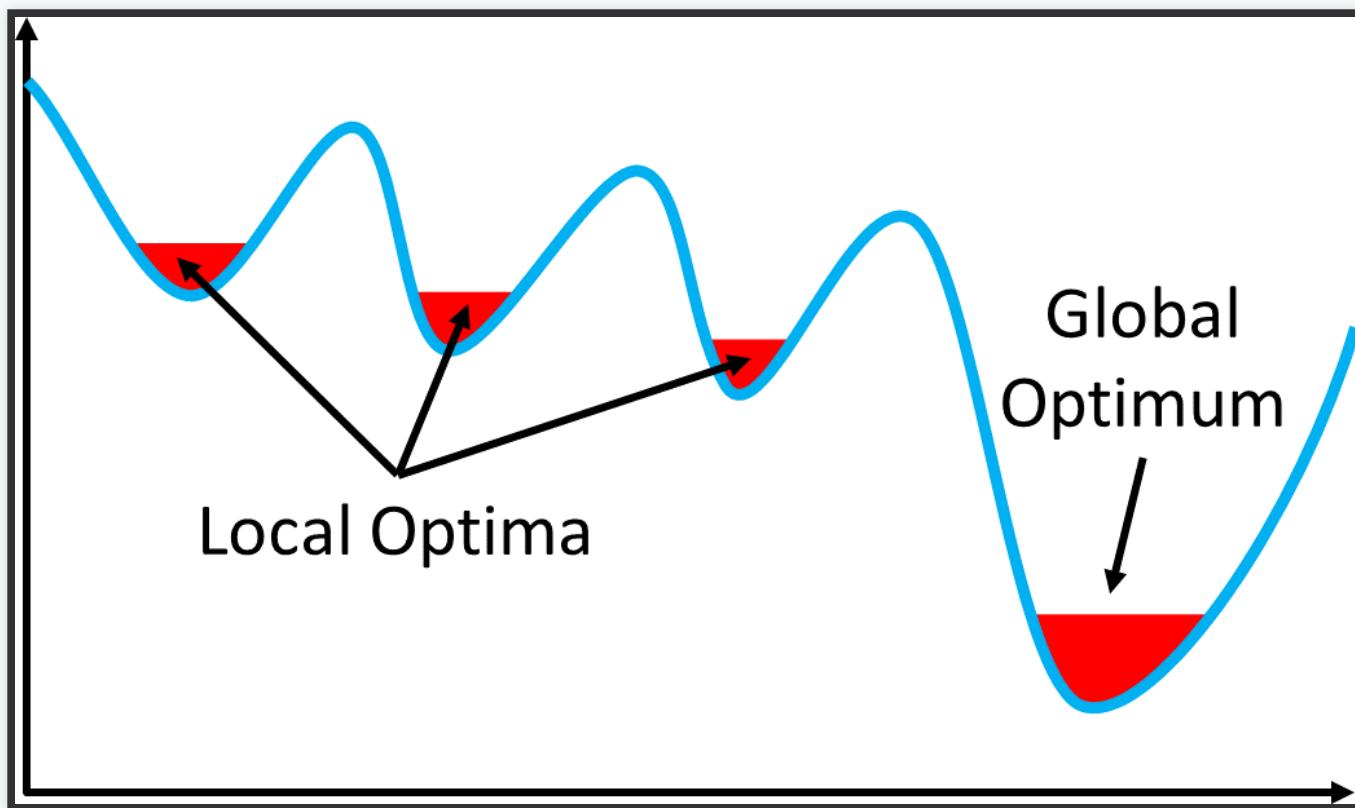
Uninformed

Informed

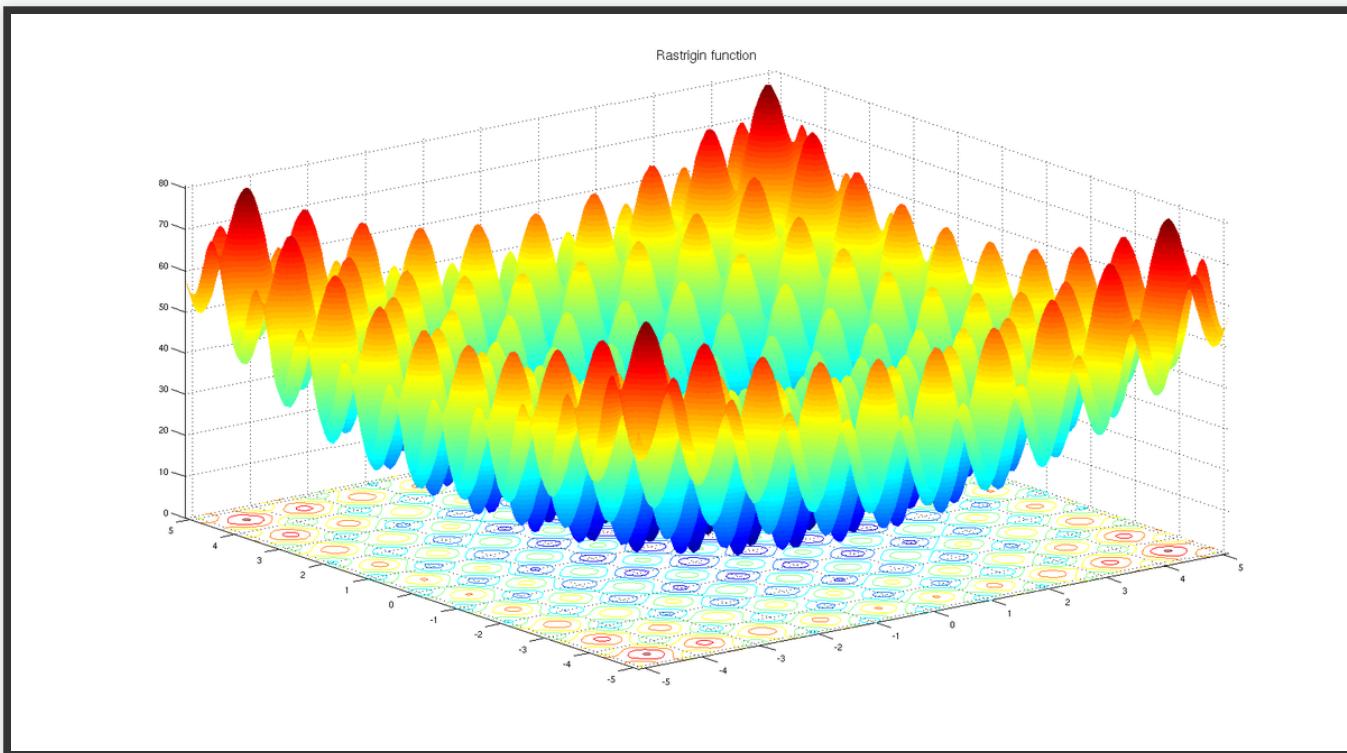
METAHEURISTIC



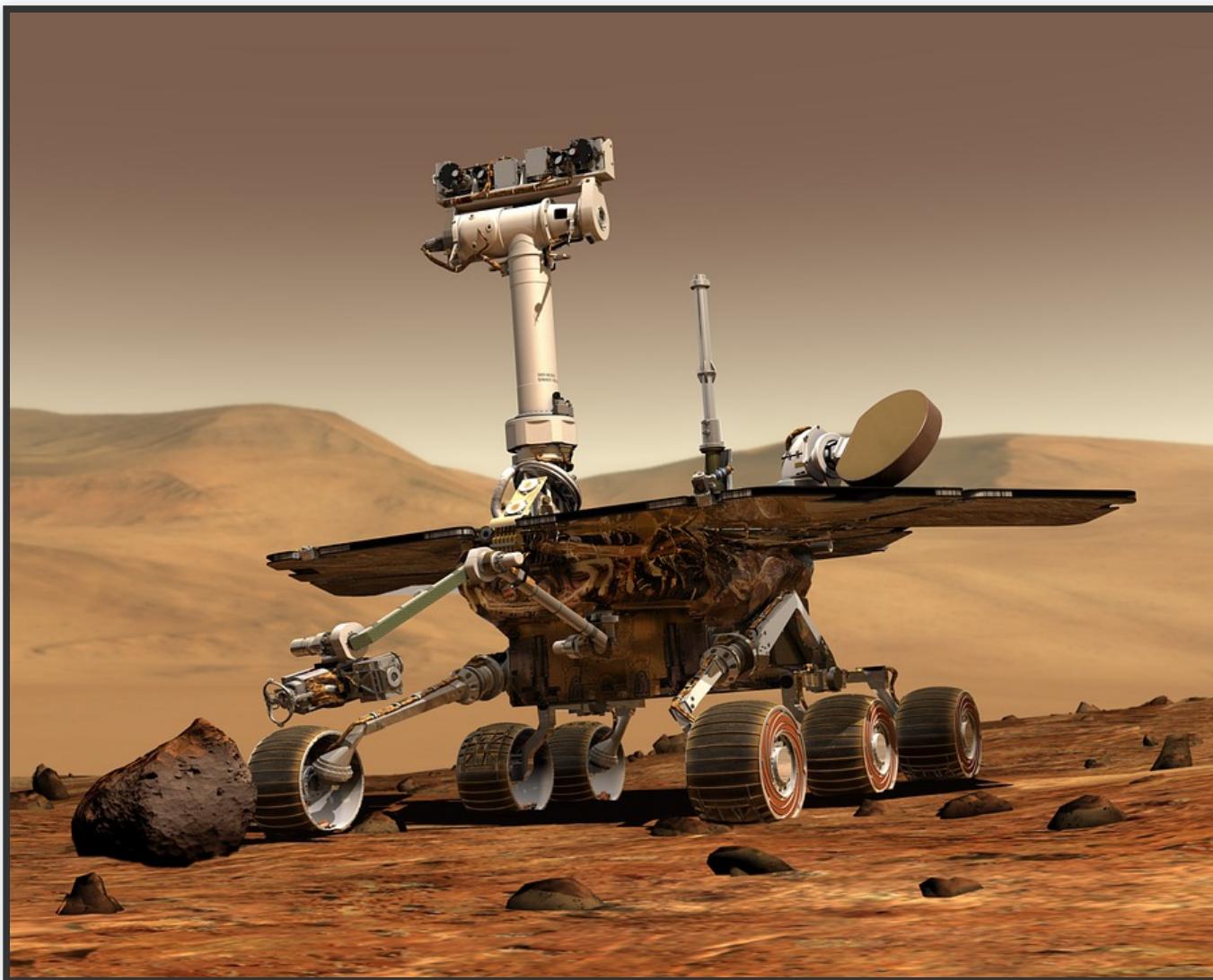
LOCAL & GLOBAL OPTIMUM



COMPLEX SPACES



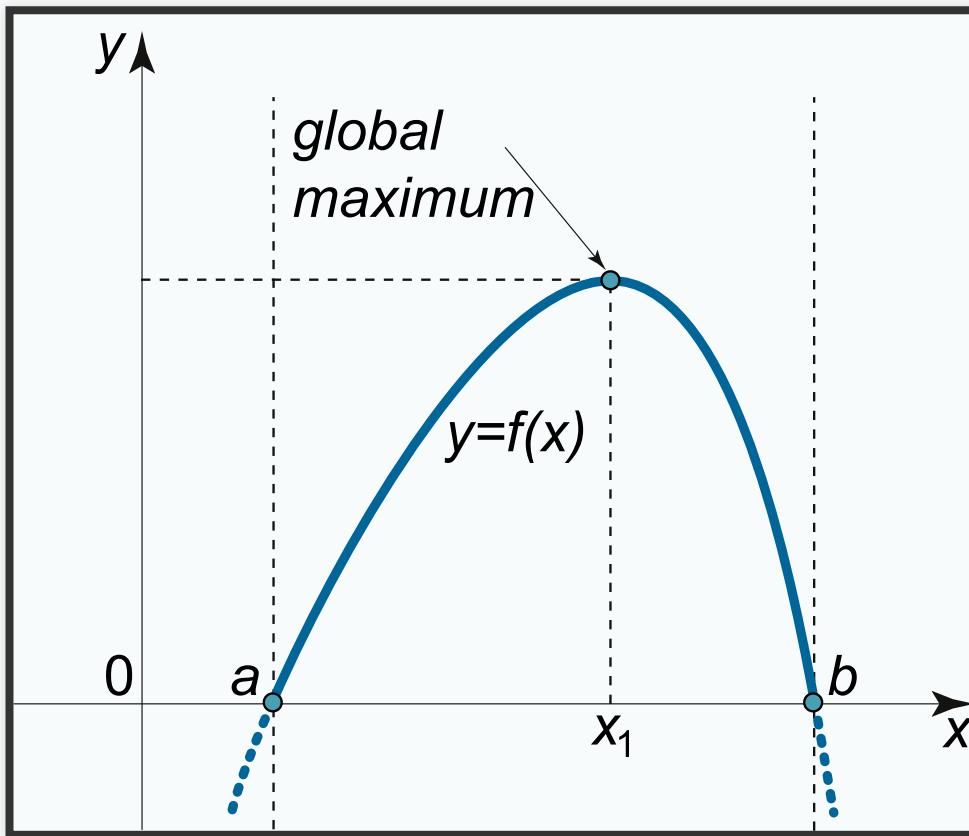
EXPLORATION



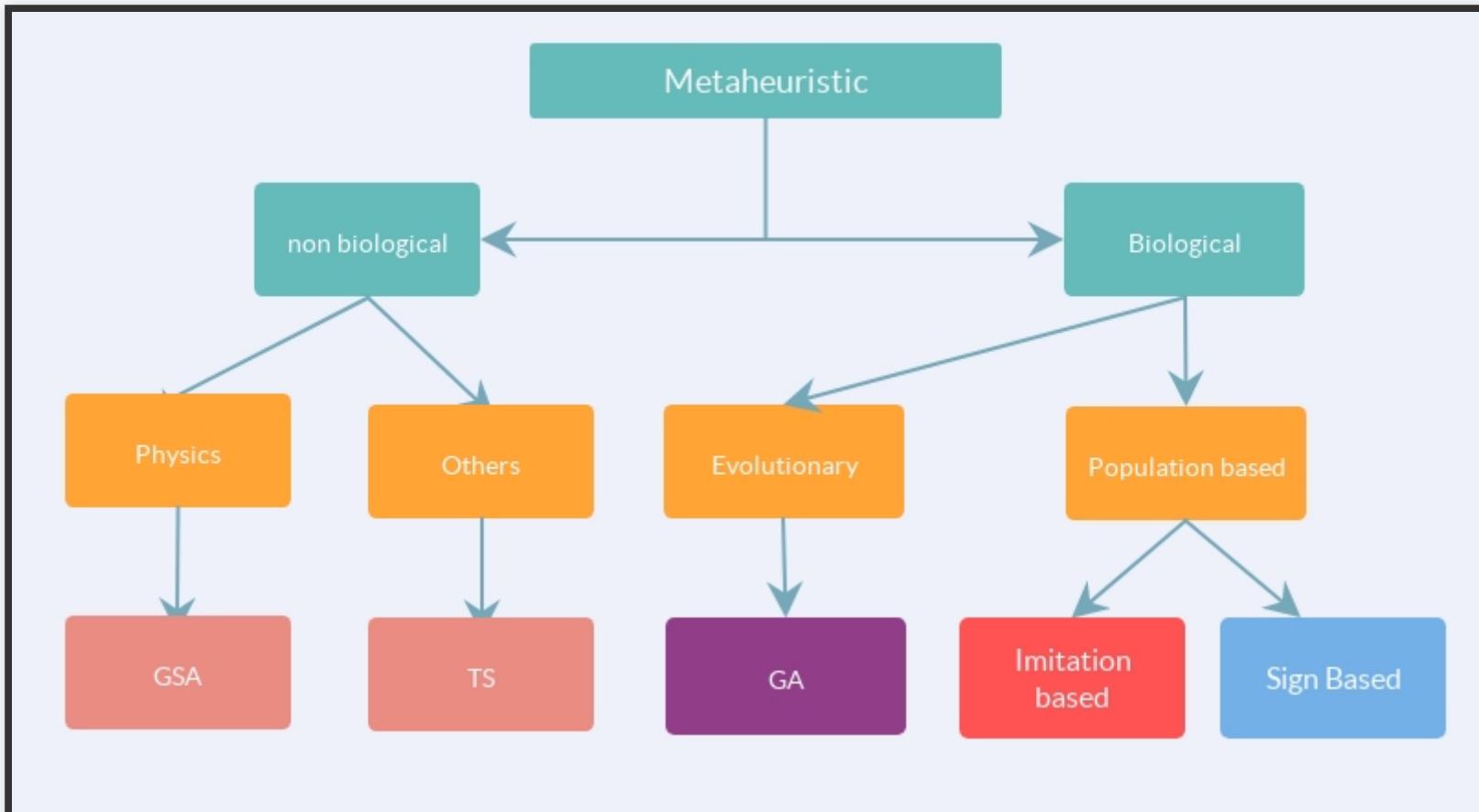
EXPLOITATION



EXPLOITATION



CATEGORIES



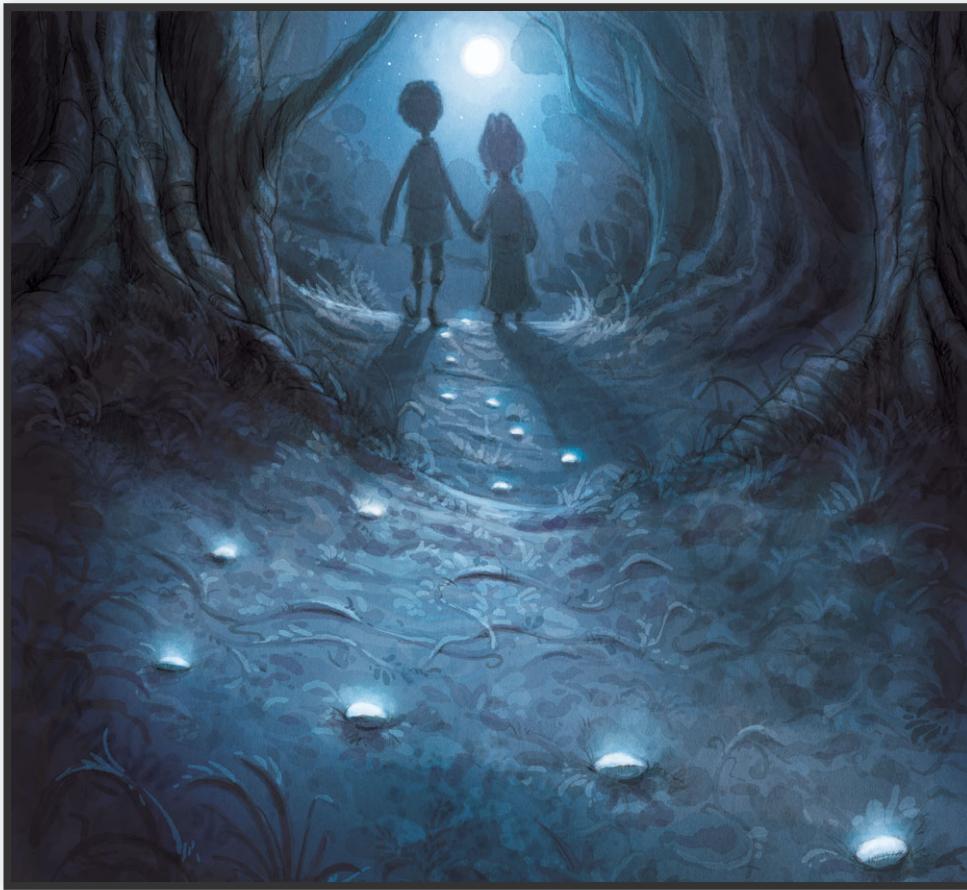
SWARM



GOAL

Is to model their simple behaviors to findout about more complex behaviors.

SIGN BASED ALGORITHMS



STEPS

STEPS

1. Init memory

STEPS

1. Init memory
2. Generate a solution

STEPS

1. Init memory
2. Generate a solution
3. Calculate the fitness of generated solution

STEPS

1. Init memory
2. Generate a solution
3. Calculate the fitness of generated solution
4. Continue this for all population

STEPS

1. Init memory
2. Generate a solution
3. Calculate the fitness of generated solution
4. Continue this for all population
5. Update signs memory

STEPS

1. Init memory
2. Generate a solution
3. Calculate the fitness of generated solution
4. Continue this for all population
5. Update signs memory
6. Repeat until stop condition meets

ACO

ACO

Marco Dorigo (1992)

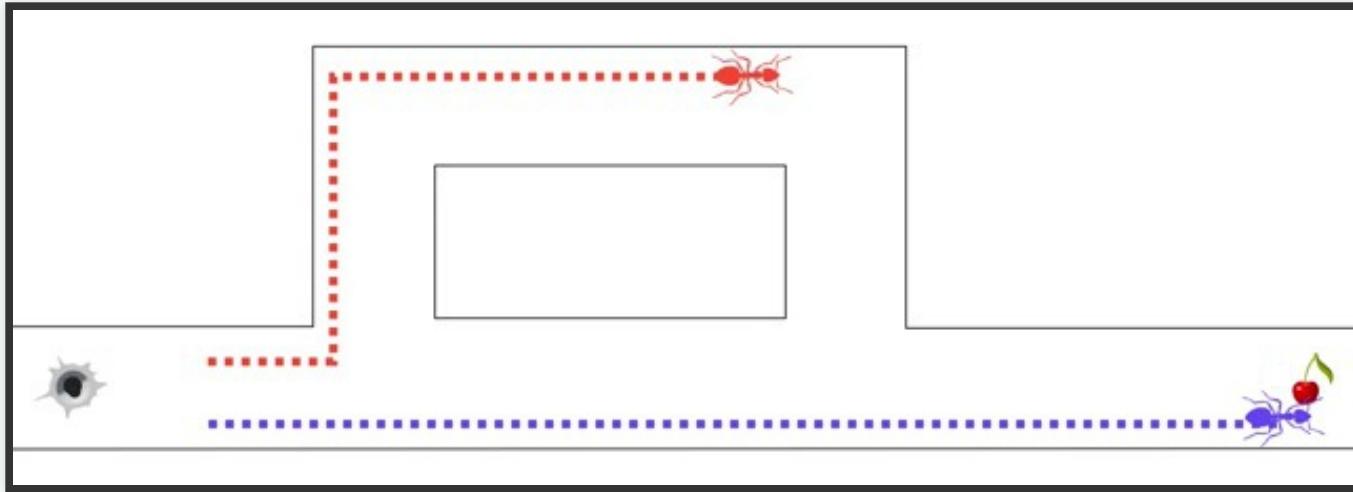
ACO

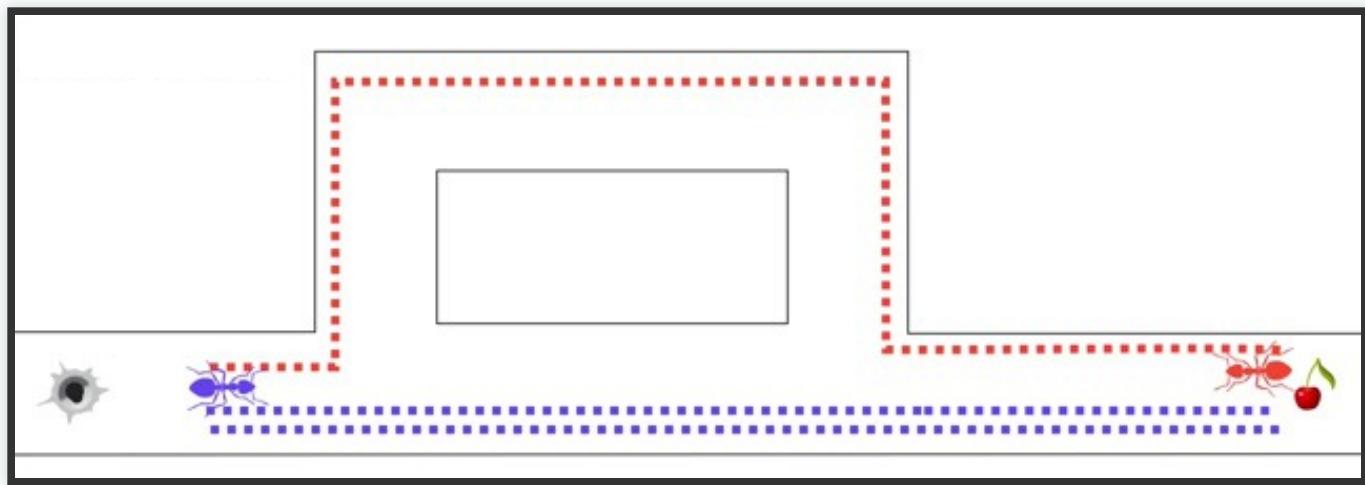
Marco Dorigo (1992)

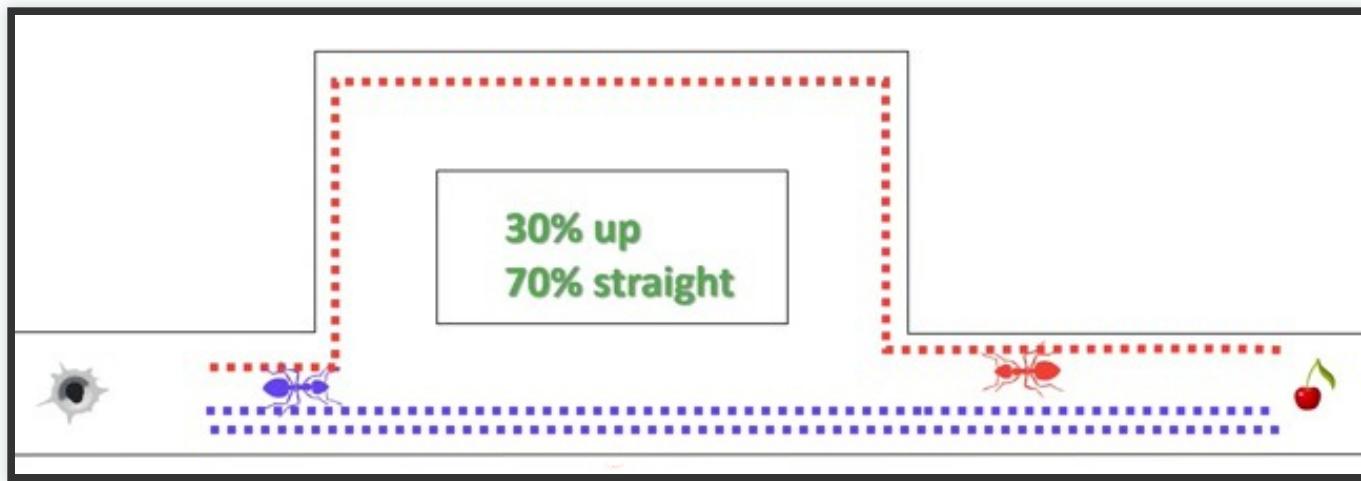
Finding good paths through graphs

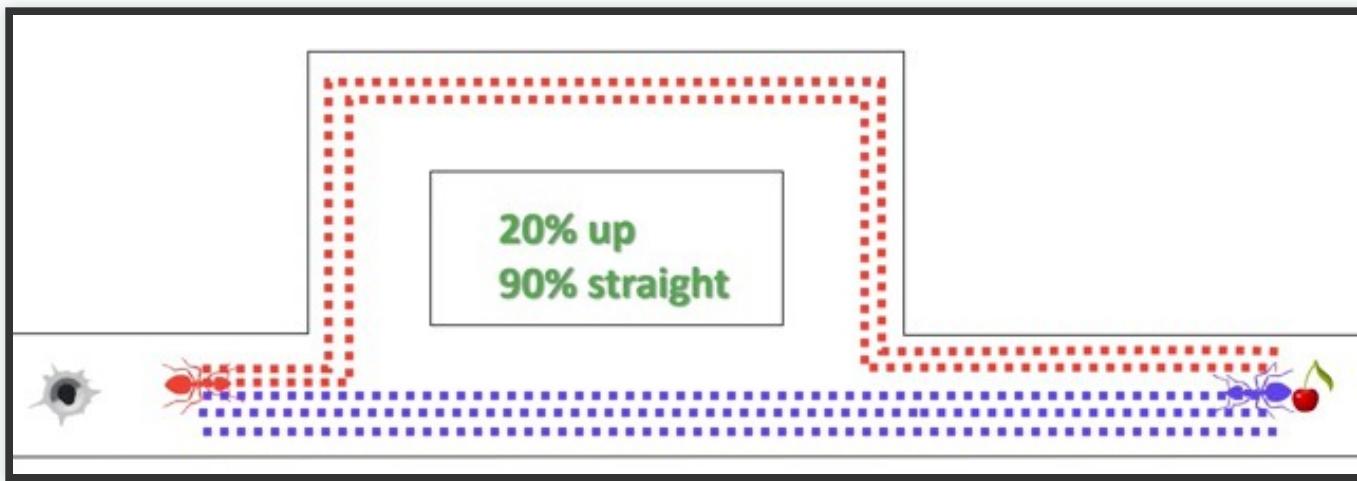
HOW IT WORKS?

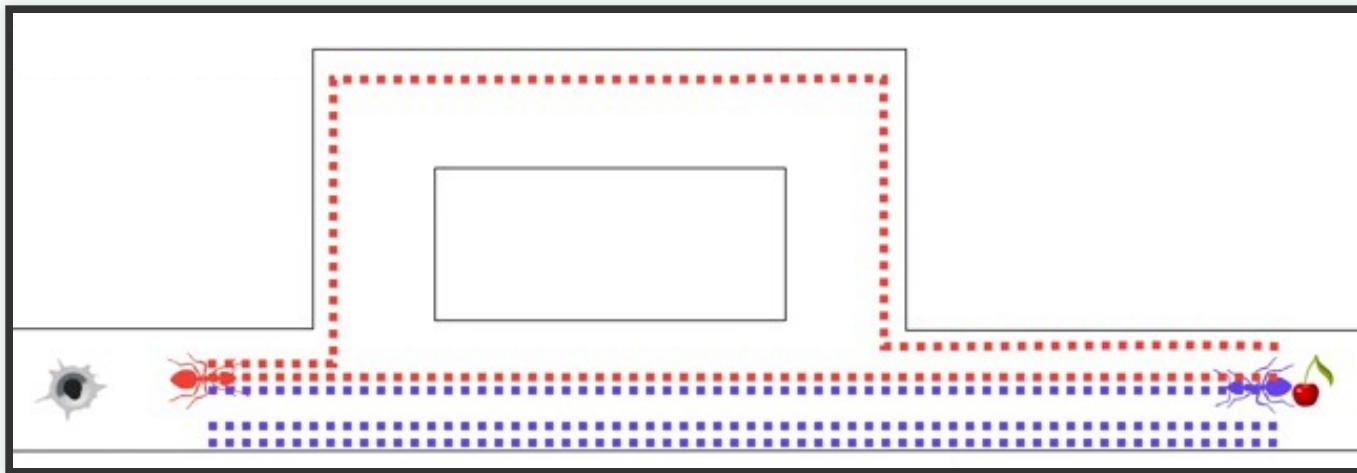


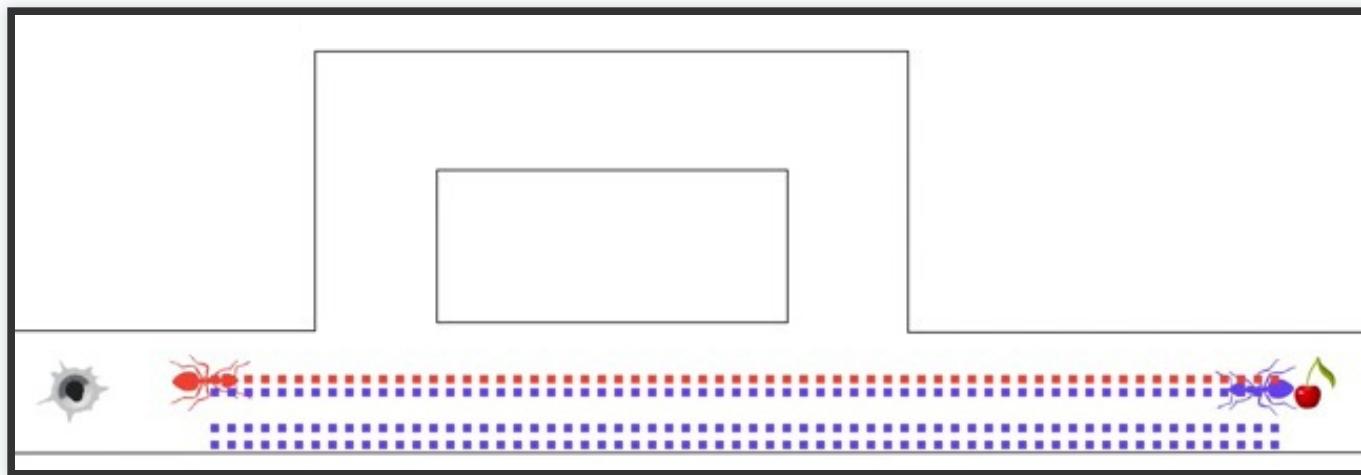


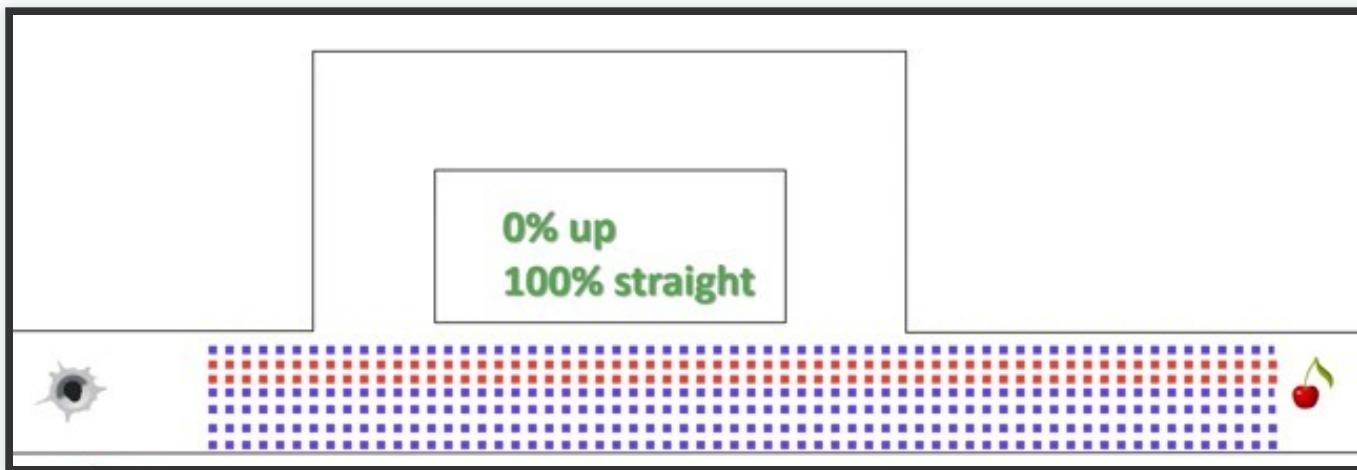


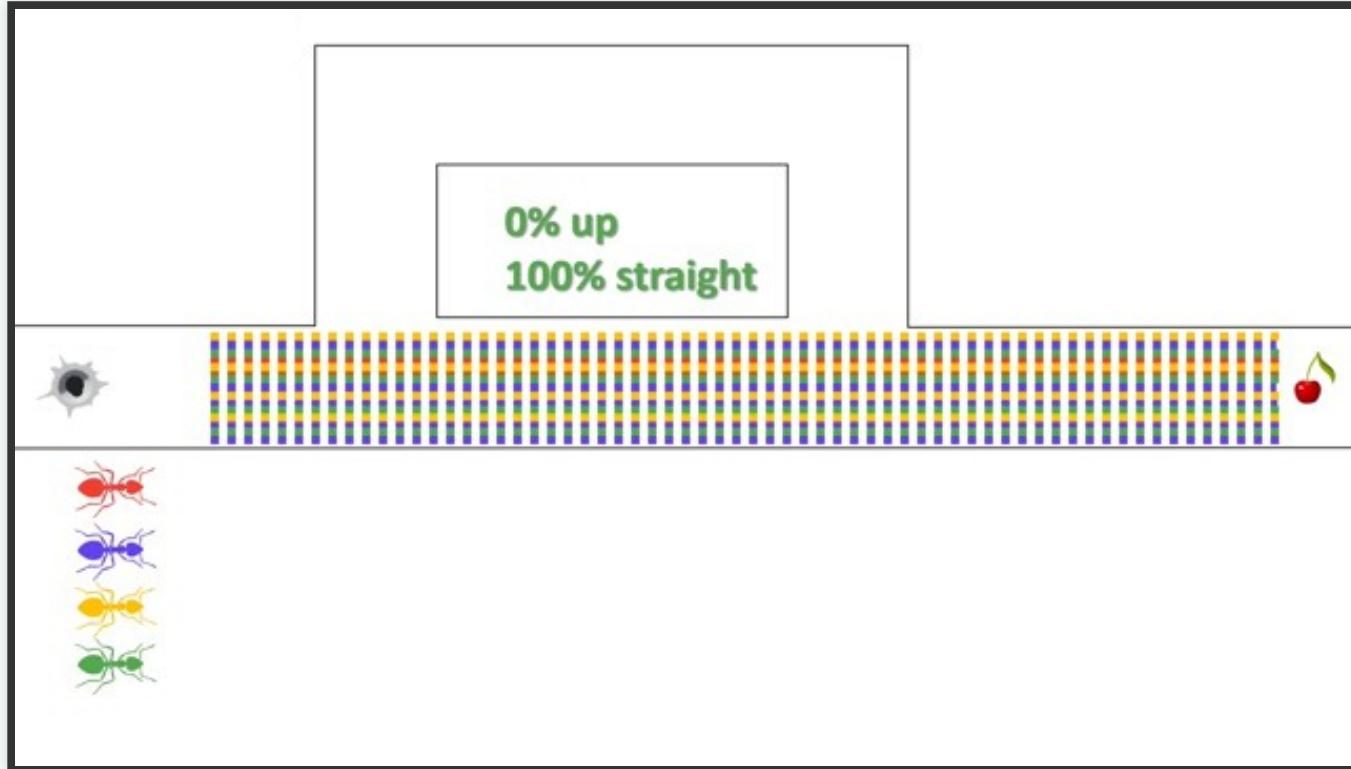












ACO ADVANTAGES

Search among a population in parallel

Can give rapid discovery of good solutions

Can adapt to changes in graph

ACO ADVANTAGES

Search among a population in parallel

Can give rapid discovery of good solutions

Can adapt to changes in graph

ACO DISADVANTAGES

Prone to stagnation

Premature convergence

Uncertain converge time

Long calculation time

Solutions might be far from optimum

IMITATION BASED ALGORITHMS



STEPS

STEPS

1. Init Parameters

STEPS

1. Init Parameters
2. Init Population

STEPS

1. Init Parameters
2. Init Population
3. Move Particles

STEPS

1. Init Parameters
2. Init Population
3. Move Particles
4. Calculate the fitness

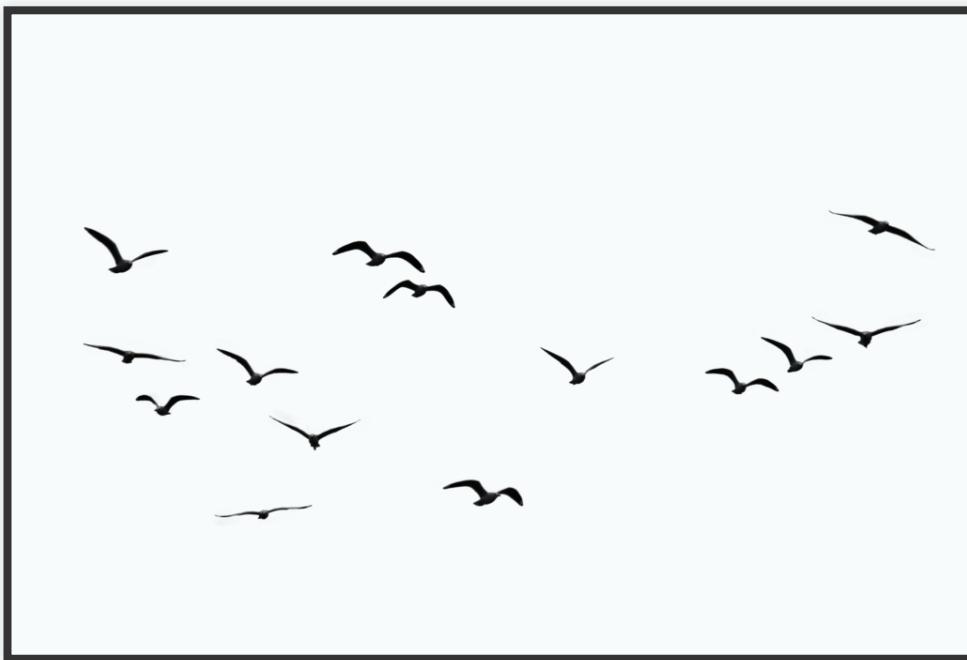
STEPS

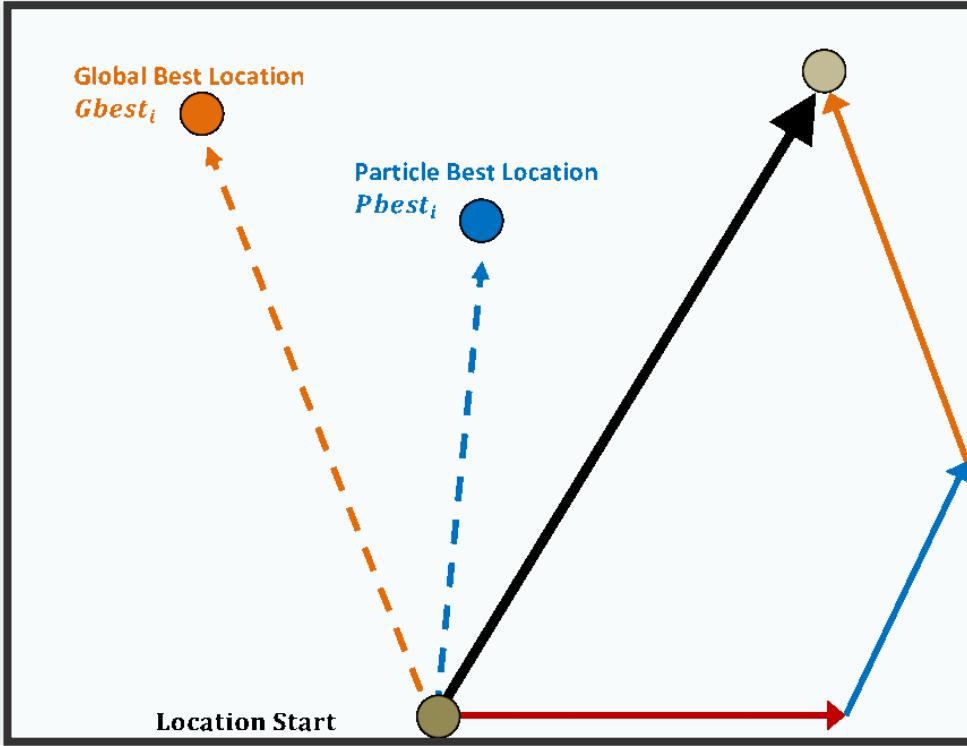
1. Init Parameters
2. Init Population
3. Move Particles
4. Calculate the fitness
5. Update particles memories

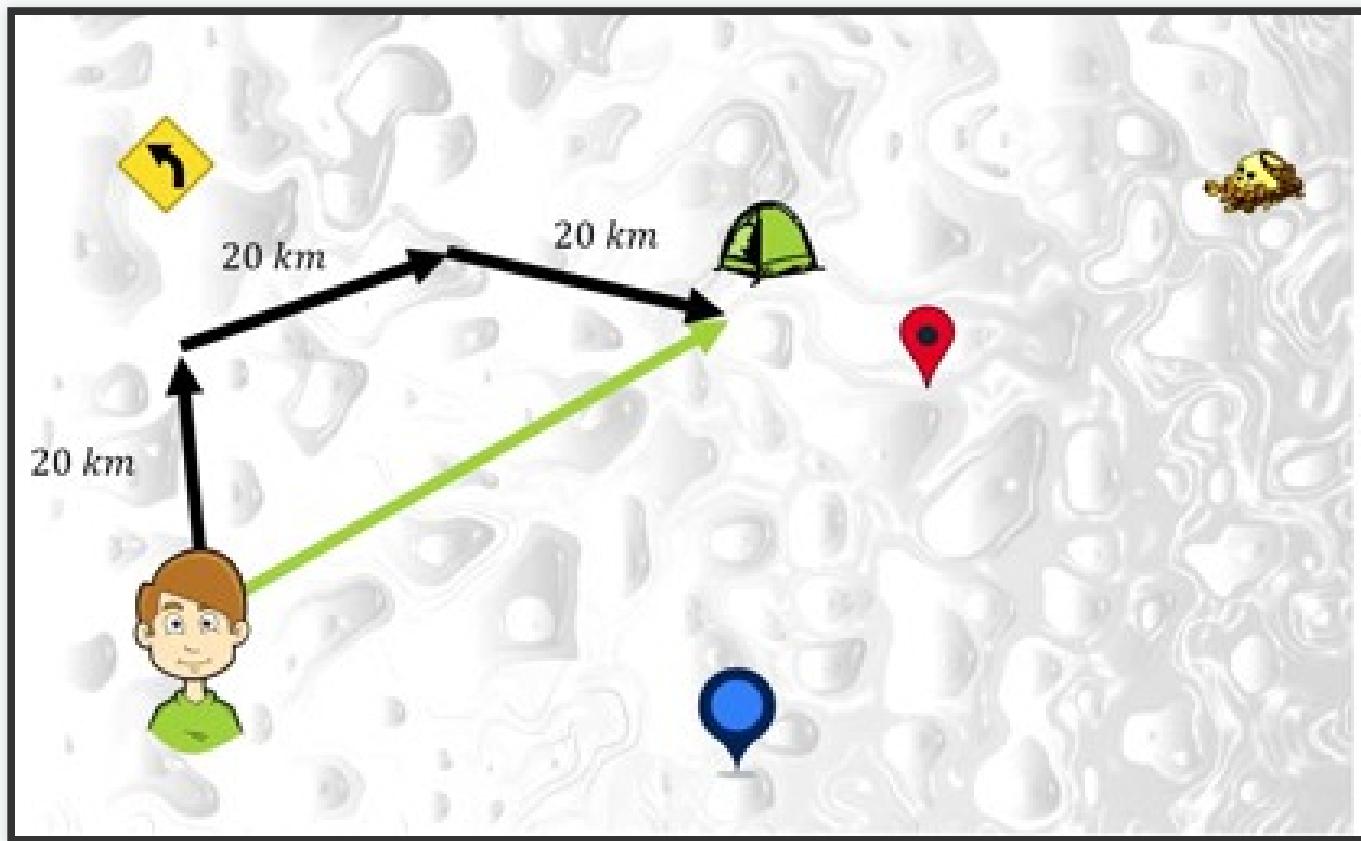
STEPS

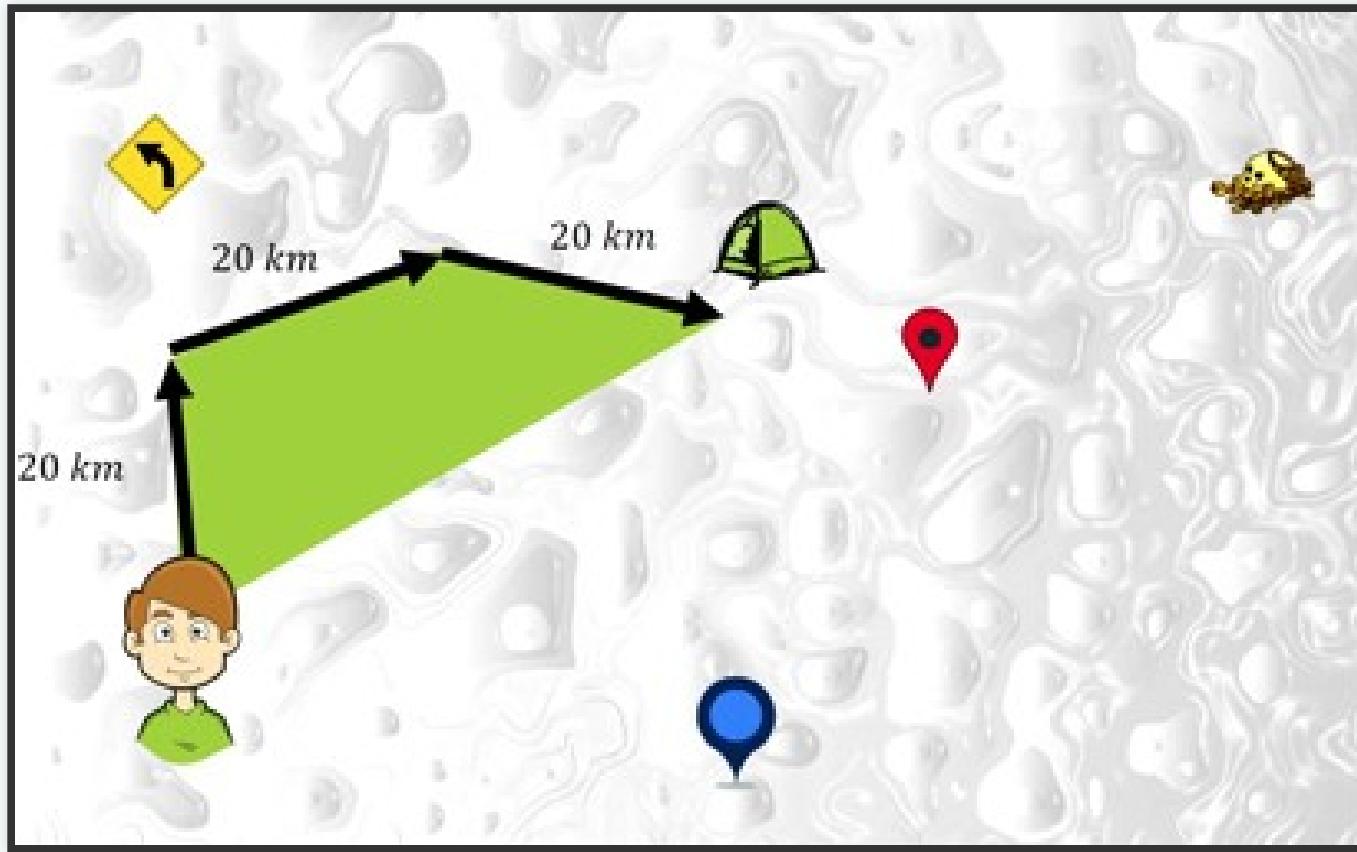
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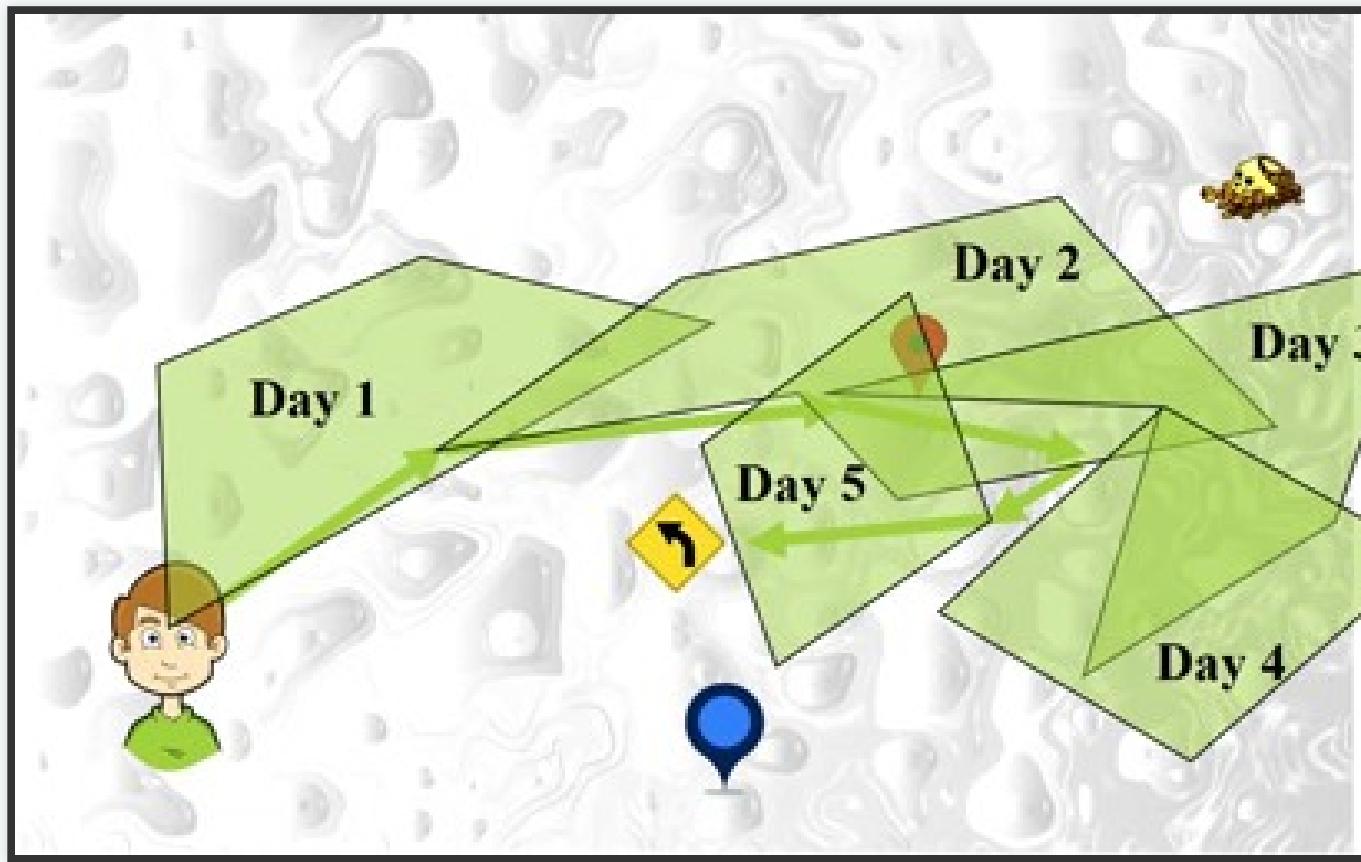
PSO

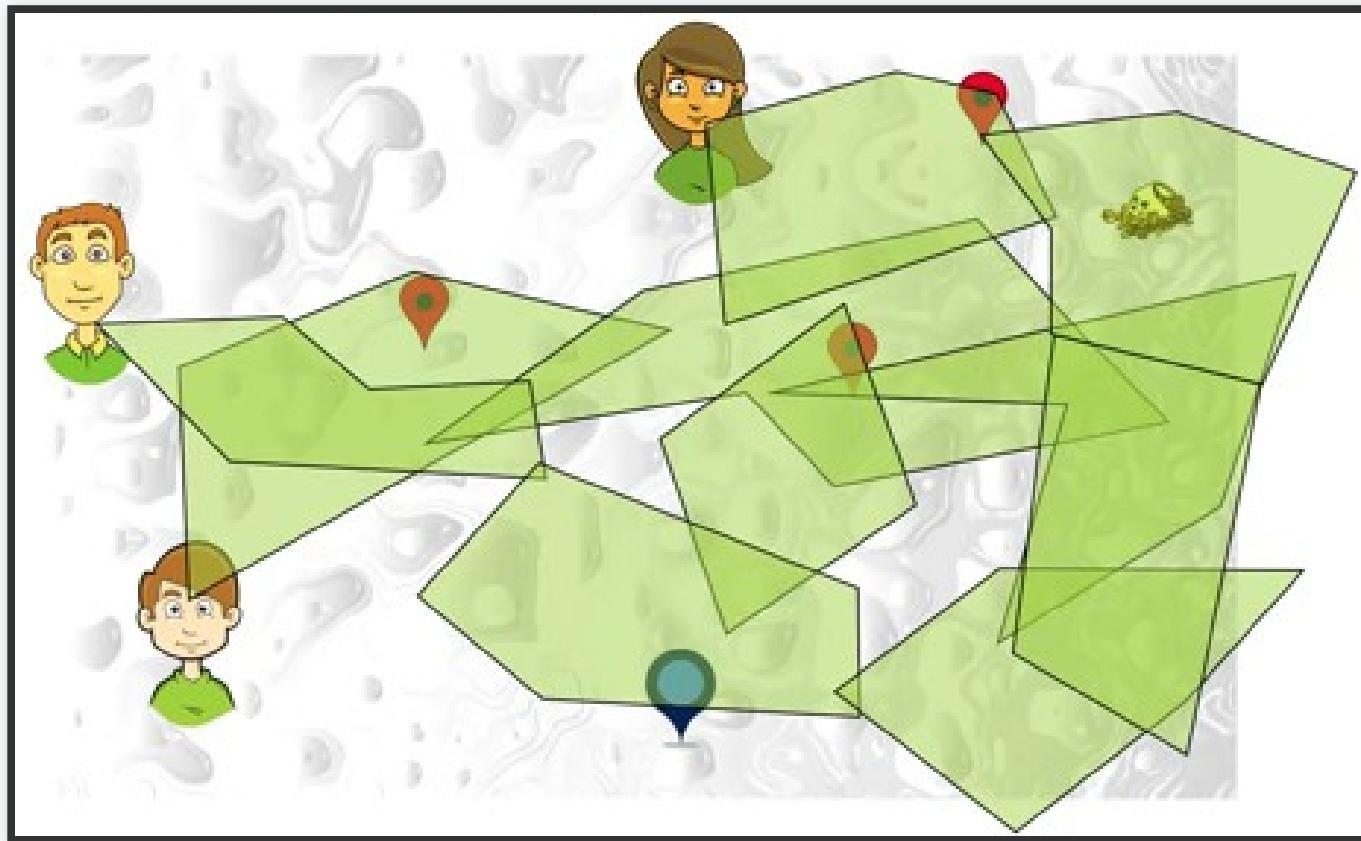


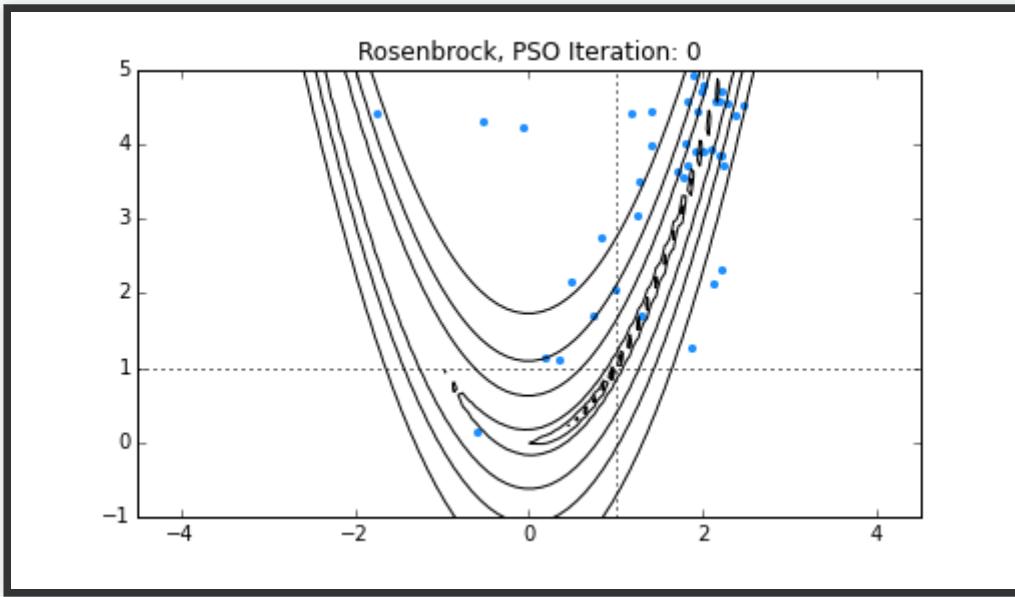


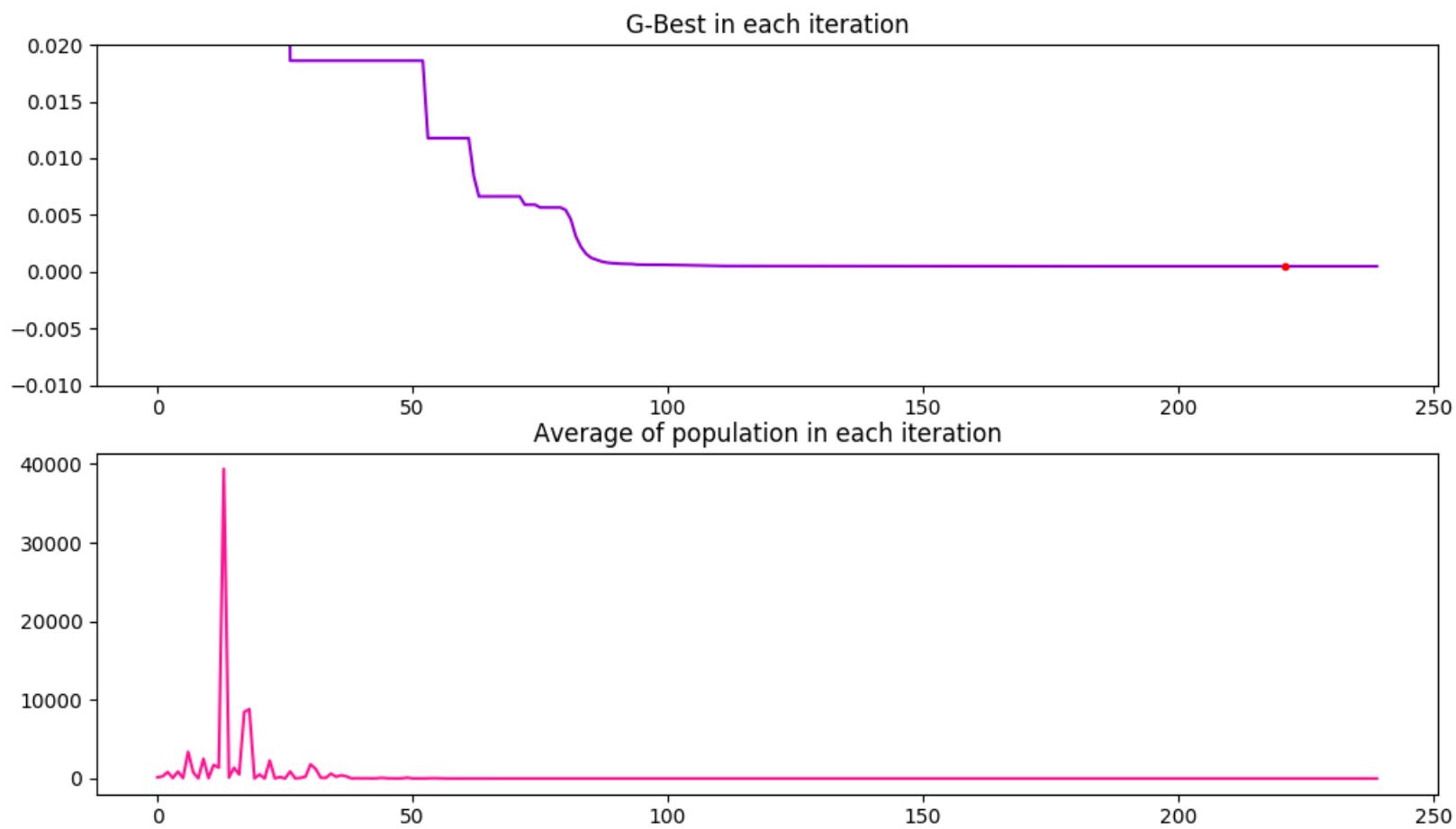












PSO ADVANTAGES

PSO ADVANTAGES

Fast

PSO ADVANTAGES

Fast

Easy to implement

PSO ADVANTAGES

Fast

Easy to implement

No complex calculations

PSO ADVANTAGES

Fast

Easy to implement

No complex calculations

Doesn't have so much parameters

PSO DISADVANTAGES

PSO DISADVANTAGES

Prone to premature convergence

LET'S HAVE A LOOK TO
OTHER ALGORITHMS

HARMONY SEARCH



HARMONY SEARCH

HARMONY SEARCH

Init Harmony Memory (RANDOM)

HARMONY SEARCH

Init Harmony Memory (RANDOM)

Improvise NEW harmony

HARMONY SEARCH

Init Harmony Memory (RANDOM)

Improvise NEW harmony

If NEW is better than min(HM)

HARMONY SEARCH

Init Harmony Memory (RANDOM)

Improvise NEW harmony

If NEW is better than min(HM)

Replace(min(HM), NEW)

HARMONY SEARCH

Init Harmony Memory (RANDOM)

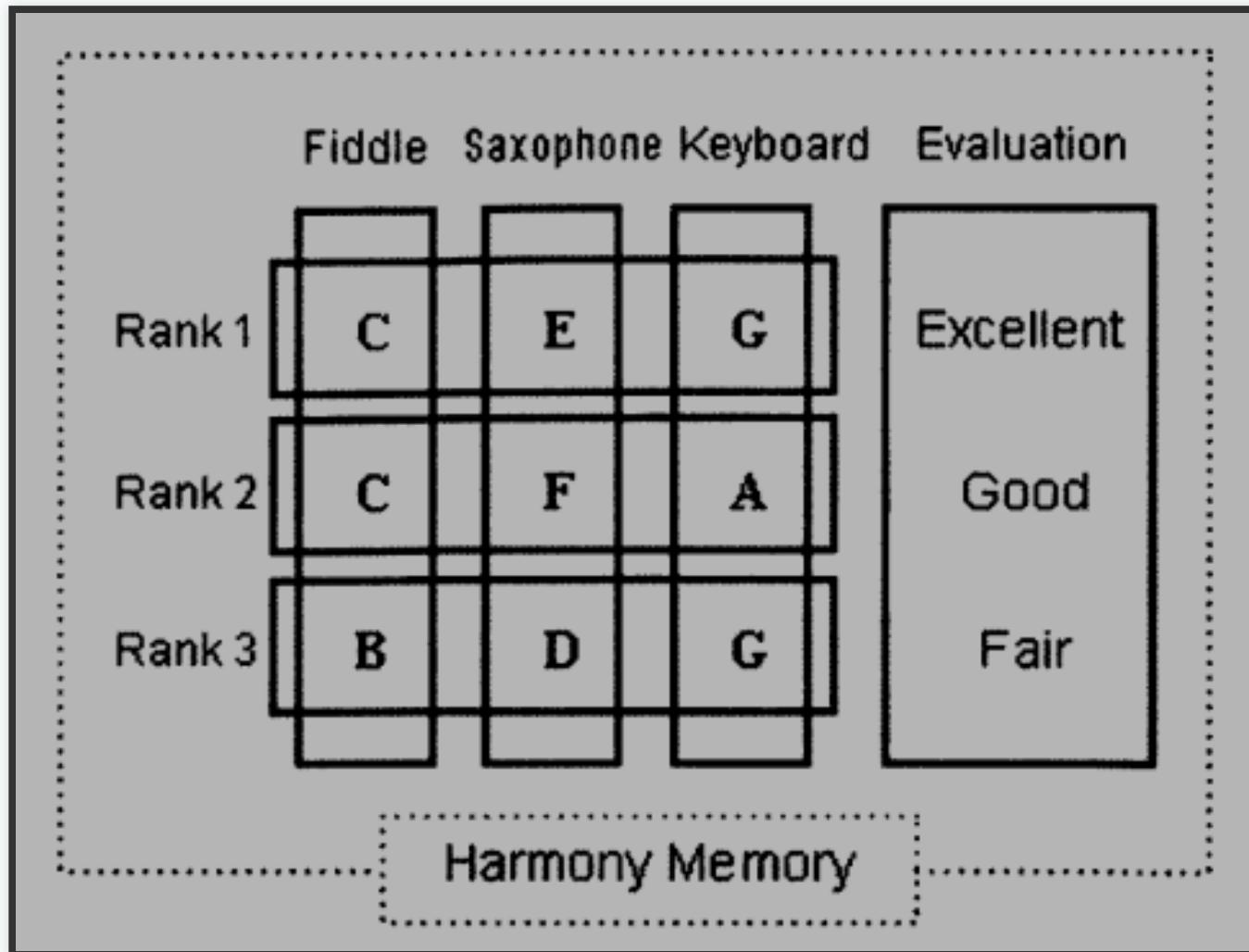
Improvise NEW harmony

If NEW is better than min(HM)

Replace(min(HM), NEW)

Loop till end condition meets

HARMONY SEARCH



HS ADVANTAGES

Quick convergence

Easy implementation

Less adjustable parameters

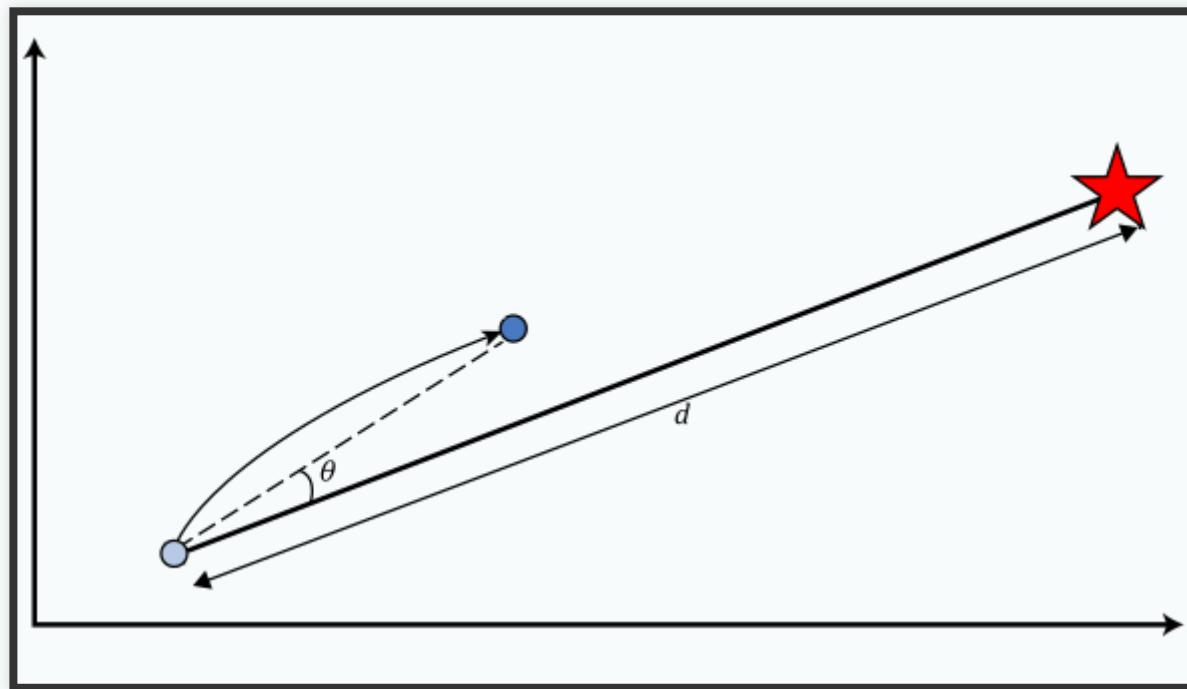
Fewer mathematical requirements

Generates a new solution, after considering all of
the existing solutions

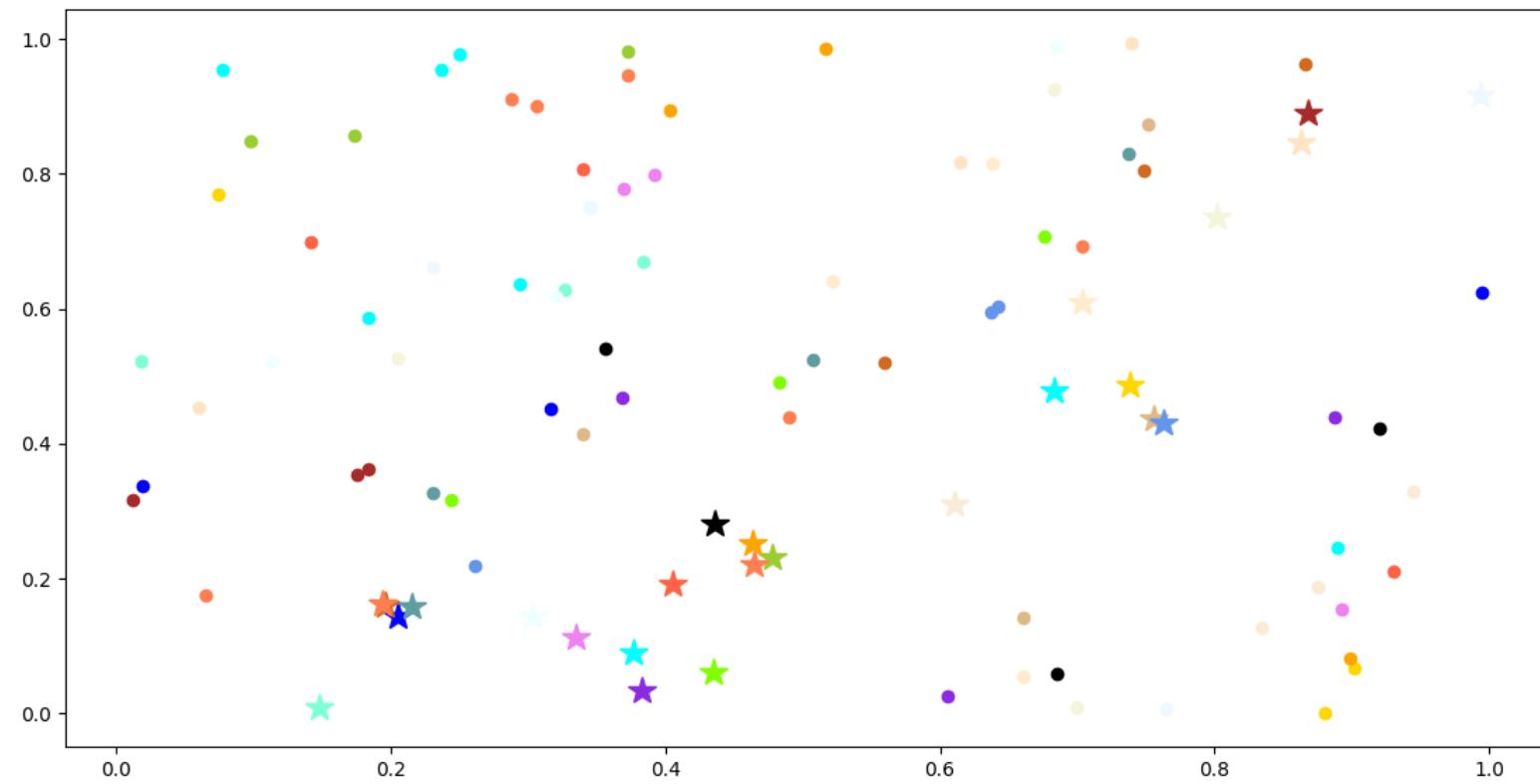
HS DISADVANTAGES

Premature convergence

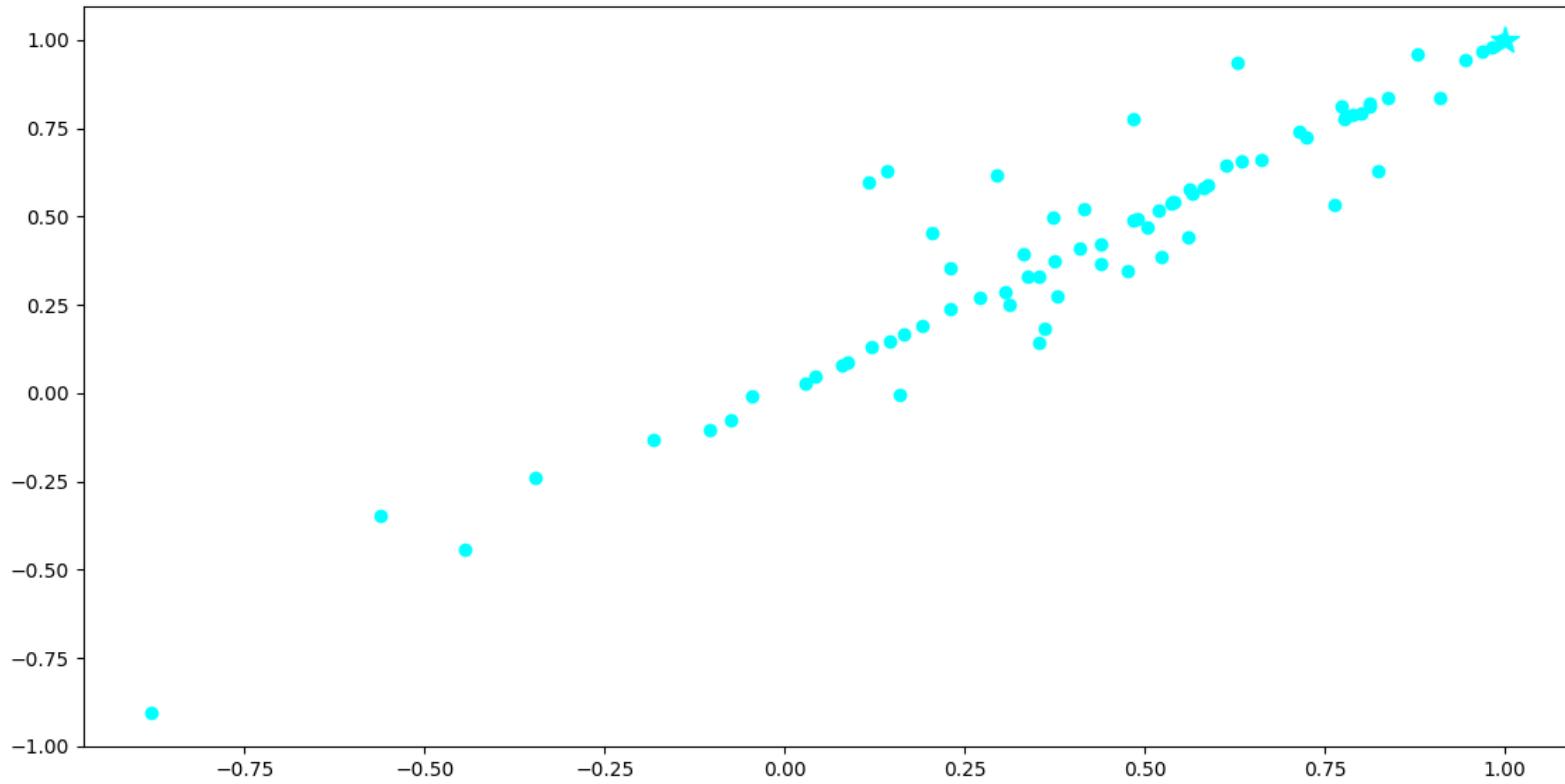
ICA



ICA



ICA



ICA PROS & CONS

PROS

Good speed

Same and better solutions compared with other
metaheuristic algorithms

PROS

Good speed

Same and better solutions compared with other metaheuristic algorithms

CONS

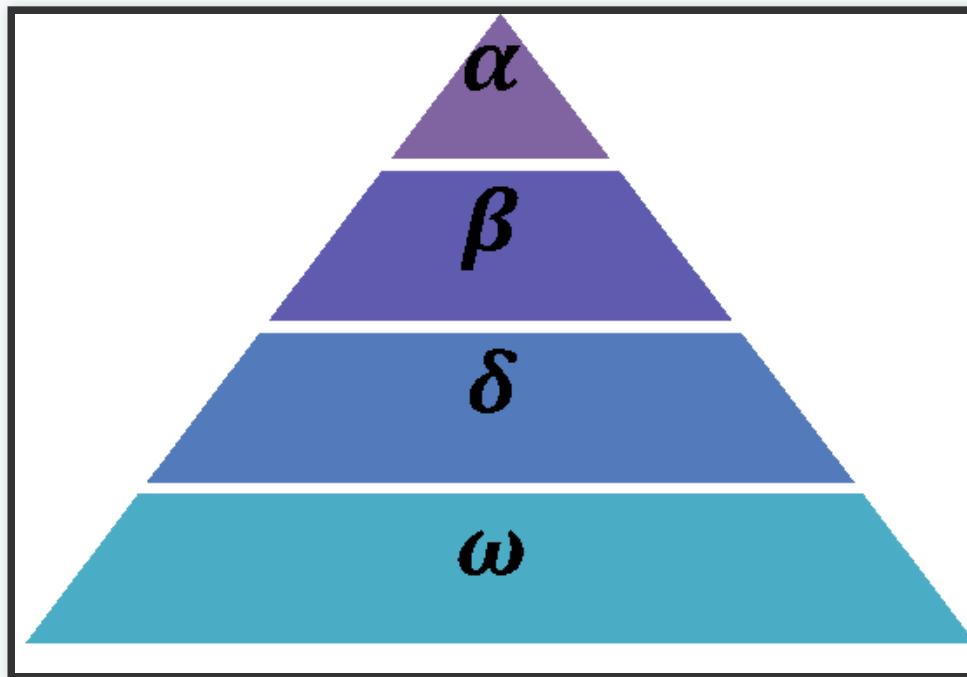
Complex implementation

GWO



Mimics leadership hierarchy of wolves

GWO HIERARCHY



SOCIAL BEHAVIOR OF GREY WOLVES

Tracking, chasing, and approaching the prey.

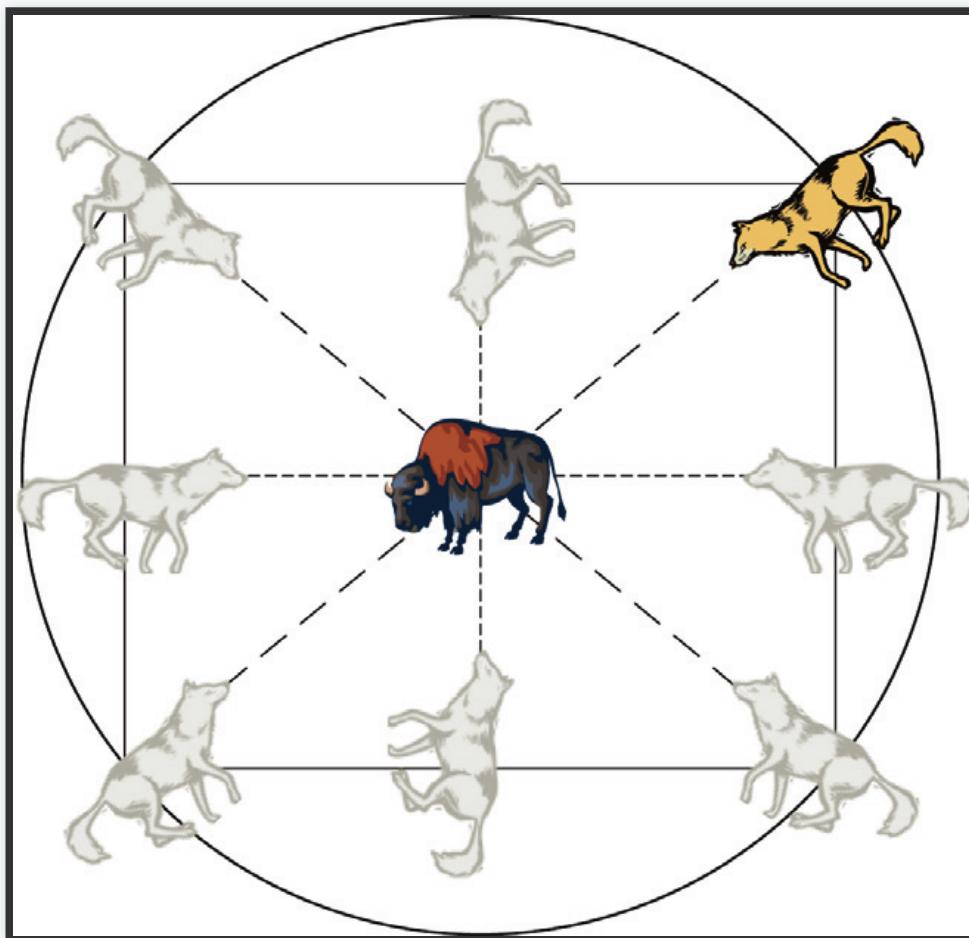
Pursuing, encircling, and harassing the prey until it stops moving.

Attack towards the prey.

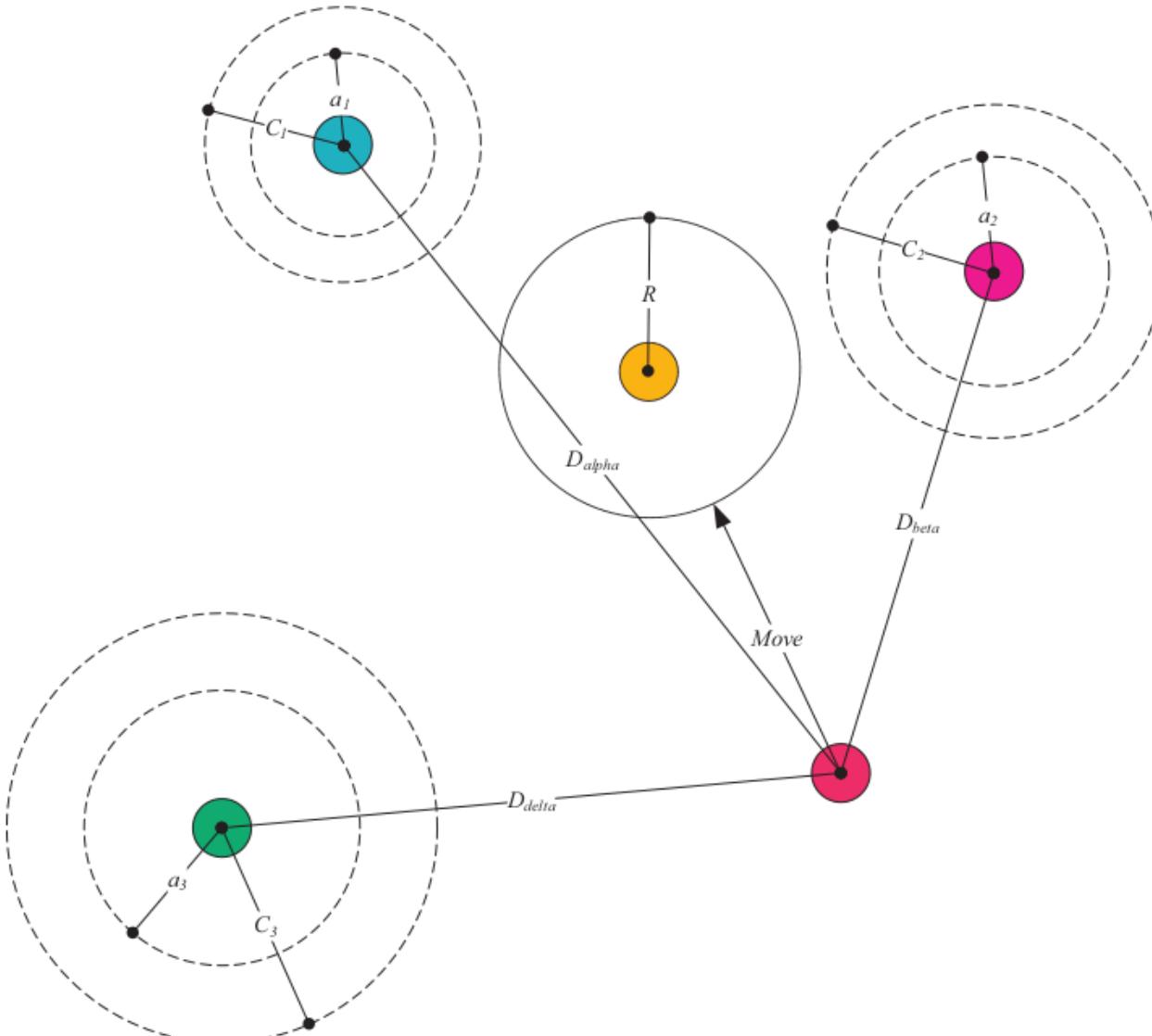


GWO

ENCIRCLING PREY



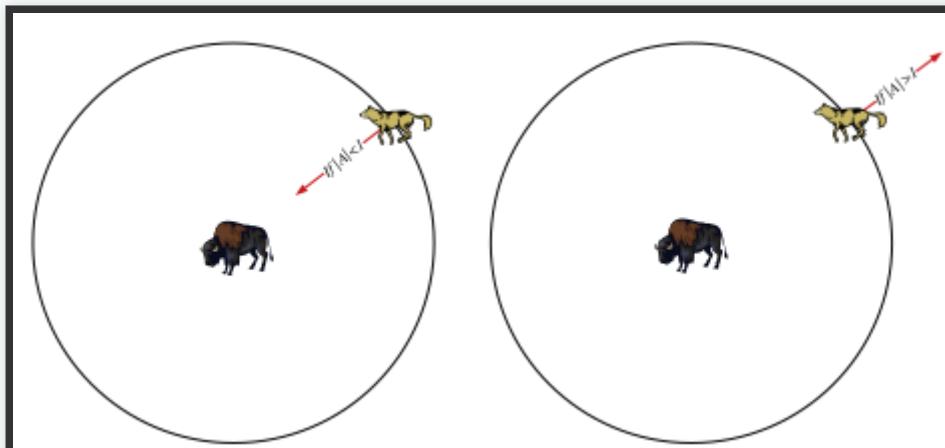
GWO



	α
	β
	δ
	ω or any other hunters
	Estimated position of the prey

GWO

ATTACK



TO SUM UP:

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Creating a random population of grey wolves

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Alpha, beta, and delta wolves estimate the probable position of the prey

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Each candidate solution updates its distance from the prey

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The parameter a is decreased from 2 to 0 in order to emphasize
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Candidate solutions tend to diverge from the prey when $j > 1$ and
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TO SUM UP:

Creating a random population of grey wolves

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Each candidate solution updates its distance from the prey

The parameter a is decreased from 2 to 0 in order to emphasize
exploration and exploitation

Candidate solutions tend to diverge from the prey when $j > 1$ and
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GW terminated by the satisfaction of an end criterion

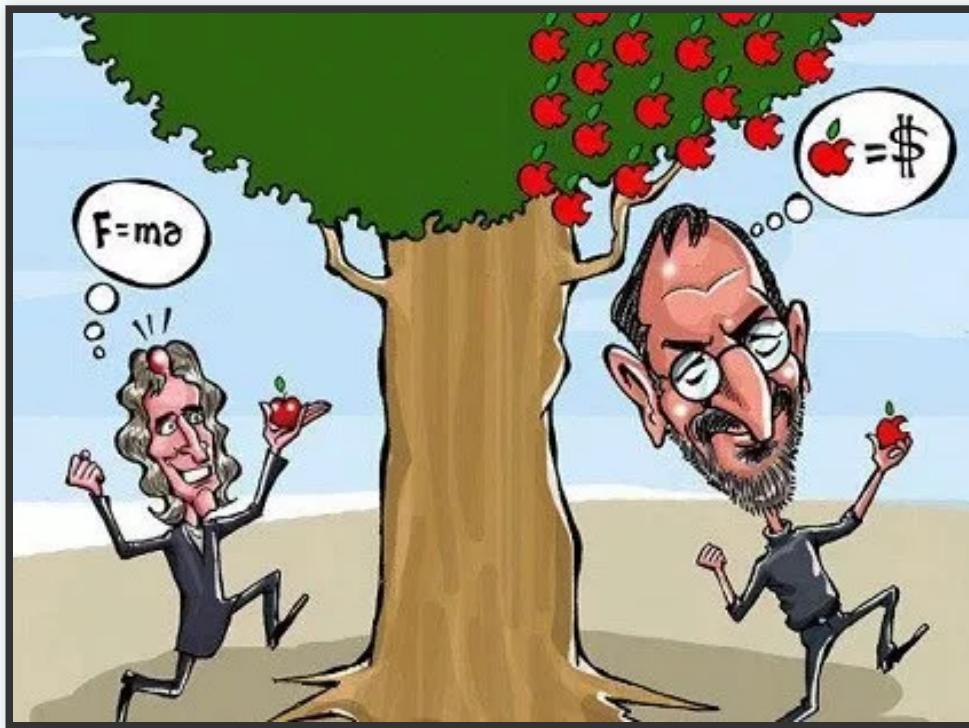
GWO ADVANTAGES

Free from the initialization of inputparameters

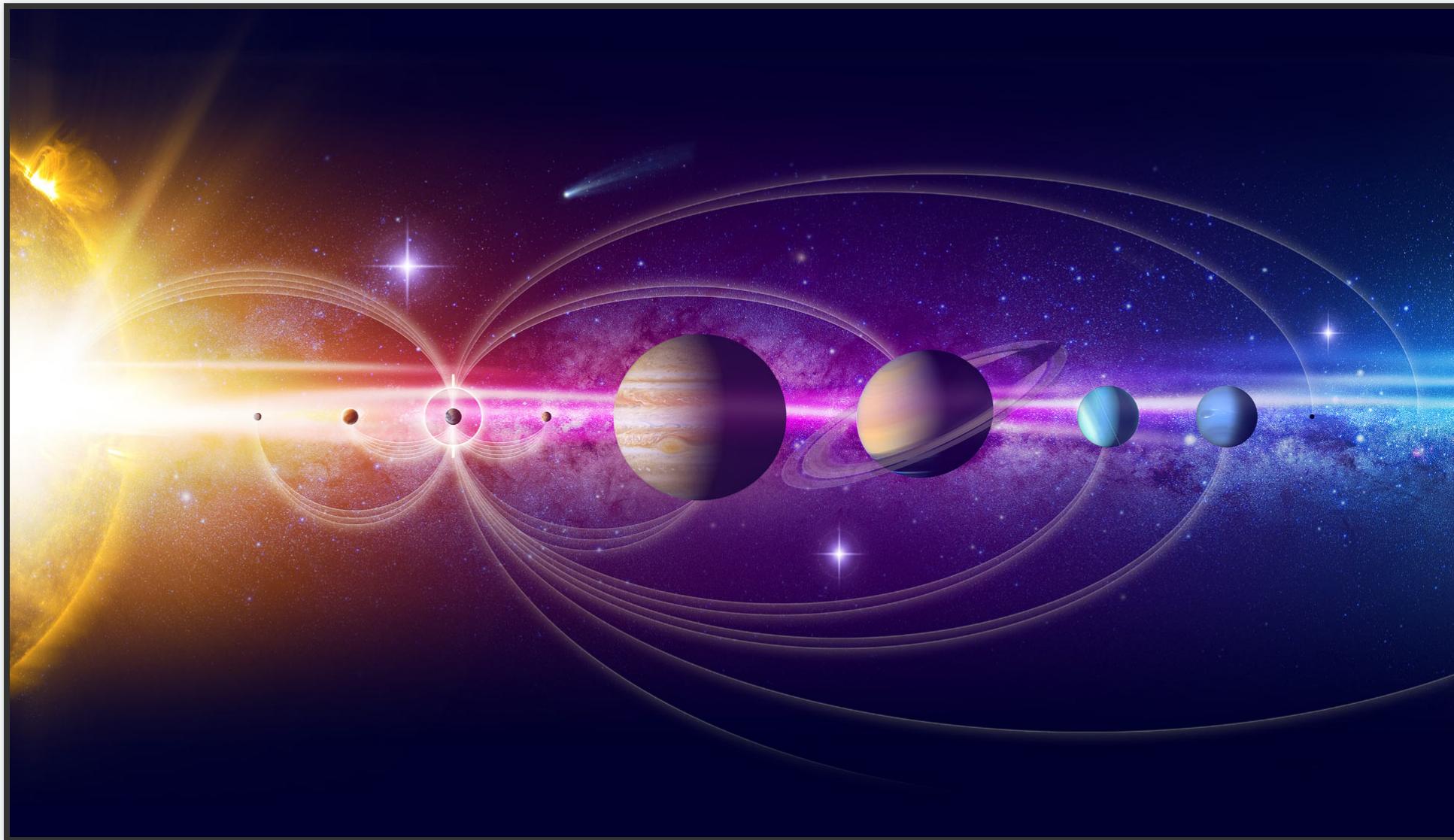
Free from computational complexity

Ease of understanding and implementation

GSA



GSA



HOW DOES IT WORKS?

ADVANTAGES

Easy implementation

Fast convergence

Low computational cost

DISADVANTAGES

Premature converge

Complexity in calculation

It is easy to fall into local optimum solution

FIREFLY



HUNTING

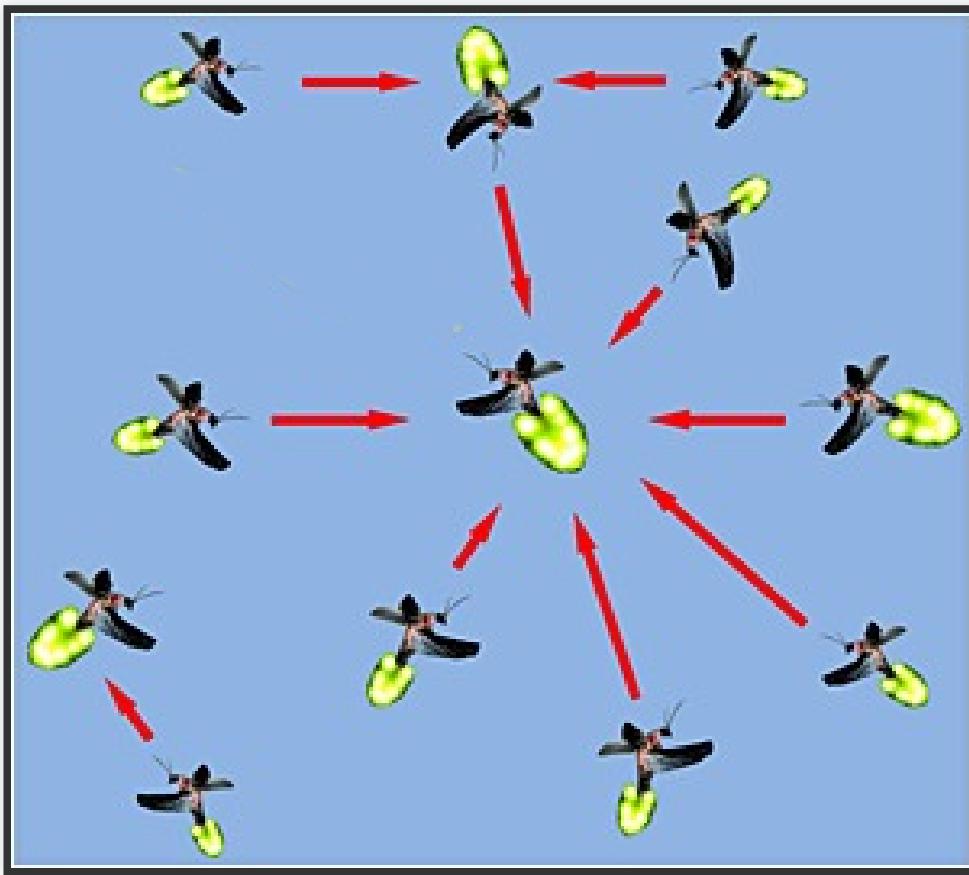






HYPOTHESES

HYPOTHESES



ADVANTAGES

Automatical Subdivision

Ability of dealing with multimodality

DISADVANTAGES

Getting trapped into several local optima

Does not memorize or remember any history of better situation for each firefly and this causes them to move regardless of its previous better situation

IDEA



REFERENCES

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