Supplementary Information

In this supplement, we survey several models in the current literature of both Theory of Evolutionary Computation and Population Genetics and analyse how well our framework fares at being able to implement them.

It should be noted that the purpose of our model is to identify structural similarity between models in population genetics and evolutionary computation. The ultimate goal of this is to initiate a transfer of results, methods and tools between the two fields. As such, we limited the scope of our framework to discrete finite search spaces, since it seems that most theoretical results focus on these. Virtually all papers in the Theory track at GECCO (the major conference on Evolutionary Computation) can be represented in our framework. Here, we chose to look at papers from the Evolutionary Computation at large, namely several issues of both IEEE Transactions of Evolutionary Computation and Evolutionary Computation Journal. This literature includes many examples of algorithms that are used for practical purposes, which have very little theory behind them. Moreover, many models in this literature deal with continuous search spaces, which are not formally included in the current framework. The major difficulty in including these models is formal: the fact that property V1 and M2 do not carry immediately to continuous spaces. The spirit of these properties, that define variation operators in general, and mutation operators in particular, is easy to understand intuitively:

Property V1 states that variation operators should generate diversity isotropically or symmetrically. For continuous spaces this could be formalized by demanding that mutation operators generate symmetric distributions of genotypes.

Property M2 states that repeated applications of the mutation operator should be able to generate the whole of the search space. The equivalent for continuous spaces could be defined in terms of distributions: repeated applications of the mutation operator should have as a limiting distribution the uniform distribution over the whole search space.

As such, it seems feasible that analogous properties could be formally defined for continuous spaces but at the cost of significantly increasing the mathematical complexity of the framework. The same is true for papers focusing on genetic programming or other algorithms whose search space is tree-based: including them would significantly increase the mathematical complexity of the framework.

Many of the models in the PG literature deal with structured populations. Even though we do not define the necessary migration operators, the framework can represent these models since it represents populations as "sequences", which extend the notion of sets so that duplicate elements can co-exist and also that their order (position in the sequence) is important. As such, structured populations can be represented by a partition of the population sequence. Migration operators would be aware of this partition and their function is simply to move individuals between these partitions. Again, we chose not to include this extension here in order to avoid unnecessary mathematical complexity.

Below is a breakdown of the numbers of relevant papers, if they can be casted without modifications to the framework, or if they need the continuous extension.

Field	Relevant models	Representable Models	Require Continuous Extension
PG	21	18	3
EC	22	8	8

Papers in Population Genetics

“Shape matters: Lifecycle of cooperative patches promotes cooperation in bulky populations” by Misevic et al. [1]		
Model 1		
Search space:	bitstrings, diploid	✓
Variation operators:	uniform mutation	✓
Selection operators:		
Notes:	structured population	✓
Model 2		
Search space:	one locus, binary	✓
Variation operators:	uniform mutation	✓
Selection operators:	cut selection	✓
Notes:	structured population	✓
Model 3		
Search space:	one locus, binary	✓
Variation operators:	uniform mutation	✓
Selection operators:	proportional selection	✓
Notes:	structured population	

“Selfish male-determining element favors the transition from hermaphroditism to androdioecy” by Billiard et al. [2]		
Search space:	diploid, two-locus, binary	✓
Variation operators:	one-point crossover	✓
Selection operators:	proportional selection (frequency-dependent selection)	✓
Notes:		

“The effective founder effect in a spatially expanding population The effective founder effect in a spatially expanding population” by Peter and Slatkin [3]		
Model 1		
Search space:	one-locus, binary	✓
Variation operators:		
Selection operators:	uniform selection	✓
Notes:	Wright-Fisher model	
Model 2		
Search space:	one-locus, binary	✓
Variation operators:		
Selection operators:	uniform selection	✓
Notes:	Wright-Fisher model with structured populations	

“The evolution of sex chromosomes in organisms with separate haploid sexes” by Immler and Otto [4]		
Search space:	three loci, binary	✓
Variation operators:	crossover with various genotype dependent rates	✓
Selection operators:	uniform selection	✓
Notes:	mix of haploid and diploid generations	

“Coevolutionary dynamics of polyandry and sex-linked meiotic drive” by Holman et al. [5]		
Model 1		
Search space:	two loci, one haploid, the other diploid, with three and two alleles	✓
Variation operators:	one-point crossover	✓

Selection operators:	proportional selection	✓
Notes:	sex linked locus	
Model 2		
Search space:	two diploid loci with three and two alleles	✓
Variation operators:	one-point crossover	✓
Selection operators:	proportional selection	✓
Notes:	mix of haploid and diploid generations	
“Evolution of female multiple mating: A quantitative model of the sexually selected sperm hypothesis” by Bocedi and Reid [6]		
Model 1		
Search space:	two traits ’preference’ and ’display’, L loci, infinite number of alleles producing a continuous distribution of genetic effects	✗
Variation operators:	uniform mutation (probability μ to mutate, effects sampled from a normal distributions; recombination not mentioned but present (diploid, no linkage)	✓
Selection operators:	multiple proportional selection	✓
Notes:	continuous space	
Model 2		
Search space:	two traits ’tendency to polyandry’ and ’fertilization efficiency’, L loci, infinite number of alleles producing a continuous distribution of genetic effects	✗
Variation operators:	uniform mutation (probability μ to mutate, effects sampled from a normal distributions; recombination not mentioned but present (diploid, no linkage)	✗
Selection operators:	uniform selection, multiple proportional selection	✓
Notes:	continuous space	
“Patterns of variation during adaptation in functionally linked loci” by Sellis and Longo [7]		
Search space:		✓
Variation operators:		✓
Selection operators:		✓
Notes:	traditional Wright-Fisher model	
“Quantifying stochastic introgression processes in random environments with hazard rates” by Ghosh, Serra, and Haccou [8]		
Search space:	three types of individuals	✓
Variation operators:		
Selection operators:	proportional selection	✓
Notes:	hybridisation used to switch between different types of individuals	
“A general condition for adaptive genetic polymorphism in temporally and spatially heterogeneous environments” by Svardal, Rueffler, and Hermisson [9]		
Search space:	four loci, infinite number of alleles	✗
Variation operators:	mutations drawn from gaussian distribution; recombination	✗
Selection operators:	proportional selection on offspring, uniform selection on offspring and parents	✓
Notes:	continuous?	
“Dying on the way: The influence of partial migration mortality on neutral models of spatial variation” by Nagylaki [10]		
Search space:	one locus, diploid	✓

Variation operators:	uniform mutation	✓
Selection operators:	uniform selection	✓
Notes:	structured populations	
“The influence of pleiotropy between viability and pollen fates on mating system evolution” by Jordan [11]		
Search space:	one locus, binary, diploid	✓
Variation operators:		
Selection operators:	uniform and proportional selection	✓
Notes:		
“Clines in quantitative traits: The role of migration patterns and selection scenarios” by Geroldinger and Bürger [12]		
Search space:	two binary loci, diploid	✓
Variation operators:	one-point crossover	✓
Selection operators:	proportional selection	✓
Notes:	structured populations	
“Estimating the scaled mutation rate and mutation bias with site frequency data” by Vogl [13]		
Model 1		
Search space:	bitstring	✓
Variation operators:	uniform mutation	✓
Selection operators:	proportional selection	✓
Notes:	Moran model	
Model 2		
Search space:	bitstring	✓
Variation operators:	uniform mutation	✓
Selection operators:	proportional selection	✓
Notes:	extension of Moran model	
“Matrix inversions for chromosomal inversions: A method to construct summary statistics in complex coalescent models.” by Rousset, Kirkpatrick, and Guerrero [14]		
Search space:	two binary loci, diploid	✓
Variation operators:	one-point crossover	✓
Selection operators:	proportional selection	✓
Notes:	structured populations	
“Frequency-dependent population dynamics: Effect of sex ratio and mating system on the elasticity of population growth rate” by Haridas et al. [15]		
Search space:	one binary locus	✓
Variation operators:		
Selection operators:	proportional selection	✓
Notes:	various stages of the same genotype (young and old males and females)	

Papers in Evolutionary Computation

"On a vector space representation in genetic algorithms for sensor scheduling in wireless sensor networks" by Martins et al. [16]

Search space:	the permutation of sensors being activated	✓
Variation operators:	mutation and crossover on the permutation with restricted swaps	✓
Selection operators:	cut selection and binary tournament selection	✓
Notes:	permutation space.	

"Etea: A Euclidean Minimum Spanning Tree-based Evolutionary Algorithm for Multi-objective Optimization" by Li et al. [17]

Search space:	Since the algorithm is not fixed to solve any particular problem the search space is not defined.	
Variation operators:	Crossover and mutation operators are named in the pseudo-code but not defined in more detail due to the generality of the model.	✓
Selection operators:	cut selection	✓
Notes:	This algorithm uses the Euclidean distance according to objective function values to determine the level of diversity in the population. It uses this metric to select which solutions to keep or delete from its archive.	

"Genetic Programming and Serial Processing for Time Series Classification" by Alfaro-Cid, Sharman, and Esparcia-Alczar [18]

Search space:	tree of no predefined size, infinite and countable	✗
Variation operators:	mutation and crossover	✓
Selection operators:	tournament selection	✓
Notes:	trees	✗

"Asymptotic Properties of a Generalized Cross-Entropy Optimization Algorithm" by Wu and Kolonko [19]

Search space:	any discrete	✓
Variation operators:	The variation operator samples a solution according to a distribution so it is akin to a mapping from distribution to population space.	✓
Selection operators:	Selection operator incorporates functionalities such as feasibility and desirability	✓
Notes:	an EDA with some extra features that establishes feasibility and other desirability factors that might guide the algorithm	

"The Dynamics of Self-Adaptive Multirecombinant Evolution Strategies on the General Ellipsoid Model" by Beyer and Melkozerov [20]

Search space:	continuous n loci	✗
Variation operators:	Variation operator moves the solution to a random direction for a normally distributed step size that also depends on a solution component (mutation strength).	✗
Selection operators:	The next generation keeps the average of best μ of λ solutions.	✓
Notes:	subset of the EDA model, continuous	

"Automated Map Generation for the Physical Traveling Salesman Problem" by Perez et al. [21]

Search space:	real valued variables, coordinates of a set of waypoints, coordinates of a set of obstacles, a starting point. The algorithm (CMA-ES) keeps a multivariate normal distribution with a vector for mean and a vector for covariance.	✗

Variation operators:		
Selection operators:	cut selection	✓
Notes:	Other components: Travelling salesman solvers that establishes the objective values. The process is similar to EDA which is one of the covered models. Continuous space.	
"Multilocal Search and Adaptive Niching Based Memetic Algorithm With a Consensus Criterion for Data Clustering" by Sheng et al. [22]		
Search space:	continuous	✗
Variation operators:	two-point crossover, Gaussian mutation	✓
Selection operators:	restricted tournament selection	✓
Notes:	continuous space	✗
"A Simple Approach to Lifetime Learning in Genetic Programming-Based Symbolic Regression" by Azad and Ryan [23]		
Search space:	trees	✗
Variation operators:	crossover, point mutation	✓
Selection operators:	tournament selection	✓
Notes:	continuous space	✗
"Choosing the Appropriate Forecasting Model for Predictive Parameter Control" by Aleti et al. [24]		
Search space:	both discrete and continuous	✓
Variation operators:	any	✓
Selection operators:	any	✓
Notes:	This algorithm adapts its parameters, which are continuous.	✗
"On the Behaviour of the (1, λ)-ES for Conically Constrained Linear Problems" by Arnold [25]		
Search space:	continuous (two-dimensional)	✗
Variation operators:	mutation, Gaussian kernel	✗
Selection operators:	cut selection	✓
Notes:	continuous space	✗
"Genetic Programming for Evolving Due-date Assignment Models in Job Shop Environments" by Nguyen et al. [26]		
Search space:	tree	✗
Variation operators:	subtree crossover, subtree mutation	✗
Selection operators:	tournament selection	✓
Notes:		
"An Evolutionary Approach for Image Segmentation" by Amelio and Pizzuti [27]		
Search space:	k-ary strings	✓
Variation operators:	uniform crossover, mutation	✓
Selection operators:	proportional selection	✓
Notes:		
"Genetic Algorithms for Evolving Computer Chess Programs" by David et al. [28]		
Search space:	bitstrings	✓
Variation operators:	mutation, crossover	✓
Selection operators:	cut selection	✓
Notes:	standard GA	
"General Upper Bounds on the Runtime of Parallel Evolutionary Algorithms" by Lässig and Sudholt [29]		

Search space:	bitstrings	✓
Variation operators:	uniform mutation	✓
Selection operators:	cut selection	✓
Notes:	parallel algorithm	

"Reevaluating Immune-Inspired Hypermutations Using the Fixed Budget Perspective" by Jansen and Zarges [30]

Search space:	bitstrings	✓
Variation operators:	single-point mutation, uniform mutation, somatic contiguous hypermutations	✗
Selection operators:	cut selection	✓
Notes:	somatic contiguous hypermutations are used in artificial immune systems; they are not contained in our model, but do respect properties of mutation. CLONALG uses uniform mutation with inversely fitness-proportional mutation rate.	

"Convergence of hypervolume-based archiving algorithms I: Effectiveness" by Bringmann and Friedrich [31]

Search space:	arbitrary fixed set	✓
Variation operators:	mutation, crossover (arbitrary)	✓
Selection operators:	$(\mu + \lambda)$-archiving selection: retain μ of the $\mu + \lambda$ individuals in such a way that the hypervolume of the retained population is maximized	✓
Notes:		

"Differential Evolution With Dynamic Parameters Selection for Optimization Problems" by Sarker, Elsayed, and Ray [32]

Search space:	continuous	✗
Variation operators:	binomial crossover, DE mutation	✗
Selection operators:	cut selection	✓
Notes:	continuous space	

"A Knowledge-Based Evolutionary Multiobjective Approach for Stochastic Extended Resource Investment Project Scheduling Problems" by Xiong et al. [33]

Search space:	two loci, continuous + one locus, permutation	✗
Variation operators:	crossover (separate crossover for resource capacity list (single point), allocated resource list (two point), activity list (two point position-based)). Mutation (separate resource cap list, allocated resource list, activity list), specialized operator for mutation on activity list	
Selection operators:		
Notes:	Extended Resource Investment Project Scheduling Problem (Type of RCPSP) very problem-specific algorithm. Multi-Objective. Continuous space.	✗

"Evolving spiking networks with variable resistive memories" by Howard et al. [34]

Search space:	Each genotype is represented by two variable-length vectors, one contains neurons, the other connections. Neuron defined by type, membrane potential, last spike value. Connection defined by type, weight, charge, β/S_n, and the neurons it connects. These two vectors are augmented by self-adaptive parameters that control the rate of mutation. Mutable network parameters are neuron type, synaptic weight, β, S_n, and associated self-adaptive parameters. Neurons and connections may be added/removed from vectors by the GA.	✓
Variation operators:	mutation, controlled by self-adaptive mechanism.	✓
Selection operators:	proportional selection, cut selection	✓
Notes:	Difficult because of self-adaptation, variable-length representation, and different, problem-tailored mutation operations (topology and weight mutation), continuous space	
"MOEA/D with adaptive weight adjustment" by Qi et al. [35]		
Search space:	($\mathbb{R}^n$) (bounded region)	✗
Variation operators:	SBX operator, polynomial mutation operator	✓
Selection operators:		
Notes:	continuous space	✗
"Parameterized runtime analyses of evolutionary algorithms for the planar Euclidean traveling salesperson problem" by Sutton, Neumann, and Nallaperuma [36]		
Search space:	Euclidean Travelling Salesman problem	✗
Variation operators:	2-opt mutation	✗
Selection operators:	cut-selection	✓
Notes:	permutation space	
"Pareto Front Estimation for Decision Making" by Giagkiozis and Fleming [37]		
Search space:	n loci, continuous ($\mathbb{R}^n$)	✗
Variation operators:		
Selection operators:		
Notes:	continuous space	✗

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