Evolutionary Computation Homework 2

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1. In Evolutionary Computation, there are two operators that can be done. One of the is 'mutation' and the other one is 'crossover'
   Mutation operator requires only one individual to be operated on, while crossover need at least two selected individual to be operated on.
   In GA, 'crossover' is a must, while in ES, 'crossover' can be omitted and mostly used 'mutation' as its operator.
   Because of the above factor, GA usually needs bigger population size than ES. This is due to the need to increase the search space of the 'crossover' operation, which need the population size to be larger.

2. For the given population:
   a. There will not be any change in the 0 and 1 frequency after one-point crossover or uniform crossover
   b. The crossover that is done on this population is only changing the combination of allele in each individual, and will not affect the count of 0 or 1

3. (1+1)-ES and (1,1)-ES with fixed step-sizes for Gaussian mutation

(1+1)-ES	**σ = 0.01**	**σ = 0.1**	**σ = 1.0**	**(1,1)-ES**	**σ = 0.01**	**σ = 0.1**	**σ = 1.0**
Run #1	860	209582	10000000	**Run #1**	10000000	10000000	10000000
Run #2	822	310581	10000000	**Run #2**	10000000	10000000	10000000
Run #3	853	376226	10000000	**Run #3**	10000000	10000000	10000000
Run #4	825	138102	10000000	**Run #4**	10000000	10000000	10000000
Run #5	876	199790	10000000	**Run #5**	10000000	10000000	10000000
Run #6	841	295032	10000000	**Run #6**	10000000	10000000	10000000
Run #7	874	364086	10000000	**Run #7**	10000000	10000000	10000000
Run #8	860	134655	10000000	**Run #8**	10000000	10000000	10000000
Run #9	797	162088	10000000	**Run #9**	10000000	10000000	10000000
Run #10	811	345933	10000000	**Run #10**	10000000	10000000	10000000

4. (1+1)-ES
   a. We choose the better individual compared from the parent and the resulting offspring, therefore, in this method we could reach the optimal solution which minimizes the objective value
   b. In the case of step size of 1.0, this is too large for the model. Resulting in it skipping throughout the model and cannot reach close enough to the threshold

objective value of 0.005. In this case, the mutation reach maximum generation allowed and terminated without reaching global or even local minima.

c. By choosing the appropriate value of step size, we could reach the minima in different speed. Too large of step size resulting in overshooting, and too small of step size resulting in slow convergence of the model.

(1,1)-ES

a. This model does not approach the minima in any direct way, but relying on random chance to approach the minima.

b. Due to the problem above, this method could not reach the optimum solution in all of the chosen step size and reach the maximum generation allowed

5. (1+1)-ES and (1,1)-ES with uncorrelated Gaussian mutation

Parameter used in this method:

$$\boldsymbol{\tau = \frac{0.1}{\sqrt{2n}} \approx 0.02}$$

$$\boldsymbol{\tau' = \frac{0.1}{\sqrt{2\sqrt{n}}} \approx 0.039}$$

$$\epsilon_0 = \mathbf{0.01}$$

(1+1)-ES	σ = 0.01	σ = 0.1	σ = 1.0	(1,1)-ES	σ = 0.01	σ = 0.1	σ = 1.0
Run #1	854	434	308	**Run #1**	10000000	10000000	10000000
Run #2	894	539	274	**Run #2**	10000000	10000000	10000000
Run #3	807	493	216	**Run #3**	10000000	10000000	10000000
Run #4	854	420	265	**Run #4**	10000000	10000000	10000000
Run #5	848	594	279	**Run #5**	10000000	10000000	10000000
Run #6	906	456	241	**Run #6**	10000000	10000000	10000000
Run #7	889	616	202	**Run #7**	10000000	10000000	10000000
Run #8	891	564	283	**Run #8**	10000000	10000000	10000000
Run #9	862	681	221	**Run #9**	10000000	10000000	10000000
Run #10	866	513	231	**Run #10**	10000000	10000000	10000000

6. The parameter used in this method is provided in number 5. Boundary rule is set to 0.01 to prevent the σ value to get too small and let the step size to be too slow to converge. This value is chosen considering the good result that we achieve using step size of 0.01 in number 3

(1+1)-ES

a. Using self-adapted step size, this method is able to converge quite fast. This is due to the fast approach in the initial step to be quite nearer onto the optimum solution and have the step size slowly getting smaller to get the accuracy that we wanted

   b. Due to the reasoning above, in this case, starting step size of 1.0 achieve even better result than 0.01 which is significantly better in question number 3.

(1,1)-ES

   a. This model does not approach the minima in any direct way, but relying on random chance to approach the minima. Although the step size has been improved, without any clear direction, this method still could not converge
   b. Due to the problem above, this method could not reach the optimum solution in all of the chosen step size and reach the maximum generation allowed

7. (1+1)-ES and (1,1)-ES with 1/5-rule

   Parameter used in this method:

   G = 20

   a = 0.87

(1+1)-ES	σ = 0.01	σ = 0.1	σ = 1.0	(1,1)-ES	σ = 0.01	σ = 0.1	σ = 1.0
Run #1	390	270	358	**Run #1**	10000000	10000000	10000000
Run #2	429	321	402	**Run #2**	10000000	10000000	10000000
Run #3	404	277	306	**Run #3**	10000000	10000000	10000000
Run #4	326	308	376	**Run #4**	10000000	10000000	10000000
Run #5	434	353	313	**Run #5**	10000000	10000000	10000000
Run #6	405	237	364	**Run #6**	10000000	10000000	10000000
Run #7	417	333	353	**Run #7**	10000000	10000000	10000000
Run #8	341	278	359	**Run #8**	10000000	10000000	10000000
Run #9	370	314	369	**Run #9**	10000000	10000000	10000000
Run #10	383	252	358	**Run #10**	10000000	10000000	10000000

8. In this method, it is similar to the condition with number 5. It has the similar advantage of number 5 over number 3. However, in this case, due to the success movement affect the probability of step size being smaller or larger, this method is quite successful, however, not always being better than method used in number 5 with fine-tuned parameter. Fine-tuned method in number 5 could let the model to converge smoother and more directly without relying on probability. However, the process of fine-tuning is quite troublesome considering the small difference with the method used in number 7.