METU EE 449 Computational Intelligence

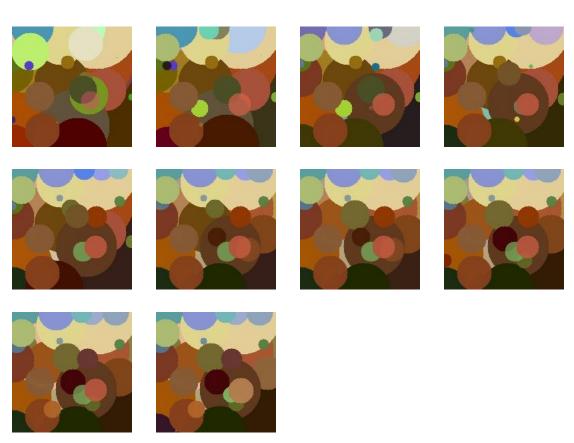
Homework 2 - Evolutionary Algorithms

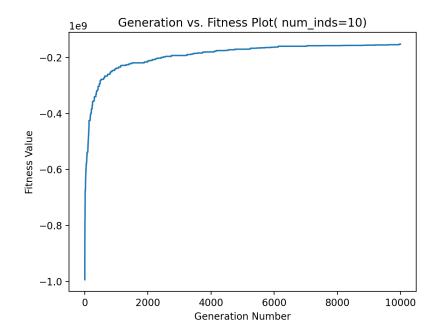
Parameter: <num_inds> :

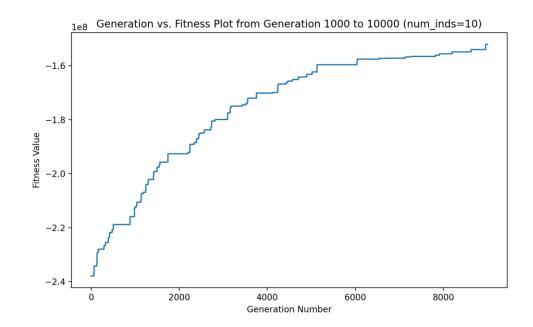
<num_inds> parameter represents the number of individuals (images containing circles in our case) each population contains. Having a greater number of individuals in a certain population increases the amount of best fitness candidates hence a high value given to this parameter means better chances of producing the required output. Below figures also support this claim and the best result is achieved when the parameter is equal to 75.

a. 5

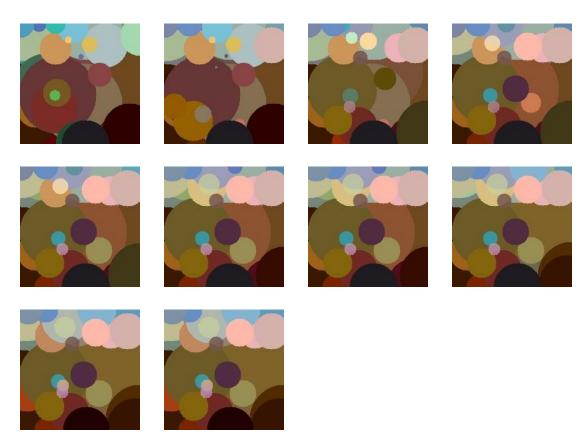
b. 10

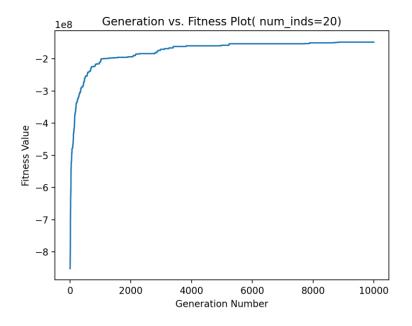


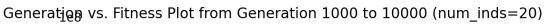


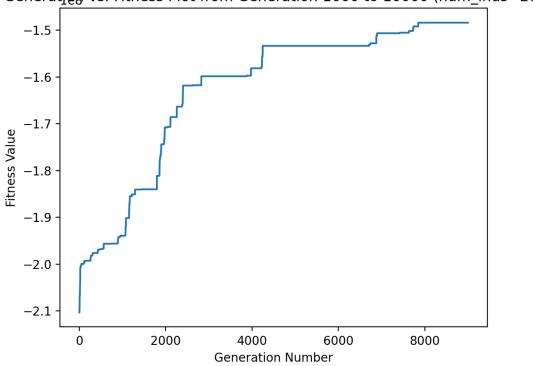


c. 20 (DEFAULT)







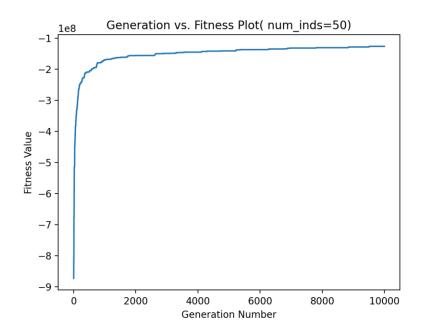


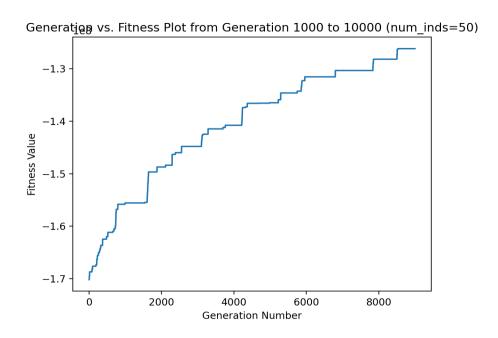
d. 50





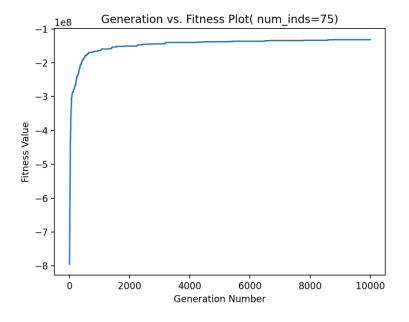


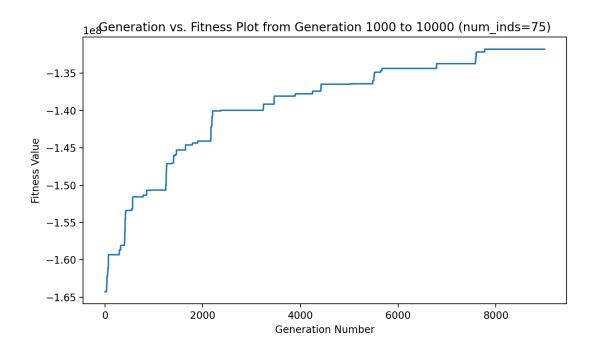




e. 75







Parameter: <num_genes>:

<num_genes> parameter represents the number of genes each individual contains in a given population. In our case, the number of circles to be drawn on each image. Higher number of genes means more circles that might have different colors drawn and it increases the possibility for our output image to resemble the given painting. Hence, higher numbers mean better outputs and the best result is achieved when this parameter equals 150. (Although difference between 100 and 150 is not dramatically big.)

a.10



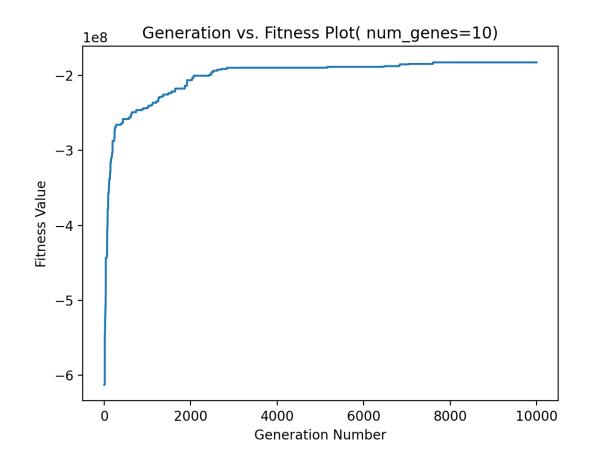


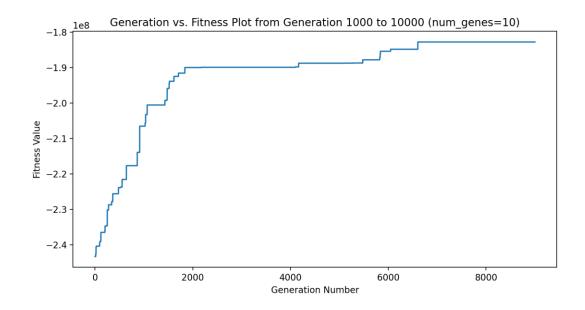




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b.25



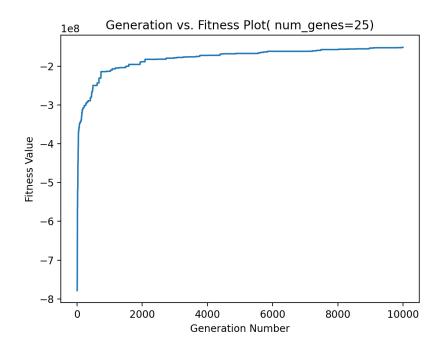
-1.9

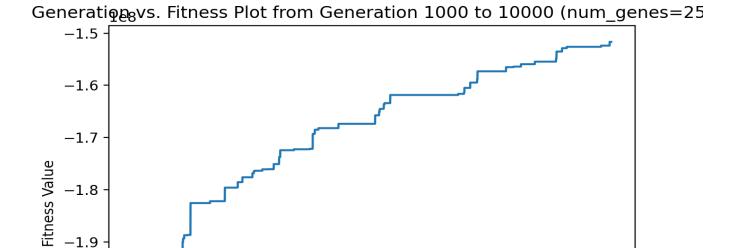
-2.0

-2.1

0

2000





4000

Generation Number

6000

8000

c.50(default)

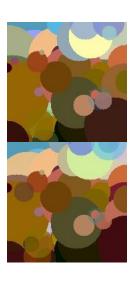
d.100







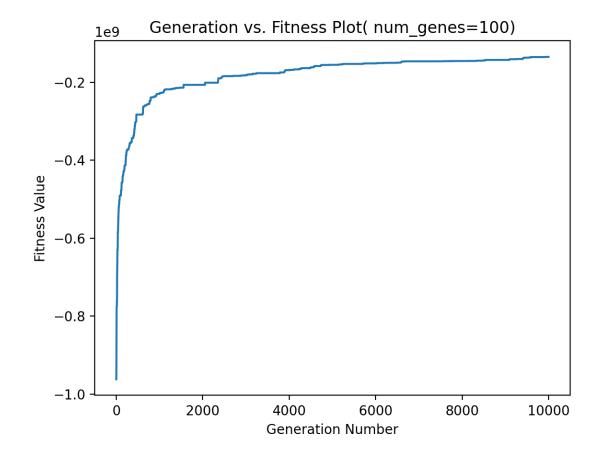




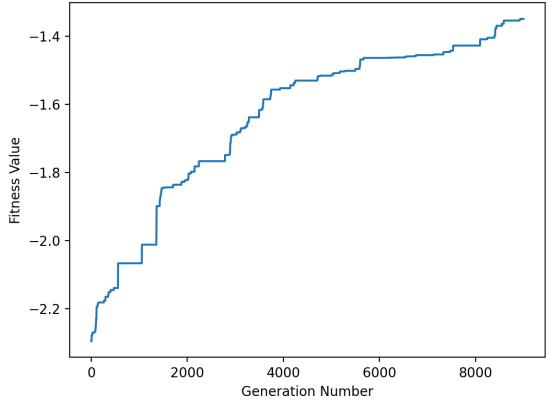




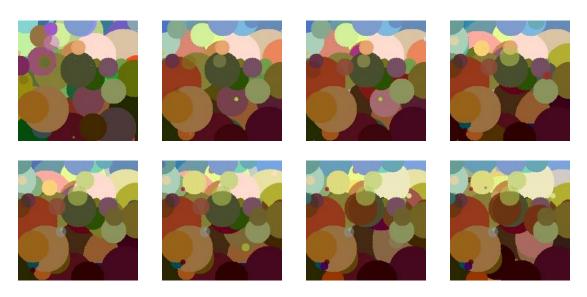




Generation 2000 to 10000 (num_genes=10)



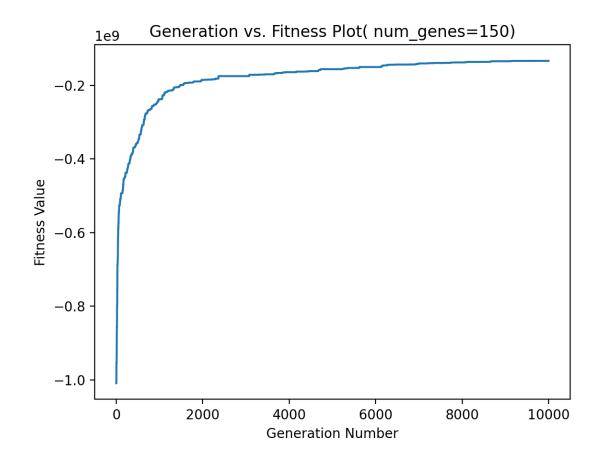
e.150

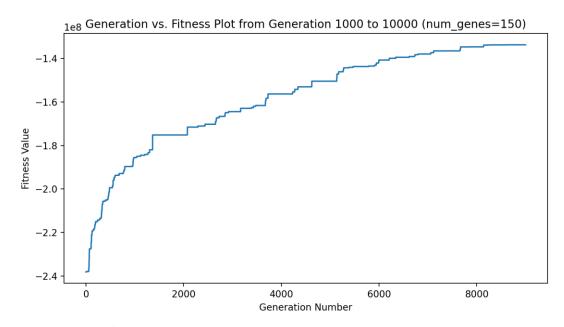


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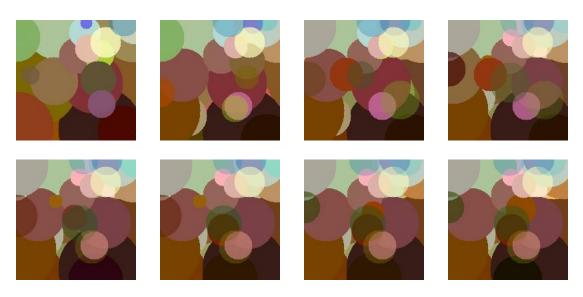




Parameter: <tm_size>:

Parameter <tm_size> represents the number of individuals to enter a tournament. When <tm_size> is too low, individuals with small fitness values may advance to next generation, so, higher values for <tm_size> is preferred. Below figures show that in our case, output is the best when this parameter equals to **20**. However, we must be aware that if number of tournaments to be done were to be higher this could cause an overflow problem since in case of 20, the tournament winner is always the fittest hence tournaments produce the same individuals repetitively.

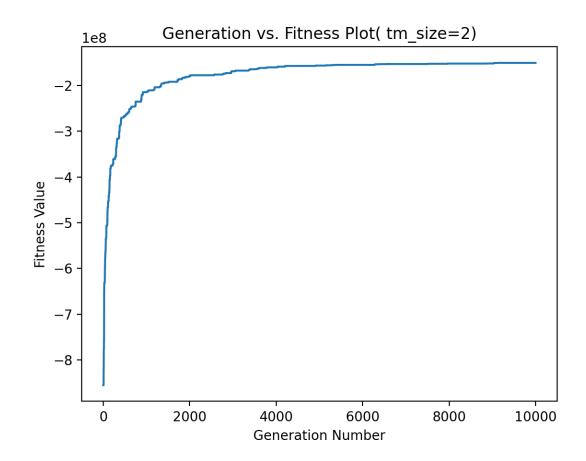
a.2

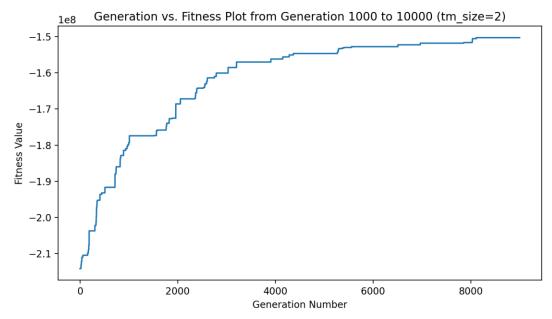


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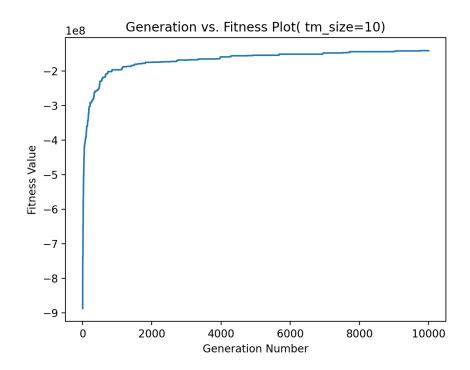


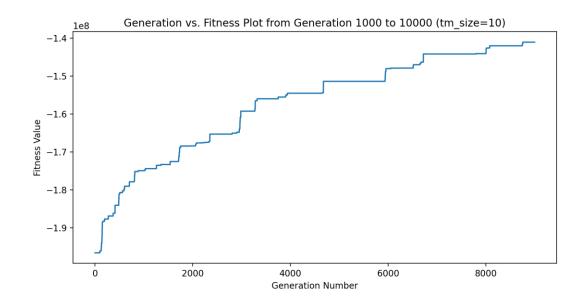




b. 5 (Default)

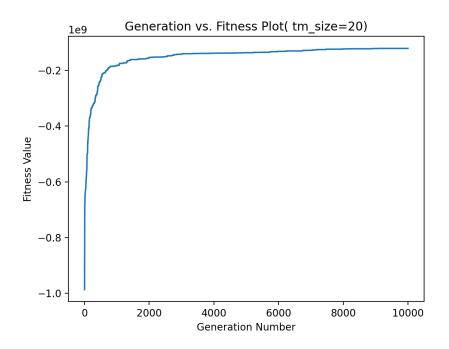


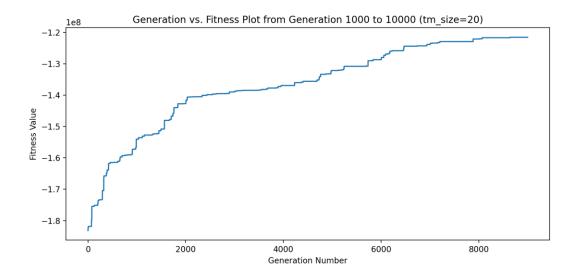




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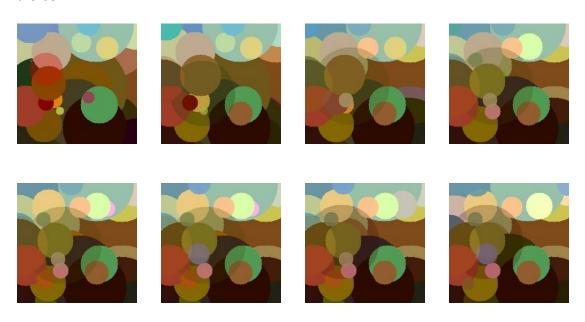




Parameter: <frac_elites>:

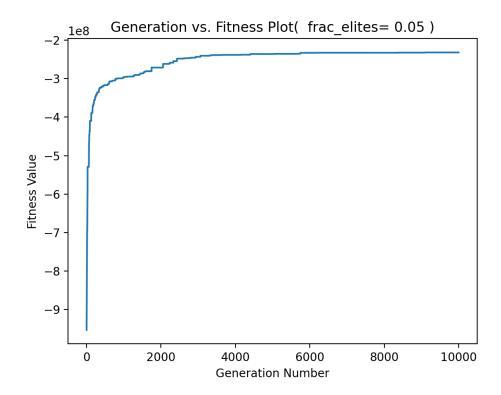
<frac_elites> represents the fraction of the population which will remain the same and advanace to the next generation, which are the best fitness individuals. This number must also be choosen carefully as not too high or low. As shown from figures below, **0.2** gave the best results. High value for his parameter means a lot of individuals advance unchanged and this drops efficiency dramatically.

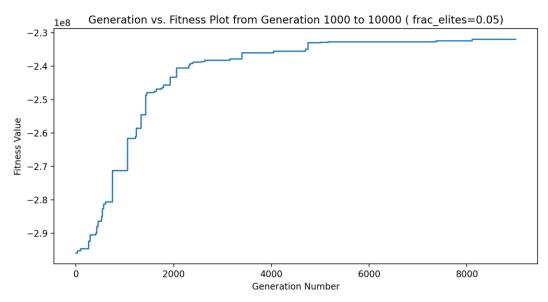
a.0.05







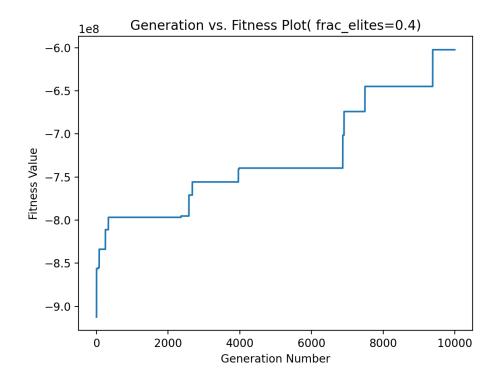


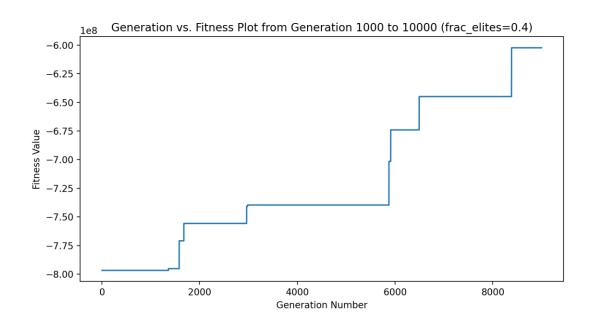


b. 0.2 (Default)

c. 0.4





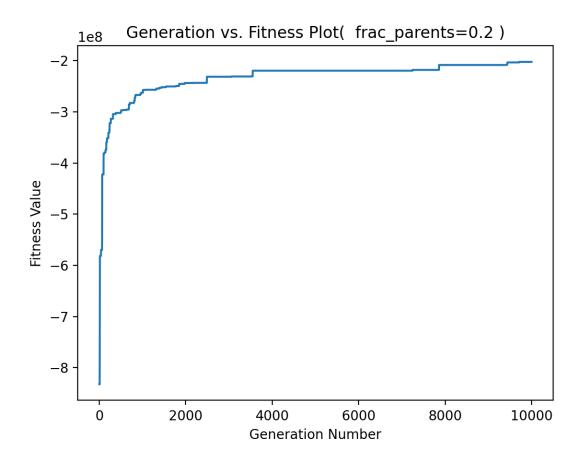


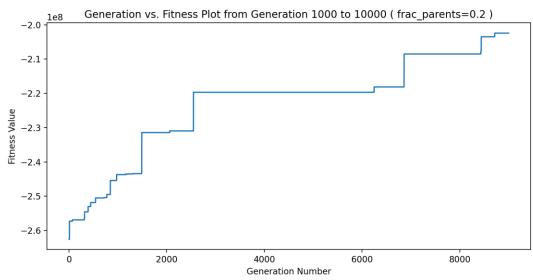
Parameter: <frac_parents>:

<frac_parents> parameter represents the fraction of individuals which will be chosen as parents to create children. In our case the best result is achieved when this parameter equals to **0.4.** This number must be chosen carefully as not too high or too low to avoid killing fit individuals and still keep the benefits of cross-over.

a.0.2

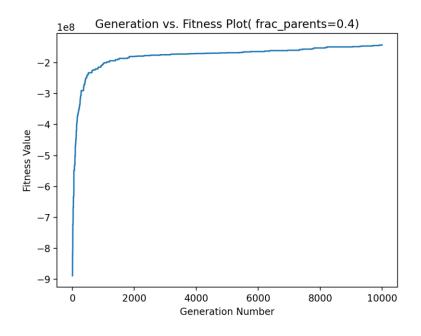


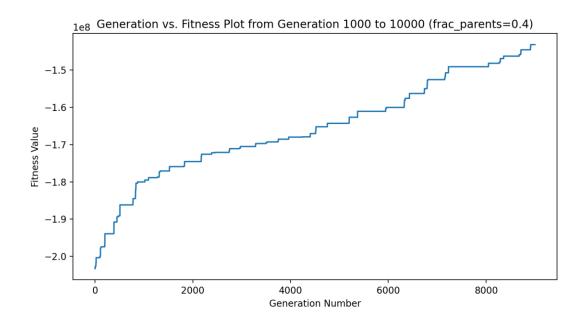




b. 0.4

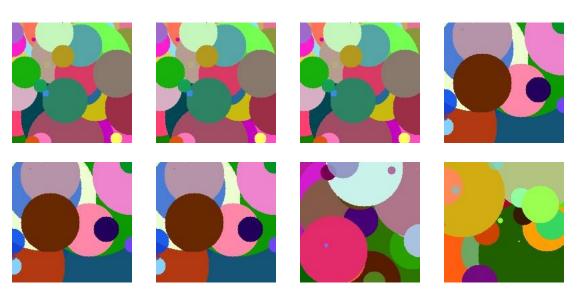






c. 0.6 (Default)

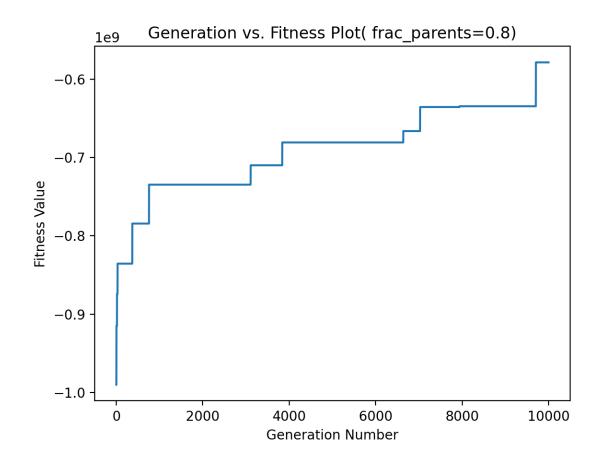
d. 0.8

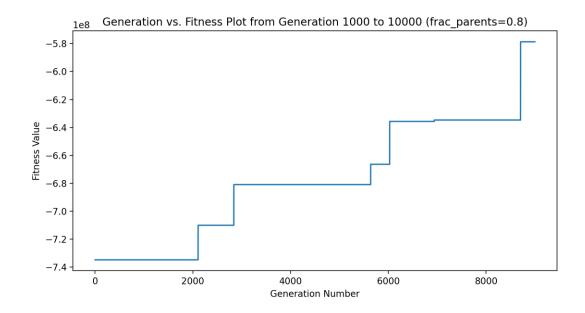


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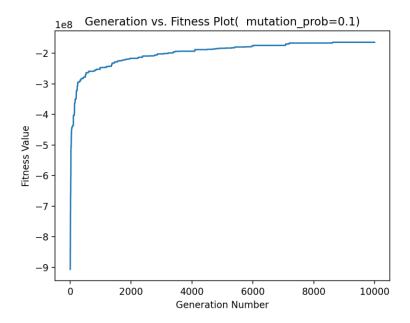
Parameter: <mutation_prob>:

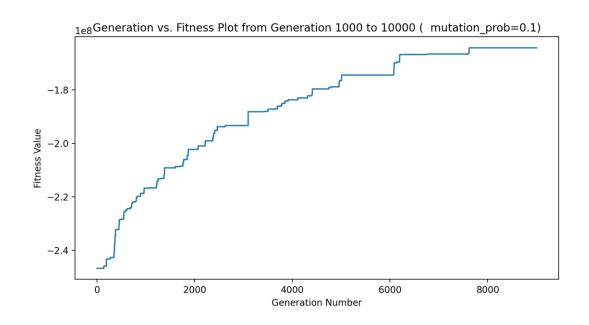
This parameter gives the probability that an individual will be exposed to mutation. As shown from figures below, **0.5** gives the best result. When higher, cross-over and tournament selection benefits are lost. When lower, required variety between individuals can be provided.







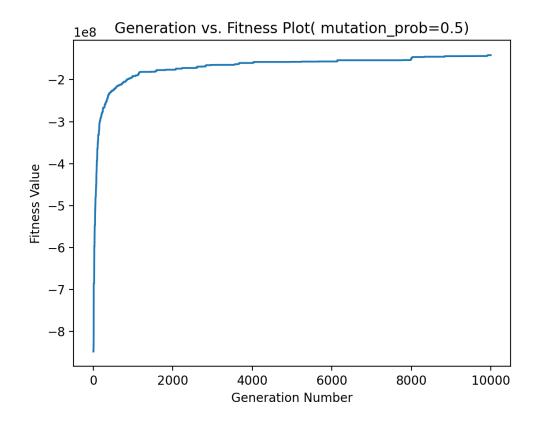


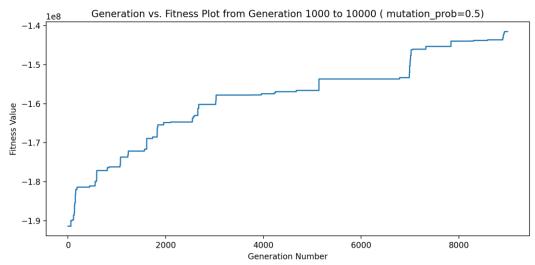


b. 0.2 (Default)

c. 0.5

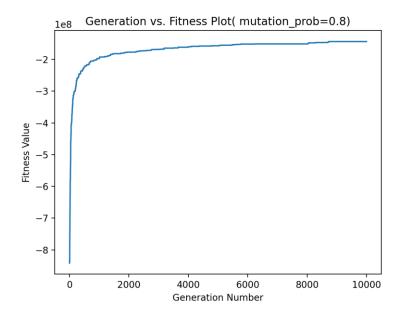


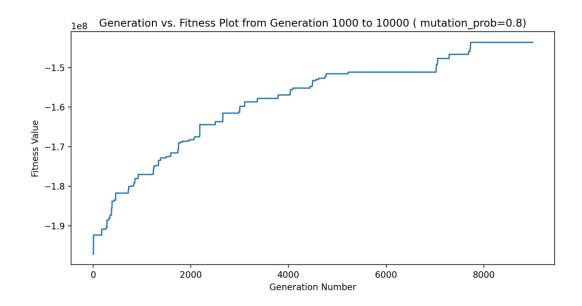




d.0.8





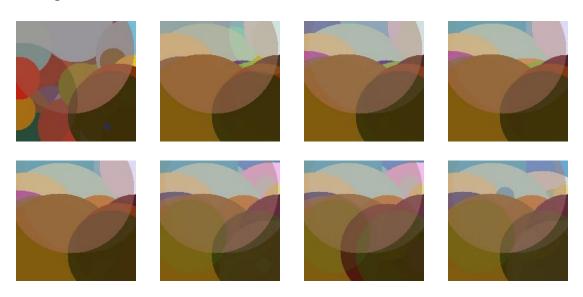


Parameter: 'guided' / 'unguided'

This parameter decides whether the mutation is all random or applied according to individuals current state. As shown from figures guided mutations is more favorable. This is because it helps keep the beneficial traits gained by cross-over and tournaments.

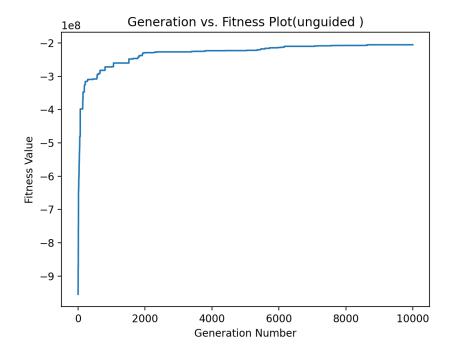
a. 'guided' (Default)

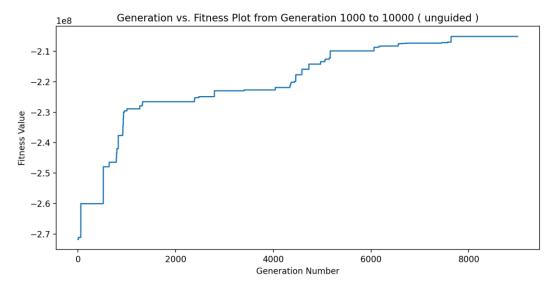
b. 'unguided'











Improving Algorithm

- 1. New selection methods may be added to the algorithm such as Roulette-wheel Selection
- 2. Tournament winners could not return to the pool where individuals are selected for another tournament.
- 3. Gene and individual numbers may be increased. Although it will take more time to run, would give better results significantly.

CODE

```
from __future__ import print_function
import cv2
import copy
from random import uniform
from random import sample
from random import seed
from random import randint
from random import random, randrange
import numpy as np
from operator import attrgetter
from matplotlib import pyplot as plt
path = '/Users/gulceonder/Desktop/evolutionary/painting.png'
image = cv2.imread(path)
window_name = 'Image'
blank_image = np.zeros((180,180,3), np.uint8)
blank_image[:,:]= [255,255,255]
def sort_pop(pop):
  pop.ind_list.sort(key=lambda x: x.fitness,reverse=True)
#function to sort the gene list that is genotype according to radius magnitude
def sort_list(ind):
  ind.genotype.sort(key= lambda x: x.r, reverse= True)
#function to draw the circles
def draw_circles(pop,i,k):
  # create two copies of the original image -- one for
  center_coordinates = (pop.ind_list[i].genotype[k].x, pop.ind_list[i].genotype[k].y)
  # Radius of circle
  radius = pop.ind_list[i].genotype[k].r
```

```
# Red color in BGR
  color = (pop.ind_list[i].genotype[k].R, pop.ind_list[i].genotype[k].G, pop.ind_list[i].genotype[k].B)
  # Using cv2.circle() method
  cv2.circle(pop.ind_list[i].overlay, center_coordinates, radius, color, -1)
  cv2.addWeighted(pop.ind_list[i].overlay, pop.ind_list[i].genotype[k].A, pop.ind_list[i].output, 1 -
pop.ind_list[i].genotype[k].A,
       0, pop.ind_list[i].output)
  return pop.ind_list[i].output
def check_fitness(output): #check fitness of an individuals output image
  fitness=0
  squared_dist = np.int64(output)-np.int64(image)
  squared_dist = squared_dist*squared_dist
  fitness=np.sum(squared_dist,dtype=np.int64)
            x=(np.int64(output[i,j,k])- np.int64(image[i,j,k]))**2 #convert uint8 to int64 to avoid overflow
  return fitness*(-1)
def evaluate_pop(pop, num_inds):
    for i in range(num_inds):
       pop.ind_list[i].overlay = blank_image.copy()
       pop.ind_list[i].output = blank_image.copy()
       for k in range(pop.ind_list[i].num_genes):
       #self.genotype[i].print_gene()
          #pop.ind_list[i].output=draw_circles(pop.ind_list[i].genotype[k],pop.ind_list[i].overlay,pop.ind_list[i].output)
          pop.ind list[i].output=draw circles(pop,i,k)
```

```
pop.ind_list[i].fitness= check_fitness(pop.ind_list[i].output)
     # # closing all open windows
def evaluate_ind2(ind):
       ind.overlay = blank_image.copy()
       ind.output = blank_image.copy()
       for k in range(ind.num_genes):
       #self.genotype[i].print_gene()
         output=draw_circles2(ind,k)
       ind.fitness= check_fitness(ind.output)
def draw_circles2(ind,k):
    # Center coordinates
  center_coordinates = (ind.genotype[k].x, ind.genotype[k].y)
  # Radius of circle
  radius = ind.genotype[k].r
  color = (ind.genotype[k].R, ind.genotype[k].B)
  cv2.circle(ind.overlay, center_coordinates, radius, color, -1)
  cv2.addWeighted(ind.overlay, ind.genotype[k].A, ind.output, 1 - ind.genotype[k].A,
       0, ind.output)
  return ind.output
```

```
def cross_over(mom,dad,child1,child2,num_genes):
  #assign genes from mom or dad with prob 0.5 for each gene
  for i in range(num_genes):
    x= random()
    if(x<0.5):#do with 0.5 prob
       child1.genotype.append(mom.genotype[i])
       child2.genotype.append(dad.genotype[i])
    else:
       child1.genotype.append(dad.genotype[i])
       child2.genotype.append(mom.genotype[i])
def unguided_mutant(pop,i, gene_index):
  pop.ind_list[i].genotype[gene_index].x = randint(0,180)
  pop.ind_list[i].genotype[gene_index].y = randint(0,180)
  pop.ind_list[i].genotype[gene_index].r = randint(0,100)
  pop.ind_list[i].genotype[gene_index].R = randint(0,255)
  pop.ind_list[i].genotype[gene_index].G = randint(0,255)
  pop.ind_list[i].genotype[gene_index].B = randint(0,255)
  pop.ind_list[i].genotype[gene_index].A = random()
def guided_mutant(pop,i, gene_index):
   #print("new mutant RGB")
   mutantgene=copy.deepcopy(pop.ind_list[i].genotype[gene_index])
   number = randrange(-64, 64)
   if(number+mutantgene.R<0):mutantgene.R=0
   elif(number+mutantgene.R>255):mutantgene.R=255
   else:mutantgene.R+= number
   number = randrange(-64, 64)
   if(number+mutantgene.G<0):mutantgene.G=0
   elif(number+mutantgene.G>255):mutantgene.G=255
   else:mutantgene.G+= number
   number = randrange(-64, 64)
   if(number+mutantgene.B<0):mutantgene.B=0
   elif(number+mutantgene.B>255):mutantgene.B=255
   else:mutantgene.B+= number
   number = randrange(-45, 45)
   if(number+mutantgene.x<0):mutantgene.x=0
   elif(number+mutantgene.x>180):mutantgene.x=180
```

```
else:mutantgene.x+= number
  number = randrange(-45, 45)
  if(number+mutantgene.y<0):mutantgene.y=0
  elif(number+mutantgene.y>180):mutantgene.y=180
  else:mutantgene.y+= number
  number = randrange(-10, 10)
  if(number+mutantgene.r<0):mutantgene.r=0
  else:mutantgene.r+= number
  number = uniform(-0.25, 0.25)
  if(number+mutantgene.A<0):mutantgene.A=0
  elif(number+mutantgene.A>1):mutantgene.A=1
  else:mutantgene.A+= number
  pop.ind_list[i].genotype[gene_index]=mutantgene
class gene:
#call constructor according to the given argument
  def __init__(self, *args): #if no argument initiliaze to 0
    if len(args) == 0:
      self.x=0
      self.y= 0
      self.r= 0
      self.R=0
      self.G= 0
      self.B= 0
      self.A= 0
    elif len(args) == 7:#assign values to each gene
      self.x= args[0]
      self.y= args[1]
      self.r= args[2]
      self.R= args[3]
      self.G= args[4]
      self.B= args[5]
      self.A= args[6]
    elif args[0] == 'rand': #initiliaze gene randomly
```

```
seed(random())
     self.x = randint(0,180)
     self.y = randint(0,180)
     self.r = randint(0,100)
     self.R = randint(0,255)
     self.G = randint(0,255)
     self.B = randint(0,255)
     self.A = random()
def print_gene(self):
  print(self.x)
  print(self.y)
  print(self.r)
  print(self.R)
  print(self.G)
  print(self.B)
  print(self.A)
def __init__(self, num_genes):
  if(num_genes):
     self.num_genes=num_genes
     self.genotype = []#list of genes for individual
     self.fitness = 0
     for i in range(num_genes):
       randomgene= gene('rand')
       self.genotype.append(randomgene) #check radius first
     sort_list(self)
     self.overlay = blank_image.copy()
     self.output = blank_image.copy()
     for i in range(num_genes):
     #self.genotype[i].print_gene()
       draw_circles2(self,i)
     self.fitness= check_fitness(self.output)
     cv2.imshow("Output", self.output)
     cv2.waitKey(0)
  # closing all open windows
```

```
cv2.destroyAllWindows()
       cv2.waitKey(1)
       self.genotype=[]
       self.fitness=0
       self.num_genes=num_genes
       self.overlay = blank_image.copy()
       self.output = blank_image.copy()
class pop:
  def __init__(self,num_inds,num_genes):
    if(num_genes):
       self.num_inds = num_inds
       self.ind_list = []
       for i in range(num_inds):
         random_ind = ind(num_genes)
         self.ind_list.append(random_ind)
       self.num_inds = num_inds
       self.ind_list = []
#main function to run
def main():
  fittest_list=[]
  num_inds=20
  num_genes=50
  tm_size=5
  frac_elites = 0.05
  frac_parents=0.2
  mutation_prob=0.2
  num_generations=10001
  mutation_type='unguided'
  num_elites= int(num_inds*frac_elites)
  num_parents=int(num_inds*frac_parents)
  num_birth=int(num_parents/2)
  num_tm= num_inds- num_elites-num_parents#number of tournaments to be done
  pop1 = pop(num inds,num genes)
```

```
gen=1
  found= False
  while not (gen==num_generations):
    sort_pop(pop1)
    pop2= pop(num_inds,0)#generation containing children and tournament winners
    pop3=pop(num_inds,0)#new gen
    pop2.num_inds= num_inds-num_elites
    pop3.num_inds = num_inds
     #apply elitism :pick the best num_elites and insert into the next generation
    for i in range(num_elites):
       # print("elite ",i ,", fitness: ",pop1.ind_list[i].fitness)
       pop3.ind_list.append(copy.deepcopy(pop1.ind_list[i]))#elites advance directlty to new gen
    print("report the best fitness of gen ", gen," : ",pop1.ind_list[0].fitness )
     fittest_list.append(pop1.ind_list[0].fitness)
    if(gen%1000==0):
       filename = 'savedImage' + str(gen)+ '.jpg'
       # Saving the image
       cv2.imwrite(filename, pop1.ind_list[0].output)
     # cv2.imshow("Output", pop1.ind_list[0].output)
    #enter tournament
    for i in range(num_tm):
       tournament_list=sample(pop1.ind_list[num_elites:],tm_size) #randomly pick (tournament size) number of
individuals from population
```

```
tournament_list.sort(key=lambda x: x.fitness,reverse=True)#sort tournmnt list
  tournament_winner= max(tournament_list, key=attrgetter('fitness'))
  # print("gen: ", gen, " tournament winner: ",tournament_winner.fitness)
  pop2.ind_list.append(copy.deepcopy(tournament_winner))
  #print(len(pop2.ind_list))
for i in range(num_birth):
  parents=pop1.ind_list[num_elites:(num_elites+num_parents)]#pick parents from the fittest individuals which
  mom = parents[i]#pick two parents for the current child-to-be
  dad = parents[num_parents-i-1]
  child1 = ind(0) #initiliaze new individual child with empty genotype
  child2 = ind(0)
  child1.num_genes=num_genes
  child2.num_genes=num_genes
  cross_over(mom,dad,child1,child2,num_genes)
  pop2.ind_list.append(copy.deepcopy(child1))#add child to new pop
  pop2.ind_list.append(copy.deepcopy(child2))#add child to new pop
#population 2 holds the population to be exposed to mutation which excludes elite individuals
if(mutation_type=='unguided'):
  for i in range(len(pop2.ind_list)):
     mut=random()
     #mutant= pop2.ind_list[i].genotype#extract genotype of thr current individual
     if(mut<mutation_prob):</pre>
       gene_index=randint(0, num_genes-1)
       unguided_mutant(pop2,i,gene_index)
elif(mutation_type=='guided') :
  for i in range(len(pop2.ind_list)):
     mut=random()
```

```
if(mut<mutation_prob):</pre>
            gene_index=randint(0, num_genes-1)
            guided_mutant(pop2,i,gene_index)
    evaluate_pop(pop2,pop2.num_inds)
    # print("pop2 after mutation: ")
    # #evaluate_ind(pop2.ind_list[i])
    # print(pop2.ind_list[k].fitness)
    for k in range(len(pop2.ind_list)):
       #evaluate_ind(pop2.ind_list[i])
       pop3.ind_list.append(copy.deepcopy(pop2.ind_list[k]))
    pop1=pop(num_inds,0)
    pop1 = copy.deepcopy(pop3)
    # print(pop1.ind_list[i].fitness)
    del pop2
    del pop3
    gen +=1
#PLOT THE FITNESS LISTS
  plt.plot(fittest_list)
  plt.xlabel('Generation Number')
  plt.ylabel('Fitness Value')
  plt.title('Generation vs. Fitness Plot( frac_elites= 0.05 )')
  plt.show()
  fit2= fittest_list[999:]
  plt.plot(fit2)
 plt.xlabel('Generation Number')
```

```
plt.ylabel('Fitness Value')
plt.title('Generation vs. Fitness Plot from Generation 1000 to 10000 ( frac_elites=0.05)')
plt.show()

# sort pop according to fitness

# carry first num_elites to next pop.

# randomly pick from sorted population to create offspring

# recomb for offsprings

# mutate some of offsprings

# evaluate new gen

#

#return best indv of pop.

if __name__ == '__main__':
    main()
```