

# Computational Intelligence

## Unit # 2

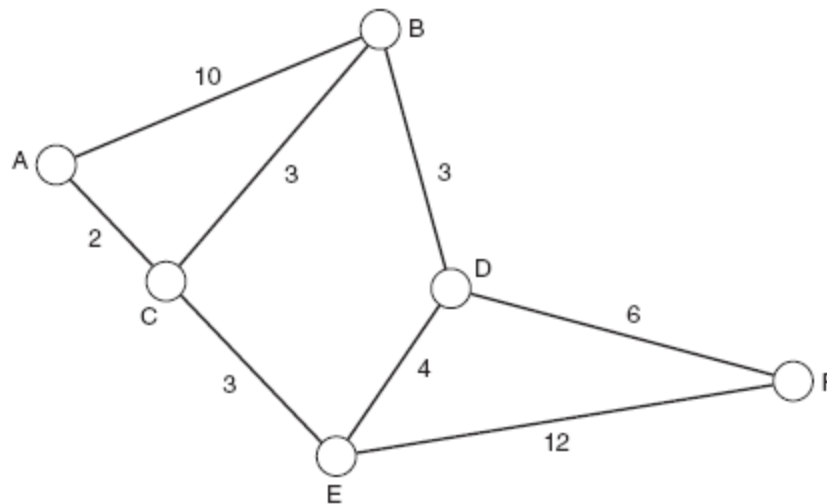
# Acknowledgement

- The slides of this lecture have been taken from the lecture slides of “CSE659 – Computational Intelligence” by Dr. Sajjad Haider.

# What is Optimization?

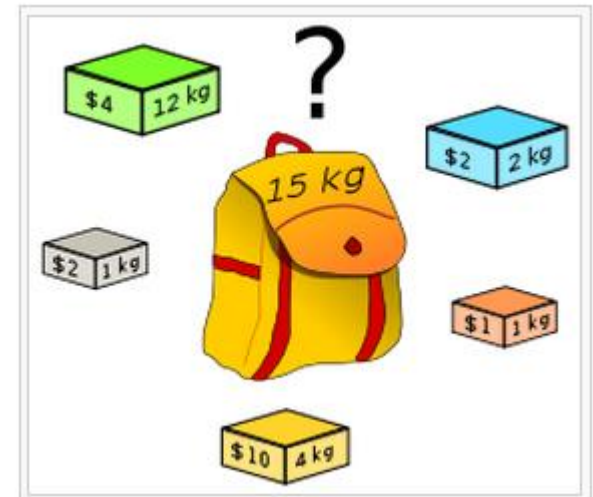
# Travelling Salesman Problem

- Given a list of cities and the distances between each pair of cities, what is the shortest possible route that visits each city exactly once and returns to the origin city?



# Knapsack Problem

- Given a set of items, each with a weight and a value, determine the number of each item to include in a collection so that the total weight is less than or equal to a given limit and the total value is as large as possible.



# Profit Maximization

- An automobile manufacturer produces several kinds of cars. Each kind requires a certain amount of factory time per car to produce, and yields a certain profit per car. A certain amount of factory time has been scheduled for the next week, and it is desired to use all this time; but at least a certain number of each kind of car must be manufactured to meet dealer requirements.

# Other similar problems

- Resource Allocations
- Scheduling Problems
- Shelf Placement
- Graph Coloring
- VLSI Design
- .....
- And many more combinatorial optimization problems

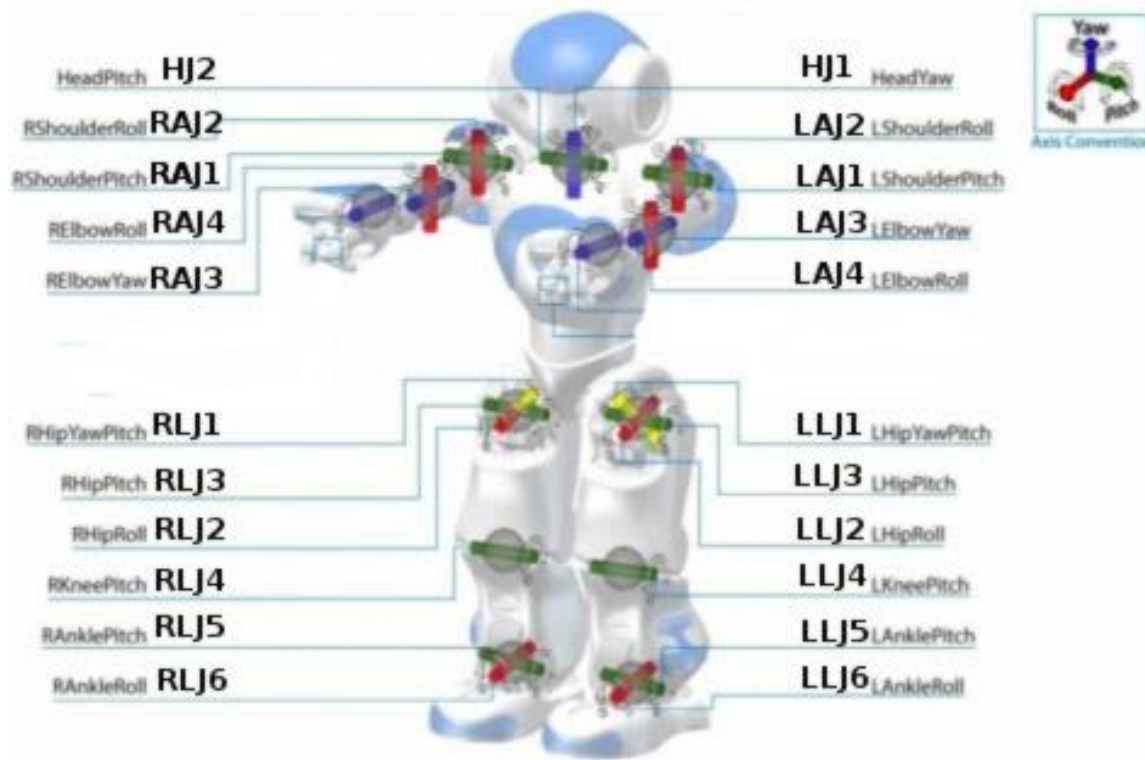
# Combinatorial optimization

- **Combinatorial optimization** is a topic that consists of finding an optimal object from a finite set of objects. In many such problems, exhaustive search is not tractable.



# Evolving Bipedal Robot Walk

# Nao Body



<http://www.youtube.com/watch?v=3cj-UQN6rj0>

# Evolutionary Art: Mona Lisa Evolution

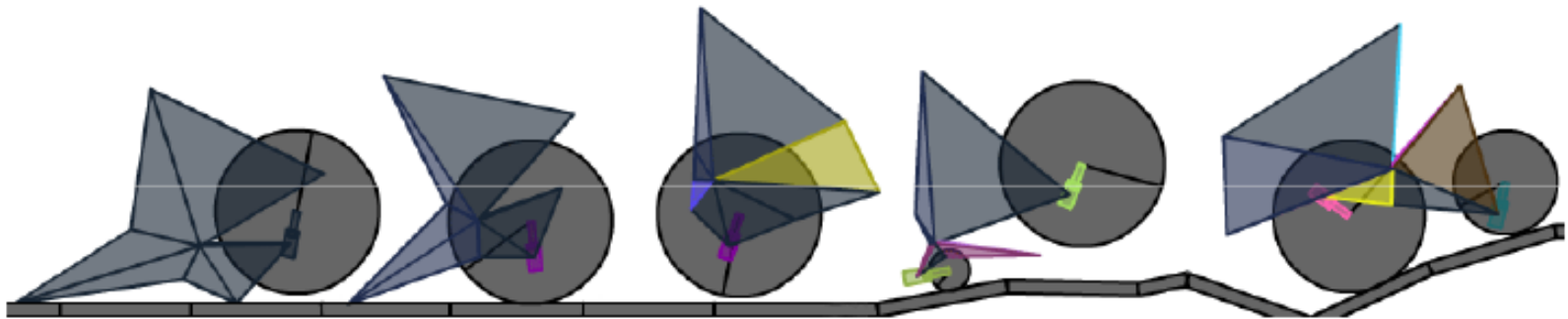


Problem: paint a replica of the Mona Lisa using only 50 semi transparent polygons

[Genetic Programming: Evolution of Mona Lisa – Roger Johansson Blog](#)

# Structure Design – Car Evolution

Design a car using polygons and wheels which able to run on a terrain.



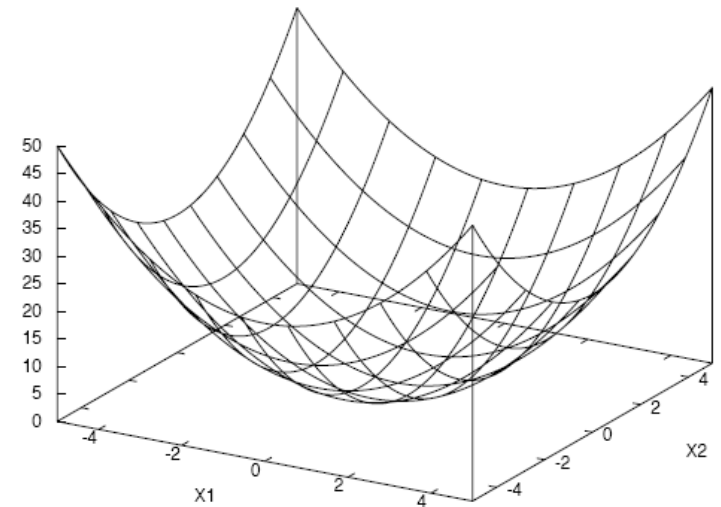
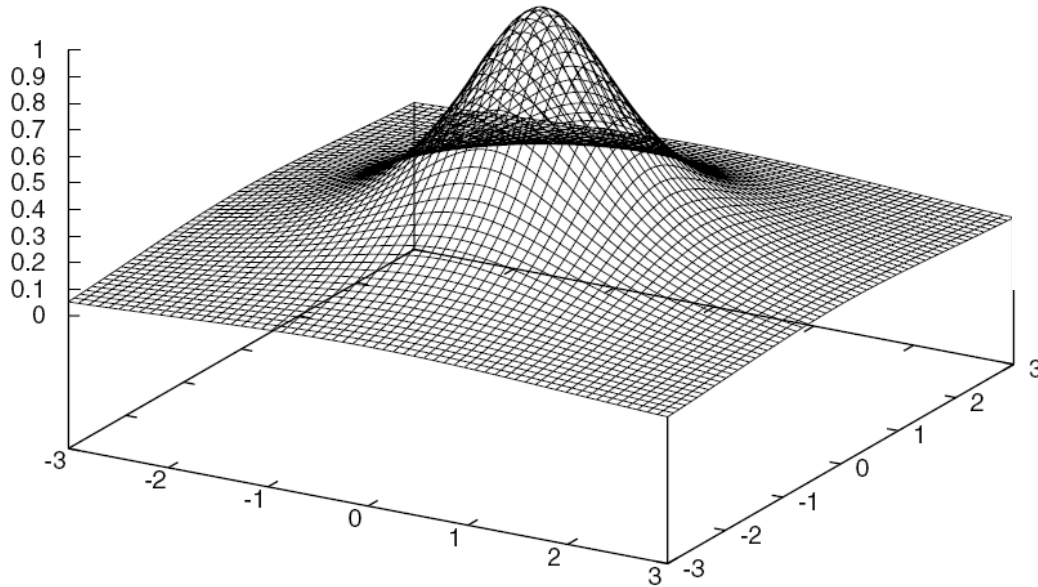
<http://boxcar2d.com/about.html>

[BoxCar2D. Self Evolving computer at work. \(youtube.com\)](https://www.youtube.com/watch?v=...)

# Search vs. Optimization

- The difference between optimization algorithms and search algorithms is that when performing a search algorithm, we know the element  $x_i$  we are looking for and just want to find its position in a structured set.
- In global optimization algorithms on the other hand we do not even know the characteristics of the  $x_i$  beforehand and are only given some criteria which describe if a given configuration is good or not.

# Simple Functions



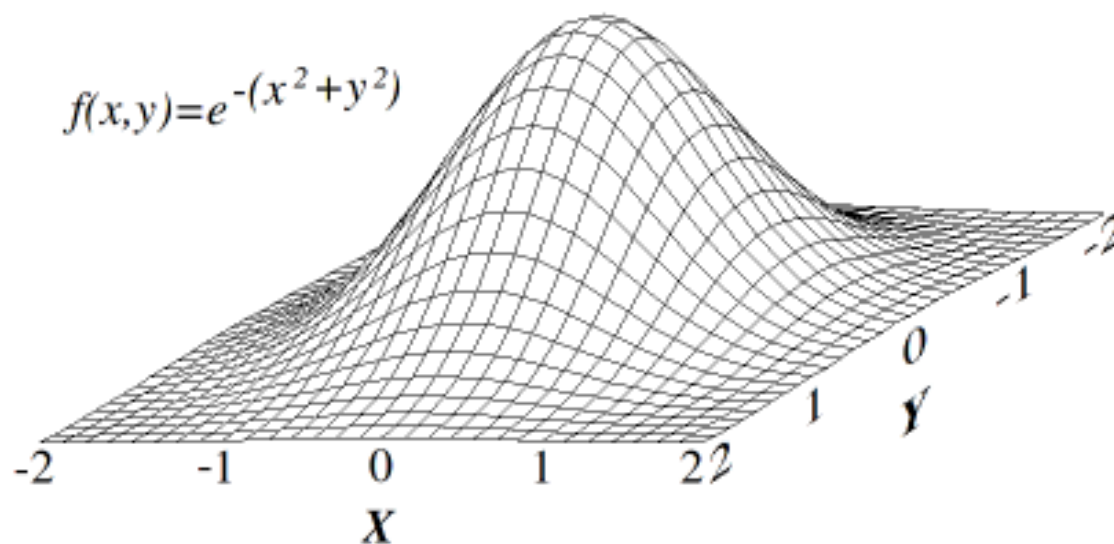
# Hill Climbing

- General Idea:
  - Start wherever
  - Always choose the best neighbor
  - If no neighbors have better scores than current, quit

Why can this be a terrible idea?

# Local vs Global Optimum?

What is the optimum point?

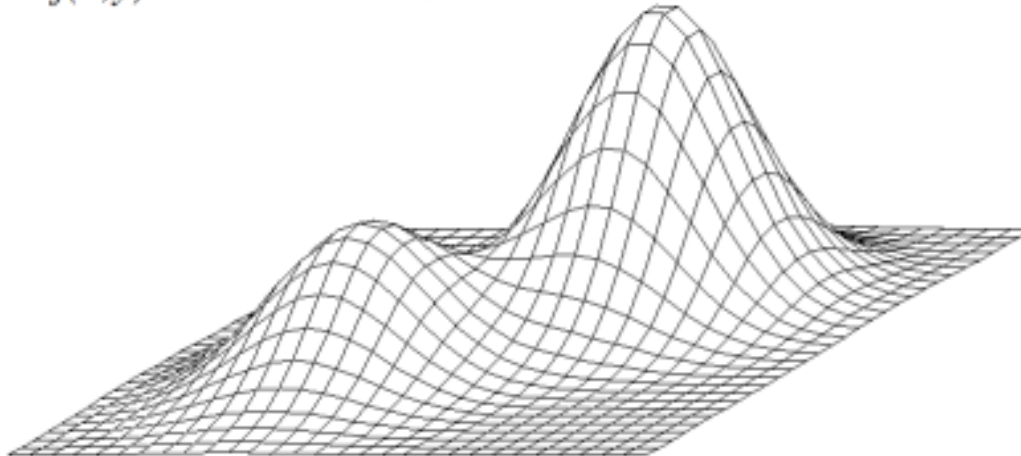




# Local vs Global Optimum?

What do you think about the optimum point now?

$$f(x,y) = e^{-(x^2+y^2)} + 2e^{-((x-1.7)^2+(y-1.7)^2)}$$



# Greedy Algorithm

(Source: Wikipedia)

- Greedy algorithms can be characterized as being 'short sighted', and as 'non-recoverable'. They are ideal only for problems which have 'optimal substructure'. Despite this, greedy algorithms are best suited for simple problems.

# Global Optimization

- Global optimization is the branch of applied mathematics and numerical analysis that deals with the optimization of single or maybe even multiple, possible conflicting, criteria.
- These criteria are expressed as a set of mathematical functions  $F = \{f_1, f_2, \dots, f_n\}$ , the so-called objective functions.
- The result of the optimization process is the set of inputs for which these objective functions return optimal values.

# Local Maximum and Minimum

**Definition 2 (Local Maximum).** A (local) maximum  $\hat{x}_l \in X$  of an objective function  $f : X \mapsto \mathbb{R}$  is an input element with  $f(\hat{x}_l) \geq f(x)$  for all  $x$  neighboring  $\hat{x}_l$ .

If  $X \subseteq \mathbb{R}$ , we can write:

$$\hat{x}_l : \exists \varepsilon > 0 : f(\hat{x}_l) \geq f(x) \quad \forall x \in X, |x - \hat{x}_l| < \varepsilon \quad (1.1)$$

**Definition 3 (Local Minimum).** A (local) minimum  $\check{x}_l \in X$  of an objective function  $f : X \mapsto \mathbb{R}$  is an input element with  $f(\check{x}_l) \leq f(x)$  for all  $x$  neighboring  $\check{x}_l$ .

If  $X \subseteq \mathbb{R}$ , we can write:

$$\check{x}_l : \exists \varepsilon > 0 : f(\check{x}_l) \leq f(x) \quad \forall x \in X, |x - \check{x}_l| < \varepsilon \quad (1.2)$$

**Definition 4 (Local Optimum).** An (local) optimum  $x_l^* \in X$  of an objective function  $f : X \mapsto \mathbb{R}$  is either a local maximum or a local minimum (or both).

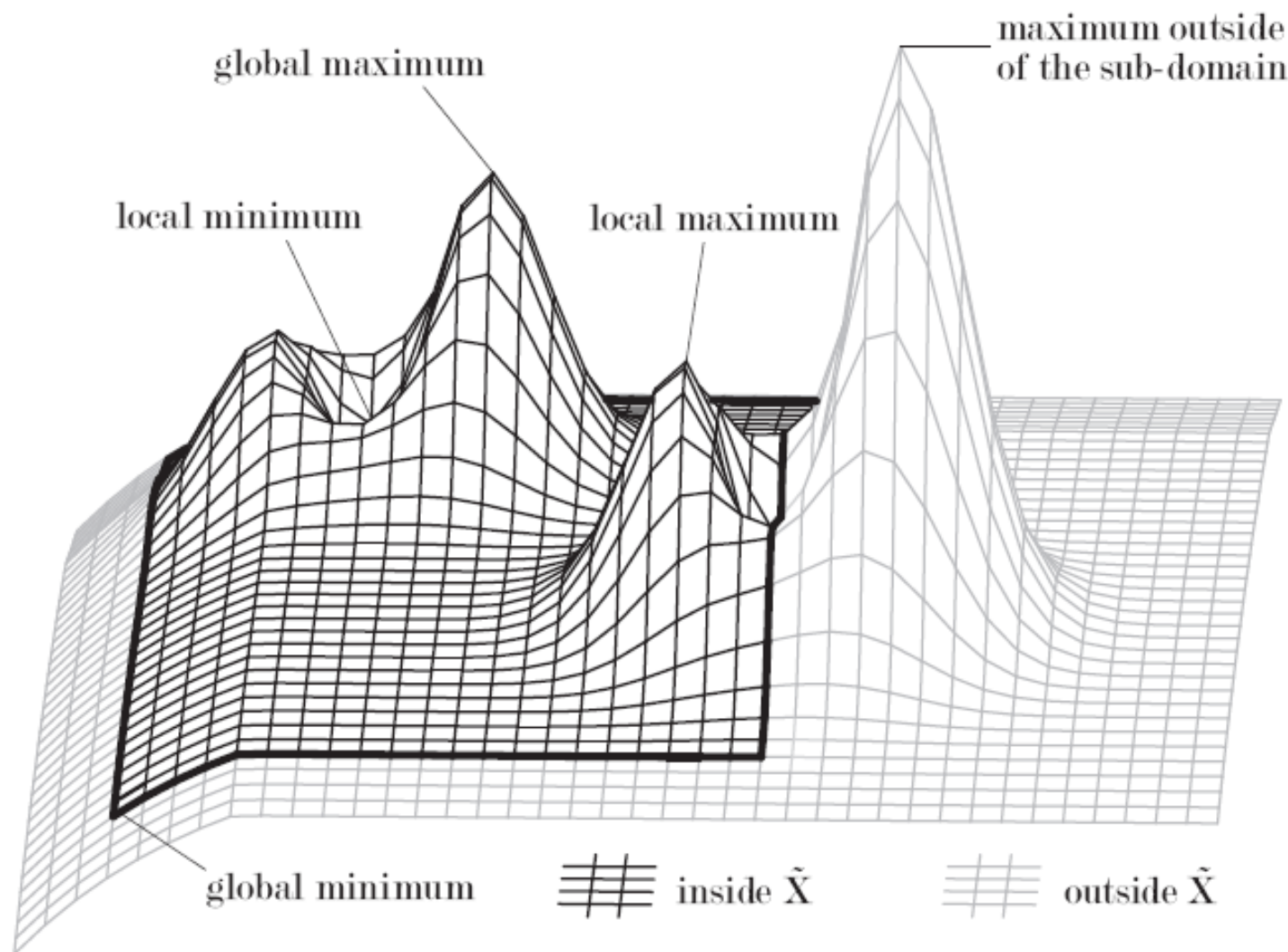
# Global Maximum and Minimum

**Definition 5 (Global Maximum).** A global maximum  $\hat{x} \in X$  of an objective function  $f : X \mapsto \mathbb{R}$  is an input element with  $f(\hat{x}) \geq f(x) \forall x \in X$ .

**Definition 6 (Global Minimum).** A global minimum  $\check{x} \in X$  of an objective function  $f : X \mapsto \mathbb{R}$  is an input element with  $f(\check{x}) \leq f(x) \forall x \in X$ .

**Definition 7 (Global Optimum).** A global optimum  $x^* \in X$  of an objective function  $f : X \mapsto \mathbb{R}$  is either a global maximum or a global minimum (or both).

# Global and Local Optima



# Continuous vs Combinatorial Optimization

| Aspect                            | Continuous Optimization                       | Combinatorial Optimization  |
|-----------------------------------|---|---|
| Decision Variables                | Continuous                                    | Discrete  |
| Problem Structure                 | Smooth, continuous functions                  | Discrete, often combinatorial                                     |
| Algorithms                        | Gradient-based, metaheuristics                | Integer programming, greedy algorithms, etc.                      |
| Complexity                        | Analytically tractable, efficient convergence | Often computationally challenging, exponential solutions possible |
| Applications                      | Engineering, finance, machine learning        | Logistics, scheduling, network design, etc.                       |
| Sensitivity to Initial Conditions | Crucial, especially for local methods         | Important, discrete nature impacts exploration                    |

# Thanks