# Inteligencia Computacional:

## Evolución Diferencial

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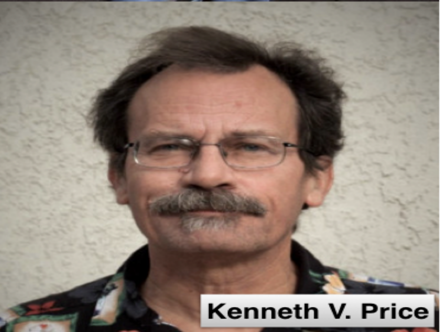
# Evolución diferencial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# Differential Evolution – A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces

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**Abstract.** A new heuristic approach for minimizing possibly nonlinear and non-differentiable continuous space functions is presented. By means of an extensive testbed it is demonstrated that the new method converges faster and with more certainty than many other acclaimed global optimization methods. The new method requires few control variables, is robust, easy to use, and lends itself very well to parallel computation.

**Key words:** Stochastic optimization, nonlinear optimization, global optimization, genetic algorithm, evolution strategy.

## 1. Introduction

Problems which involve global optimization over continuous spaces are ubiquitous throughout the scientific community. In general, the task is to optimize certain properties of a system by pertinently choosing the system parameters. For convenience, a system's parameters are usually represented as a vector. The standard approach to an optimization problem begins by designing an objective function that can model the problem's objectives while incorporating any constraints. Especially in the circuit design community, methods are in use which do not need an objective function but operate with so-called regions of acceptability: Brayton *et al*. (1981), Lueder (1990), Storn (1995). Although these methods can make formulating a problem simpler, they are usually inferior to techniques which make use of an objective function. Consequently, we will only concern ourselves with optimization methods that use an objective function. In most cases, the objective function defines the optimization problem as a minimization task. To this end, the following investigation is further restricted to minimization problems. For such problems, the objective function is more accurately called a "cost" function.

When the cost function is nonlinear and non-differentiable, direct search approaches are the methods of choice. The best known of these are the algorithms

# Operadores de Mutación



| | |
|---|---|
| DE/rand/1 | $v_i = x_{r1} + F_1(x_{r2} - x_{r3})$ |
| DE/best/1 | $v_i = x_{best} + F_1(x_{r2} - x_{r3})$ |
| DE/rand to best/1 | $v_i = x_{r1} + F_1(x_{r2} - x_{r3}) + F_2(x_{best} - x_{r1})$ |
| DE/curr. to best/1 | $v_i = x_i + F_1(x_{r2} - x_{r3}) + F_2(x_{best} - x_i)$ |
| DE/rand/2 | $v_i = x_{r1} + F_1(x_{r2} - x_{r3} + x_{r4} - x_{r5})$ |
| DE/best/2 | $v_i = x_{best} + F_1(x_{r2} - x_{r3} + x_{r4} - x_{r5})$ |

donde $r_1$, $r_2$, $r_3$, $r_4$, y $r_5$ son índices aleatorios diferentes entre ellos y diferentes de $i$.

Como puede verse, el individuo $i$ no participa en la mutación, sino que participará más tarde en la recombinación.

# Recombinación



$$u_{i,j} = \begin{cases} v_{i,j} & \text{if } r[0,1] \leq CR \text{ or } j = irand \\ x_{i,j} & \text{else} \end{cases}$$

$$x_i^{t+1} = \begin{cases} u_i^t & \text{if } f(u_i^t) < f(x_i^t) \\ x_i^t & \text{else} \end{cases}$$

# Evolución Diferencial



Inicializar parámetros;
$t \leftarrow 0$;
Crear población inicial $\mathscr{P}(0)$ con $\mu$ individuos;
**for** *each* $x_i \in \mathscr{P}(0)$ **do**
  Evaluar individuo $x_i$;
**repeat**
  **for** $x_i \in \mathscr{P}(t)$ **do**
    Aplicar mutación a $x_i$;
    Crear un vector $u$ mediante la recombinación del individuo
    original y el individuo mutado;
    Evaluar individuo $u$;
    **if** $f(u)$ *es mejor que* $f(x_i)$ **then**
      $\mathscr{P}(t+1) \leftarrow \mathscr{P}(t+1) \cup u$;
    **else**
      $\mathscr{P}(t+1) \leftarrow \mathscr{P}(t) \cup x_i$;
  $t \leftarrow t+1$;
**until** *se cumpla criterio de terminación*;

# Evolución Diferencial: mutación y recombinación



$r_1, r_2, r_3 \leftarrow$ Individuos aleatorios donde: $r_1 \neq r_2 \neq r_3$;

$irand \leftarrow$A random integer in the range $[1, n]$;

**for** $j \leftarrow 1$ *to* $n$ **do**

    **if** $rand(0,1) < CR$ $OR$ $j = irand$ **then**

        $u_j \leftarrow x_{r_3,j} + F * (x_{r_1,j} - x_{r_2,j})$;

        **if** $u_j > limite\_superior_j$ $OR$ $u_j < limite\_superior_j$ **then**

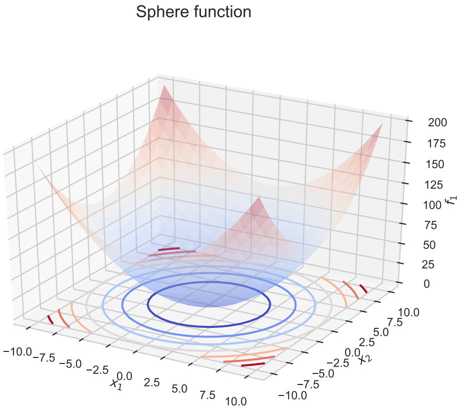
            $u_j \leftarrow$ evitar que viole los rangos;

    **else**

        $u_j \leftarrow x_{i,j}$;

# Función esfera

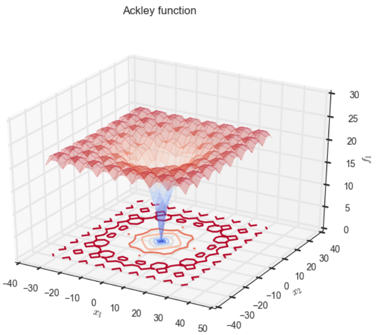
$$f(x) = \sum_{i=1}^{n} x_i^2$$



# Función de Ackley



$$
\begin{aligned}
f(x, y) = &-20 \exp\left(-0.2\sqrt{0.5\left(x^2 + y^2\right)}\right) \\
&- \exp\left(0.5\left(\cos\left(2\pi x\right) + \cos\left(2\pi y\right)\right)\right) \\
&+ e + 20 \\
&x, y \in [-32.768, 32.768]
\end{aligned}
$$

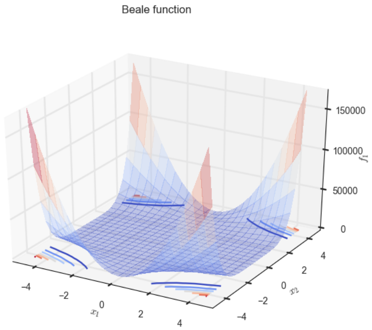


# Función de Beale

$$f(x,y) = (1.5 - x + xy)^2 + \left(2.25 - x + xy^2\right)^2 + \left(2.625 - x + xy^3\right)^2$$

$$x, y \in [-4.5, 4.5]$$

$$f(x^* = 3, y^* = 0.5) = 0$$



# Otras funciones



https://en.wikipedia.org/wiki/Test_functions_for_optimization

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# ¿Preguntas?



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