Evolving Mean-Update Selection Methods for CMA-ES

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Introduction

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- Search space mean is updated every generation using sampled points

Overview

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- We evolve a new method of selecting the points used to update the mean

Objective

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- Step 1: define a representation for selection functions to form a search space
- Step 2: explore this space and determine the quality of the selection functions to find the best one

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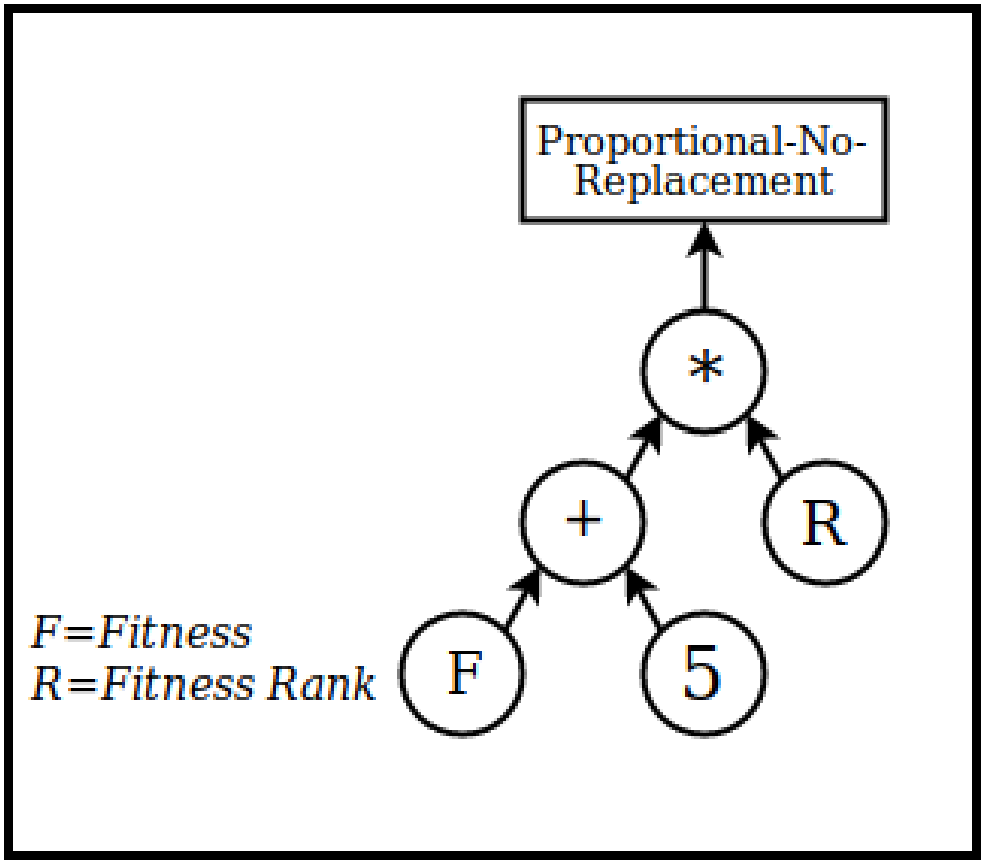
- The second part is a final selection step that selects points based on their desirability scores

Representation

A selection function is represented by a mathematical function (encoded in a parse tree) and a selection method.



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- Each run of the meta-EA targets one of the 24 noiseless test functions in the Comparing Continuous Optimizers function set
- Dimensions of 2, 3, 5, and 10 are used, each with their own meta-EA

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- CMA-ES is run on a number of instances from the problem class. The solution rate is used as the fitness of the selection function
- After the meta-EA concludes, CMA-ES is run with the best selection function on new instances, to test for generalization

Meta-EA Parameters

Parameter	Value
Population Size	40
Offspring Size	40
Evaluation Count	4000
Max GP-Tree Initialization Depth	4
Parent Selection	k-tournament, k=4
Survival Selection	Truncation
Mutation	Subtree Regeneration
Crossover	Subtree Crossover
Parsimony Pressure Coefficient	0.0005
Mutation Rate	0.25
Range for Constant Terminals	[-100, 100]
Range for Random Terminals	[-100, 100]
Number of Runs (Training)	5
Number of Runs (Testing)	200

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- For function class 6 and $D = 10$, success rate increased from 0% to 96%
- For function class 12, success rate increased from 44% to 100%
- Very few cases where the tuned CMA-ES performs worse, and only 7.4% worse at worst

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- Tune more CMA-ES variants

“Take Home Message”

Performance of CMA-ES can be improved on a particular problem class by using a meta-EA to tune the method by which sampled points are selected and used to update the search space mean