Population Distributions in Biogeography-Based Optimization

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Outline

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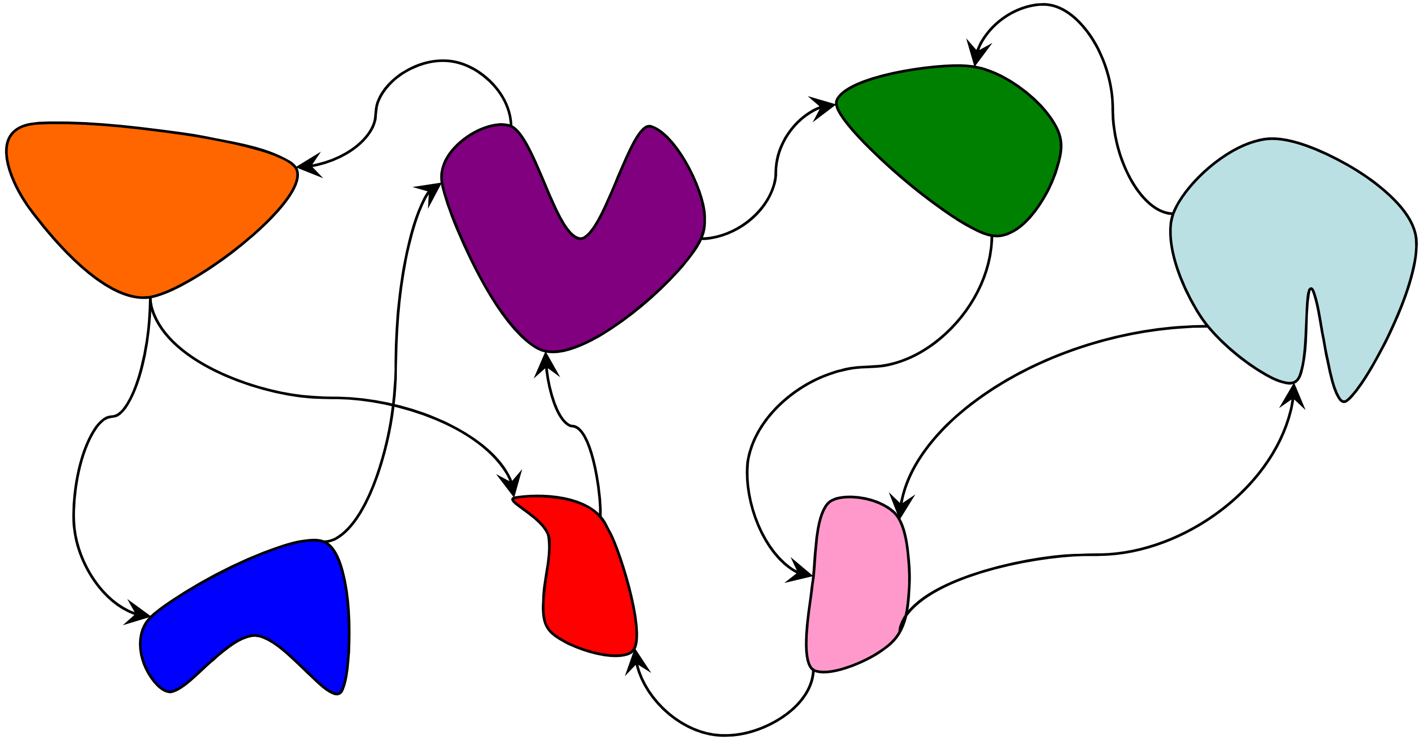
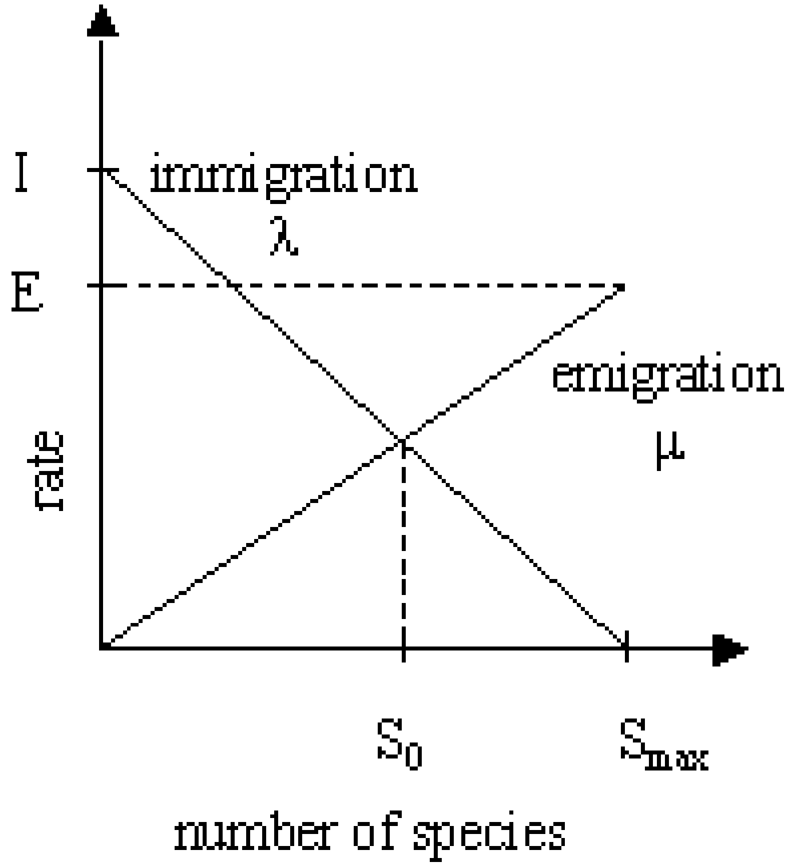
Biogeography-Based Optimization



Species migrate between “islands” via flotsam, wind, flying, swimming, …

Biogeography-Based Optimization



As habitatability improves:

1. Number of species increases
2. Emigration increases (more species exit the habitat)
3. Immigration decreases (fewer species come into the habitat)

Biogeography-Based Optimization

1. Initialize a set of solutions to a problem.
2. Compute fitness (habitability) of each solution.
3. Compute *S*, λ, and μ for each solution.
4. Modify habitats (migration) based on λ, μ.
5. Mutate based on probability.
6. Implement elitism.
7. Go to step 2 for the next iteration if needed.

Markov Analysis

Population size = N

Search space cardinality = n

Search space = $\{x_1, x_2, \ldots, x_n\}$

$$\text{Population} = \{y_1, \cdots, y_N\} =$$

$$\{\underbrace{x_1, x_1, \cdots, x_1}_{v_1 \text{ copies}}, \underbrace{x_2, x_2, \cdots, x_2}_{v_2 \text{ copies}}, \cdots \underbrace{x_n, x_n, \cdots, x_n}_{v_n \text{ copies}}\}$$

Markov Analysis

$$
\begin{aligned}
u &= \begin{bmatrix} u_1 & \cdots & u_n \end{bmatrix}^T \\
v &= \begin{bmatrix} v_1 & \cdots & v_n \end{bmatrix}^T \\
\Pr(u|v) &= \sum_{Y} \prod_{k=1}^{N} \prod_{i=1}^{n} P_{ki}^{J_{ki}}(v) \\
Y &= \Big\{ J \in \mathbf{R}^{N\times n} : J_{ki} \in \{0,1\}, \\
&\qquad \sum_{i=1}^{n} J_{ki} = 1 \text{ for all } k, \sum_{k=1}^{N} J_{ki} = u_i \text{ for all i} \Big\}
\end{aligned}
$$

The notation is defined in the conference paper

Simulation Results

Three-bit problem (N = 4, n = 8), maximum # one-bits
Pop. vector = [000, 001, 010, 011, 100, 101, 110, 111]

Mutation	Pop. Vector	Markov	Simulation
0.1	0 0 0 0 0 0 1 3	0.0290	0.0285
	0 0 0 0 0 1 0 3	0.0290	0.0284
	0 0 0 1 0 0 0 3	0.0290	0.0284
	* * * * * * * 0	0.2999	0.3026
0.01	0 0 0 0 0 0 0 4	0.5344	0.5322
	* * * * * * * 0	0.1134	0.1138
0.001	0 0 0 0 0 0 0 4	0.8605	0.8437
	* * * * * * * 0	0.0923	0.1092

BBO vs. GA Comparison

Four-bit unimodal problem ($N = 4$, $n = 16$)
GA/sp: GA with single-point crossover
GA/gur: GA with global uniform recombination

Mutation	Pop. Vector	Population Probability		
		GA/sp	GA/gur	BBO
0.1	Uniform Optimal	0.0084	0.0079	0.0044
	No Optima	0.5826	0.5623	0.5111
0.01	Uniform Optimal	0.2492	0.2513	0.3484
	No Optima	0.5436	0.5372	0.2128
0.001	Uniform Optimal	0.4029	0.4034	0.7616
	No Optima	0.5696	0.5690	0.1679

BBO vs. GA Comparison

Four-bit multimodal problem

Mutation	Pop. Vector	Population Probability		
		GA/sp	GA/gur	BBO
0.1	Uniform Optimal	0.0119	0.0106	0.0066
	No Optima	0.5006	0.4939	0.4370
0.01	Uniform Optimal	0.3675	0.3701	0.4715
	No Optima	0.4139	0.4079	0.1450
0.001	Uniform Optimal	0.5655	0.5670	0.8502
	No Optima	0.4069	0.4053	0.0968

BBO vs. GA Comparison

Four-bit deceptive problem

Mutation	Pop. Vector	Population Probability		
		GA/sp	GA/gur	BBO
0.1	Uniform Optimal	0.0131	0.0109	0.0120
	No Optima	0.8120	0.8325	0.7954
0.01	Uniform Optimal	0.4601	0.4760	0.6506
	No Optima	0.4308	0.4103	0.1915
0.001	Uniform Optimal	0.6230	0.6383	0.9074
	No Optima	0.3638	0.3482	0.0730

Conclusions

- New Markov model for BBO
- Lower mutation gives better performance
- BBO far outperforms GAs
- Future work
  - Extension to dynamic systems model
  - Extension to BBO variations
  - Extension to other evolutionary algorithms