Population-Based Metaheuristics 1

Ch. 3.1-3.2

Marcus Posada

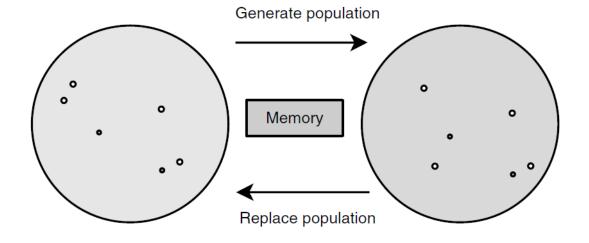


Common concepts

Ch. 3.1



Common concepts



Algorithm 3.1 High-level template of P-metaheuristics.

```
P = P_0; /* Generation of the initial population */
t = 0;

Repeat

Generate(P_t'); /* Generation a new population */
P_{t+1} = \text{Select-Population}(P_t \cup P_t'); /* Select new population */
t = t + 1;

Until Stopping criteria satisfied

Output: Best solution(s) found.
```

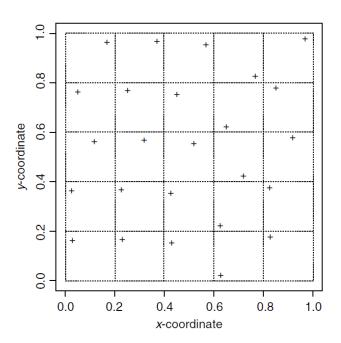


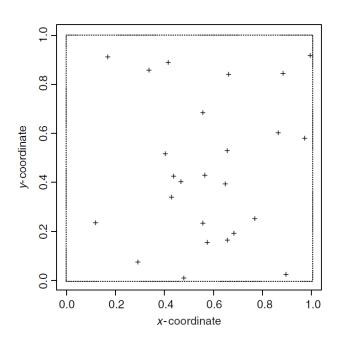
Initial population

- Pseudo- or Quasi-random
- Sequential or Parallel diversification
- •Heuristic



Initial population: parallel diversification







Initial population

- Pseudo- or Quasi-random
- Sequential or Parallel diversification
- •Heuristic



Initial population

Strategy	Diversity	Computational Cost	Quality of Initial Solutions
Pseudo-random	++	+++	+
Quasi-random	+++	+++	+
Sequential diversification	++++	++	+
Parallel diversification	++++	+++	+
Heuristic	+	+	+++



Stopping criteria

- •Static: *a priori* knowledge of when the search will end. E.g. a maximum number of iterations.
- •Adaptive: no *a priori* knowledge. E.g. number of iterations without improvement.
- •There are also criteria which are specific to Pheuristics.



Ch. 3.2



- •Genetic algorithms
- •Evolution strategies
- Evolutionary programming
- Genetic programming

Evolutionary computation

•They are all inspired by the prinicple of heredity from parents to offspring in natural evolution.



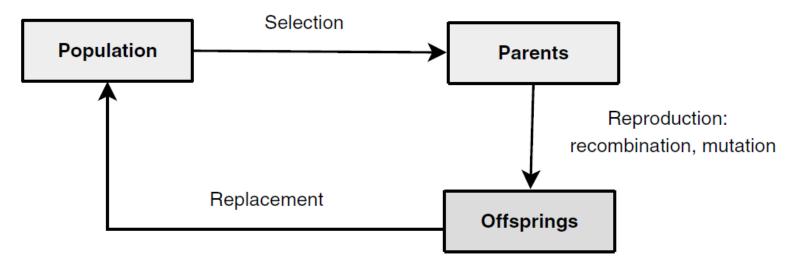


FIGURE 3.7 A generation in evolutionary algorithms.



Metaphor	Optimization	
Evolution	Problem solving	
Individual	Solution	
Fitness	Objective function	
Environment	Optimization problem	
Locus	Element of the solution	
Allele	Value of the element (locus)	

Algorithm 3.2 Template of an evolutionary algorithm.

```
Generate(P(0)); /* Initial population */
t = 0;

While not Termination_Criterion(P(t)) Do

Evaluate(P(t));

P'(t) = Selection(P(t));

P'(t) = Reproduction(P'(t)); Evaluate(P'(t));

P(t+1) = Replace(P(t), P'(t));

t = t+1;

End While

Output Best individual or best population found.
```



Genetic algorithms

- •J. Holland 1970, USA. Applied to optimization in the 1980s.
- •Classical characteristics: binary representation. Crossover + mutation. Parents are replaced by offspring.



Evolution strategies

- •Rechenberg and Schewefel, 1964, Berlin. Used in continuous optimization.
- •Classical characteristics: real-valued representation. Elitist replacement (offspring do not necessarily replace parents). Deterministic selection (fitness). No single step size in mutation.
- •Efficient in terms of time complexity.



Evolution strategies

Algorithm 3.3 Template of evolution strategies.

Initialize a population of μ individuals;

Evaluate the μ individuals;

Repeat

Generate λ offsprings from μ parents;

Evaluate the λ offsprings;

Replace the population with μ individuals from parents and offsprings;

Until Stopping criteria

Output Best individual or population found.



Evolutionary programming

- •L. Fogel, 1960s, USA.
- •Classical characteristics: real-valued representation. No recombination. Normally distributed mutations. Deterministic parent selection, stochastic replacement selection (*n* species, tournament selection).
- •Less used then the other families of EAs.



Genetic programming

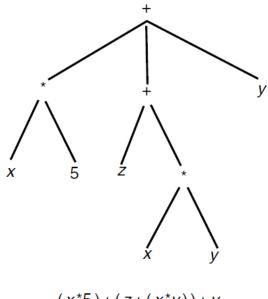
- •J Koza, 1980s. The individuals are themselves programs (not fixed length strings, as in the other methods).
- •Classical characteristics: deterministic parent selection, generational replacement. Crossover: subtree exchange. Mutation: random changes in the tree.
- •Computationally intensive. Used for data mining.

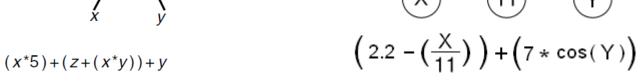


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Genetic programming: symbolic regression







Reading advise

•Sörensen, Kenneth. "Metaheuristics—the metaphor exposed." *International Transactions in Operational Research* 22.1 (2015): 3-18.



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