

# **Exponential Distribution Optimizer (EDO): A Novel Math-Inspired Algorithm for Global Optimization and Engineering Problems**

Code link:

[https://www.researchgate.net/publication/367248867\\_Exponential\\_Distribution\\_Optimizer\\_Codes](https://www.researchgate.net/publication/367248867_Exponential_Distribution_Optimizer_Codes)

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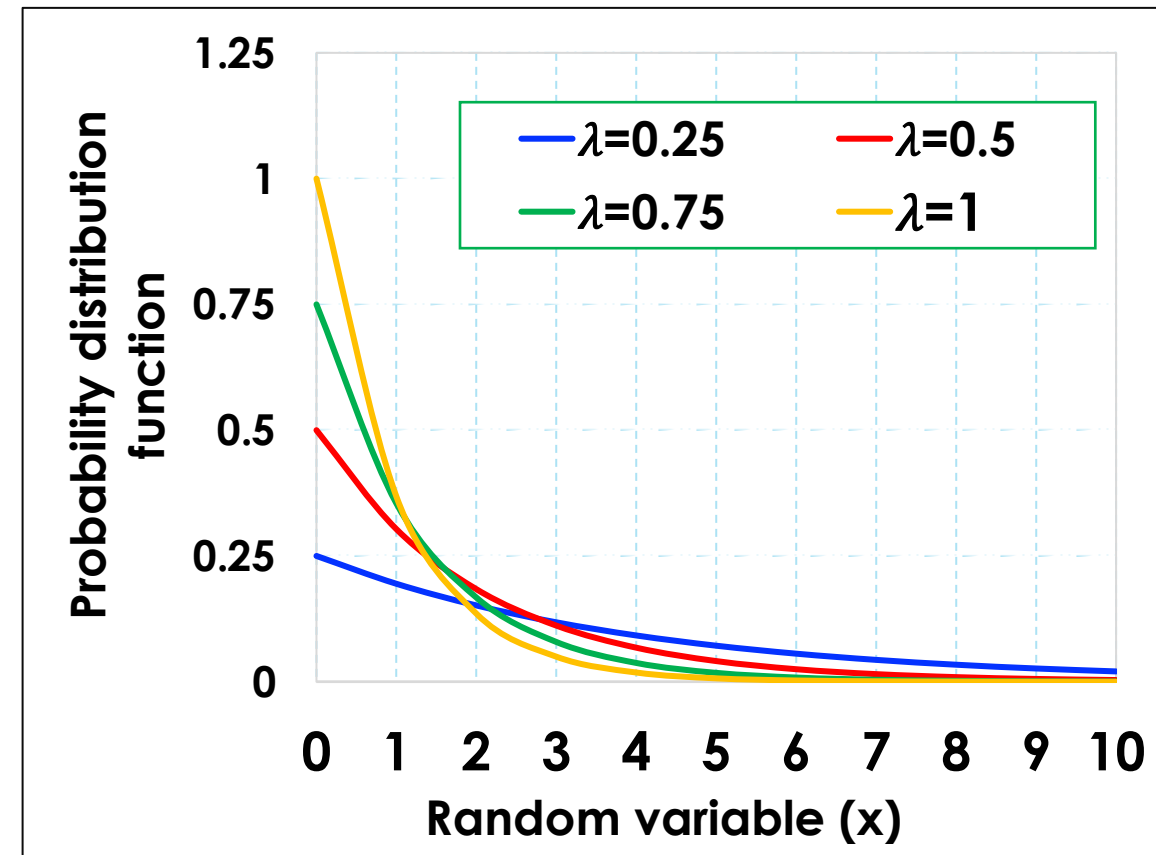
# Exponential distribution optimizer

- ❑ Inspired from the **exponential distribution** model.
- ❑ The exponential distribution is a **continuous** distribution that **concerns with the waiting time** until a specific event occurs.
- ❑ The Probability Density Function (PDF) of random variable  $x$  is given by:

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & , otherwise \end{cases}$$

$x$  : waiting time until an event occurs.

$\lambda$  : exponential rate.



# Memoryless property of the exponential distribution

- The exponential distribution is the only continuous distribution that has a **memoryless property**.

- A random variable  $x$  has a memoryless property if for all  $t > 0$  and  $s > 0$ .

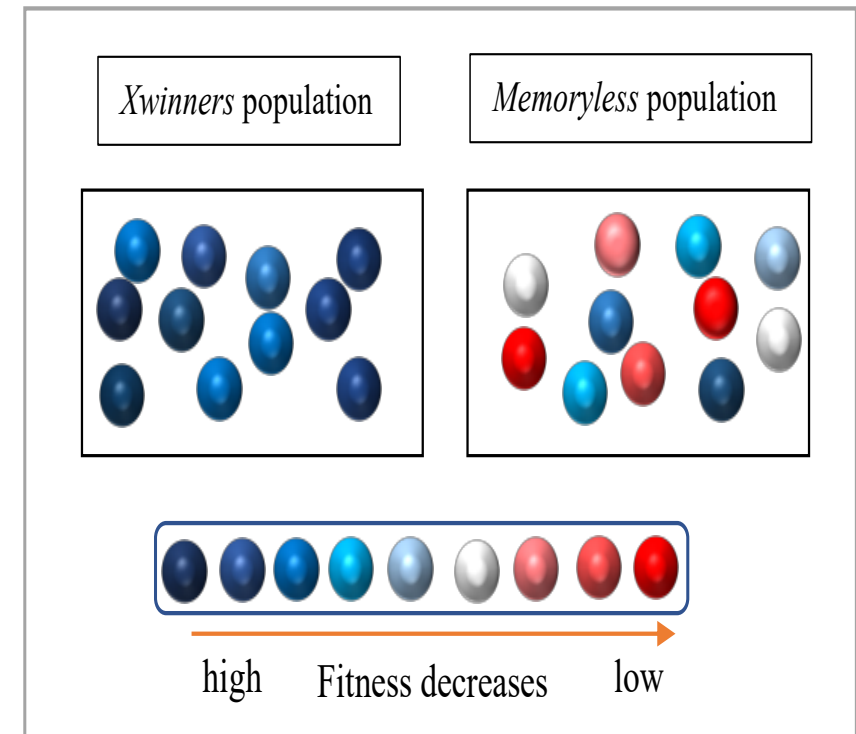
$$P(x > s + t \mid x \geq s) = P(x > t)$$

- **Memoryless property** assumes that the knowledge of the past has no effect on the future probabilities.



# Memoryless property

- ▶ According to the **memoryless property**, we disregard and do not memorize the previous history of the solutions because past failures are independent and have no influence on the future.
- ▶ To simulate the memoryless property of the exponential distribution, the **new solutions are copied to the memoryless matrix** regardless their fitness as previous history can't affect the future.
- ▶ As a result, the memoryless matrix stores two types of solutions: **winners and losers**.
- ▶ The **memoryless** matrix is first **initialized** equal to the original population  $X_{winners}$ .



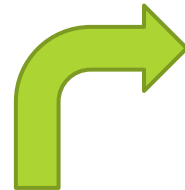
# Variance

- The **variance** ( $\sigma^2$ ) of an exponentially random variable can be defined as:

$$\sigma^2 = \frac{1}{\lambda^2}$$

$$\lambda = \frac{1}{\mu}$$

exponential rate



The random variable in the exponential distribution represents **the waiting time** until the next event occurs. Thus, the term "**time**" is used instead of "**iteration**". *Max\_time* refers to the total number of iterations.

mean

$$\mu = (\text{memoryless}_i^{\text{time}} + X_{\text{guide}}^{\text{time}}) / 2$$

- $X_{\text{guide}}^{\text{time}}$  determines the guiding solution obtained at iteration *time*. is defined as the mean of the first three best solutions of a sorted population.

$$X_{\text{guide}}^{\text{time}} = \frac{X_{\text{winners}}^{\text{time}}_{\text{best1}} + X_{\text{winners}}^{\text{time}}_{\text{best2}} + X_{\text{winners}}^{\text{time}}_{\text{best3}}}{3}$$

- **Note:** The guiding solution is selected instead of the best solution as the solutions will gradually move toward the best solution. When the best solution is trapped in the local optima, all the solutions still move toward the best solution.

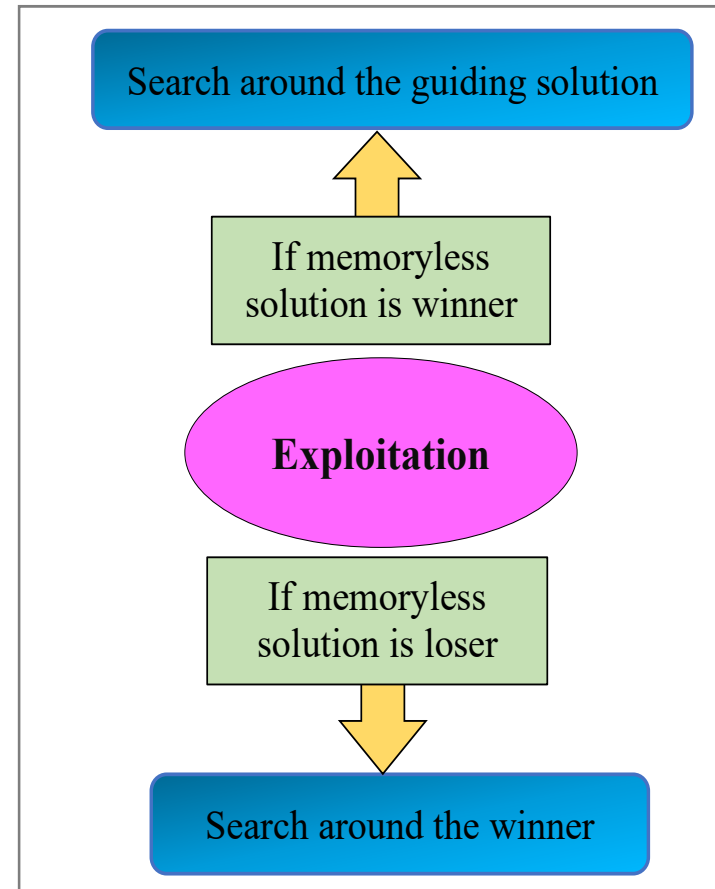
# Exploitation

- The region around a good solution is promising for finding the global optimum, which is why many algorithms exploit the search space surrounding good solutions by attracting poor ones. →
- This phase uses several characteristics of the exponential distribution model, such as the **memoryless property**, **standard variance** and **mean to update the new solution**:

$$V_i^{time+1} = \begin{cases} a.(memoryless_i^{time} - \sigma^2) + b.Xguide^{time} & \text{if } Xwinners_i^{time} = memoryless_i^{time} \\ b.(memoryless_i^{time} - \sigma^2) + \log(\phi).Xwinners_i^{time} & , \text{otherwise} \end{cases}$$

$$a = (f)^{10} \quad , \quad b = (f)^5$$

- $a$  and  $b$  are adaptive parameters.  $\phi$  is a random number uniformly generated in  $[0, 1]$ .  $f$  is a random number generated in  $[-1, 1]$ .



# Exploration

- The optimization model for the EDO exploration phase is built using **two random winners** from the original population obeying the exponential distribution ( $X_{winners_{rand1}}$ ,  $X_{winners_{rand2}}$ ) and updated using:

$$V_i^{time+1} = X_{winners_i}^{time} - M^{time} + (c.Z_1 + (1-c).Z_2)$$

$$M^{time} = \frac{1}{N} \cdot \sum_{i=1}^N X_{winners_{j,i}}^{time}, \quad j = 1, 2, \dots, d$$

$$Z_1 = M - D_1 + D_2, \quad Z_2 = M - D_2 + D_1$$

$$D_1 = M - X_{winners_{rand1}}, \quad D_2 = M - X_{winners_{rand2}}$$

$$d = \frac{1-time}{Max\_time}, \quad c = d \times f$$

$M^{time}$  indicates the mean of all solutions obtained in the original population. N is population size. d is the problem size (dimension).

d is an adaptive parameter that starts with zero and is gradually reduced during the course of time. c is an adjusted parameter denoting the ratio of information shared from  $Z_1$  and  $Z_2$  vectors.



# EDO optimizer

```
Initialize the population Xwinners
Evaluate the population and detect best solution
Calculate guiding solution
Construct memoryless matrix
while stopping condition not met
    Generate  $\alpha \in [0,1]$ 
    if  $\alpha < 0.5$ 
        if memorylessi = xwinneri
            Search around the guiding solution
        else
            Search around the winner solution
    else
        Select two random winners from population
        Apply exploration phase
end while
Check bounds of solutions
Copy new population to memoryless matrix
Update best solution
return best solution
```



