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The Automated Design of Probabilistic Selection Methods for Evolutionary Algorithms

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Introduction

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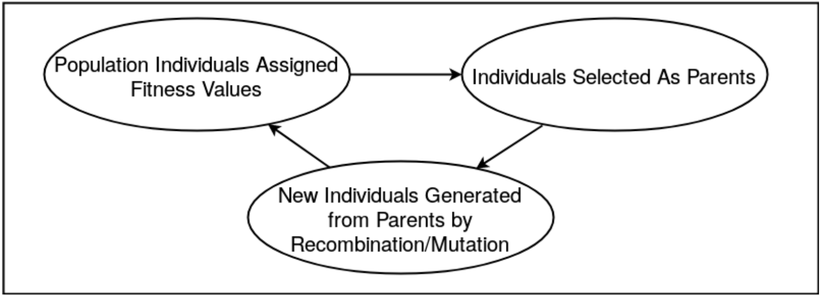
- Manual Tuning of selection strategy can lead to improvement but is still limited to existing/conventional methods
- Generation of new selection methods, specialized to particular problems, can improve performance further

Overview



Parent Selection and Survival Selection both strongly influence how genes survive in the population

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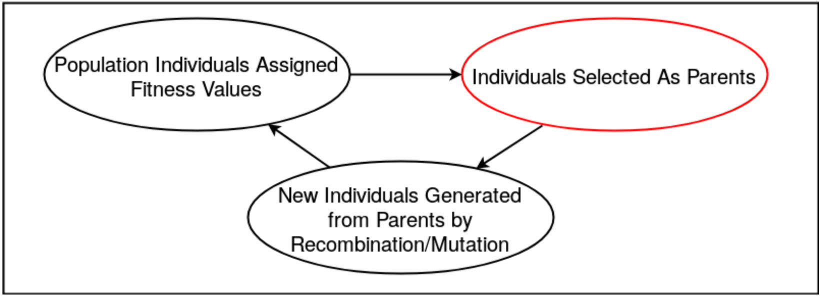

We wish to develop a customized selection function specialized to a particular problem class. For this study, we chose to specialize parent selection, while keeping survival selection static.

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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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- However, the space of Turing-complete algorithms is large and complex, making it difficult to search through

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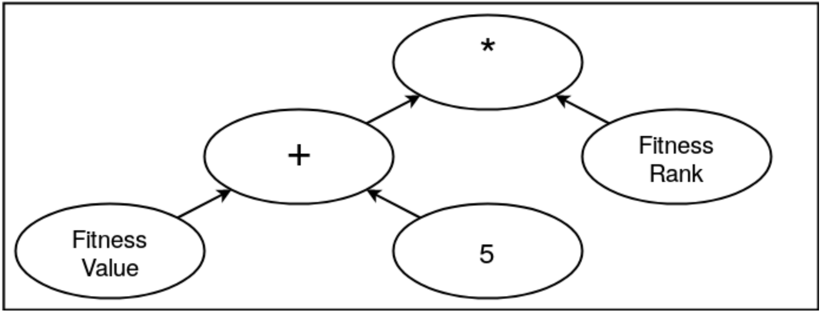
- The function is evaluated for each individual, and a weighted random selection is performed, using the function output as the weight for each individual
- An additional boolean variable controls whether selection is performed with replacement

Representation

A selection function is represented by a mathematical function (encoded in a parse tree), and the boolean variable.



Representation - Psuedocode

Algorithm 1 Probabilistic Selection Function

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procedure ProbabilisticSelection(P)
    for i ← 1, n do
        W(i) ← (P(i).Fitness + 5) · P(i).FitnessRank
    end for
    selected ← WeightedSelection(P, W)
    remove selected from P
    return selected
end procedure
procedure WeightedSelection(P, W)
    w_min ← minimum(W)
    s ← 0
    for all w ∈ W do
        if w_min < 0 then
            s ← s + (w − w_min)
        else
            s ← s + w
        end if
    end for
    r ← random(0, s)
    i ← 1
    while r > W(i) do
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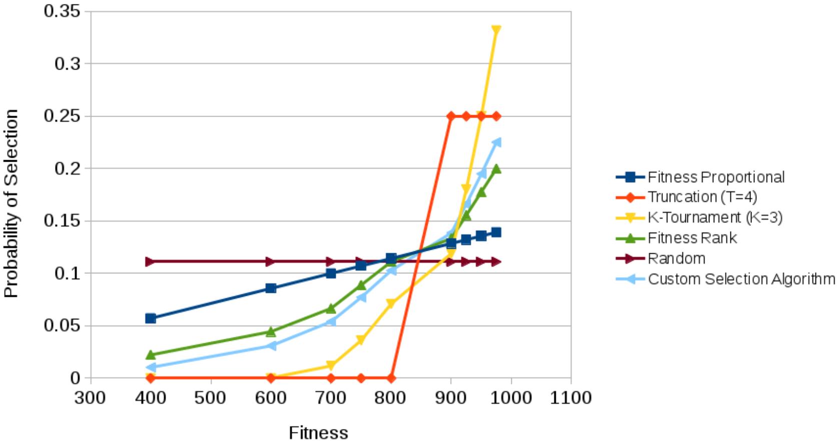
P(fitness-proportional)	0.273	0.227	0.182	0.318
P(fitness-ranking)	0.3	0.2	0.1	0.4

Representation

Different selection functions, including conventional and our evolved selection functions, offer different probability distributions over the population



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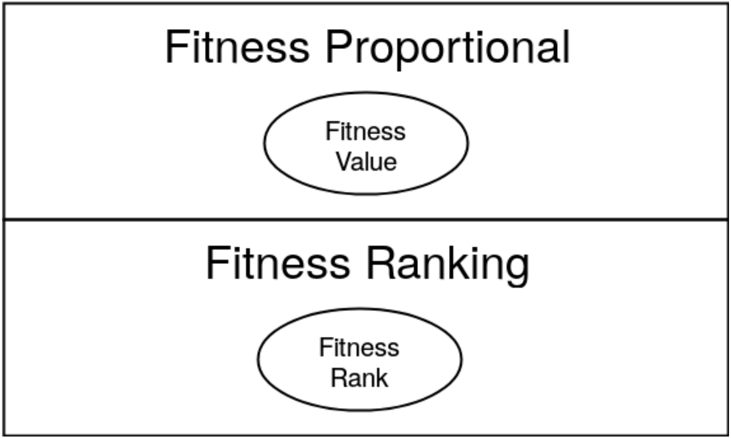

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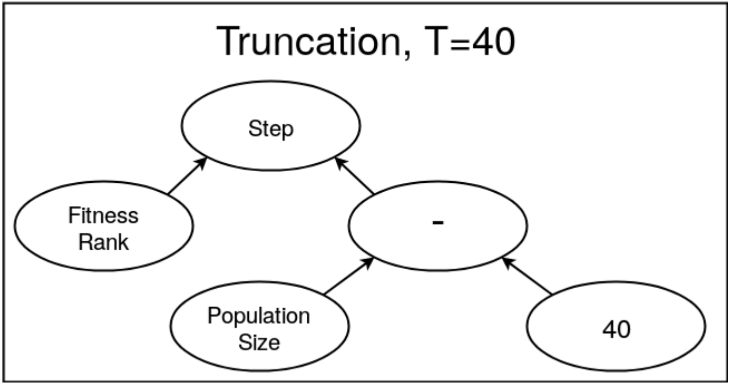

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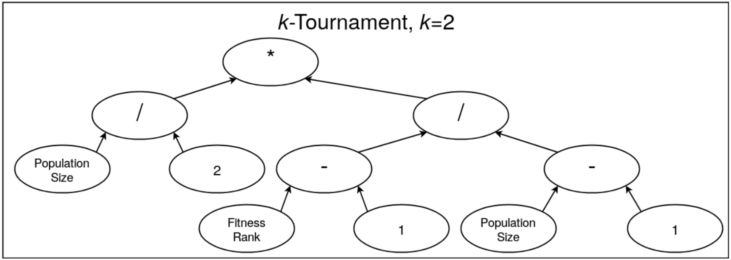

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- In addition, we can guarantee that all functions in this space are valid selection functions
- We cannot guarantee that all possible selection functions can be represented in this format, but this is an acceptable tradeoff for the more easily-searchable space of selection functions

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- Each strategy is evaluated by running a sub-level EA utilizing that strategy on a fixed set of benchmark instances from the NK-Landscape problem class, with N=40 and K=8
- After the meta-EA is run, the selection strategies are tested for generalization on a separate set of "testing" instances from the same problem class

Meta-EA Parameters

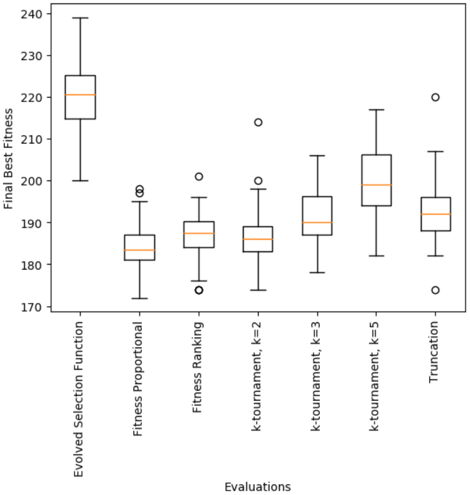
Parameter	Value
Population Size	50
Offspring Size	50
Evaluation Count	2500
Max GP-Tree Initialization Depth	3
Parent Selection	k-tournament, k=10
Survival Selection	Random
Mutation	Subtree Regeneration
Crossover	Subtree Crossover
Parsimony Pressure Coefficient	1
Mutation Rate	0.1
Training Instances	20
Runs per Training Instance	3
Testing Instances	50
Runs per Testing Instance	100
Range for Constant Terminals	[-100, 100]
Range for Random Terminals	[-100, 100]

Base EA Parameters

Parameter	Value
Population Size	100
Offspring Size	20
Genome Length (N)	40
Locus Length (K)	8
Locus Minimum Value	0
Locus Maximum Value	8
Parent Selection	(evolved in Meta-EA)
Survival Selection	Random
Termination Criteria	Convergence
Generations to Convergence	25
Mutation	Random Bit Flip
Mutation Rate	0.05
Crossover	Uniform Crossover

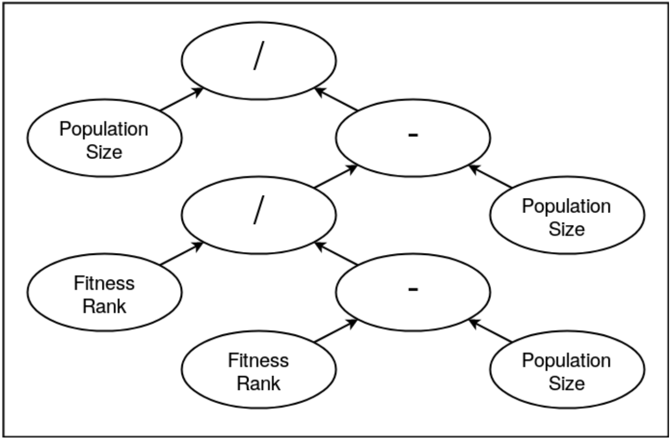
Results - Comparison with Conventional Selection Methods

The final best selection strategy evolved by the Meta-EA outperformed all conventional selection strategies tested on 94% of the 50 testing instances.



Results - Final Best Evolved Selection Strategy

$P(selection) \propto PopulationSize/((FitnessRank/(FitnessRank - PopulationSize)) - PopulationSize)$, selecting **with** replacement



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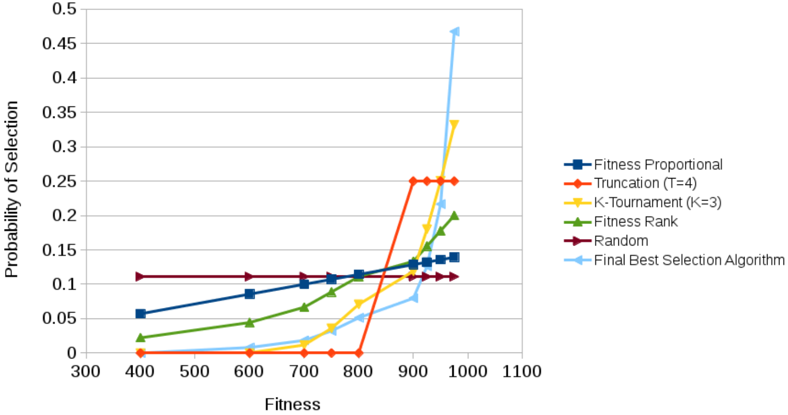

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- The evolved selection methods are static, and do not adapt/self-adapt as the evolution progresses
- The sub-level EA uses static parameters for population size, number of offspring generated, mutation rate, and survival selection

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- Investigate other weighted selection strategies apart from a weighted random selection.
- Investigate systems to encourage more diversity in parents selected, beyond a binary "with/without replacement" setting

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- An EA running on a problem class can gain a performance benefit with a selection function specialized to that problem class (with all other parameters unchanged)

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- An EA running on a problem class can gain a performance benefit with a selection function specialized to that problem class (with all other parameters unchanged)
- A Meta-EA Hyper-heuristic can be used to search through a space of selection functions to find one that significantly outperforms common selection functions for a particular problem class