30/04/2019

# Trabajo Práctico 1: Algoritmo Genético Canónico

ALGORITMOS GENÉTICOS 2019

ANTONELLI (44852) – RECALDE (44704) – ROHN (41355)

# Índice

# Introducción

Implementamos algoritmos genéticos como una simulación computacional en la cual una población de las representaciones abstractas de las soluciones candidata (individuos) de un problema de optimización, evoluciona hacia mejores soluciones.

En este caso utilizamos *Python* y *C++* para la creación de un programa, mediante el uso de un ***algoritmo genético canónico***, que nos permite buscar el máximo de la función objetivo:

$$f(x) = \left(\frac{x}{coef}\right)^2 \text{ en el dominio } [0, 2^{30} - 1]$$

Donde: $coef = 2^{30} - 1$

Para lograr la implementación del algoritmo genético se tuvieron en cuenta los siguientes datos:

- Probabilidad de Corssover = 0,75
- Probabilidad de Mutación = 0,05
- Población inicial: 10 individuos
- Ciclos del programa: 20
- Método de Selección: Ruleta
- Método de Crossover: 1 punto
- Método de Mutacion: invertida

# Código

## *Python*

- __init__

```
from GeneticAlgorithms.Population import Population
from GeneticAlgorithms.Graphs import Graphic
# from GeneticAlgorithms.Chromosome import Chromosome
# import random


if __name__ == '__main__':
    # ImportantValues
    iterationLimit = 50  # 20,100,200  # Population Iterations
    initPopulationNum = 10  # Initial Population Size
    chromsomeSize = 30  # Chromosome Size
    crossoverProb = 0.75  # Probability of CrossOver
    mutationProb = 0.05  # Probability of Mutation

    # Initialize
    class Main(object):
        # First Population
        pob = Population(initPopulationNum, chromsomeSize, crossoverProb, mutationProb)
        graphicsData = {'averageOPs': [], 'minOPs': [], 'maxOPs': []}  # Dictionary for Graphics

        # Iterations
        for iterationCount in range(iterationLimit):
            print()
            averageOP, minOP, maxOP = pob.showPopulation(iterationCount)  # Show Actual Population and Return Data


            # Update Dictionary with important values
            graphicsData['averageOPs'].append(averageOP)
            graphicsData['minOPs'].append(minOP)
            graphicsData['maxOPs'].append(maxOP)

            # In the last iteration, the chromosomes population mustn't reproduce
            if iterationCount < iterationLimit - 1:
                pob.reproduce()  # Reproduction of Actual Generation

        # Graph Population's Evolution
        graph = Graphic(graphicsData, iterationLimit)
        graph.showPlots()

        # Last Reproduction Message
        print("Last Generation Reached Correctly")
        print("------------")
        print()
        print()

        # Final Tables
        print("TABLAS FINALES")
        print()
        print("Población ------------ Mínimo ------------ Máximo ------------ Promedio")
        for value in range(iterationLimit):
            print("Generación ", value, ":", graphicsData['minOPs'][value], "---
", graphicsData['maxOPs'][value], "---",
graphicsData['averageOPs'][value])
```

- Chromosome

```
#!/usr/bin/env python
# -*- coding: utf-8 -*-
import random
```

```
•
•
•   class Chromosome(object):
•       # Class Attribute (Constant)
•       # coef = random.randint(1, 230 - 1)
•       coef = (2**30)-1  # (2^30)-1
•
•       # Constructor / Instance Attributes
•       def __init__(self, large, newBody):
•
•           # Chromosome's Genes
•           if newBody is None:
•               self.body = []
•               for _ in range(large):
•                   self.body.append(str((random.randint(0, 1))))
•           else:
•               self.body = newBody
•           self.large = large
•           # Initialize Objective Function Punctuation and Fitness
•           self.setObjectivePunctuation()
•           self.fitness = 0
•
•       # Show All Genes of the Chromosome
•       def getBody(self):
•           return self.body
•
•       def toBinInteger(self):
•           str_bin_num = ''.join(str(i) for i in self.body)
•
•           return int(str_bin_num)
•
•       # Real Number to pass on Objective Function
•       def getRealValue(self):
•           num = ''.join(str(i) for i in self.body)
•           return int(num, 2)  # Convert body to String and then to Binary Int
•
•       def calcObjPunc(self):
•           return (self.getRealValue() / self.getCoef()) ** 2
•
•       def calcFitness(self, totalObj):
•           # if totalObj == 0: totalObj = 1  # Prevent Division by Zero Error
•           self.fitness = (self.getObjectivePunctuation() / totalObj)  # Update Fitness
•           return self.fitness
•
•       # def copy(self, Chrom, num1, num2): pass
•       # def mutate(self): pass
•
•       # Class Methods
•       @classmethod
•       def getCoef(cls):
•           return cls.coef
•
•       @classmethod
•       def setCoef(cls, coeficient):
•           cls.coef = coeficient
•
•       # Getters and Setters
•       def getLarge(self):
•           return self.large
•
•       def setLarge(self, large):
•           self.large = large
•
•       def getObjectivePunctuation(self):
•           return self.objectivePunctuation
•
•       def setObjectivePunctuation(self):
```

```
            self.objectivePunctuation = self.calcObjPunc()

        def getFitness(self):
            return self.fitness

        def setFintess(self, fitness):
            self.fitness = fitness

        def copy(self, another_crom, start, end):
            for i in range(start, end):
    self.body[i] = (another_crom.body[i])
```

- Population

```
    #!/usr/bin/env python
    # -*- coding: utf-8 -*-
    from GeneticAlgorithms.Chromosome import Chromosome
    import random


    class Population(object):
        # Class Attributes
        population = []  # Initial Population (Array of Chromosomes)
        totalObjPunc = 0  # The Sum of All Objective Functions Punctuation
        totalFitness = 0  # The Sum of All Objective Values

        # Constructor / Instance Attributes
        def __init__(self, numChroms, chromSize, crossProb, mutProb):
            self.numChroms = numChroms
            self.chromSize = chromSize
            self.crossProb = crossProb
            self.mutProb = mutProb
            # print("Objective Function Coeficient:", Chromosome.getCoef())
            print("Start Algorithm")
            for _ in range(numChroms):
                oneChrom = Chromosome(chromSize, None)  # Initialization of Chromosomes
                self.addChrom(oneChrom)  # Add to Population

        # Show Actual Population and Stats
        def showPopulation(self, numIter):
            self.setTotalFitness(0)
            self.setTotalObjPunc(self.calcTotalObjPunc())
            large = self.getChromSize()
            averageObjPunc = self.getTotalObjPunc() / len(self.population)
            fitness = 0
            maxVal = 0
            minVal = 0
            maxChrom = 0
            minChrom = 0
            print("Population ", (numIter + 1), ":")
            for i in range(len((self.population))):
                fitness = self.population[i].calcFitness(self.getTotalObjPunc())
                self.updateTotalFitness(fitness)
                if i == 0:
                    maxVal = fitness
                    minVal = fitness
                elif fitness > maxVal:
                    maxVal = fitness
                    maxChrom = i
                elif fitness < minVal:
                    minVal = fitness
                    minChrom = i
                for j in range(large):
```

```
                print(self.population[i].getBody()[j], end='')
            print()
        fitness = self.getTotalFitnessAverage()
        print()
        print("Chromosome --- Value --- Objective Punctuation --- Fitness")
        print("Max Values: Chrom Nº", maxChrom, "with:", self.population[maxChrom].getRealValue(), "Val,",
              self.population[maxChrom].getObjectivePunctuation(), "OP,", round(maxVal, 4), "Fit")
        print("Min Values: Chrom Nº", minChrom, "with:", self.population[minChrom].getRealValue(), "Val,",
              self.population[minChrom].getObjectivePunctuation(), "OP,", round(minVal, 4), "Fit")
        print("Average OP:", averageObjPunc, "--- Average Fitness:", fitness)  # round(fitness,6)
        print()
        # Return Important Data to use on Graphics
        return (averageObjPunc, self.population[minChrom].getObjectivePunctuation(),
                self.population[maxChrom].getObjectivePunctuation())

    # Calculate Total of Objective Functions Punctuation in the actual Generation
    def calcTotalObjPunc(self):
        acumObjPunc = 0
        for chromosome in self.population:
            acumObjPunc += chromosome.getObjectivePunctuation()  # Add Every Objective Function Punctuation
        #  self.setTotalObjPunc(acumulator)
        return acumObjPunc

    # Update Total Fitness
    @classmethod
    def updateTotalFitness(cls, fitness):
        cls.totalFitness += fitness

    # Add to Population
    def addChrom(self, Chrom):
        self.population.append(Chrom)

    # Reproduction
    def reproduce(self):
        parents = []  # List of Potential Parents
        newGeneration = []  # List of Children
        print("Roulette Results: ", end='')
        #  lastParent = None  # Check if a Chromosome tries to reproduce with himself
        for _ in range(0, len(self.population), 2):
            lastParent = None
            for i in range(2):
                lastParent = self.roulette(lastParent)  # Parents Selected by Roulette
                parents.append(self.population[lastParent])
        print()
        for i in range(0, len(parents), 2):
            father1 = parents[i]
            father2 = parents[i + 1]
            if self.crossPosibility():  # CrossOver Probability Evaluation
                son1, son2 = self.cross(father1, father2)  # CrossOver
                print("Successful CrossOver in reproduction:", (i + 2) / 2)  # Only Print
            else:
                son1, son2 = self.copy(father1, father2)  # Direct Assignation (Without CrossOver)
                print("CrossOver didn't happen in reproduction:", (i + 2) / 2)  # Only Print
            # Individual Mutation Probability Evaluation
            if self.mutationPosibility():
                son1 = self.mutation(son1)
            if self.mutationPosibility():
                son2 = self.mutation(son2)
            self.addChildren(son1, son2, newGeneration)
        self.replacePopulation(newGeneration)
        self.setTotalFitness(0)

    # Genetic Operator (Roulette Method)
    def roulette(self, lastParent):
        # Generator of a Bidimensional List (Fitness Range of Chromosomes)
        newRoulette = [[0] * 2 for _ in range(len(self.population))]
        acum = 0  # Acumulator of Relative Fitness from 0 to 1 (Fills Roulette)
```

```
            for i in range(len(self.population)):
                newRoulette[i][0] = acum  # Range Min: Last Acum Value
                acum += round(self.population[i].getFitness(), 6)  # Acum's Value From Zero
                newRoulette[i][1] = acum  # Range Max: New Acum Value
            ranNum = round(random.uniform(0, 1), 6)  # Random Number from 0.000000 to 0.999999
            # print("Random: ", ranNum)  # Only Print
            count = 0
            while count <= 100:  # If the same parent is selected more than 100 times... select the next or last one
                for i in range(len(newRoulette)):
                    if newRoulette[i][0] < ranNum < newRoulette[i][1]:
                        # Return Selected Chromosome if the Random Number Exists in its Range
                        if lastParent != i:
                            print(i, end=', ')
                            return i
                        else:
                            print("REP", end=', ')
                            ranNum = round(random.uniform(0, 1), 6)
                            break
                count += 1
                if count == 100:  # Reach Only if the same parent goes selected 100 times
                    if lastParent < len(newRoulette)-1:
                        print(lastParent, end=', ')
                        return lastParent+1
                    else:
                        print(lastParent, end=', ')
                        return lastParent-1
            print("Error")
            return "Error"  # Error Exit

        def crossPosibility(self):  # CrossOver posibility evaluation
            if self.getCrossProb()*100 >= random.randint(1, 100):
                return True
            else:
                return False

        def cross(self, parent1, parent2):
            crom_size = parent1.getLarge()
            son1 = Chromosome(crom_size, None)
            son2 = Chromosome(crom_size, None)
            cut = random.randint(1, crom_size - 2)  # Random Cut Point (Except by zero or all genes)

            son1.copy(parent1, 0, cut)
            son1.copy(parent2, cut, crom_size)

            son2.copy(parent2, 0, cut)
            son2.copy(parent1, cut, crom_size)

            son1.setObjectivePunctuation()
            son2.setObjectivePunctuation()

            print()
            print("Son 1:", son1.toBinInteger())  # Only Print
            print("Son 2:", son2.toBinInteger())  # Only Print
            print("Cut Point on:", cut)  # Only Print
            return son1, son2

        def copy(self, chrom1, chrom2):
            # newGeneration.append(chrom1)
            # newGeneration.append(chrom2)
            son1 = chrom1
            son2 = chrom2
            print()
            print("Son 1 (Identical):", self.listToInt(chrom1.getBody()))  # Only Print
            print("Son 2 (Identical):", self.listToInt(chrom2.getBody()))  # Only Print
            return son1, son2

        def mutationPosibility(self):  # Mutation posibility evaluation
```

```
            if self.getMutProb() * 100 >= random.randint(1, 100):
                return True
            else:
                return False

        def mutation(self, chrom):  # Select one random Gen and Switch its Value
            mutPos = random.randint(1, len(self.population))
            newBody = []
            for i in range(len(chrom.getBody())):
                if i != mutPos:
                    newBody.append(chrom.getBody()[i])
                else:
                    if chrom.getBody()[mutPos] == 1:  # If is a '0' then change to '1', and vice-versa
                        newBody.append(0)
                    else:
                        newBody.append(1)
            son = Chromosome(self.chromSize, newBody)
            print("Mutated Chrom in position:", mutPos, ":", self.listToInt(chrom.getBody()))  # Only Print
            return son

        def addChildren(self, son1, son2, newGeneration):
            newGeneration.append(son1)
            newGeneration.append(son2)

        def replacePopulation(self, newGeneration):  # Replace All Population in every Iteration
            self.population = []
            for i in range(len(newGeneration)):
                self.population.append(newGeneration[i])

        def listToInt(self, arr):
            num = ''.join(str(i) for i in arr)
            return int(num)

        # Class Getters and Setters
        @classmethod
        def getTotalObjPunc(cls):
            return cls.totalObjPunc

        @classmethod
        def setTotalObjPunc(cls, total):
            cls.totalObjPunc = total

        @classmethod
        def getTotalFitness(cls):
            return cls.totalFitness

        @classmethod
        def setTotalFitness(cls, total):
            cls.totalFitness = total

        @classmethod
        def getTotalFitnessAverage(cls):
            return cls.totalFitness / len(cls.population)

        # Getters and Setters
        def getNumChroms(self):
            return self.numChroms

        def setNumChroms(self, numChroms):
            self.numChroms = numChroms

        def getChromSize(self):
            return self.chromSize

        def setChromSize(self, chromSize):
            self.chromSize = chromSize

```

```
    def getCrossProb(self):
        return self.crossProb

    def setCrossProb(self, crossProb):
        self.crossProb = crossProb

    def getMutProb(self):
        return self.mutProb

    def setMutProb(self, mutProb):
self.mutProb = mutProb
```

- Graphs

```
#!/usr/bin/env python
# -*- coding: utf-8 -*-

from matplotlib import pyplot
# import math
# import numpy as np

# pyplot.plot(x1,y1,'b-',x2,y2,'r-',x3,y3,'g-')
# pyplot.legend('value 1', 'value 2', 'value 3')


class Graphic(object):
    def __init__(self, graphicsData, iterationLimit):
        self.averageOPs = graphicsData['averageOPs']
        self.minOPs = graphicsData['minOPs']
        self.maxOPs = graphicsData['maxOPs']
        self.generations = []
        for i in range(iterationLimit):
            self.generations.append(i)
        # pyplot.ion()

    # Show one Plot with all Graphs
    def showPlots(self):
        # with pyplot.style.context(('dark_background')):
        self.drawAll(self.minOPs, self.generations, "Puntuación Objetiva", "Generación", "PUNTUACIÓN OBJETIVA MÍNIMA", 221)
        self.drawAll(self.maxOPs, self.generations, "Puntuación Objetiva", "Generación", "PUNTUACIÓN OBJETIVA MÁXIMA", 222)
        self.drawAll(self.averageOPs, self.generations, "Puntuación Objetiva", "Generación", "PUNTUACIÓN OBJETIVA PROMEDIO", 212)
        pyplot.show()  # Draw all the "Subplots"

    # Show one Graph in each Plot
    def showPlotsApart(self):
        self.draw(self.minOPs, self.generations, "Puntuación Objetiva", "Generación", "PUNTUACIÓN OBJETIVA MÍNIMA")
        self.draw(self.maxOPs, self.generations, "Puntuación Objetiva", "Generación", "PUNTUACIÓN OBJETIVA MÁXIMA")
        self.draw(self.averageOPs, self.generations, "Puntuación Objetiva", "Generación", "PUNTUACIÓN OBJETIVA PROMEDIO")

    # Generate one Subplot for every Graph (and Show all Graphs)
    def drawAll(self, axisY, axisX, labY, labX, title, region):
        pyplot.subplot(region)
        pyplot.axis([-1, len(self.generations), 0, 1])
        pyplot.grid(True)
```

```
        pyplot.plot(axisX, axisY)
        pyplot.ylabel(labY)
        pyplot.xlabel(labX)
        pyplot.title(title)

    # Generate one plot for every Graph
    def draw(self, axisY, axisX, labY, labX, title):
        pyplot.axis([-1, len(self.generations), 0, 1])
        pyplot.grid(True)
        pyplot.plot(axisX, axisY)
        pyplot.ylabel(labY)
        pyplot.xlabel(labX)
        pyplot.title(title)
        pyplot.show()
```

Repositorio GitHub:
https://github.com/NicoCaptain/Genetic-Algorithms

### *Código también en C++*

Repositorio GitHub:
https://github.com/alereca/Genetic-Algorithms-Cpp

# Explicación de Funcionamiento

**Funcionamiento de Cromosoma:**

- Mostrar sus genes en diferentes formatos
- Setear sus genes de manera random al inicializarse con el numero indicado de estos
- Calcular función objetivo a partir del cuadrado de la valuación a número real del conjunto de genes dividido el coeficiente
- Calcular su fitness a partir de dividir la valuación de la función objetivo por la valuación de la función objetivo acumulada por todos los cromosomas
- Mutar un gen en una posición random
- Copiar en sí mismo la parte indicada de otro cromosoma

**Funcionamiento de Población:**

- Mostrar los cromosomas que la conforman
- Inicializarse con el numero de cromosomas, la probabilidad de crossover y la probabilidad de mutación indicados
- Reproducirse, lo que incluiría la selección y crossover
- Seleccionar a los cromosomas dentro de una ruleta de manera probabilística según su fitness
- Crear una ruleta que permita que los cromosomas más aptos tengan mayores posibilidades
- Calcular la puntuación objetivo acumulada por todos los cromosomas que la conforman
- Calcular el mínimo, máximo y promedio en cada generación (al inicializarse y después de cada reproducción)

**Funcionamiento de la Grafica:**

- Mostrar la grafica de líneas de los valores máximo, mínimo y promedio de cada generación
- Setearse a través de una tabla enviada desde población que contenga todos estos valores

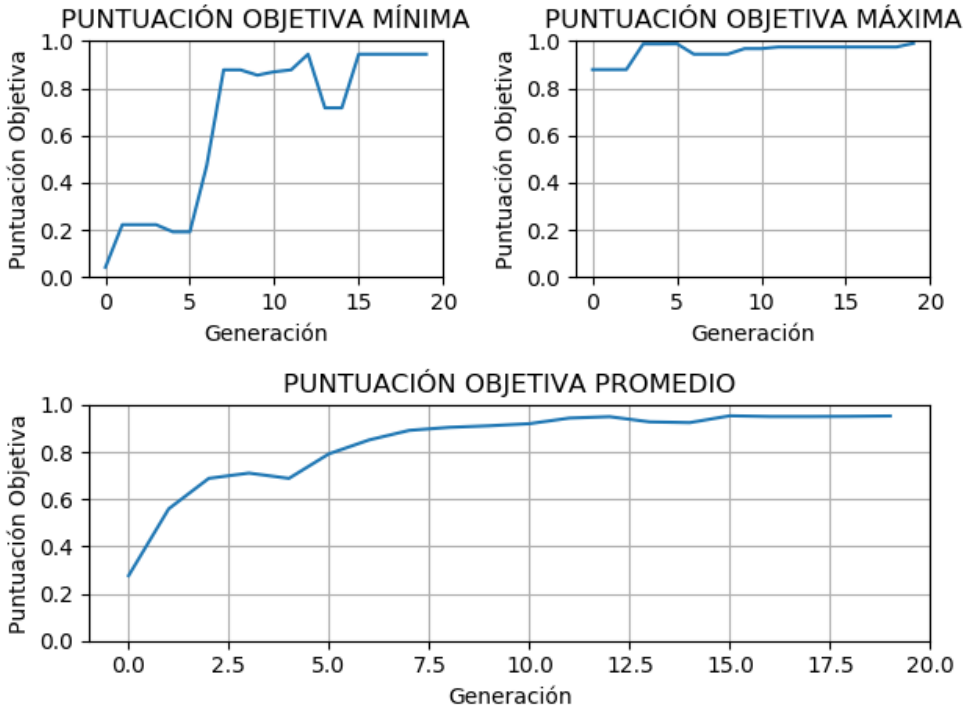
**Funcionamiento Conjunto:**

- Se inicializa la población con el numero de cromosomas, el número de genes, la probabilidad de crossover indicados por el usuario *[entrada]*
- Se muestra la generación inicial *[proceso]*
- Se reproducen los cromosomas de la población y se obtiene una nueva generación generalmente mas optima que remplaza a la anterior
- Se agregan los valores máximo, mínimo y promedio de esta generación a una tabla de valores históricos
- Se repite hasta llegar al número de iteraciones indicado por el usuario
- Se generan los gráficos de línea a partir de los valores de cada generación obtenidos de la tabla de valores históricos *[salida]*
- Se analiza si la población convergió a la solución optima o se estanco en un máximo local

# Gráficas y Tablas

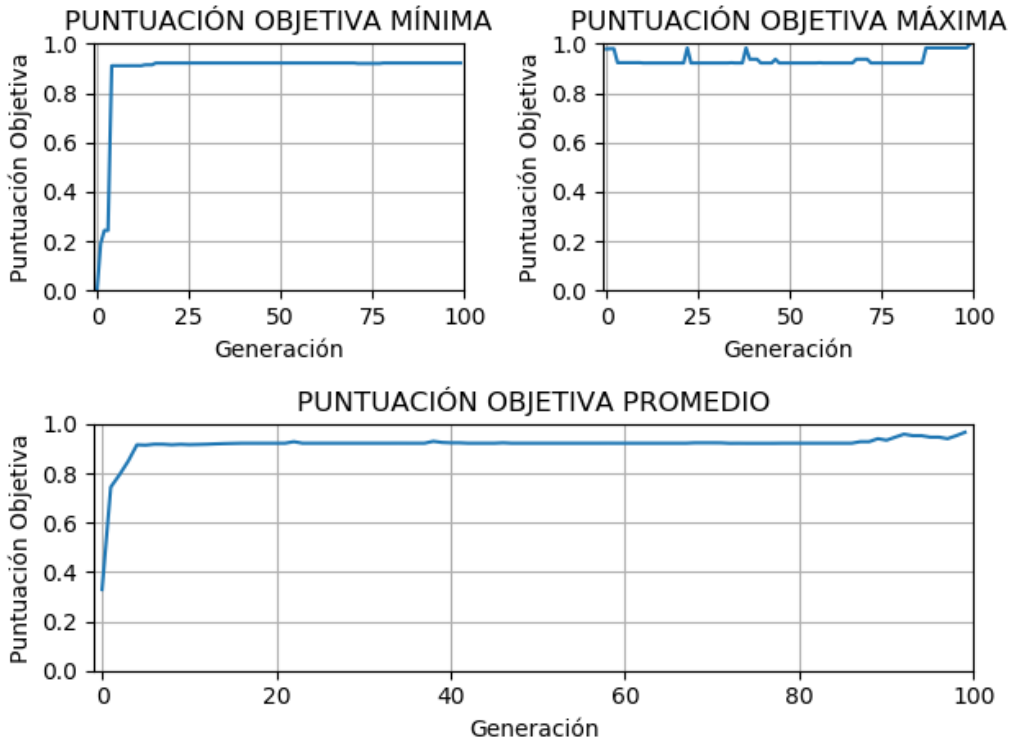
***Python: Matplotlib***

Algoritmo en 20 Generaciones




| Número de Generación | Mínimo | Máximo | Promedio |
|---|---|---|---|
| Generación 0 | 0.04136325621646656 | 0.8787327844870441 | 0.27614223876953925 |
| Generación 1 | 0.2218140906579105 | 0.8787327844870441 | 0.5590941751644709 |
| Generación 2 | 0.2218140906579105 | 0.8788508184451957 | 0.6880873504730107 |
| Generación 3 | 0.2218140906579105 | 0.9876432034378259 | 0.7105151774541307 |
| Generación 4 | 0.19138038199981344 | 0.9876432034378259 | 0.6880394742908388 |
| Generación 5 | 0.19132530358517782 | 0.9881316361420756 | 0.7922285982682917 |
| Generación 6 | 0.4725282449527984 | 0.9439619643546071 | 0.8508834954163321 |
| Generación 7 | 0.8775770511910796 | 0.9439637523422957 | 0.8913506418735189 |
| Generación 8 | 0.877571628022631 | 0.9439693769137989 | 0.904259116291855 |
| Generación 9 | 0.8550738848932281 | 0.9675984568151124 | 0.9108839858184912 |
| Generación 10 | 0.8695833896248739 | 0.9675984568151124 | 0.9198054779913676 |
| Generación 11 | 0.8775699040588221 | 0.9745772988626644 | 0.9435825658991359 |
| Generación 12 | 0.9439564013349167 | 0.974582951391214 | 0.9493878972582686 |
| Generación 13 | 0.7166927016230302 | 0.974582951391214 | 0.9273575665835887 |
| Generación 14 | 0.7166927016230302 | 0.9745678878251469 | 0.9242958153882732 |
| Generación 15 | 0.9439564049543125 | 0.974582951391214 | 0.9531476451666109 |
| Generación 16 | 0.9439564049543125 | 0.9745678289833203 | 0.9500855405787674 |
| Generación 17 | 0.9439619643546071 | 0.9745678289833203 | 0.950087584824596 |
| Generación 18 | 0.9439619643546071 | 0.9745678289833203 | 0.950843707730386 |
| **Generación 19** | **0.943961906444103** | **0.99005389572202** | **0.9523923144973881** |

## Algoritmo en 100 Generaciones

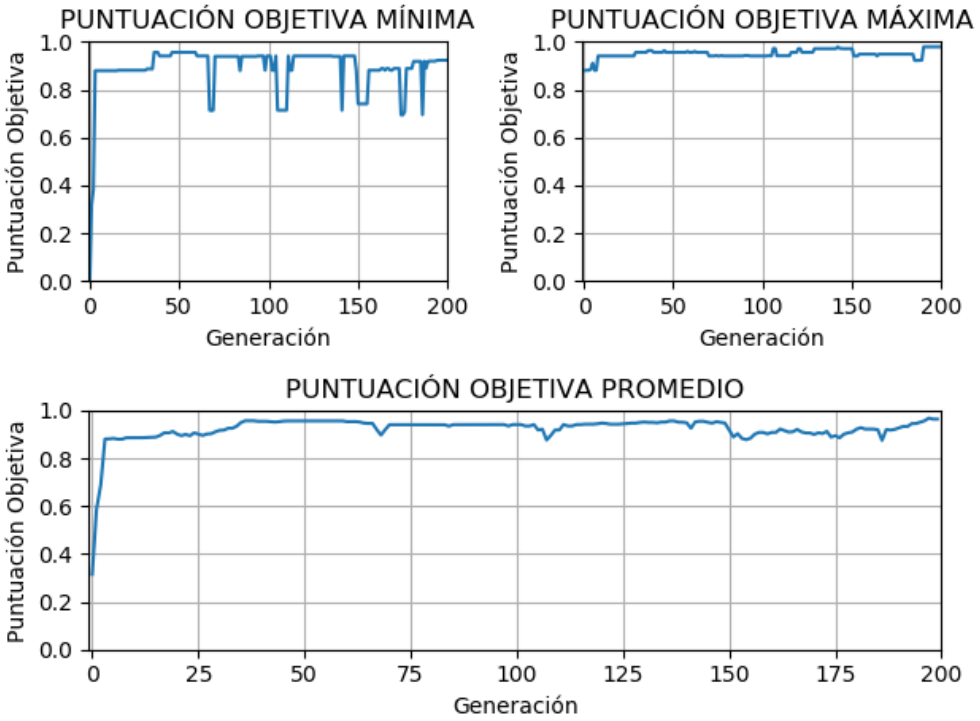



| Número de Generación | Mínimo | Máximo | Promedio |
|---|---|---|---|
| Generación 0 | 0.0005246260358118554 | 0.9786779705077044 | 0.329109243093235 |
| Generación 1 | 0.19035855844277258 | 0.9796443041836185 | 0.74396055562241 |
| Generación 2 | 0.24323216996398675 | 0.9796442949656687 | 0.7939948021062727 |
| Generación 3 | 0.24323219476699787 | 0.92311823636844 | 0.8492369519164177 |
| Generación 4 | 0.910596893578787 | 0.92311823636844 | 0.9152952934098071 |
| Generación 5 | 0.910596893578787 | 0.9231181898385384 | 0.9140433548636093 |
| Generación 6 | 0.910596893578787 | 0.9231181898385384 | 0.9177996567112894 |
| Generación 7 | 0.910596893578787 | 0.9231181898385384 | 0.9176446916600411 |
| Generación 8 | 0.910596893578787 | 0.92311823636844 | 0.9154139765126088 |
| Generación 9 | 0.9107024619315998 | 0.9232208430226426 | 0.9173516430753317 |
| Generación 10 | 0.9107279910811472 | 0.9218138665760793 | 0.9159327584292034 |
| Generación 11 | 0.9107134311386875 | 0.9218139148614438 | 0.9167025501845796 |
| Generación 12 | 0.9105969415694752 | 0.9219311196863949 | 0.9176735768949378 |
| Generación 13 | 0.9140839281785269 | 0.9219311196863949 | 0.9191431185339434 |
| Generación 14 | 0.9144450312600445 | 0.9219311196863949 | 0.9202992315209924 |
| Generación 15 | 0.9144450312600445 | 0.9219311196863949 | 0.9210975258262082 |
| Generación 16 | 0.9217992415338697 | 0.9219311196863949 | 0.9218446719856213 |
| Generación 17 | 0.9218138916129349 | 0.9219311196863949 | 0.9218695777722719 |
| Generación 18 | 0.9218138916129349 | 0.9219311196863949 | 0.9218475972584894 |
| Generación 19 | 0.9218138916129349 | 0.9219311196863949 | 0.9218695707972943 |
| Generación 20 | 0.9218138916129349 | 0.9219310964364079 | 0.921868108021088 |
| Generación 21 | 0.9218138916129349 | 0.9219310964364079 | 0.9218563900425556 |
| Generación 22 | 0.9218138916129349 | 0.9827974163843114 | 0.9279547382276723 |
| Generación 23 | 0.9218138916129349 | 0.9219164686758223 | 0.9218754337370916 |
| Generación 24 | 0.9217992647821939 | 0.9219310964364079 | 0.9218856893903586 |

| | | | |
|---|---|---|---|
| Generación 25 | 0.9217992647821939 | 0.9219310964364079 | 0.9218959492427927 |
| Generación 26 | 0.9219164454260201 | 0.9219310982248684 | 0.9219179228673399 |
| Generación 27 | 0.9219164454260201 | 0.9219164686758223 | 0.9219164574086106 |
| Generación 28 | 0.9219164454260201 | 0.9219164686758223 | 0.9219164550836304 |
| Generación 29 | 0.9219164454260201 | 0.9219164686758223 | 0.9219164581239891 |
| Generación 30 | 0.9219164543682518 | 0.9219164686758223 | 0.9219164672450653 |
| Generación 31 | 0.9219164543682518 | 0.9219164686758223 | 0.9219164672450653 |
| Generación 32 | 0.9219164543682518 | 0.9219164686758223 | 0.9219164658143081 |
| Generación 33 | 0.9219164543682518 | 0.9219164686758223 | 0.9219164672450653 |
| Generación 34 | 0.9219164543682518 | 0.9228543680457514 | 0.922010255751301 |
| Generación 35 | 0.9219164543682518 | 0.9219164686758223 | 0.9219164629527942 |
| Generación 36 | 0.9219164543682518 | 0.9219164686758223 | 0.9219164658143082 |
| Generación 37 | 0.9219164543682518 | 0.9219164686758223 | 0.9219164658143081 |
| Generación 38 | 0.9219164543682518 | 0.9829033320640121 | 0.9295215131909227 |
| Generación 39 | 0.9219164543682518 | 0.9369800790537787 | 0.9249291878898994 |
| Generación 40 | 0.9219164543682518 | 0.9369800790537787 | 0.9234228254213466 |
| Generación 41 | 0.9219164543682518 | 0.9369800790537787 | 0.9234228282828608 |
| Generación 42 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 43 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 44 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 45 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 46 | 0.9219164686758223 | 0.9369800790537787 | 0.9234228297136179 |
| Generación 47 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 48 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 49 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 50 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 51 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 52 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 53 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 54 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 55 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 56 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 57 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 58 | 0.9219164686758223 | 0.9228543680457514 | 0.9220102586128153 |
| Generación 59 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 60 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 61 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 62 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 63 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 64 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 65 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 66 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 67 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 68 | 0.9219164686758223 | 0.9369800790537787 | 0.923422829713618 |
| Generación 69 | 0.9219164686758223 | 0.9369800790537787 | 0.923422829713618 |
| Generación 70 | 0.9219164686758223 | 0.9369800790537787 | 0.923422829713618 |
| Generación 71 | 0.9200421004474414 | 0.9369800790537787 | 0.9232353928907798 |
| Generación 72 | 0.9200421004474414 | 0.9219164686758223 | 0.9215415950301461 |

| | | | |
|---|---|---|---|
| Generación 73 | 0.9200421004474414 | 0.9219164686758223 | 0.9217290318529843 |
| Generación 74 | 0.9200421004474414 | 0.9219164686758223 | 0.9215415950301461 |
| Generación 75 | 0.9200421004474414 | 0.9219164686758223 | 0.9215415950301461 |
| Generación 76 | 0.9200421004474414 | 0.9219164686758223 | 0.9215415950301461 |
| Generación 77 | 0.9200421004474414 | 0.9219164686758223 | 0.9215415950301461 |
| Generación 78 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 79 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 80 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 81 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 82 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 83 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 84 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 85 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 86 | 0.9219164686758223 | 0.9219164686758223 | 0.9219164686758223 |
| Generación 87 | 0.9219164686758223 | 0.9829033320640121 | 0.9280151550146412 |
| Generación 88 | 0.9219164686758223 | 0.9829033320640121 | 0.9280151550146414 |
| Generación 89 | 0.9219164686758223 | 0.9829033320640121 | 0.9402125276922793 |
| Generación 90 | 0.9219164686758223 | 0.9829033320640121 | 0.9341138413534603 |
| Generación 91 | 0.9219164686758223 | 0.9829033320640121 | 0.9463112140310983 |
| Generación 92 | 0.9219164686758223 | 0.9829033320640121 | 0.9585085867087362 |
| Generación 93 | 0.9219164686758223 | 0.9829033320640121 | 0.9524099003699172 |
| Generación 94 | 0.9219164686758223 | 0.9829033320640121 | 0.9524099003699172 |
| Generación 95 | 0.9219164686758223 | 0.9829033320640121 | 0.9463112140310983 |
| Generación 96 | 0.9219164686758223 | 0.9829033320640121 | 0.9463112140310983 |
| Generación 97 | 0.9219164686758223 | 0.9829033320640121 | 0.9402125276922793 |
| Generación 98 | 0.9219164686758223 | 0.9829033320640121 | 0.9524099003699172 |
| **Generación 99** | **0.9219164686758223** | **0.998455223692878** | **0.9661624622104418** |

## Algoritmo en 200 Generaciones




| Número de Generación | Mínimo | Máximo | Promedio |
|---|---|---|---|
| Generación 0 | 0.002277189352044981 | 0.879173799643822 | 0.3146832063053033 |
| Generación 1 | 0.31959097399855274 | 0.8810205015964007 | 0.5856649153341211 |
| Generación 2 | 0.381358639544012 | 0.8810205015964007 | 0.6884245744599695 |
| Generación 3 | 0.8791738083763 | 0.8810205068413873 | 0.8802115823925238 |
| Generación 4 | 0.879173799643822 | 0.8865143918950918 | 0.8809441996042452 |
| Generación 5 | 0.879173799643822 | 0.910582078736037 | 0.8829214757202848 |
| Generación 6 | 0.879173799643822 | 0.881006086683685 | 0.8796374840872184 |
| Generación 7 | 0.879173799643822 | 0.881006086683685 | 0.8795172891446628 |
| Generación 8 | 0.8791165801396651 | 0.9406463520392986 | 0.8855844159123955 |
| Generación 9 | 0.879173799643822 | 0.9406463520392986 | 0.8855500728819591 |
| Generación 10 | 0.879173799643822 | 0.9406463520392986 | 0.8857333015859454 |
| Generación 11 | 0.879173799643822 | 0.9406463520392986 | 0.8857333015859453 |
| Generación 12 | 0.879173799643822 | 0.9406463520392986 | 0.8858707409953286 |
| Generación 13 | 0.879173799643822 | 0.9406463520392986 | 0.8867880289244419 |
| Generación 14 | 0.879173799643822 | 0.9406463520392986 | 0.8879812804768583 |
| Generación 15 | 0.879173799643822 | 0.9406463520392986 | 0.8884399482832727 |
| Generación 16 | 0.881006086683685 | 0.9406463520392986 | 0.8955044914519339 |
| Generación 17 | 0.881006086683685 | 0.9406463520392986 | 0.9065146843893525 |
| Generación 18 | 0.881006086683685 | 0.9406463520392986 | 0.9059638538682118 |
| Generación 19 | 0.881006086683685 | 0.9406463520392986 | 0.9119278804037732 |
| Generación 20 | 0.881006086683685 | 0.9406463520392986 | 0.9005453172776093 |
| Generación 21 | 0.881006086683685 | 0.9406463520392986 | 0.8943972990986072 |
| Generación 22 | 0.881006086683685 | 0.9406463520392986 | 0.899621162893405 |
| Generación 23 | 0.881006086683685 | 0.9406463520392986 | 0.8938464685774665 |
| Generación 24 | 0.881006086683685 | 0.9406463520392986 | 0.9061360199501072 |

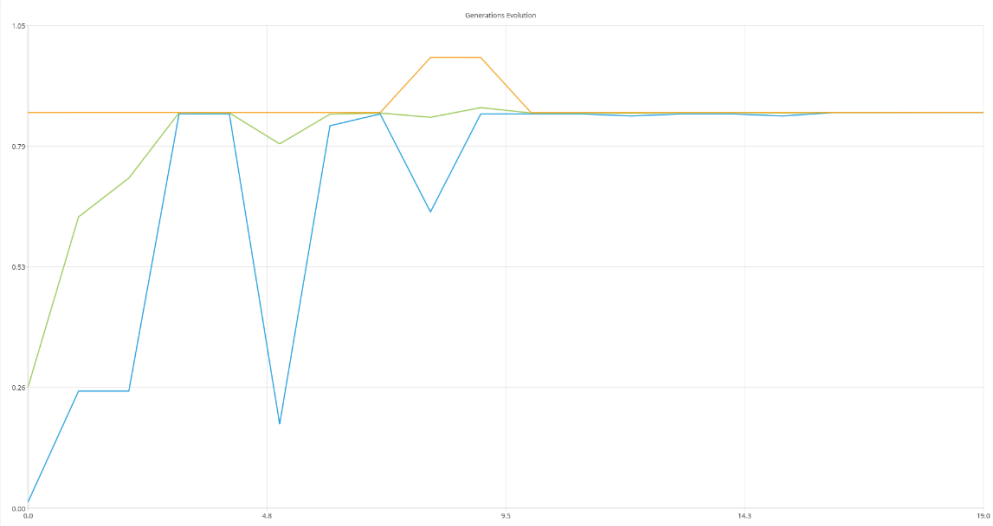
| | | | |
|---|---|---|---|
| Generación 25 | 0.881006086683685 | 0.9406463520392986 | 0.9003613256341685 |
| Generación 26 | 0.881006086683685 | 0.9406463520392986 | 0.8952291477169375 |
| Generación 27 | 0.881006086683685 | 0.9406463520392986 | 0.9011931742524988 |
| Generación 28 | 0.881006086683685 | 0.9406463520392986 | 0.9025787620986403 |
| Generación 29 | 0.881006086683685 | 0.9558615941600204 | 0.9104429772855192 |
| Generación 30 | 0.881006086683685 | 0.9558615941600204 | 0.9164924530399897 |
| Generación 31 | 0.881006086683685 | 0.9558615941600204 | 0.9176860860621335 |
| Generación 32 | 0.8865143918950918 | 0.9558615941600204 | 0.9251662962335852 |
| Generación 33 | 0.8865143918950918 | 0.9558615941600204 | 0.9254476481167864 |
| Generación 34 | 0.8865143918950918 | 0.9558615941600204 | 0.9337199009119104 |
| Generación 35 | 0.8865143918950918 | 0.9558615941600204 | 0.9489268739335275 |
| Generación 36 | 0.9558615941600204 | 0.9635149915876541 | 0.9566269339027837 |
| Generación 37 | 0.9558615941600204 | 0.9635149915876541 | 0.9566269339027837 |
| Generación 38 | 0.9558615941600204 | 0.9635149915876541 | 0.9566269339027837 |
| Generación 39 | 0.9406463520392986 | 0.9558615941600204 | 0.9543400699479481 |
| Generación 40 | 0.9406463520392986 | 0.9558615941600204 | 0.9543400699479481 |
| Generación 41 | 0.9406463520392986 | 0.9558615941600204 | 0.9543400699479481 |
| Generación 42 | 0.9406463520392986 | 0.9558615941600204 | 0.952818545735876 |
| Generación 43 | 0.9406463520392986 | 0.9558615941600204 | 0.9512970215238038 |
| Generación 44 | 0.9406463520392986 | 0.9558615941600204 | 0.952818545735876 |
| Generación 45 | 0.9406463520392986 | 0.9635149915876541 | 0.9551054096907116 |
| Generación 46 | 0.9558615941600204 | 0.9558615941600204 | 0.9558615941600201 |
| Generación 47 | 0.9558615941600204 | 0.9558615941600204 | 0.9558615941600201 |
| Generación 48 | 0.9558615941600204 | 0.9558615941600204 | 0.9558615941600201 |
| Generación 49 | 0.9558615941600204 | 0.9558615941600204 | 0.9558615941600201 |
| Generación 50 | 0.9558615941600204 | 0.9558615941600204 | 0.9558615941600201 |
| Generación 51 | 0.9558615941600204 | 0.9558615941600204 | 0.9558615941600201 |
| Generación 52 | 0.9558615941600204 | 0.9558615941600204 | 0.9558615941600201 |
| Generación 53 | 0.9558615941600204 | 0.9558615941600204 | 0.9558615941600201 |
| Generación 54 | 0.9558615941600204 | 0.9558615941600204 | 0.9558615941600201 |
| Generación 55 | 0.9558615941600204 | 0.9558615941600204 | 0.9558615941600201 |
| Generación 56 | 0.9558615941600204 | 0.9558615941600204 | 0.9558615941600201 |
| Generación 57 | 0.9558615941600204 | 0.9558615941600204 | 0.9558615941600201 |
| Generación 58 | 0.9558615941600204 | 0.9596844781765644 | 0.9562438825616747 |
| Generación 59 | 0.9558615941600204 | 0.9558615941600204 | 0.9558615941600201 |
| Generación 60 | 0.9406463520392986 | 0.9558615941600204 | 0.952818545735876 |
| Generación 61 | 0.9406463520392986 | 0.9558615941600204 | 0.952818545735876 |
| Generación 62 | 0.9406463520392986 | 0.9596844781765644 | 0.9532008341375302 |
| Generación 63 | 0.9406463520392986 | 0.9558615941600204 | 0.9512970215238038 |
| Generación 64 | 0.9406463520392986 | 0.9558615941600204 | 0.9467324488875872 |
| Generación 65 | 0.9406463520392986 | 0.9558615941600204 | 0.9455901613193513 |
| Generación 66 | 0.9406463520392986 | 0.9558615941600204 | 0.9455901613193511 |
| Generación 67 | 0.7138040406386721 | 0.9558615941600204 | 0.9196735495355217 |
| Generación 68 | 0.7121548590679002 | 0.9558615941600204 | 0.8968244002383818 |
| Generación 69 | 0.7138040406386721 | 0.9558615941600204 | 0.9196735495355215 |
| Generación 70 | 0.938753029843072 | 0.9406463520392986 | 0.9402676876000532 |
| Generación 71 | 0.938753029843072 | 0.9406463520392986 | 0.9402676876000531 |
| Generación 72 | 0.938753029843072 | 0.9406463520392986 | 0.9400783553804306 |

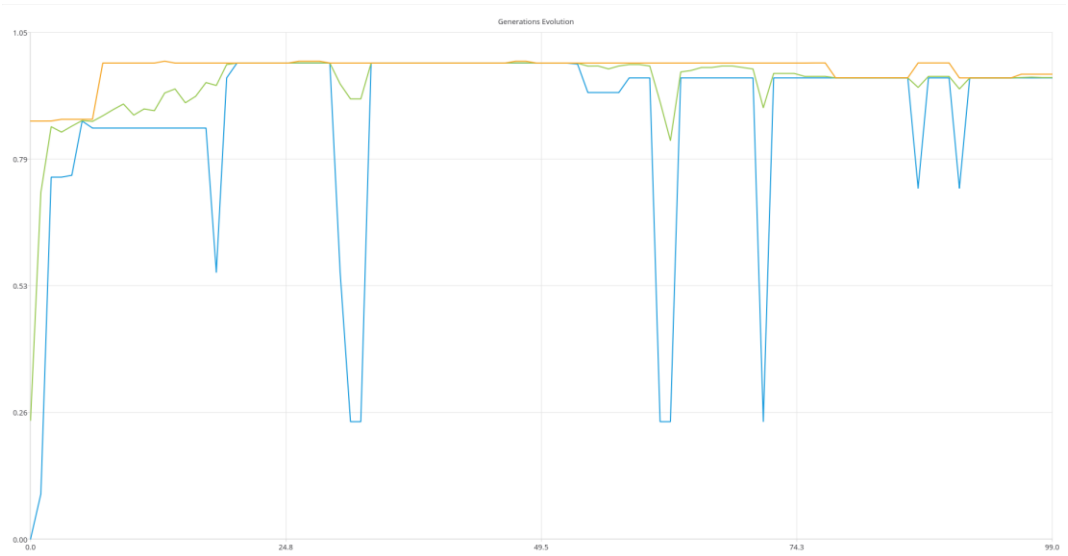
| | | | |
|---|---|---|---|
| Generación 73 | 0.938753029843072 | 0.9406463520392986 | 0.939889023160808 |
| Generación 74 | 0.938753029843072 | 0.9425415815841615 | 0.9402678783349169 |
| Generación 75 | 0.938753029843072 | 0.9406463520392986 | 0.9398890231608078 |
| Generación 76 | 0.938753029843072 | 0.9406463520392986 | 0.9402676876000531 |
| Generación 77 | 0.938753029843072 | 0.9425415815841615 | 0.9400785461152943 |
| Generación 78 | 0.938753029843072 | 0.9406463520392986 | 0.9398890231608078 |
| Generación 79 | 0.938753029843072 | 0.9406463520392986 | 0.9400783553804304 |
| Generación 80 | 0.938753029843072 | 0.9406463520392986 | 0.9400783553804306 |
| Generación 81 | 0.938753029843072 | 0.9406463520392986 | 0.9398890231608078 |
| Generación 82 | 0.938753029843072 | 0.9406463520392986 | 0.9400783553804304 |
| Generación 83 | 0.938753029843072 | 0.9406463520392986 | 0.9398890231608078 |
| Generación 84 | 0.879173799643822 | 0.9406463520392986 | 0.9343097645801283 |
| Generación 85 | 0.938753029843072 | 0.9406463520392986 | 0.9404570198196758 |
| Generación 86 | 0.938753029843072 | 0.9406463520392986 | 0.9404570198196758 |
| Generación 87 | 0.938753029843072 | 0.9406463520392986 | 0.9404570198196758 |
| Generación 88 | 0.938753029843072 | 0.9406463520392986 | 0.9404570198196758 |
| Generación 89 | 0.938753029843072 | 0.9406463520392986 | 0.9404570198196758 |
| Generación 90 | 0.938753029843072 | 0.9425415815841615 | 0.940646542774162 |
| Generación 91 | 0.938753029843072 | 0.9425415815841615 | 0.9404572105545395 |
| Generación 92 | 0.938753029843072 | 0.9425415815841615 | 0.9404572105545395 |
| Generación 93 | 0.938753029843072 | 0.9406463520392986 | 0.9404570198196758 |
| Generación 94 | 0.9406463520392986 | 0.9406463520392986 | 0.9406463520392985 |
| Generación 95 | 0.9406463520392986 | 0.9406463520392986 | 0.9406463520392985 |
| Generación 96 | 0.9406463520392986 | 0.9406463520392986 | 0.9406463520392985 |
| Generación 97 | 0.9406463520392986 | 0.9406463520392986 | 0.9406463520392985 |
| Generación 98 | 0.881006086683685 | 0.9406463520392986 | 0.9346823255037371 |
| Generación 99 | 0.9406463520392986 | 0.9406463520392986 | 0.9406463520392985 |
| Generación 100 | 0.9406463520392986 | 0.9406463520392986 | 0.9406463520392985 |
| Generación 101 | 0.9406463520392986 | 0.9406463520392986 | 0.9406463520392985 |
| Generación 102 | 0.881006086683685 | 0.9406463520392986 | 0.9346823255037371 |
| Generación 103 | 0.881006086683685 | 0.9415937283931505 | 0.9347770631391222 |
| Generación 104 | 0.9406463520392986 | 0.9415937283931505 | 0.9408358273100689 |
| Generación 105 | 0.7138040406386721 | 0.9415937283931505 | 0.9181515961700063 |
| Generación 106 | 0.7138040406386721 | 0.9721615417364124 | 0.921397852775103 |
| Generación 107 | 0.7138040406386721 | 0.9721615417364124 | 0.8760293904949774 |
| Generación 108 | 0.7138040406386721 | 0.9415937283931505 | 0.8956568403007141 |
| Generación 109 | 0.7138040406386721 | 0.9415937283931505 | 0.9182463338053914 |
| Generación 110 | 0.7138040406386721 | 0.9415937283931505 | 0.9180568585346209 |
| Generación 111 | 0.9406463520392986 | 0.9415937283931505 | 0.9408358273100689 |
| Generación 112 | 0.881006086683685 | 0.9415937283931505 | 0.9347770631391222 |
| Generación 113 | 0.881006086683685 | 0.9415937283931505 | 0.9347770631391222 |
| Generación 114 | 0.9406463520392986 | 0.9415937283931505 | 0.9407410896746837 |
| Generación 115 | 0.9406463520392986 | 0.9415937283931505 | 0.9407410896746835 |
| Generación 116 | 0.9406463520392986 | 0.9558615941600204 | 0.9422626138867558 |
| Generación 117 | 0.9406463520392986 | 0.9558615941600204 | 0.9422626138867558 |
| Generación 118 | 0.9406463520392986 | 0.9558615941600204 | 0.942357351522141 |
| Generación 119 | 0.9406463520392986 | 0.9558615941600204 | 0.9439736133695986 |
| Generación 120 | 0.9406463520392986 | 0.9711989065934695 | 0.9469341311896304 |

| | | | |
|---|---|---|---|
| Generación 121 | 0.9406463520392986 | 0.9711989065934695 | 0.9452231317067877 |
| Generación 122 | 0.9406463520392986 | 0.9558615941600204 | 0.9421678762513708 |
| Generación 123 | 0.9406463520392986 | 0.9558615941600204 | 0.9421678762513708 |
| Generación 124 | 0.9406463520392986 | 0.9558615941600204 | 0.9421678762513708 |
| Generación 125 | 0.9406463520392986 | 0.9558615941600204 | 0.9436894004634429 |
| Generación 126 | 0.9406463520392986 | 0.9558615941600204 | 0.9452109246755149 |
| Generación 127 | 0.9406463520392986 | 0.9558615941600204 | 0.9467324488875872 |
| Generación 128 | 0.9406463520392986 | 0.9558615941600204 | 0.9467324488875871 |
| Generación 129 | 0.9406463520392986 | 0.9711989065934695 | 0.9497877043430044 |
| Generación 130 | 0.9406463520392986 | 0.9711989065934695 | 0.9513214355863491 |
| Generación 131 | 0.9406463520392986 | 0.9711989065934695 | 0.9497877043430043 |
| Generación 132 | 0.9406463520392986 | 0.9711989065934695 | 0.9497877043430044 |
| Generación 133 | 0.9406463520392986 | 0.9711989065934695 | 0.9480753220324004 |
| Generación 134 | 0.9406463520392986 | 0.9711989065934695 | 0.9511427845190902 |
| Generación 135 | 0.9406463520392986 | 0.9711989065934695 | 0.9511280979345902 |
| Generación 136 | 0.938753029843072 | 0.9711989065934695 | 0.9559094686107932 |
| Generación 137 | 0.938753029843072 | 0.9711989065934695 | 0.9559094686107932 |
| Generación 138 | 0.938753029843072 | 0.9711989065934695 | 0.9509372398360585 |
| Generación 139 | 0.938753029843072 | 0.9711989065934695 | 0.9505580031922222 |
| Generación 140 | 0.938753029843072 | 0.9711989065934695 | 0.9480770386461732 |
| Generación 141 | 0.7138040406386721 | 0.9711989065934695 | 0.9254032979236104 |
| Generación 142 | 0.9406463520392986 | 0.9789133391774669 | 0.9520104912917843 |
| Generación 143 | 0.9406463520392986 | 0.9721615417364124 | 0.9543905670030959 |
| Generación 144 | 0.9406463520392986 | 0.9721615417364124 | 0.9542943034888017 |
| Generación 145 | 0.9406463520392986 | 0.9711989065934695 | 0.949906856040935 |
| Generación 146 | 0.9406463520392986 | 0.9711989065934695 | 0.9467568629501327 |
| Generación 147 | 0.9406463520392986 | 0.9711989065934695 | 0.9528673738609668 |
| Generación 148 | 0.9406463520392986 | 0.9711989065934695 | 0.9498121184055499 |
| Generación 149 | 0.881006086683685 | 0.9711989065934695 | 0.9469033473254056 |
| Generación 150 | 0.7404503451855672 | 0.9711989065934695 | 0.9177179802737812 |
| Generación 151 | 0.7404503451855672 | 0.9406463520392986 | 0.8886790975974297 |
| Generación 152 | 0.7404503451855672 | 0.9406463520392986 | 0.9027346717472413 |
| Generación 153 | 0.7404503451855672 | 0.9406463520392986 | 0.8827150710618683 |
| Generación 154 | 0.7404503451855672 | 0.9482387143105685 | 0.8775102807534338 |
| Generación 155 | 0.7404503451855672 | 0.9482387143105685 | 0.8834743072889951 |
| Generación 156 | 0.881006086683685 | 0.9482387143105685 | 0.9004166387446231 |
| Generación 157 | 0.881006086683685 | 0.9482387143105685 | 0.9078991377344385 |
| Generación 158 | 0.881006086683685 | 0.9482387143105685 | 0.9078991377344385 |
| Generación 159 | 0.881006086683685 | 0.9482387143105685 | 0.9019106971363318 |
| Generación 160 | 0.881006086683685 | 0.9482387143105685 | 0.9078991377344385 |
| Generación 161 | 0.881006086683685 | 0.9482387143105685 | 0.907874723671893 |
| Generación 162 | 0.881006086683685 | 0.9482387143105685 | 0.9220316572993058 |
| Generación 163 | 0.8883543083295002 | 0.9482387143105685 | 0.9160188026386535 |
| Generación 164 | 0.8883543083295002 | 0.9406463520392986 | 0.9092711258134196 |
| Generación 165 | 0.881006086683685 | 0.9482387143105685 | 0.9107743394785827 |
| Generación 166 | 0.8883543083295002 | 0.9482387143105685 | 0.9204887707825062 |
| Generación 167 | 0.8883543083295002 | 0.9482387143105685 | 0.9100303620405465 |
| Generación 168 | 0.881006086683685 | 0.9482387143105685 | 0.9055451351076028 |

| | | | |
|---|---|---|---|
| Generación 169 | 0.881006086683685 | 0.9482387143105685 | 0.9055451351076028 |
| Generación 170 | 0.8883543083295002 | 0.9482387143105685 | 0.899571953298587 |
| Generación 171 | 0.8883543083295002 | 0.9482387143105685 | 0.9063196301238208 |
| Generación 172 | 0.8883543083295002 | 0.9482387143105685 | 0.9033009957622218 |
| Generación 173 | 0.8883543083295002 | 0.9482387143105685 | 0.9122592425968366 |
| Generación 174 | 0.6941397467994102 | 0.9482387143105685 | 0.8883281454483383 |
| Generación 175 | 0.6941397467994102 | 0.9482387143105685 | 0.8943165860464453 |
| Generación 176 | 0.7072187584474029 | 0.9482387143105685 | 0.8852795081213063 |
| Generación 177 | 0.8883543083295002 | 0.9482387143105685 | 0.9004664960952116 |
| Generación 178 | 0.8883543083295002 | 0.9482387143105685 | 0.9063140412209331 |
| Generación 179 | 0.8883543083295002 | 0.9482387143105685 | 0.9093774406836446 |
| Generación 180 | 0.8883543083295002 | 0.9482387143105685 | 0.9217289808869669 |
| Generación 181 | 0.9180523706945796 | 0.9482387143105685 | 0.927670119238892 |
| Generación 182 | 0.9180523706945796 | 0.9482387143105685 | 0.922007509522803 |
| Generación 183 | 0.9180523706945796 | 0.9482387143105685 | 0.9220075095228031 |
| Generación 184 | 0.9180523706945796 | 0.9482387143105685 | 0.9217264437418976 |
| Generación 185 | 0.9180523706945796 | 0.9217989607656691 | 0.9193632480660178 |
| Generación 186 | 0.6949536087487165 | 0.9217989607656691 | 0.8747434956768452 |
| Generación 187 | 0.9189883029566134 | 0.9217989607656691 | 0.9201125660802356 |
| Generación 188 | 0.889274981802443 | 0.9227368003763392 | 0.9177035562614936 |
| Generación 189 | 0.9180523706945796 | 0.9227368003763392 | 0.9207686723379774 |
| Generación 190 | 0.9189883029566134 | 0.9789133391774669 | 0.9270423371084002 |
| Generación 191 | 0.9189883029566134 | 0.9789133391774669 | 0.9330348407304856 |
| Generación 192 | 0.9189883029566134 | 0.9789133391774669 | 0.93275377494958 |
| Generación 193 | 0.9189883029566134 | 0.9789133391774669 | 0.9447387821937507 |
| Generación 194 | 0.9217989607656691 | 0.9789133391774669 | 0.9451136319357234 |
| Generación 195 | 0.9227368003763392 | 0.9789133391774669 | 0.9508250697769031 |
| Generación 196 | 0.9227368003763392 | 0.9789133391774669 | 0.9564427236570159 |
| Generación 197 | 0.9227368003763392 | 0.9789133391774669 | 0.9676780314172413 |
| Generación 198 | 0.9227368003763392 | 0.9789133391774669 | 0.9635674058995644 |
| **Generación 199** | **0.9227368003763392** | **0.9789133391774669** | **0.9635674058995644** |

## *C++: Qt Charts*




Generations Evolution
1.05
0.79
0.53
0.26
0.00
0.0
24.8
49.5
74.3
99.0


Generations Evolution
1.05
0.79
0.53
0.26
0.00
0.0
49.8
99.5
149.3
199.0

# Conclusión

Al ser el espacio solución tan grande y nuestra cantidad de cromosomas por población tan chico, notamos que para llegar a la mejor solución se requiere de una mayor cantidad de iteraciones o corridas del programa. Ya que mientras más sean las iteraciones, mas son las posibilidades de que se salga de un máximo local a partir de una oportuna mutación que agregue diversidad genética y permita mejores oportunidades de crossover.

Otro acercamiento al problema podría haber sido el utilizar una mayor cantidad de cromosomas por población, lo cual nos daría una gráfica parecida a una exponencial y nos provee la mejor solución con mayor certeza por cada ejecución del programa, debido a la mayor diversidad genética. Pero no necesariamente seria más eficiente ya que aumenta considerablemente el tiempo de corrida del mismo, además del consumo mucho mayor de otros recursos como memoria RAM (En este punto la implementación de Python y C++ difieren ya que en la primera se utiliza un método más eficiente en consumo de memoria inspirado en el uso del fitness relativo acumulado, en cambio la segunda se vale del tradicional método de crear una ruleta con casillas proporcionales al fitness de cada cromosoma). En la práctica al parecer el primer método más innovador tiene además mejores resultados en cuanto a la calidad de las corridas.

También se puede notar que optamos por mostrar la información de las corridas en dos formatos distintos: La primera forma, utilizada en Matplotlib (Python), fue mostrar por separado las graficas de valores de la función objetivo máximos, mínimos y promedios. A diferencia de la segunda, utilizada en Qt Charts (C++), que muestra todos los valores juntos en la misma grafica. Lo que tiene como ventaja una mejor vista de la convergencia de los valores. En cambio la primera permite ver en mucho más detalle los valores específicos y no tanto un panorama general.