

Evolutionary Computation Part 2

CS454 AI-Based Software Engineering
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(with some slides borrowed from Seongmin Lee @ COINSE)

Crossover Operators

- Offsprings inherit genes from their parents, but not in identical forms.
- Think Mendelian recombination of alleles; since we don't have alleles, we actually recombine the whole genotype.

Crossover Operators

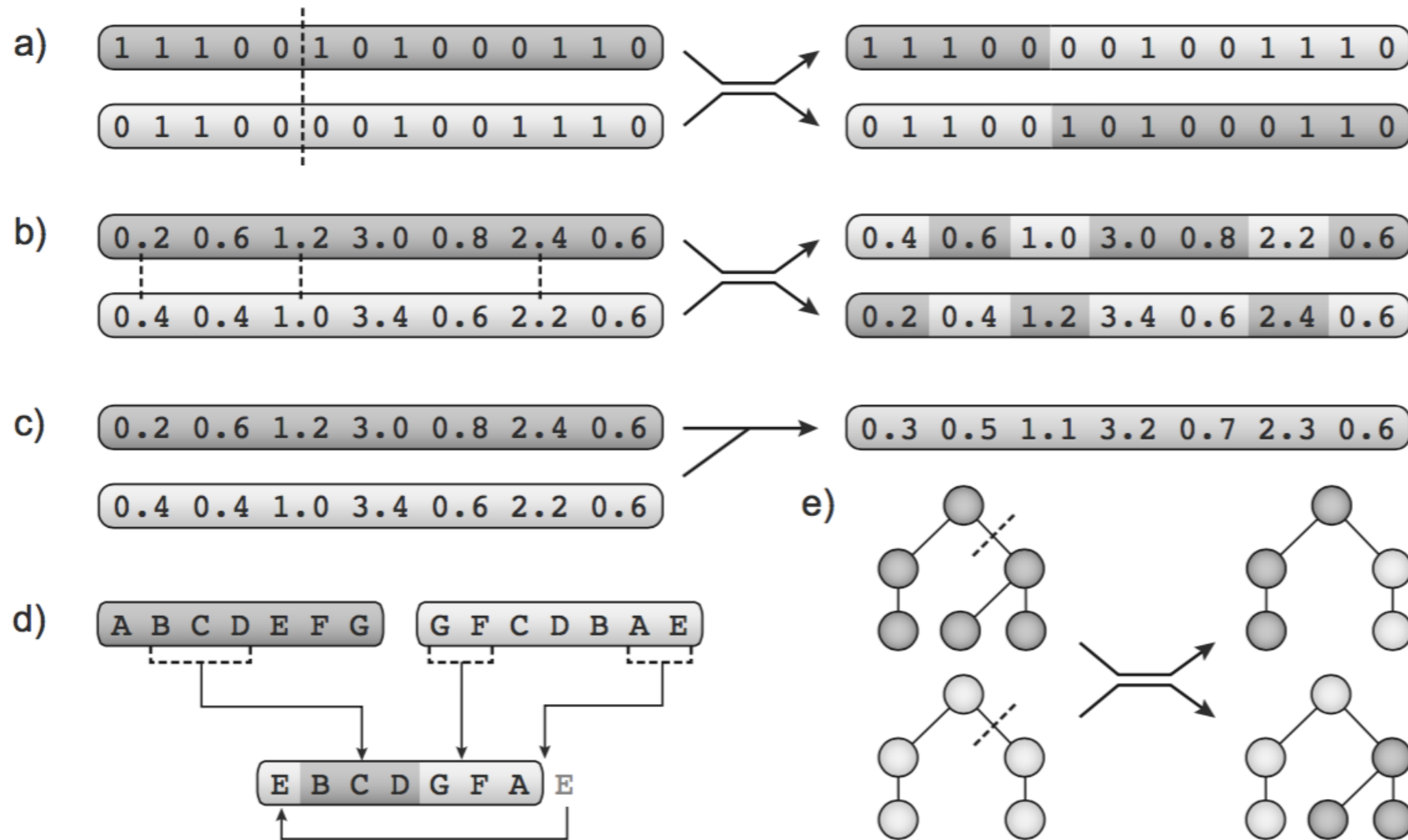


Figure 1.11 Examples of crossover operators. *a)* one-point; *b)* uniform; *c)* arithmetic; *d)* for sequences; *e)* for trees.

(from "Bio-inspired Artificial Intelligence: Theories, Methods, and Technologies"
by Dario Floreano and Claudio Mattiussi)

Mutation Operators

- This is, usually, the **only** way **new genetic material** is introduced into the population; without mutation, all we do is recombining the initial population (which was randomly generated).

Mutation Operator

- Small, local modifications to genotypes:
 - single bit-flip
 - adding/subtracting small amount to integers
 - swapping two elements in permutations
 - replacing one node in a tree with a different, compatible type

Generational Selection

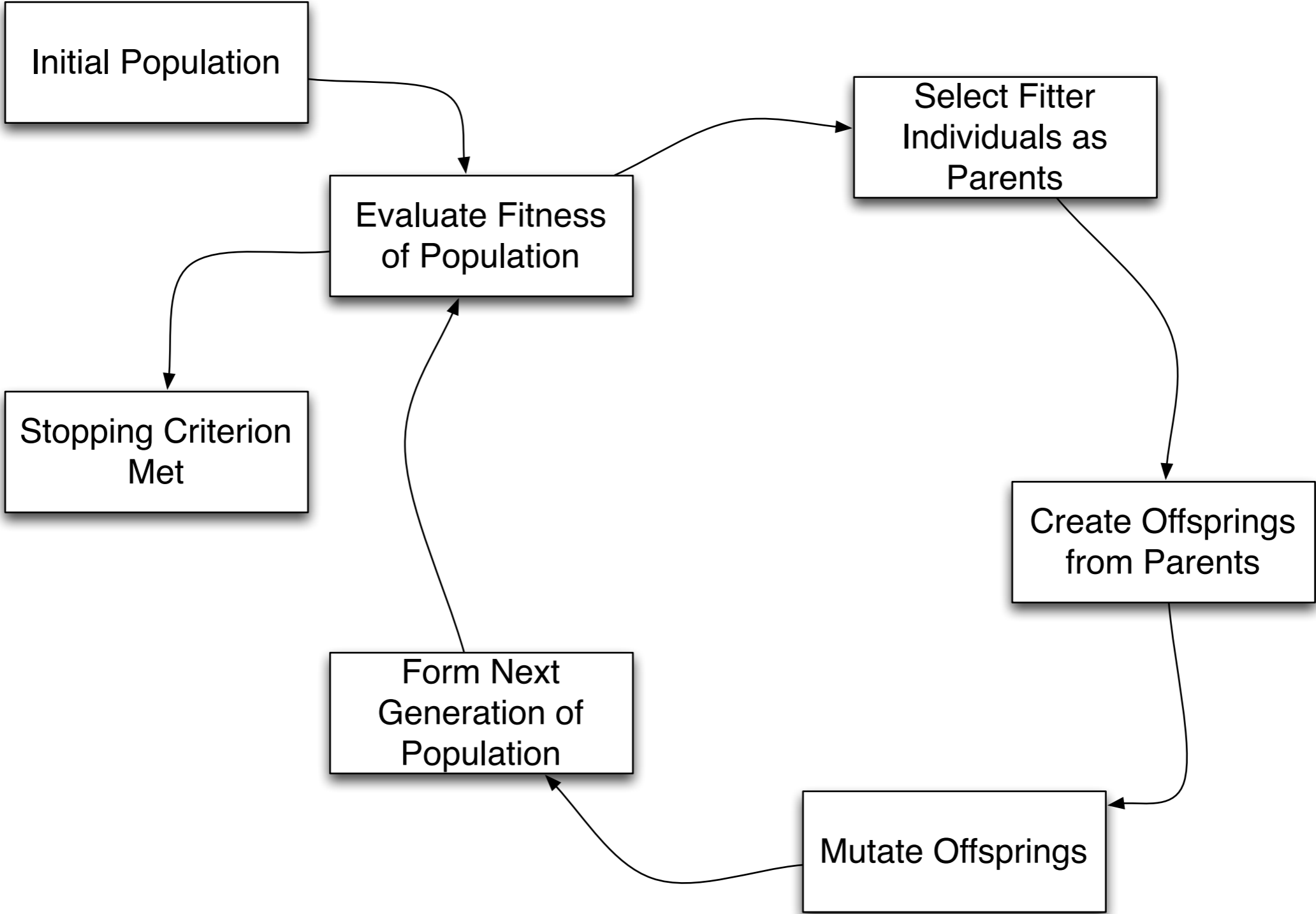
- Generational Replacement: the offsprings become the new current population (no parent survives)
- Elitism: maintain M best individuals from the parents' generation (reasons: noisy fitness, too strong mutations, too complicated search space...)
- Gradual Replacement: replace M worst individuals from the parents' generation with M best individuals from the offsprings.

Stopping Criterion

- Deciding one can be hard: these are stochastic algorithms, and you don't know what the global optimum is.
- In reality, one of the following two:
 - Fixed number of fitness evaluations, or
 - When a good enough solution has been found

Parameters

- One weakness of GAs: many parameters to tune, no fixed guideline.
 - Population Size
 - Crossover Rate (usually high, we do want to crossover)
 - Mutation rate (usually low: e.g. $\mathbf{1/N}$ for 1 bit flip for each bit of length \mathbf{N} bit string)
 - Elitism: the proportion of parent generation to preserve



Why (or when) does it work?

- Not much theoretic foundation.
- Schema Theory (John Holland, 1975): given genotypes of k symbols with length l , the schemata set is $\{s_0, \dots, s_k, *\}$ where $*$ means “don’t care”. There are $(k+1)^l$ schemas.
- Intuitively, schemas can be thought of as non-consecutive building blocks to the solution.
- Holland mathematically proved that selective reproduction allows exponentially increasing number of samples of schemas with better-than-average fitness, and exponentially decreasing number of schemas with lower-than-average fitness.

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Schema Theorem (Holland)

Schema Theorem

Schema :

Hyper place in the search space.

Schema Theorem

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Hyper place in the search space.

11###

: The “don’t care” symbol.

Schema Theorem

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Hyper place in the search space.

$$2^3 = 8$$

11###

: *The “don’t care” symbol.*

Schema Theorem

Instances :

All strings meeting this criterion.

$$2^3 = 8$$

11###

Schema Theorem

Instances :

All strings meeting this criterion.

11000

Schema Theorem

Instances :

All strings meeting this criterion.

11111

Schema Theorem

Fitness of a schema :

Mean fitness of all string instances.

11###

Schema Theorem

Global optimisation :

Highest fitness schema with zero “don’t care” symbols.

11###

Schema Theorem

Holland showed that the analysis of GA behavior was far simpler if carried out in terms of schemata.

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Aggregation :

Rather than model the evolution of all possible strings, group together in some way and model the evolution of the aggregated variables.

Schema Theorem

Two features to describe schemata.

H=1##0#1#0

Schema Theorem

Order of schemata :

Number of positions in the schemata that do not have the “don’t care” sign.

H=1##0#1#0

$$o(H) = 4$$

Schema Theorem

Defining length of schemata :

*Distance between the outermost defined position
(which equals the number of possible crossover points
between them).*

H=1##0#1#0

$$d(H) = 8 - 1 = 7$$

Schema Theorem

Standard genetic algorithm (SGA)

- *Fitness proportionate parent selection,*
- *One-point crossover (IX),*
- *Bitwise mutation,*
- *Generational survivor selection*

Schema Theorem

$$E(m(H, t + 1)) \geq \frac{m(H, t) f(H)}{a_t} (1 - p)$$

$$p = \frac{\delta(H)}{l - 1} p_c + o(H) p_m$$

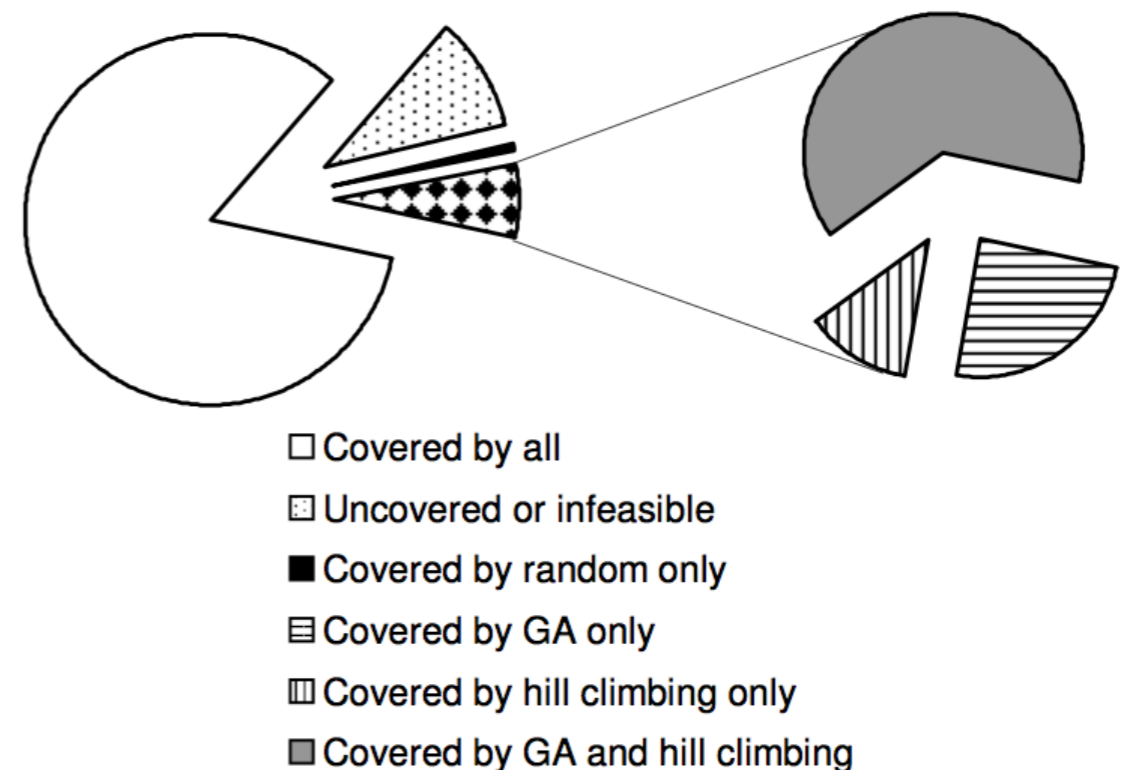
- $m(H, t)$: number of instances of schema H at generation t
- a_t : average fitness of population at t
- l : length of chromosomes
- $o(H)$: order of H , $\delta(H)$: defining length of H
- p_c : crossover rate , p_m : mutation rate

Case Study: Search-Based Software Testing

- Traditionally, GAs have been very popular with researchers: it appears fancy :)
- Is it really grounded on facts?
- Harman and McMinn (2007) compared the performance of HC and GA for automated test data generation for branch coverage for C programs.
- **bibclean, eurocheck, gimp, space, spice, tiff**

Comparison of HC and GA

- There are branches that can only be covered by HC and GA respectively.
- Branches easier for GA: **bibclean**, especially in functions **check_ISBN()** and **check_ISSN()**.
- Why?



Proportion of branches covered by different algorithms (Harman & McMinn, 2007)

Schema Theory in Work

- “...Registration group identifiers have primarily been allocated within the **978 prefix element**. The single-digit group identifiers within the **978** prefix element are: 0 or 1 for English-speaking countries; 2 for French-speaking countries; 3 for German-speaking countries; 4 for Japan; 5 for Russian-speaking countries; and 7 for People's Republic of China. An example 5-digit group identifier is **99936**, for Bhutan. The allocated group IDs are: **0–5**, **600–621**, **7**, **80–94**, **950–989**, **9926–9989**, and **99901–99976**.” (from Wikipedia entry for ISBN)

Schema Theory in Work

- Once a small schema is formed (e.g., **9***), it can be used as a building block for a larger schema (e.g. **99***). Crossover allows assembly of different building blocks.
- This is also called **Building Block Hypothesis**: GAs work best for problems with building block structure in their solutions.

Computational Complexity

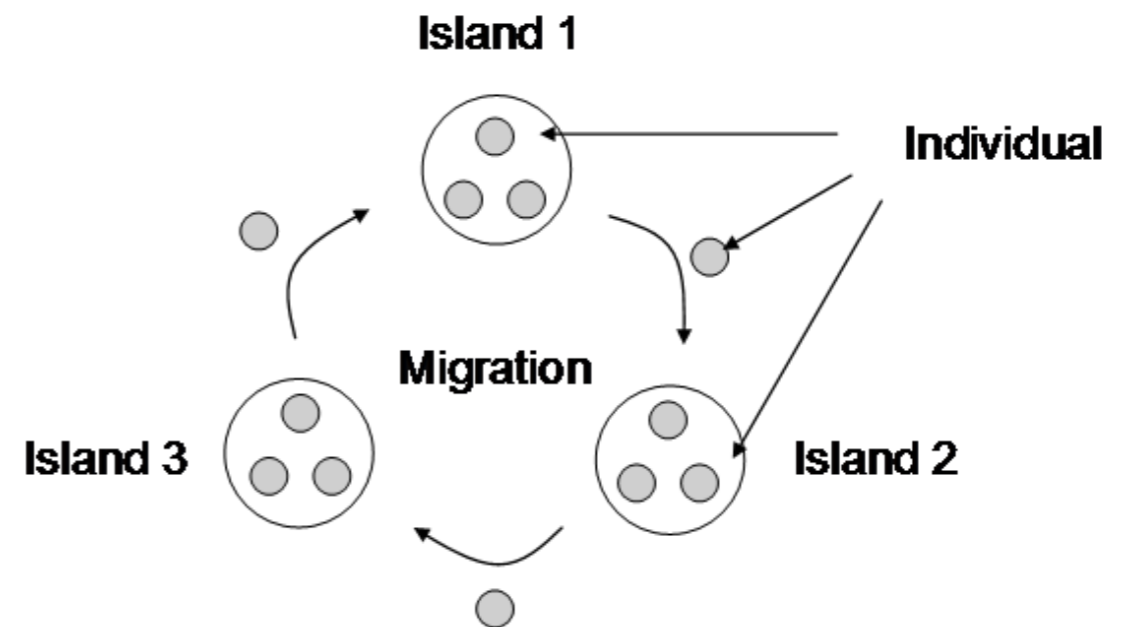
- $!!?@#?!@#!!??!?$
- Can only be considered in relation to a specific problem; often, analysis is done to problems with well defined structure, using probabilistic approach.

Population Diversity

- Just like biodiversity, population diversity is important for GA. Even solutions with worst fitness may still contain valuable schemas.
- Various auxiliary mechanisms have been developed to preserve and promote population diversity.

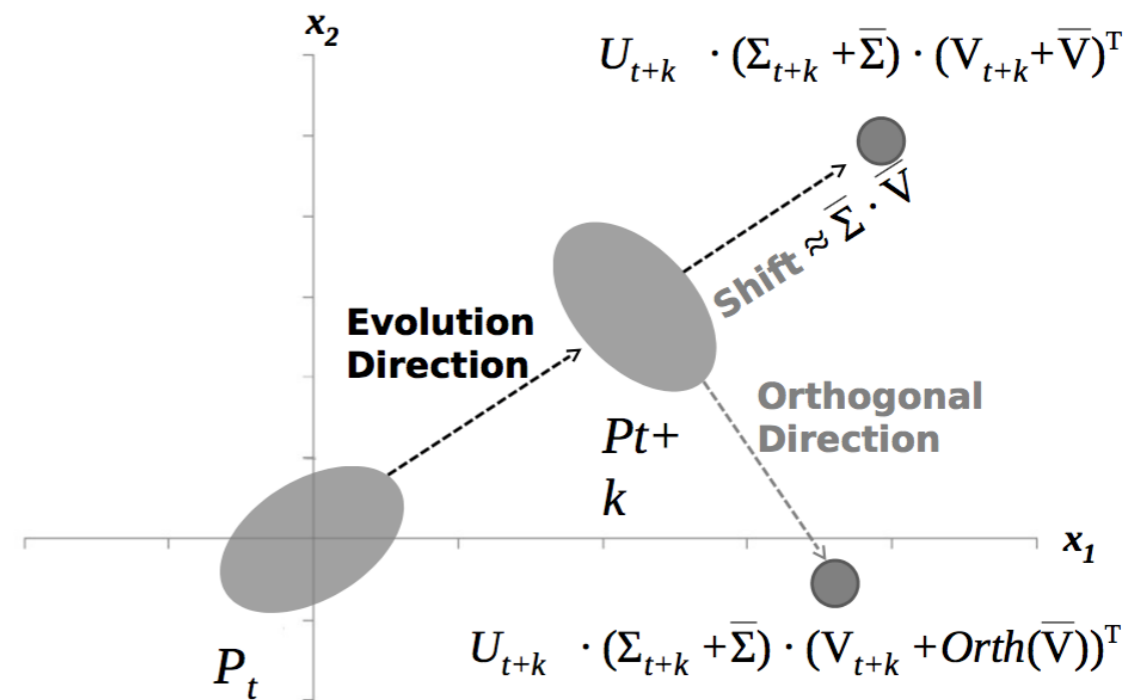
Island GA

- Let multiple populations evolve in separation; every now and then, move individuals between islands.
- The Island Model Genetic Algorithm: On Separability, Population Size and Convergence, *Darrell Whitley, Soraya Rana, Robert B. Heckendorn*, *Journal of Computing and Information Technology*, Vol. 7 (1999), pp. 33-47



Orthogonal Exploration

- Determine the direction of evolution; forcefully replace worst solutions with generated solutions that explore orthogonal direction.
- Orthogonal exploration of the search space in evolutionary test case generation, *F. M. Kifetew, A. Panichella, A. De Lucia, R. Oliveto, and P. Tonella*, in Proceedings of the 2013 International Symposium on Software Testing and Analysis, ISSTA 2013



Real Applications

- GA is a **BIG** toolbox, full of specialised operators, representation, and other assorted tricks.
- Just like any other AI technique, the more domain knowledge you have, the better your optimisation will be.

Summary

- Understand the framework of Darwinian evolution.
- Optimisation using evolution works, based on:
 - Selection pressure
 - Schema theory (one possible explanation)
- Understand various genetic operators.
- Understand the importance of population diversity.