

# EMERGING OPTIMIZATION **PROBLEMS** AND MODERN OPTIMIZATION **ALGORITHMS**

**Seyedali Mirjalili**

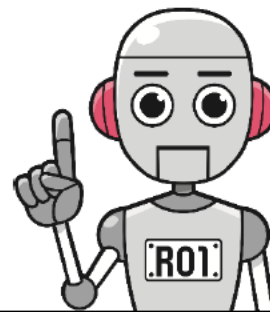
*Professor, Founding Director of the Centre for Artificial Intelligence Research and Optimisation*

*Torrens University Australia*

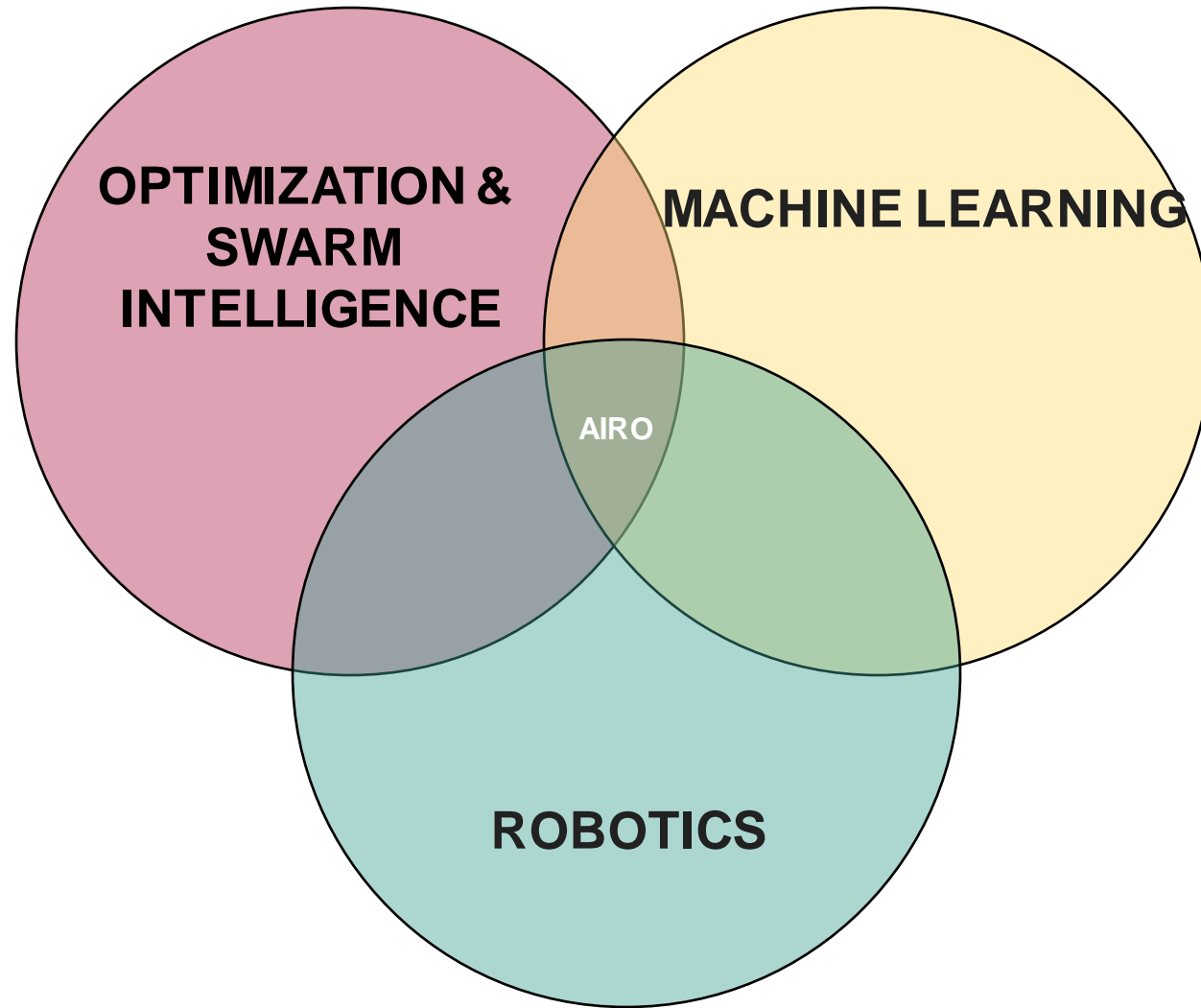
Óbuda University, 6<sup>th</sup> of September



# AIRO: Centre for Artificial Intelligence Research and Optimisation



# RESEARCH FOCUS AREAS IN AIRO CENTRE



# MY STORY

- Dad's Pentium 3
- Bee hives and ant nests in our backyard



# OUTLINES

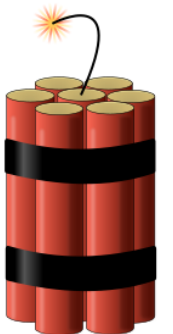
- **Optimization problems**

- Components
- Inputs
- Constraints
- Objectives



- **Optimization algorithms**

- Conventional
- Emergent complexity
- Swarm-based & evolutionary algorithms

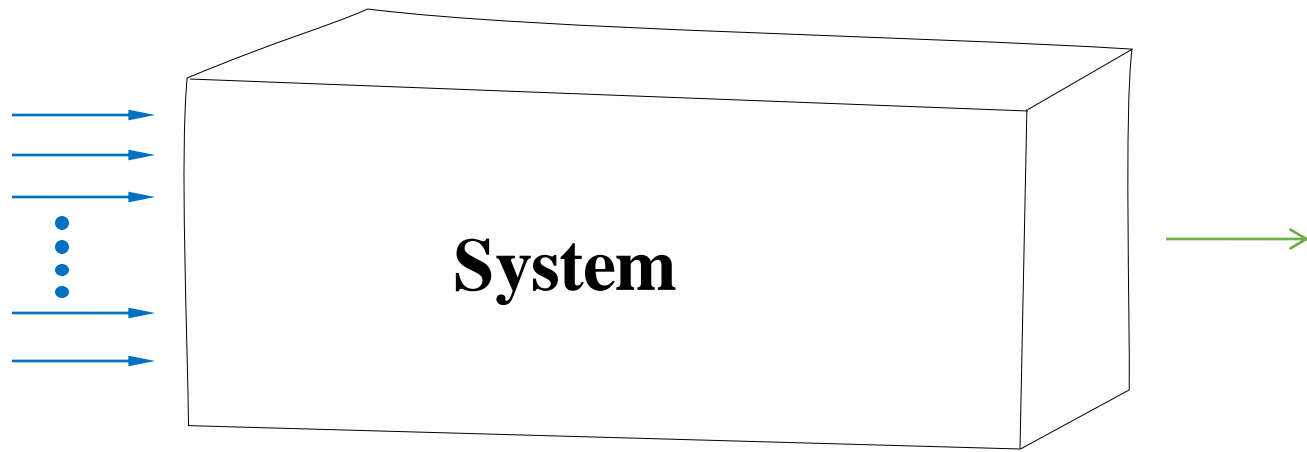


# **PART I - OPTIMIZATION PROBLEMS**

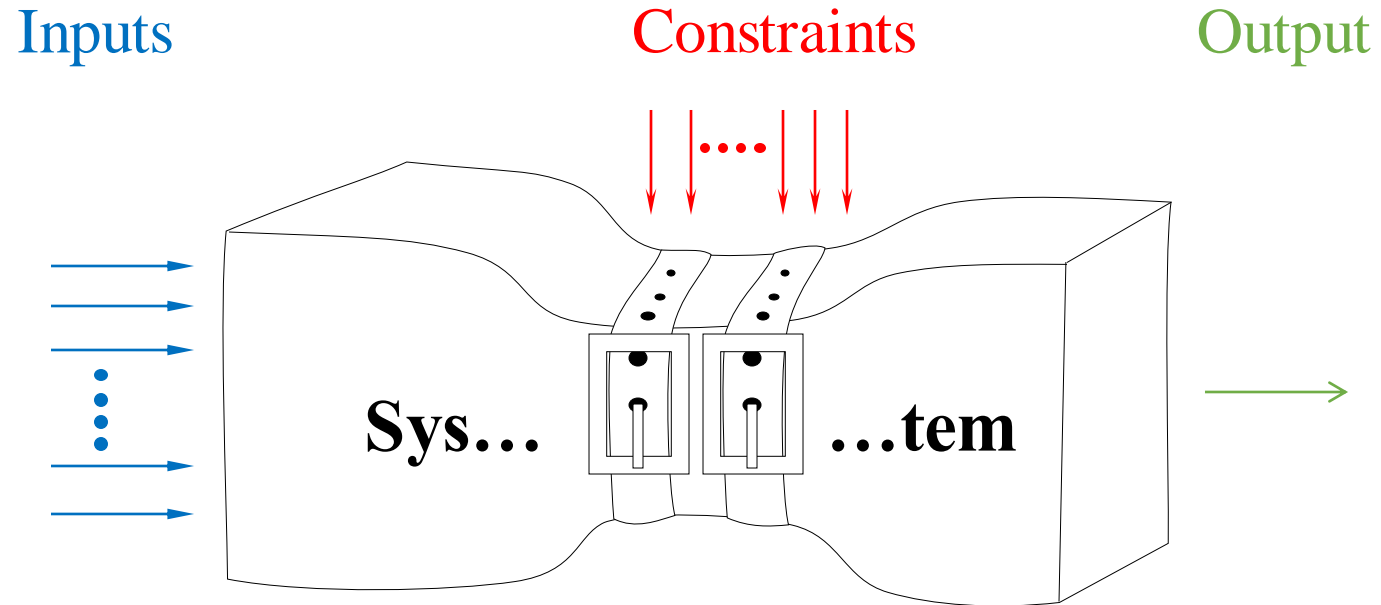
# MAIN COMPONENTS OF AN OPTIMIZATION PROBLEM

Inputs (variables)

Output (objective)

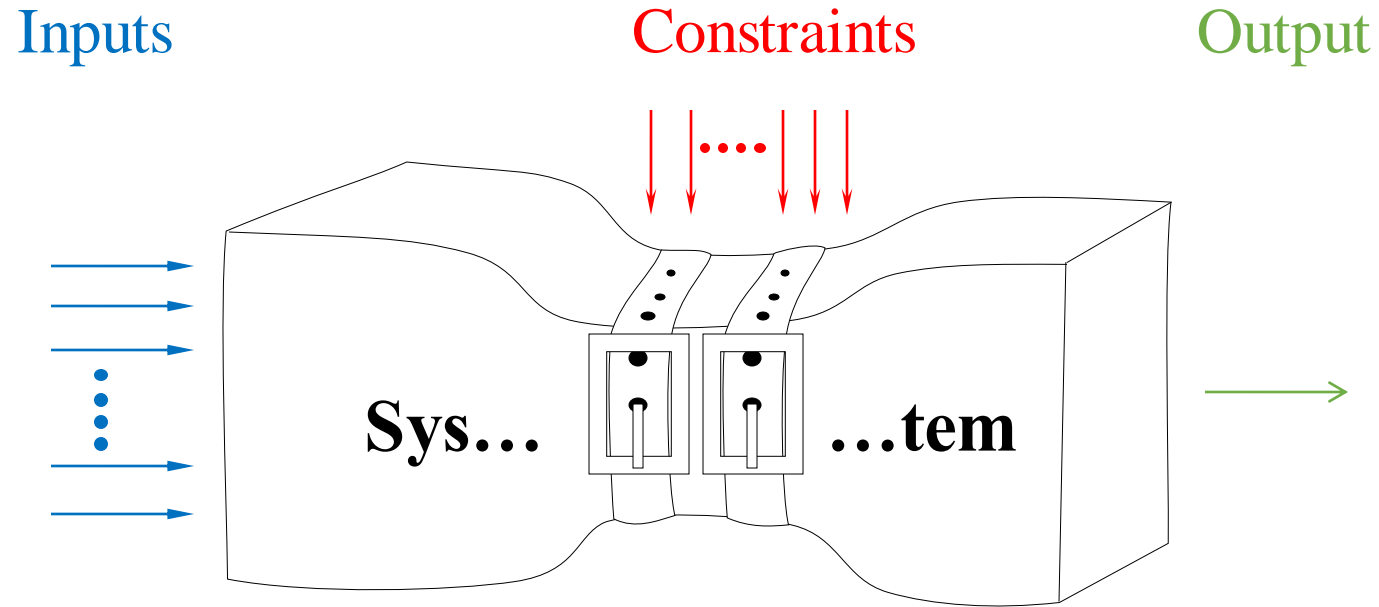


# MAIN COMPONENTS OF AN OPTIMIZATION PROBLEM





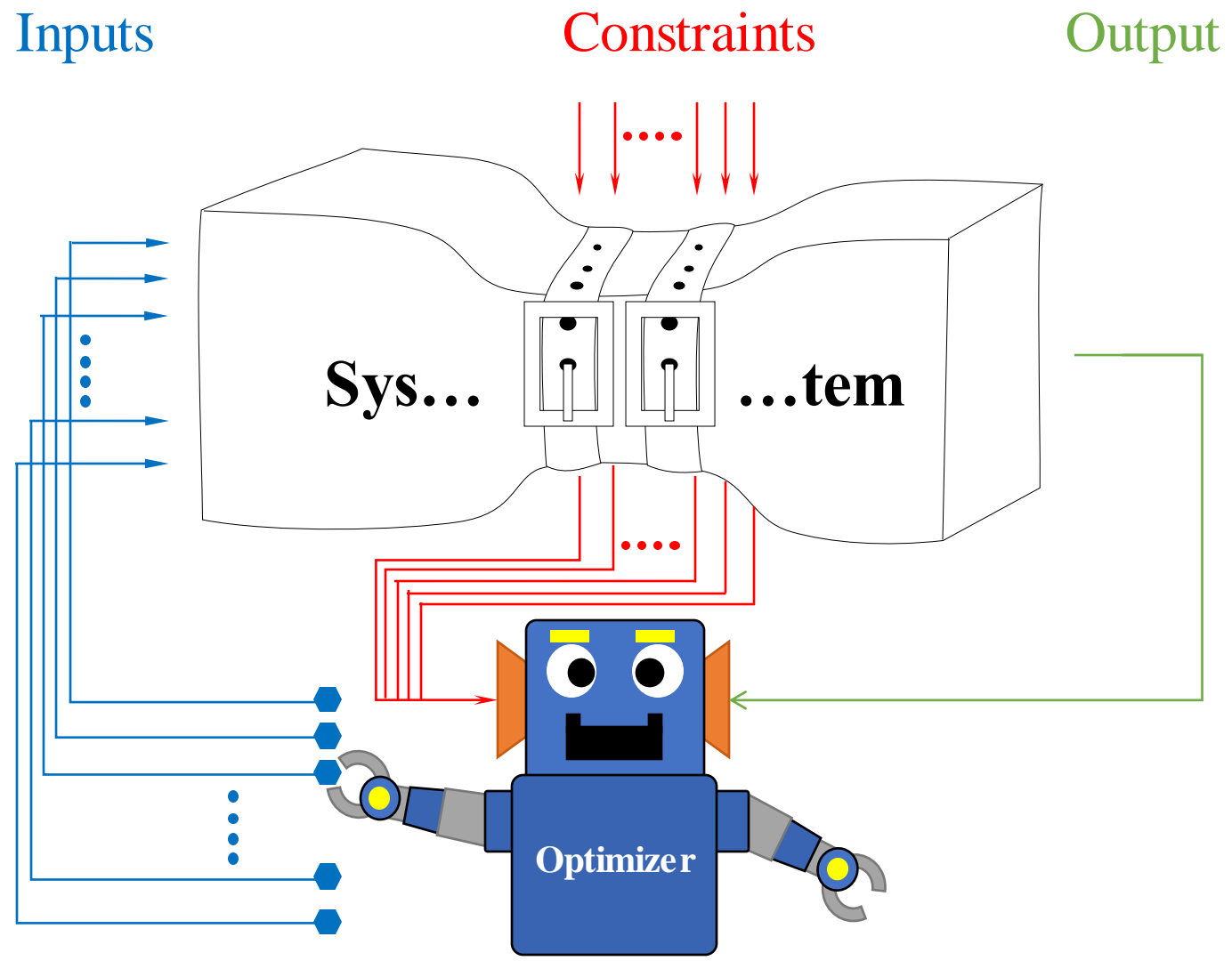
# FORMULATING AN OPTIMIZATION PROBLEM



*Minimise:*  $f(x_1, x_2, \dots, x_n)$

*Subject to:* **Constraints**

# OPTIMIZATION ALGORITHM

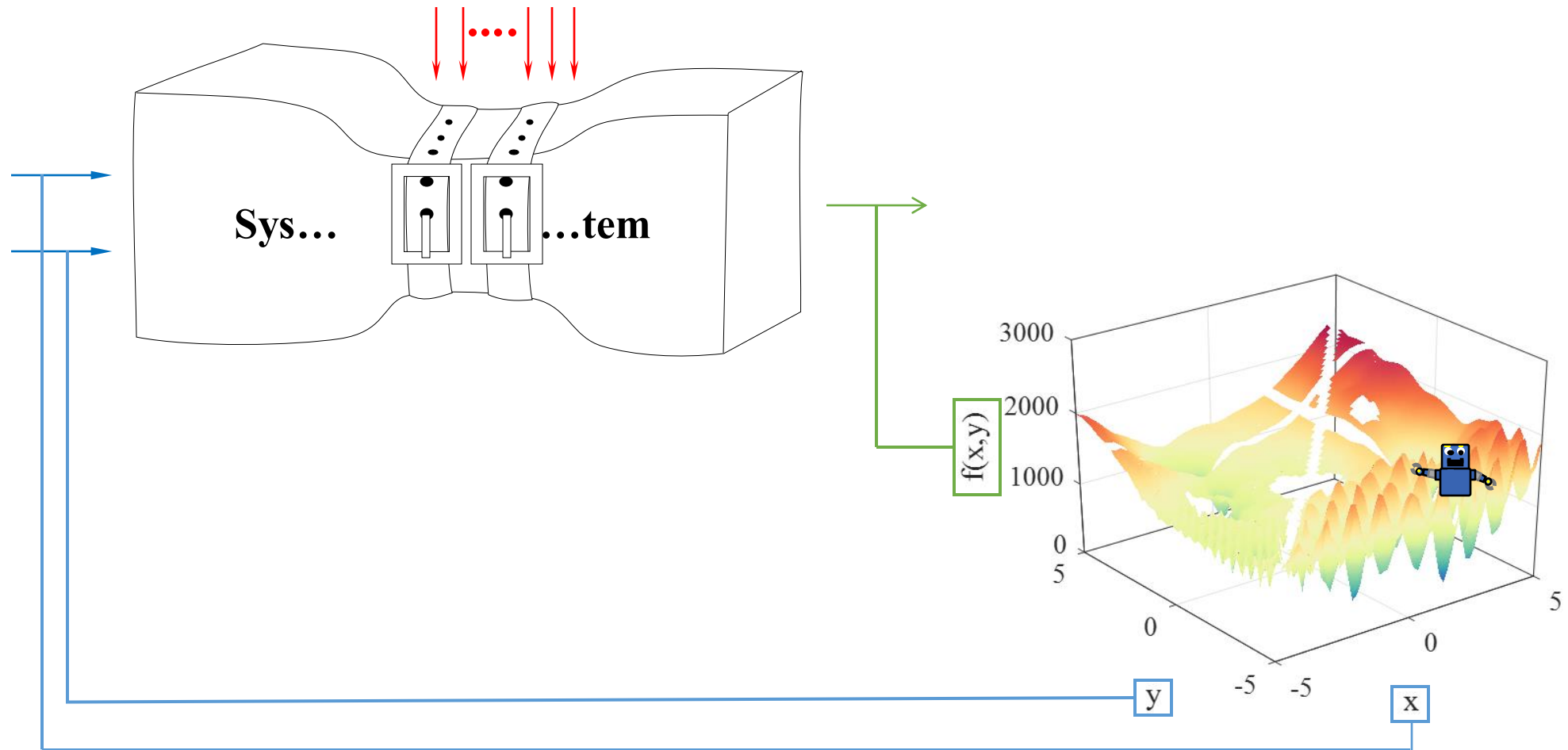


# A SEARCH SPACE

Inputs

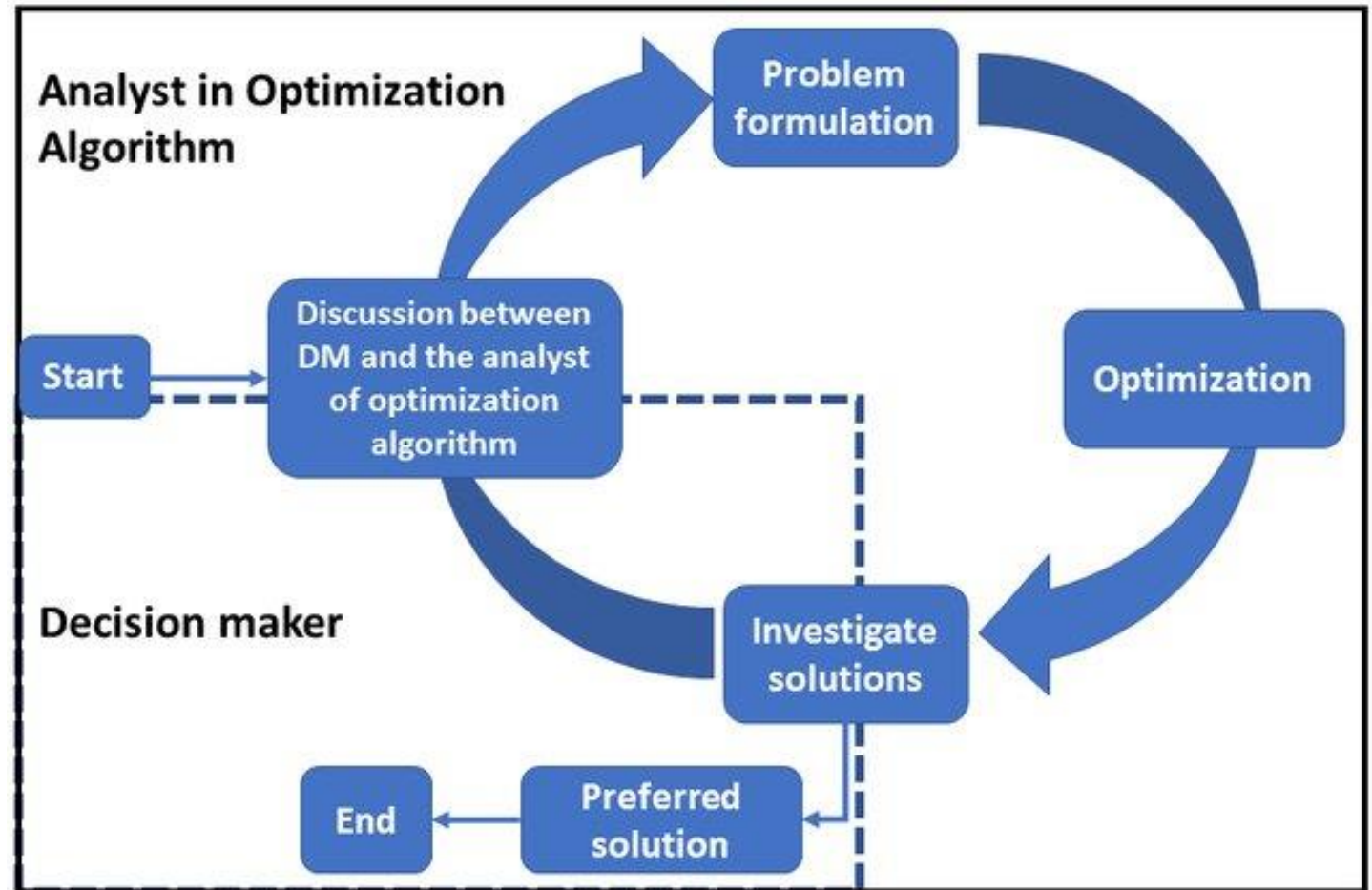
Constraints

Output

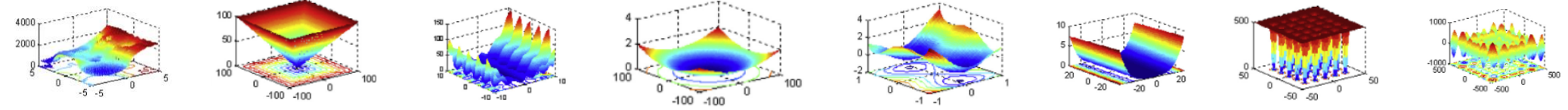
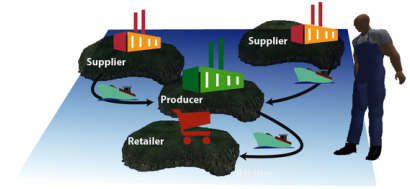
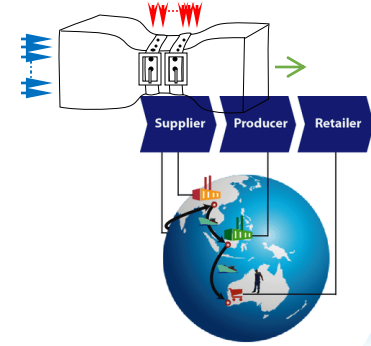
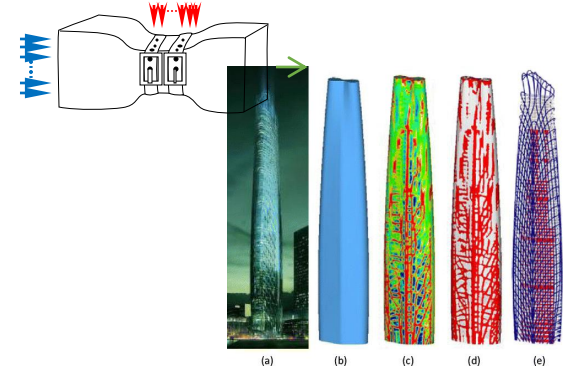
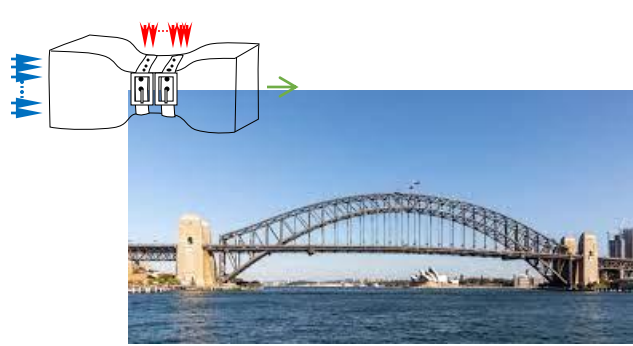


# EXISTING FRAMEWOKS TO WORK WITH PROBLEM OWNERS

- Iterative process
- Simplification over optimization



# WELCOME TO OUR WORLD

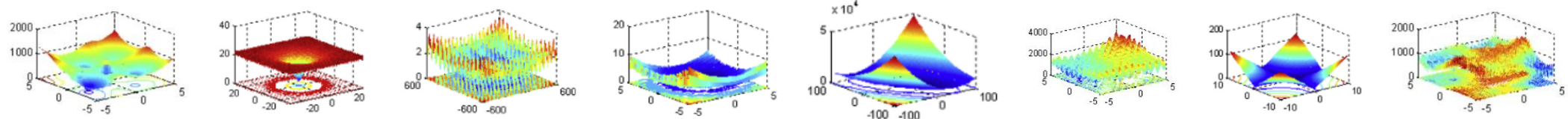
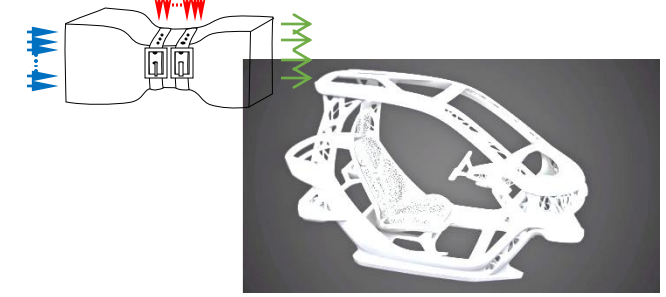
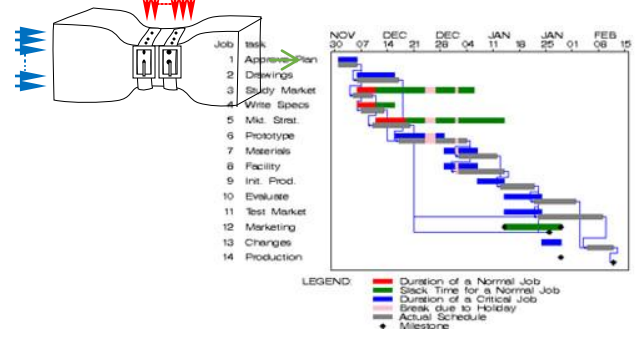


$match = 1$     $mismatch = -1$     $gap = -1$

onstraint    $\rightarrow$    inference

contact in 3D

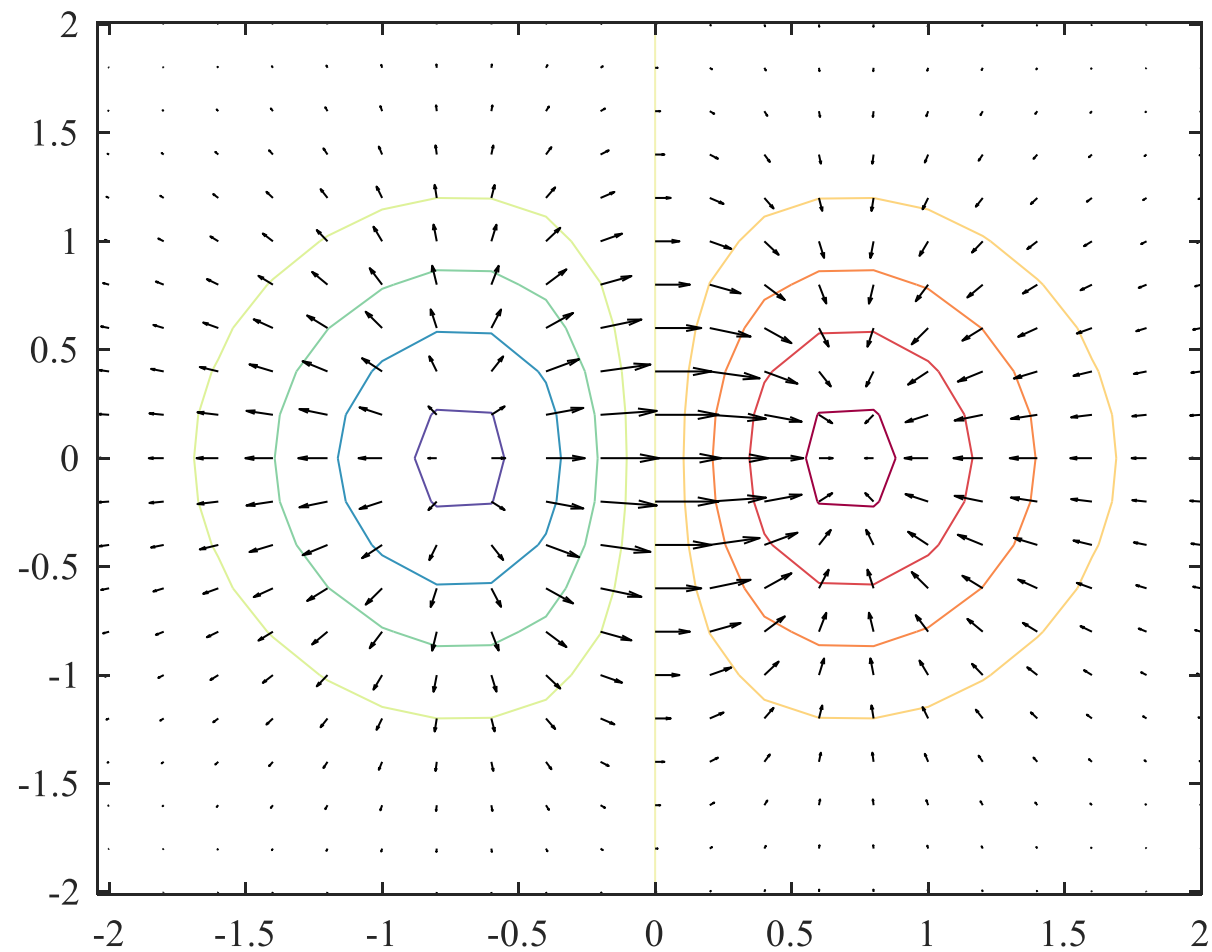
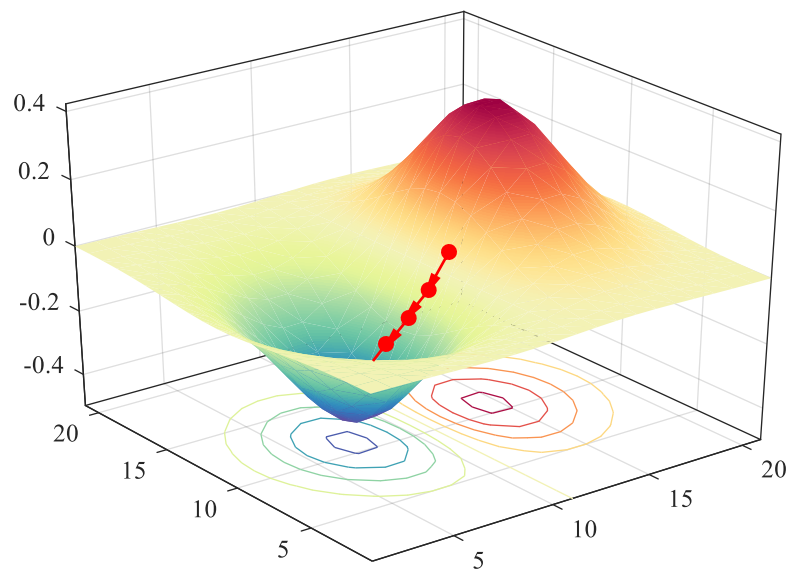
	g	c	A	T	g	c	g
g	0	-1	-2	-3	-4	-5	-6
A	3	0	0	1	0	-1	-2
T	3	-1	-1	0	2	1	-1
T	4	2	2	1	1	1	0
A	-5	-3	-3	-1	0	0	-1
C	6	4	2	2	-1	-1	0
A	-7	-5	-3	-1	-2	-2	0



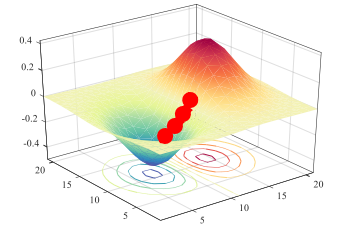
# **PART II - OPTIMIZATION ALGORITHMS**

# GRADIENT-BASED OPTIMIZATION ALGORITHMS

- Gradient descent algorithm

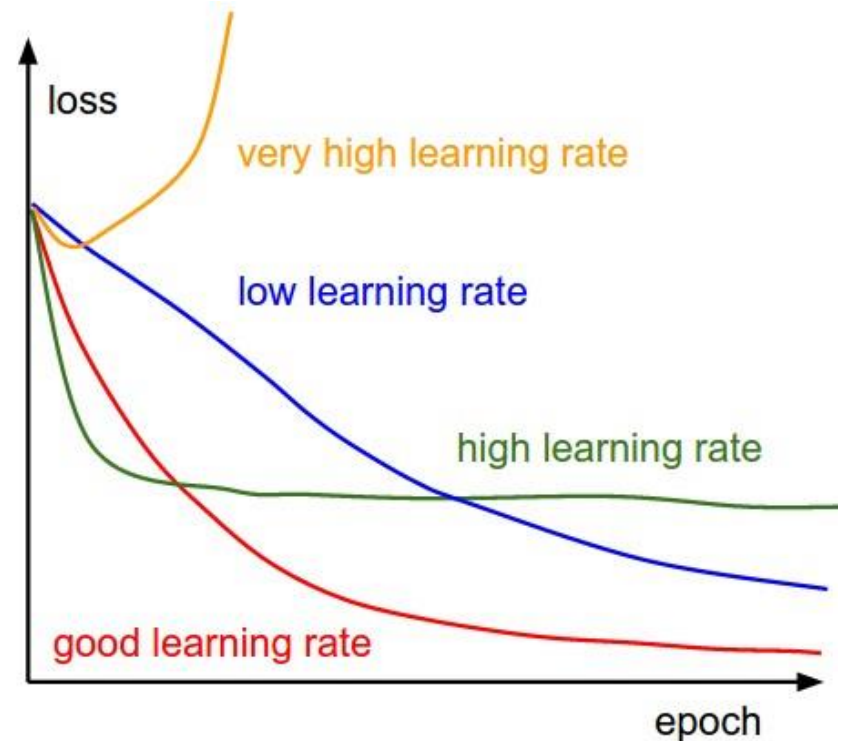


# RECENT ADVANCES TO TACKLE THESE CHALLENGES



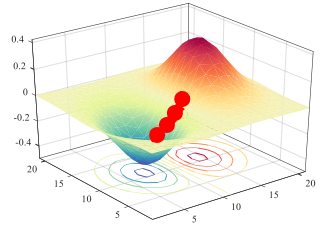
- Mostly developed by the **Deep Learning community**

- Momentum
- Nesterov accelerated gradient (NAG)
- Adagrad
- Adadelta
- RMSprop (Geoff Hinton)
- Adaptive Moment Estimation (Adam)
- AdaMax
- Nadam
- AMSGrad
- ...



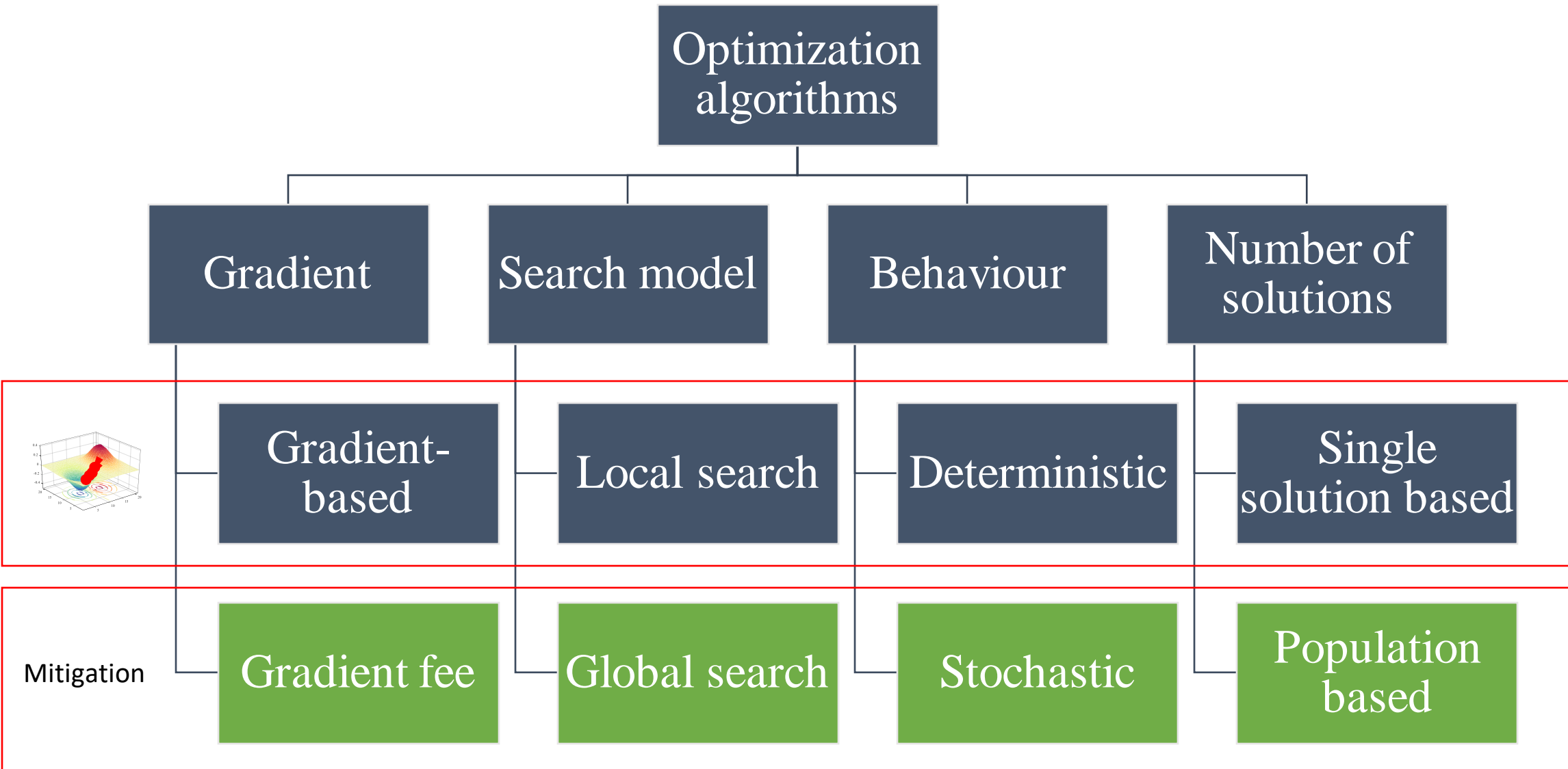


# CHALLENGES

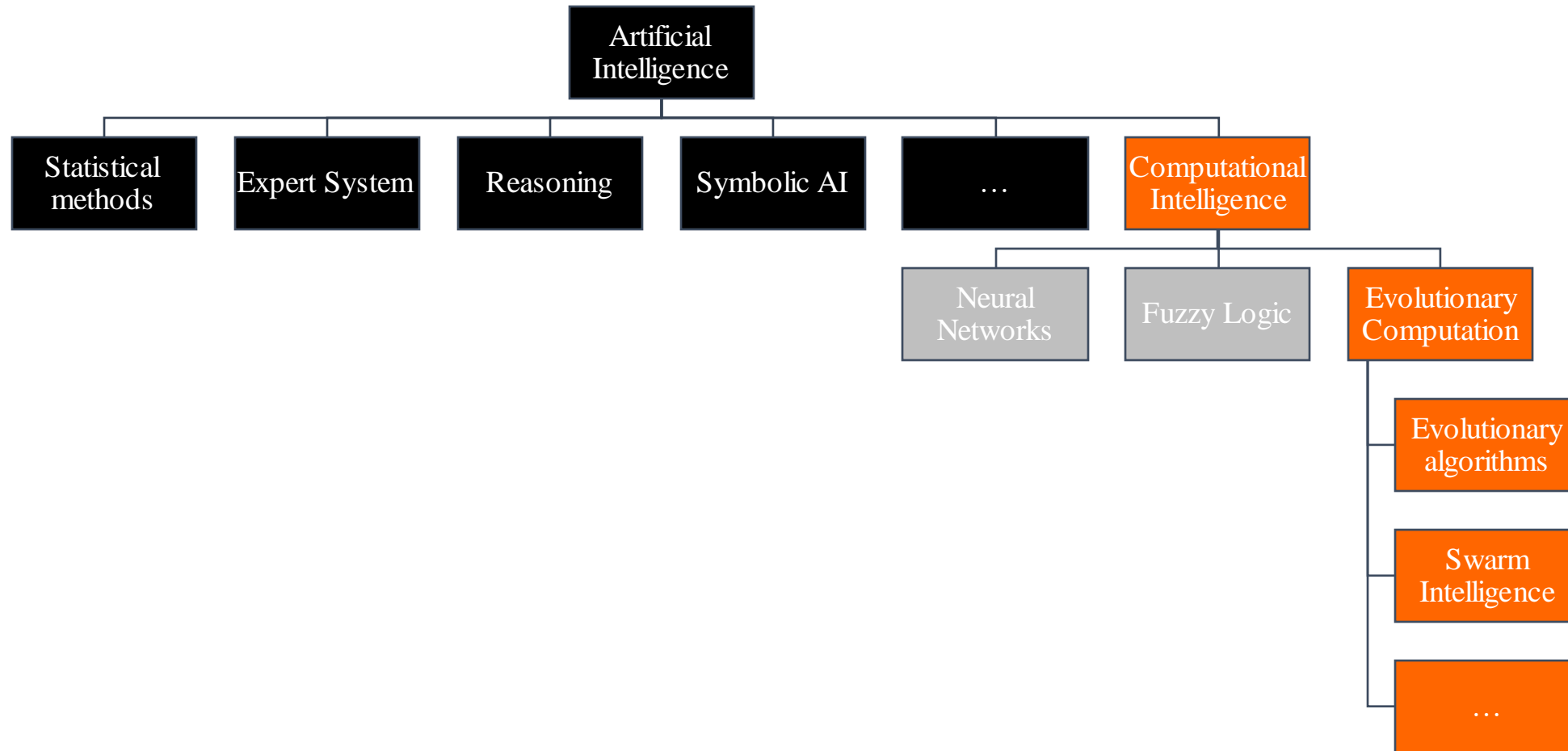


- Choosing a proper learning rate can be difficult.
- Learning rate schedules try to adjust the learning rate during training
- The same learning rate applies to all parameter updates.
- Avoiding getting trapped in their numerous suboptimal local minima
- Not practical for problems that are not differentiable

# ISSUES WITH CLASSICAL ALGORITHMS



# POSITION IN AI FIELD



# WHY DO NATURE-INSPIRED ALGORITHMS WORK?

## Emergent complexity

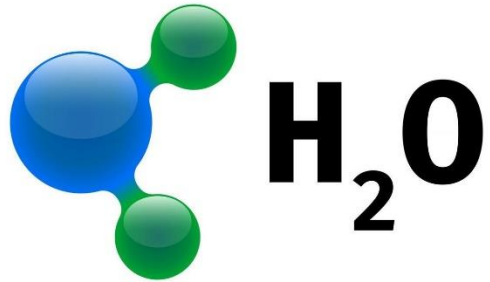
- **Emergent complexity:** “a phenomenon whereby larger entities arise through interaction among smaller or simpler entities ”
- Necessary components:
  - Units with simple behaviors
  - External force for cooperation
- What we get is some complex behavior resulting from an optimization process

# EXAMPLES OF EMERGENT COMPLEXITY

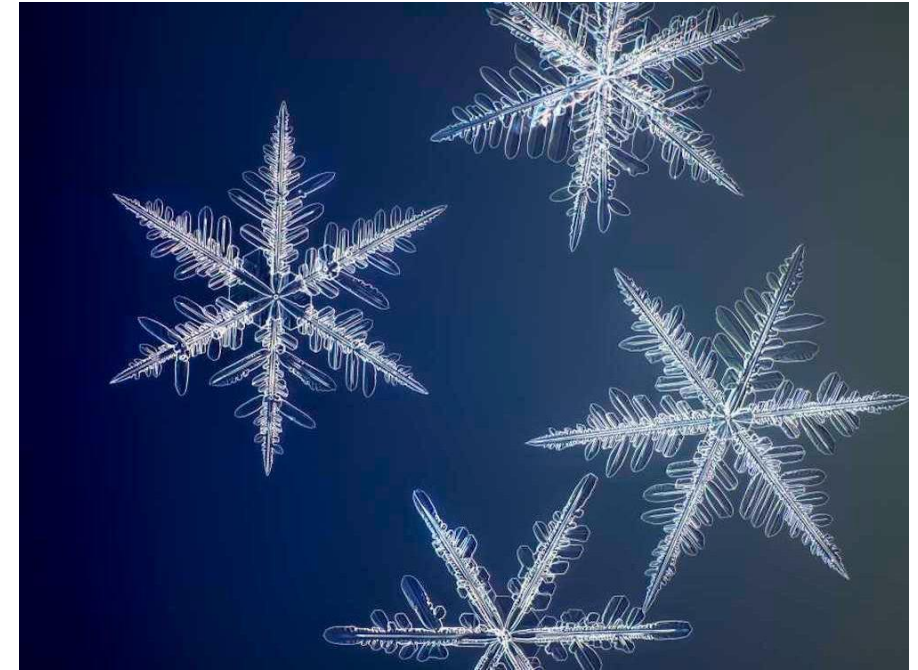
Units

EMERGENCE

Complex behaviour



EMERGENCE



# EXAMPLES OF EMERGENT COMPLEXITY

**Units**

**EMERGENCE**

**Complex behaviour**



**EMERGENCE**





**EMERGENCE**



**EMERGENCE**



**EMERGENCE**

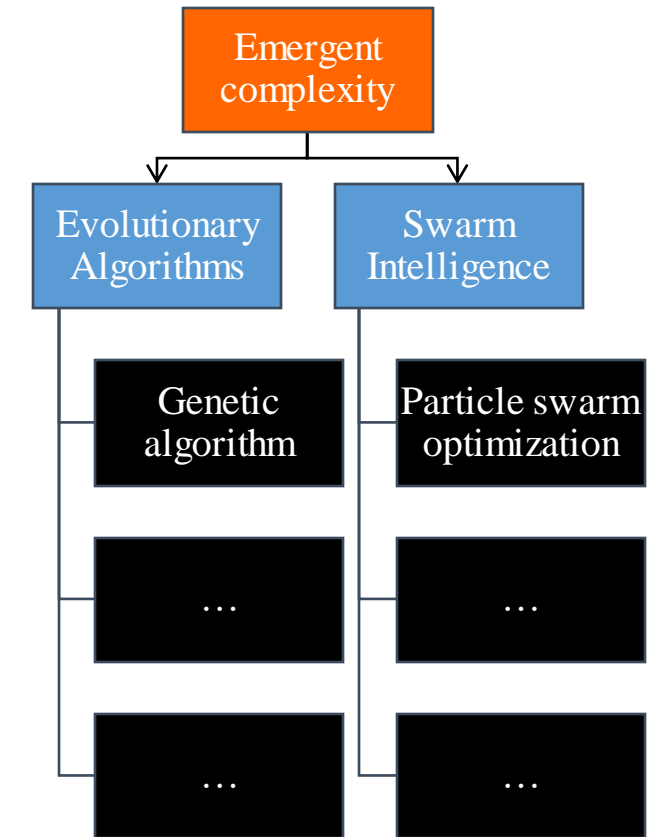


**EMERGENCE**



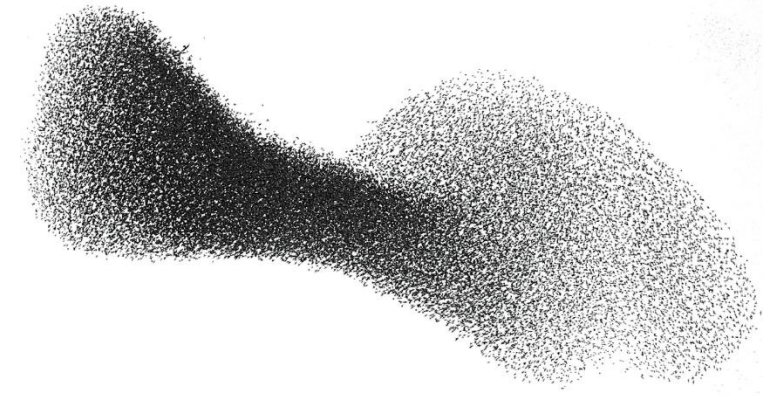
# EMERGENT COMPLEXITY

- Emergent complexity is not fundamentally natural. We can develop artificial systems that show complex behavior (e.g. game of life)
- So we can achieve complexity, the question is so what? Not every complex system is useful but what about complexity in natural systems?
- **Evolution tends to select complex systems for good reasons: OPTIMIZATION**
- So if there is a complexity in nature, it might be a good reason for that
  - **Evolutionary algorithms and swarm intelligence** techniques are useful applications of emergent complexity
- So it is wise to inspire from natural systems:
  1. Complex behavior in nature **MUST** solve problems efficiently
  2. A lot of problems in computer science are quite similar to problems in nature (path planning, scheduling, ..)
  3. They are scalable



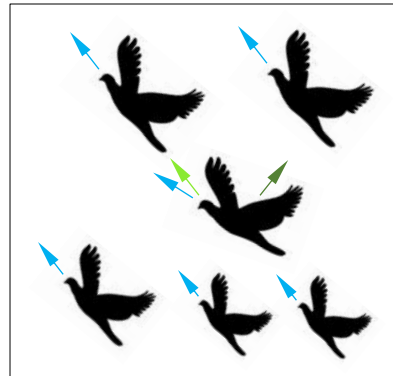


# FLOCK OF BIRDS

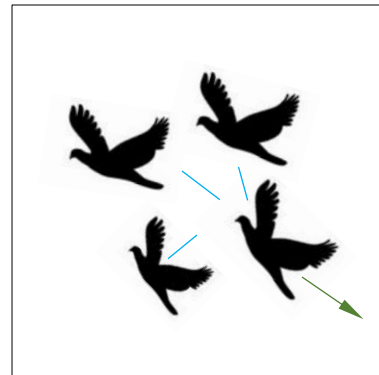


- Example: migration in a flock by birds in an unknown environment to minimize energy consumption is similar to flying in an unknown search space of a problem to minimize the cost function.

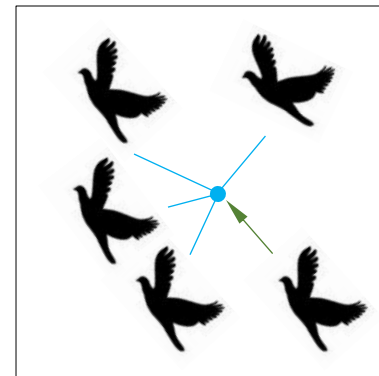
Alignment



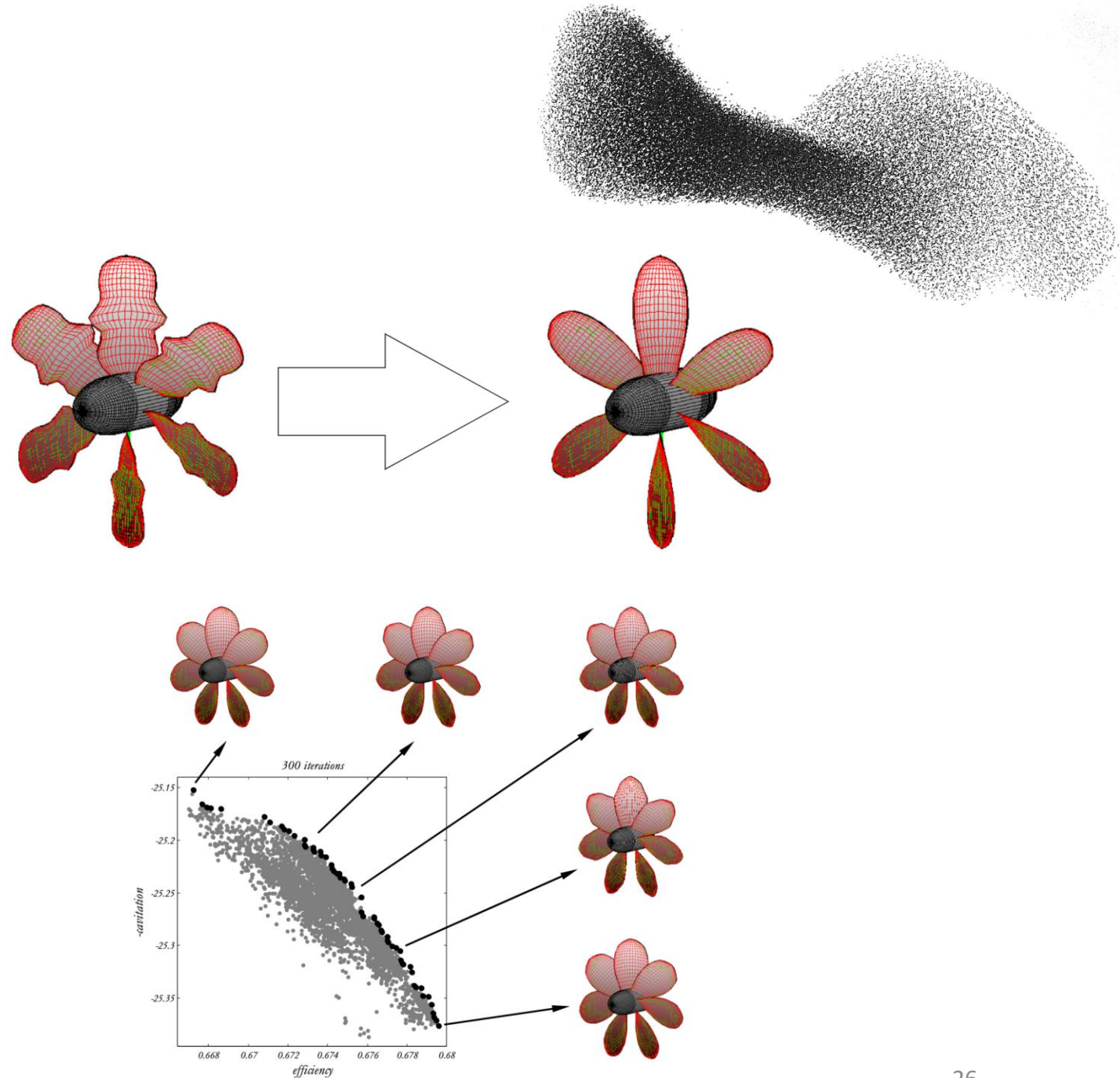
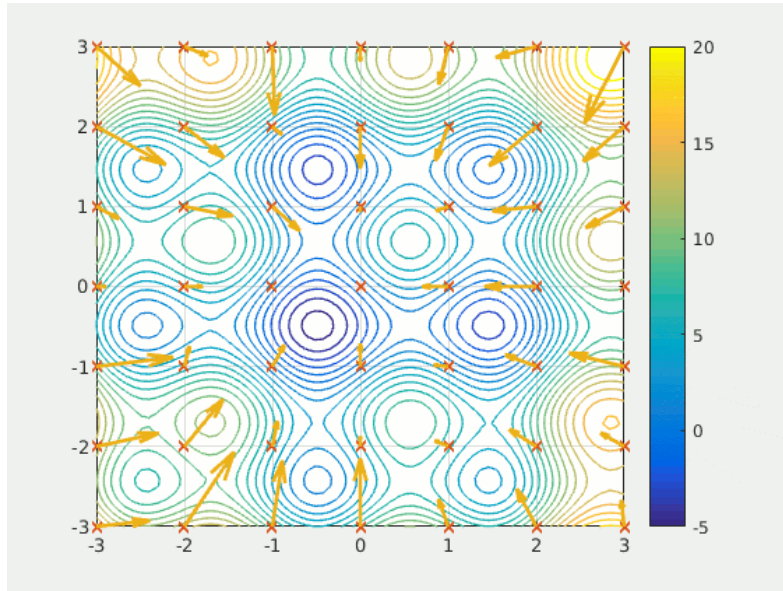
Separation



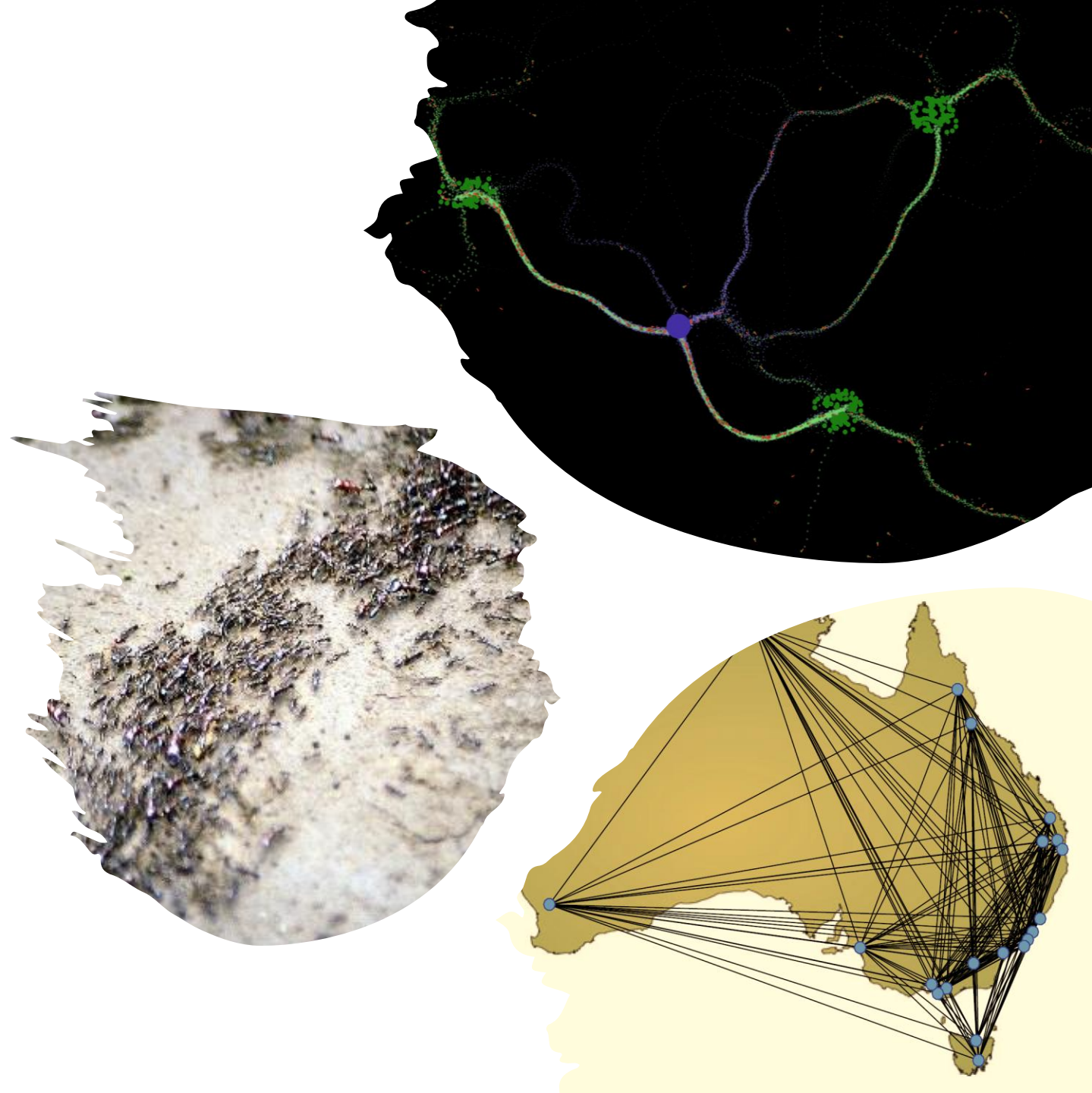
Cohesion



# FLOCK OF BIRDS



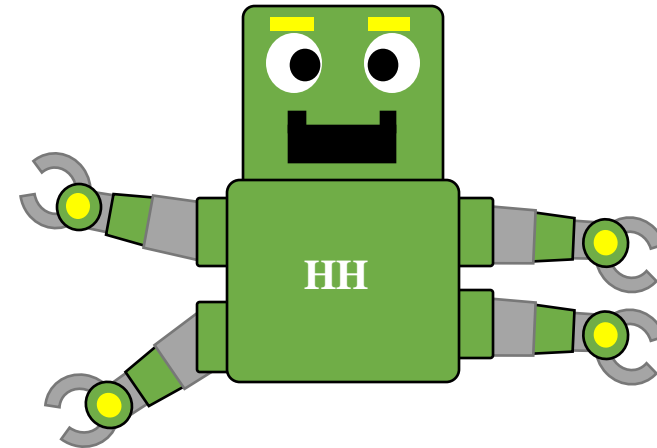
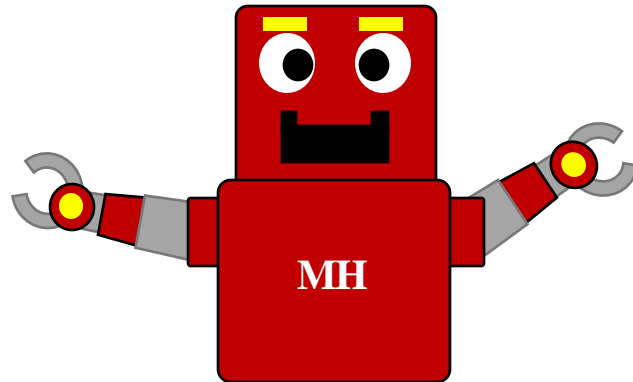
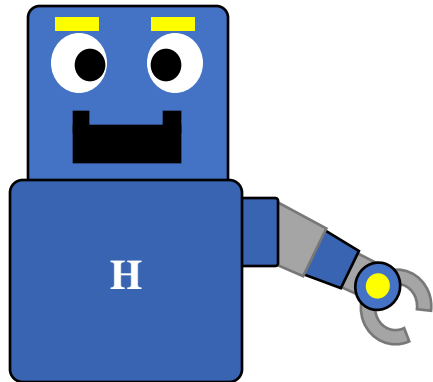
Finding an optimal path to a food source by ants in an unknown environment is similar to finding a global optimum in an unknown search space





# WHERE WE ARE HEADING

Heuristic → Meta-heuristic → Hyper-heuristic → .....



Increased Automation

# MY PLAN AS A MEMBER OF ÓBUDA UNIVERSITY

- **ÓB Research capacity and culture**

- Setting up and running a research group on optimization and evolutionary computing
- HDR Student exchanged
- Running a workshop every year on emerging areas in AI: machine learning, deep learning, and optimization

- **ÓB Research promotion and partnership**

- Enabling collaboration between researchers in my centre at Torrens University Australia and ÓU's researchers
- Collaboration with internal stakeholders

- **Research Output**

- Academic publishing strategy in the focus area
- Edited book, conference sessions, special issues, ...

- **Research Funding**

- Develop a strategy for obtaining research funding in the focus area of the research group

# RESEARCH BENEFIT AND IMPACT

- Help businesses and organisations in Hungary to be more agile and efficient
- Facilitate data-driven decision making
- Help stakeholders to understand the underlying factors and their impact in their decision making
- Help scientists and practitioners in Hungary to solve computationally expensive optimization problems
- Help with better understanding of how nature solves problem
- Developing innovative problem solving techniques inspired from nature

Love what  
you do

