



An Experimental Evaluation for OneMax Problem cGA versus GA

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Genetic Algorithm (GA)



Algorithm 3.2.1: Pseudocode for the Genetic Algorithm.

```
Input: Population_{size}, Problem_{size}, P_{crossover}, P_{mutation}
   Output: S_{best}
 1 Population \leftarrow InitializePopulation(Population_{size})
   Problem_{size});
 2 EvaluatePopulation(Population);
 S_{best} \leftarrow GetBestSolution(Population);
 4 while ¬StopCondition() do
        Parents \leftarrow SelectParents(Population, Population_{size});
        Children \leftarrow \emptyset;
 6
        for each Parent_1, Parent_2 \in Parents do
 7
           Child_1, Child_2 \leftarrow \texttt{Crossover}(Parent_1, Parent_2,
 8
           P_{crossover});
           Children \leftarrow Mutate(Child_1, P_{mutation});
 9
           Children \leftarrow Mutate(Child_2, P_{mutation});
10
       end
11
       EvaluatePopulation(Children);
12
        S_{best} \leftarrow \texttt{GetBestSolution}(\mathsf{Children});
13
        Population ← Replace(Population, Children);
14
15 end
16 return S_{best};
```

Compact Genetic Algorithm (cGA)



Algorithm 5.4.1: Pseudocode for the cGA.

```
Input: Bits_{num}, n
    Output: S_{best}
 1 V \leftarrow \text{InitializeVector}(Bits_{num}, 0.5);
 S_{best} \leftarrow \emptyset;
 3 while ¬StopCondition() do
        S_1 \leftarrow \text{GenerateSamples}(V);
        S_2 \leftarrow \texttt{GenerateSamples}(V);
 5
         S_{winner}, S_{loser} \leftarrow \texttt{SelectWinnerAndLoser}(S_1, S_2);
         if Cost(S_{winner}) \leq Cost(S_{best}) then
 7
             S_{best} \leftarrow S_{winner};
         end
         for i to Bits_{num} do
10
             if S_{winner}^i \neq S_{loser}^i then
11
                  if S_{winner}^i \equiv 1 then
12
                    V_i^i \leftarrow V_i^i + \frac{1}{n};
13
14
                   V_i^i \leftarrow V_i^i - \frac{1}{n};
15
16
             end
17
         end
18
19 end
20 return S_{best};
```

OneMax Problem



- The problem is a maximizing binary optimization problem called OneMax.
- Seeks a binary string of unity (all '1' bits).
- The objective function only provides an indication of the number of correct bits in a candidate string, not the positions of the correct bits.
- The objective function is the sum of the elements of the string.

Experimental Environment









ruby-prof / ruby-prof

Different population size: 100, 200, 300, 400, 500

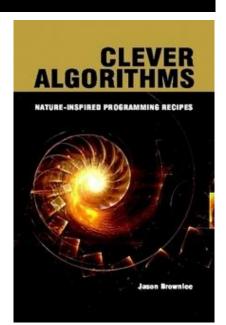
Different problem size: 16, 32, 64, 128, 256, 512

Different metrics: comparisons, memory, CPU

Number runs each instance: 10

Different algorithms: cGA, GA

Total: 1800 runs



Experimental Metrics



- M1. Number of Iterations / Generations
 - For different problem sizes and population:
 - Average
 - Standard Deviation
 - Minimum and Maximum

- M2. Number of Comparisons
 - For different problem sizes and population:
 - Average
 - Standard Deviation
 - Minimum and Maximum

Experimental Metrics



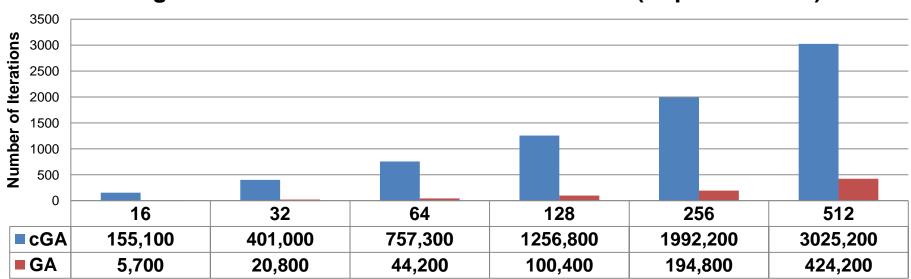
- M3. Memory Usage
 - For different problem sizes and population:
 - Average
 - Standard Deviation
 - Minimum and Maximum

- M4. CPU Time
 - For different problem sizes and population:
 - Average
 - Standard Deviation
 - Minimum and Maximum

M1. Iterations / Generations



Average Number of Iterations and Problem Size (Population 100)



In cGA, the vector update parameter (n) may be considered to be comparable to the population size parameter in the GA.

Observation #1: Iterations in cGA are not Generations in GA.

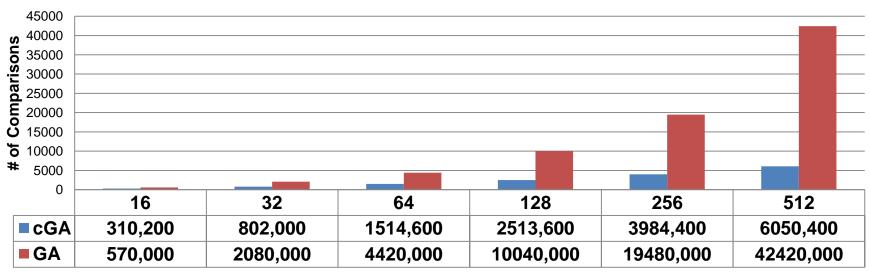
Considering that n in cGA is population size in GA, we define M2 as:

For cGA = 2 * n (considering that 2 individuals are evaluated per iteration). For GA = population size * number of generations (each individual is evaluated on each generation).

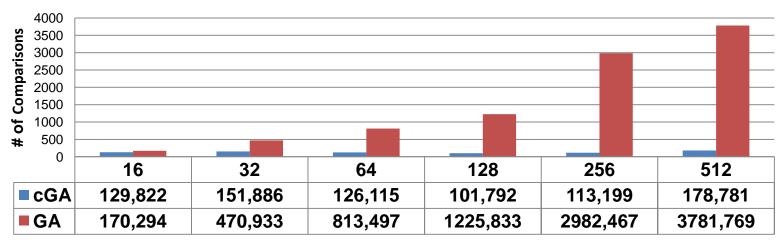
M2. Individuals Comparisons



Average Comparisons and Problem Size (Population 100)



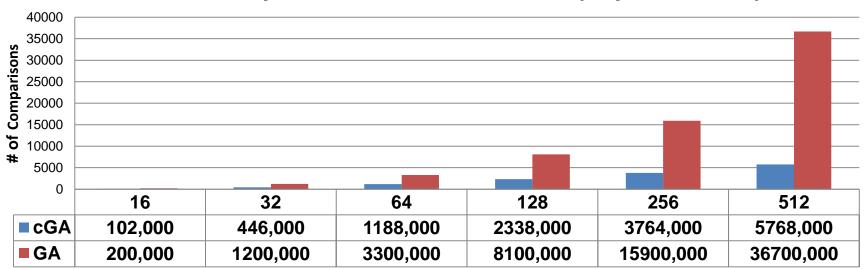
Standard Deviation and Problem Size (Population 100)



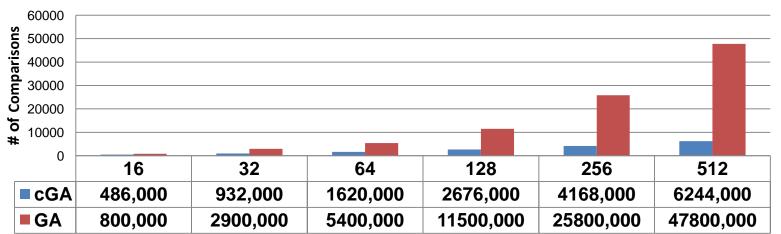
M2. Individuals Comparisons



Minimum Comparisons and Problem Size (Population 100)



Maximum Iterations and Problem Size (Population 100)



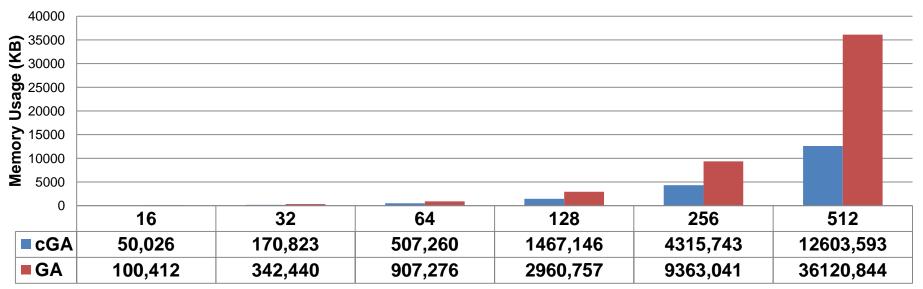
M2. Individuals Comparisons



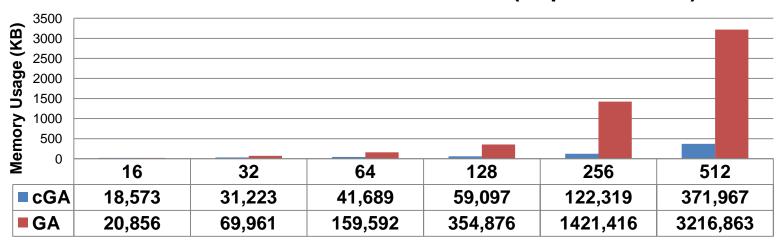
- cGA performed lower number of comparisons than GA (in all experiments)
 - As an example, with 100 individuals the cGA obtained between 45% and 85% less than GA in average.
 - 45.579% less for 16 bits
 - 61.442% less for 32 bits
 - 65.733% less for 64 bits
 - 74.964% less for 128 bits
 - 79.546% less for 256 bits
 - 85.737% less for 512 bits
 - Lower % of number of comparisons with larger number of bits.



Average Memory Usage and Problem Size (Population 100)

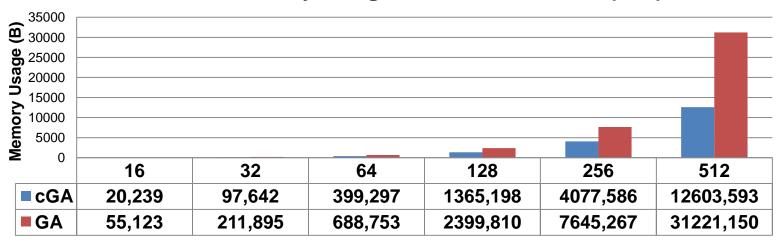


Standard Deviation and Problem Size (Population 100)

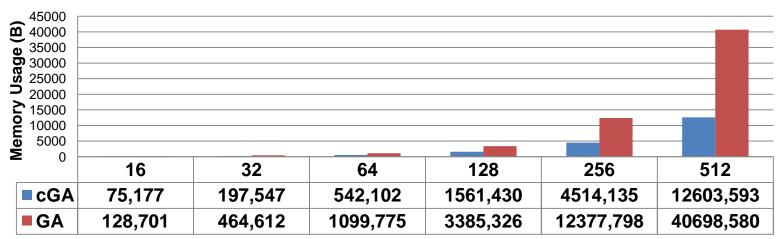




Minimum Memory Usage and Problem Size (100)



Maximum Memory Usage and Problem Size (100)

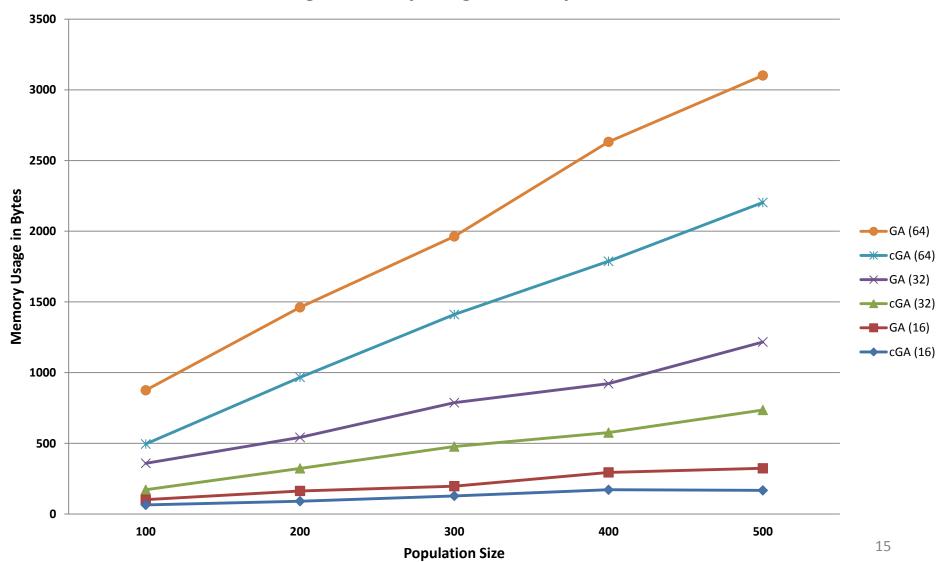




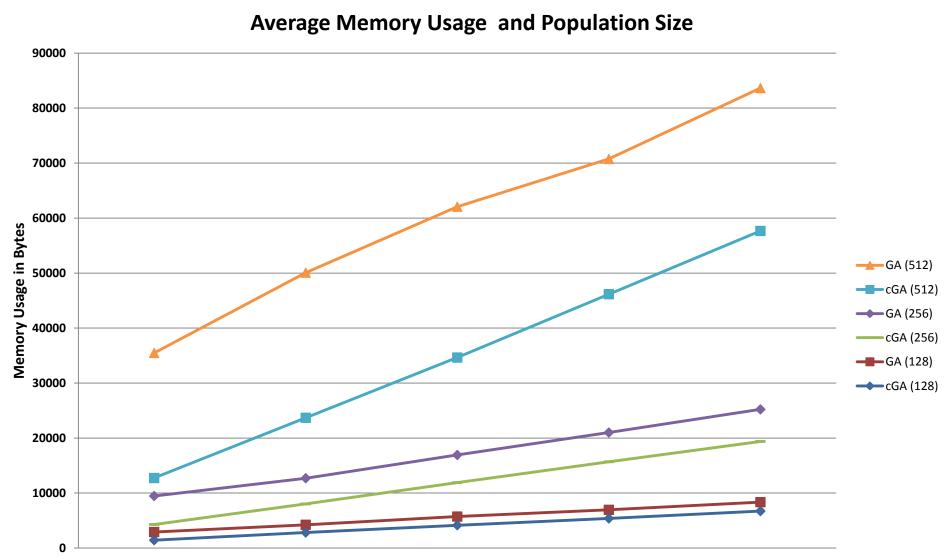
- cGA performed lower memory usage than GA (in all experiments)
 - As an example, with 100 individuals the cGA obtained between 50% and 65% less than GA in average.
 - 50.180% less for 16 bits
 - 50.116% less for 32 bits
 - 44.090% less for 64 bits
 - 50.447% less for 128 bits
 - 53.907% less for 256 bits
 - 65.107% less for 512 bits
 - Lower % of memory usage with larger number of bits.









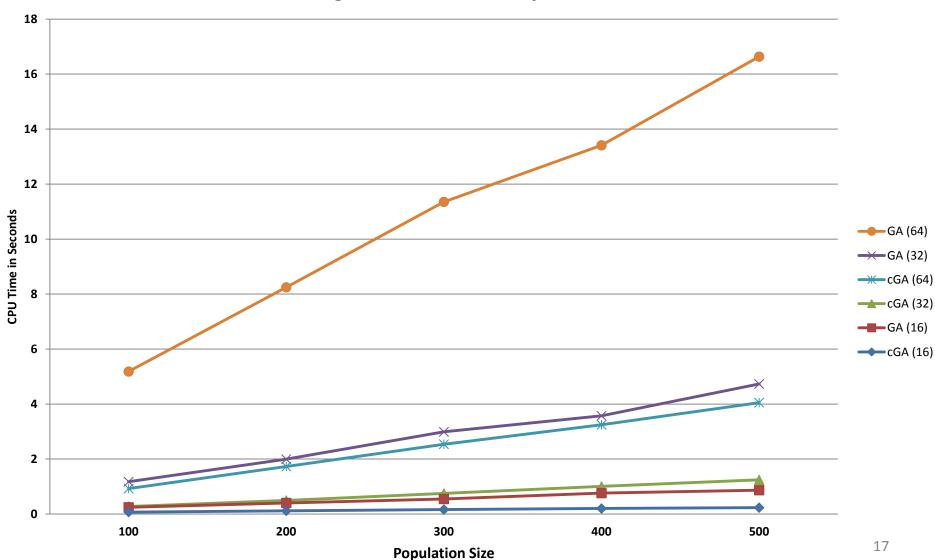


Population Size

M4. CPU Time



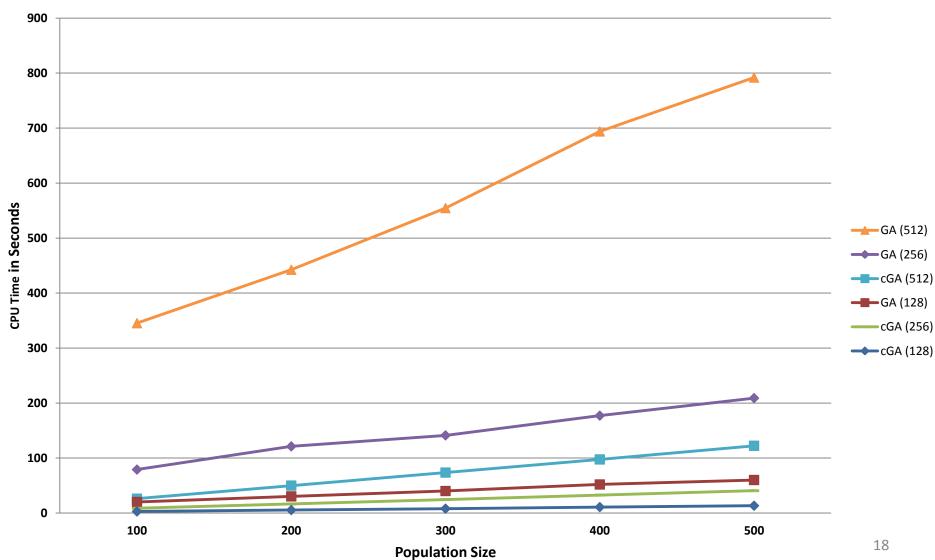




M4. CPU Time







cGA is cool, but...





The Dark Side of cGA





cGA (not) Convergence



- Convergence failed (max iterations):
 - Experiment #1: 5/300 (512-100)
 - Experiment #2: 4/300 (512-100,512-200)
 - Experiment #3: 5/400 (256-100,512-100)

1.4% of the runs do not converged.



Conclusions



- cGA and GA were evaluated considering the following metrics:
 - M1. Number of Iterations / Generations
 - M2. Number of Comparisons
 - M3. Memory Usage
 - M4. CPU Time
- M1 is not valid, considering that Iterations in cGA are not Generations in GA.
- For M2, cGA performed lower number of individual comparisons than GA (in all experiments).
- For M3, cGA performed lower memory usage than GA (in all experiments).
- For M4, cGA performed lower CPU time than GA (in all experiments).
- cGA convergence failed detected with 1M iterations.

Future Work



Analyze:

- number of individual comparisons with different population size.
- when to stop increasing population size?
- other classical problems for generalizing the conclusions of this work.
- are these results valid for other problems?
- correlation between variables of the problem
- will variable 1 increase if variable 2 increases?







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