

# **IM5110701** Metaheuristics

Dr. Hendri Sutrisno
Institute of Statistical Science
Academia Sinica

Dr. Chao-Lung Yang

Department of Industrial Management

National Taiwan University of Science and Technology



# Chapter 4: Differential Evolution

Sean Luke, Essentials of Metaheuristics, Second Edition

## **Initial work**

- Differential Evolution (DE) was proposed by Kenneth Price and Rainer Storn [1] in 1997.
- Designed to solve problem with real-valued search space.
  - □ DE might not be suitable for Discrete Optimization
- Compared to other Evolutionary-based metaheuristics, DE has two distinct "twist" strategies.

[1] Storn, R., & Price, K.V. (1997). Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces. *Journal of Global Optimization*, 11, 341-359.



## The tweaks

- 1. "Children" must compete directly against their immediate "parents" for inclusion in the population.
- 2. DE determines the size of Mutates largely based on the current variance in the population.
  - □ If the population is spread out, Mutate will make major changes.
  - □ If the population is condensed in a certain region, Mutates will be small.



## Pseudocode

```
Algorithm 38 Differential Evolution (DE)
 1: \alpha \leftarrow mutation rate

    Commonly between 0.5 and 1.0, higher is more explorative

 2: popsize ← desired population size
 3: P ← ⟨ ⟩
                      ▷ Empty population (it's convenient here to treat it as a vector), of length popsize
 4: Q ← □
                                   \triangleright The parents. Each parent Q_i was responsible for creating the child P_i
 5: for i from 1 to popsize do
        P_i \leftarrow new random individual
 7: Best ← □
 8: repeat
        for each individual P_i \in P do
             AssessFitness(P_i)
10:
             if Q \neq \square and Fitness(Q_i) > \text{Fitness}(P_i) then
11:
                                                                                                                               Tweak #1
                                                                        ▷ Retain the parent, throw away the kid
                 P_i \leftarrow Q_i
12:
             if Best = \square or Fitness(P_i) > Fitness(Best) then
13:
                 Best \leftarrow P_i
14:
        Q \leftarrow P
15:
        for each individual Q_i \in Q do
                                                                         > We treat individuals as vectors below
16:
             \vec{a} \leftarrow a copy of an individual other than Q_i, chosen at random with replacement from Q
17:
             \vec{b} \leftarrow a copy of an individual other than Q_i or \vec{a}, chosen at random with replacement from Q
18:
             \vec{c} \leftarrow a copy of an individual other than Q_i, \vec{a}, or \vec{b}, chosen at random with replacement from Q
                                                                                                                               Tweak #2
19:
             \vec{d} \leftarrow \vec{a} + \alpha(\vec{b} - \vec{c})
                                                                             D Mutation is just vector arithmetic
20:
             P_i \leftarrow \text{one child from Crossover}(\vec{d}, \text{Copy}(Q_i))
21:
22: until Best is the ideal solution or we ran out of time
```



23: return Best

# **Mutation strategy**

- Unlike the mutation in other Evolutionarybased metaheuristics, DE's mutation operators employ vector addition and subtraction
  - Designed for metric vector spaces (booleans, metric integer spaces, reals)
- To mutate a solution
  - DE generates a new child by picking three individuals from the population and doing the vector processes (Line #20 in the Pseudocode)

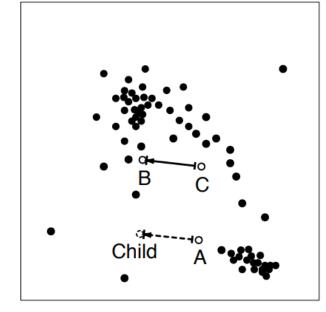


Figure 15 Differential Evolution's primary mutation operator. A copy of individual *A* is mutated by adding to it the vector between two other individuals *B* and *C*, producing a child.



## Common terms in DE

#### Target vector

- □ The old solution to be replaced by the newly generated solution
- □ In other evolutionary-based metaheuristics, target vector is also known as "Parent"

#### Mutant vector or donor vector

- □ The generated solution based on the some vector calculations in DE
- Provide some information that can be used to create the trial vector

#### Trial vector

- □ The new candidate solution, created to replace the target vector
- Obtained through crossover operation between target and mutant vectors



# Vector additions and subtractions to generate the mutant vector

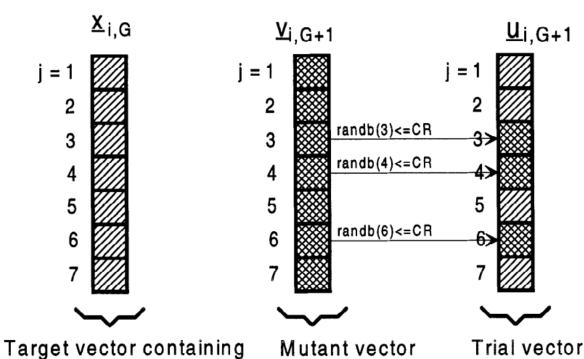
- For each member of the population
  - Select three other solutions  $(\vec{a}, \vec{b}, \vec{c})$
  - $\Box$  Generate the mutant vector  $(\vec{d})$

$$\vec{d} \leftarrow \vec{a} + \alpha(\vec{b} - \vec{c})$$

 $\alpha$  is the mutation rate, usually a real number between [0,2]. Higher  $\alpha$  means higher explorative ability.  $\alpha$  is determined by the user

### **Crossover in DE**

- The crossover constant (CR) control the probability of crossover
- CR is determined by the user
- For each vector unit, we generate a random number.
  - □ **IF** the random number is lower than *CR*; pass the vector unit from mutant vector to trial vector
  - **ELSE**; pass the vector unit from target vector to trial vector



the parameters x<sub>ii,G</sub>,

Figure 2. Illustration of the crossover process for D = 7 parameters.

Image source: Storn, R., & Price, K.V. (1997). Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces. Journal of Global Optimization, 11, 341-359.



## **Selection in DE**

- Note that DE "selects" individuals in a way quite different from what we've seen so far in Evolutionary-based metaheuristics method
- DE uses the greedy criterion in the selection process (survival selection) that only accept higher quality solution
  - □ Trial vector can only replace the target vector if it is more fitter
- Question: What is the gain and loss of this selection strategy?

## **Exploration and Exploitation in DE**

- IF the population is spread out;  $(\vec{b})$  and  $(\vec{c})$  are likely to be far from one another
  - It makes a "large" mutant vector
- **ELSE**;  $(\vec{b})$  and  $(\vec{c})$  are likely to be close from one another
  - It makes a "small" mutant vector
- This way, if the population is spread throughout the space, mutations will be much bigger than when the algorithm has later converged on fit regions of the space.

# **Takeaway**

- DE has the automatic shifting between exploration and exploitation in generating the mutant vector based on the spread of the solutions in the population
- Beside the common controlling parameters, such as the population size and number of iterations, DE has two other important parameters
  - □ Mutation Rate  $(\alpha)$  > to control how explorative the mutant vector
  - $\square$  Crossover Rate (CR) > to control how frequent the crossover process
- To run DE, the population size is at least 4
- DE utilizes the spread of the solutions in the population. Thus, larger population size could benefit DE more than it in lower population size

