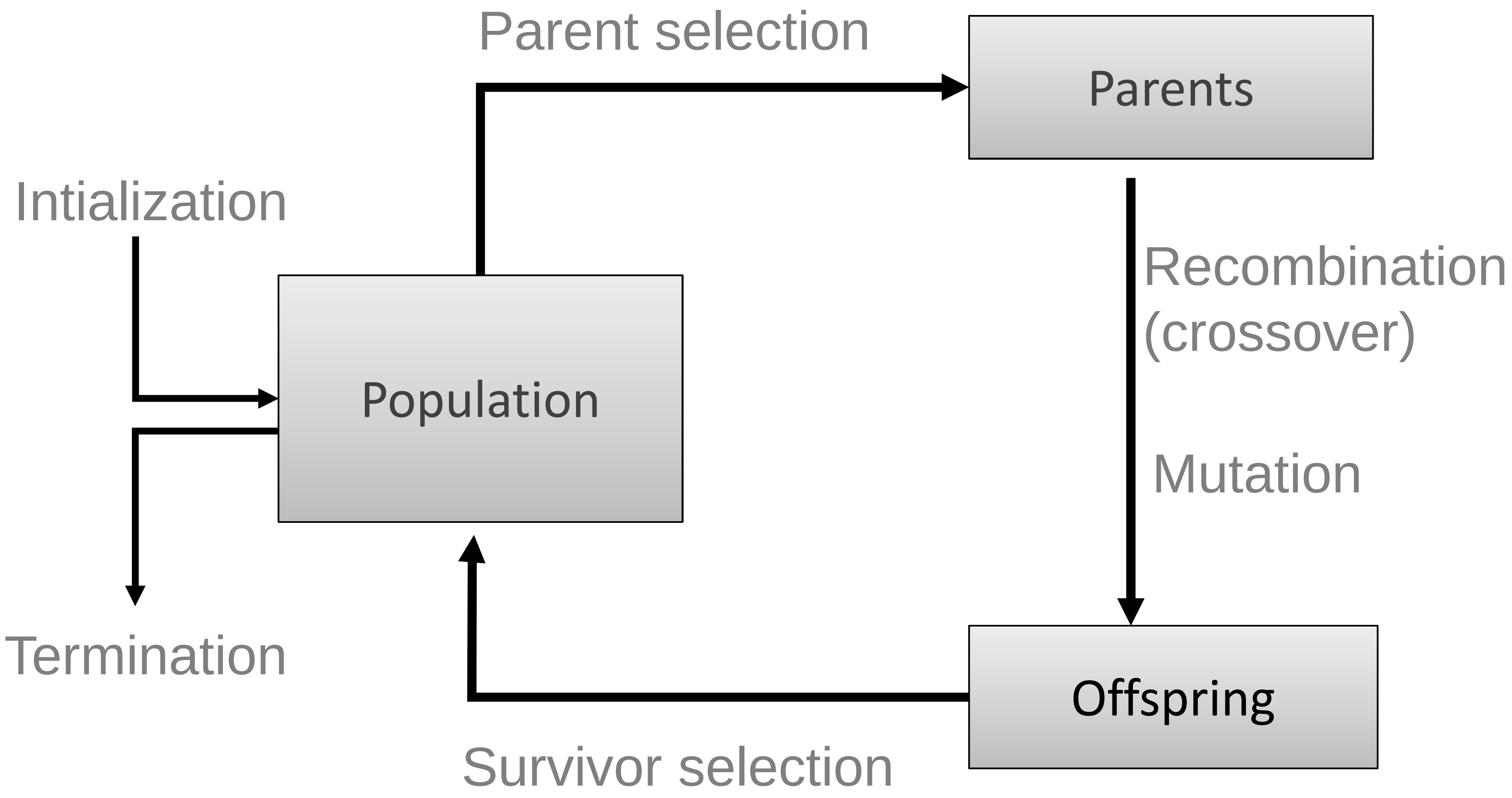
Evolutionary Computing

Chapter 5

Chapter 5: Fitness, Selection and Population Management

- Selection is second fundamental force for evolutionary systems
- Components exist of:
  - Population management models
  - Selection operators
  - Preserving diversity

Scheme of an EA:
General scheme of EAs



Population Management Models: Introduction

- Two different population management models exist:
  - Generational model
    - each individual survives for exactly one generation
    - the entire set of parents is replaced by the offspring
  - Steady-state model
    - one offspring is generated per generation
    - one member of population replaced
- Generation Gap
  - The proportion of the population replaced
  - Parameter = 1.0 for GGA, = 1/pop_size for SSGA

Population Management Models: Fitness based competition

- Selection can occur in two places:
  - Selection from current generation to take part in mating (parent selection)
  - Selection from parents + offspring to go into next generation (survivor selection)
- Selection operators work on whole individual
  - i.e. they are representation-independent !
- Distinction between selection
  - Operators: define selection probabilities
  - Algorithms: define how probabilities are implemented

Parent Selection: Fitness-Proportionate Selection

- Probability for individual *i* to be selected for mating in a population size *μ* with FPS is

$$P_{FPS}(i) = f_i \Big/ \sum_{j=1}^{\mu} f_j$$

- Problems include
  - One highly fit member can rapidly take over if rest of population is much less fit: Premature Convergence
  - At end of runs when fitnesses are similar, loss of selection pressure
  - Highly susceptible to function transposition (example next slide)
- Scaling can fix last two problems
  - Windowing: $f'(i) = f(i) - \beta^t$

  where β is worst fitness in this (last n) generations
  - Sigma Scaling: $f'(i) = \max(f(i) - (\bar{f} - c \bullet \sigma_f), 0)$

  where *c* is a constant, usually 2.0

Parent Selection: Rank-based Selection

- Attempt to remove problems of FPS by basing selection probabilities on *relative* rather than *absolute* fitness
- Rank population according to fitness and then base selection probabilities on rank (fittest has rank μ-1 and worst rank 0)
- This imposes a sorting overhead on the algorithm, but this is usually negligible compared to the fitness evaluation time

Rank-based Selection: Linear Ranking

$$P_{lin-rank}(i) = \frac{(2-s)}{\mu} + \frac{2i(s-1)}{\mu(\mu-1)}$$

- Parameterised by factor *s:* $1 < s \leq 2$
  - measures advantage of best individual
- Simple 3 member example

Individual	Fitness	Rank	P_{selFP}	P_{selLR} $(s=2)$	P_{selLR} $(s=1.5)$
A	1	0	0.1	0	0.167
B	4	1	0.4	0.33	0.33
C	5	2	0.5	0.67	0.5
Sum	10		1.0	1.0	1.0

Rank-based selection: Exponential Ranking

$$P_{\exp-rank}(i) = \frac{1-e^{-i}}{c}$$

- Linear Ranking is limited in selection pressure
- Exponential Ranking can allocate more than 2 copies to fittest individual
- Normalise constant factor *c* according to population size

Sample mating pool from the selection probability distribution (roulette wheel, stochastic universal sampling)

Parent Selection: Tournament Selection (1/2)

- All methods above rely on global population statistics
  - Could be a bottleneck esp. on parallel machines, very large population
  - Relies on presence of external fitness function which might not exist: e.g. evolving game players
- Idea for a procedure using only local fitness information:
  - Pick *k* members at random then select the best of these
  - Repeat to select more individuals

Parent Selection: Tournament Selection (2/2)

- Probability of selecting *i* will depend on:
  - Rank of *i*
  - Size of sample *k*
    - higher *k* increases selection pressure
  - Whether contestants are picked with replacement
    - Picking without replacement increases selection pressure
  - Whether fittest contestant always wins (deterministic) or this happens with probability *p*

Parent Selection: Uniform

$$P_{uniform}(i) = \frac{1}{\mu}$$

- Parents are selected by uniform random distribution whenever an operator needs one/some
- Uniform parent selection is unbiased - every individual has the same probability to be selected
- When working with extremely large populations, over-selection can be used.

Survivor Selection

- Managing the process of reducing the working memory of the EA from a set of μ parents and λ offspring to a set of μ individuals forming the next generation
- The parent selection mechanisms can also be used for selecting survivors
- Survivor selection can be divided into two approaches:
  - Age-Based Selection
    - Fitness is not taken into account
    - In SSGA can implement as “delete-random” (not recommended) or as first-in-first-out (a.k.a. delete-oldest)
  - Fitness-Based Replacement

Fitness-based replacement (1/2)

- Elitism
  - Always keep at least one copy of the fittest solution so far
  - Widely used in both population models (GGA, SSGA)
- GENITOR: a.k.a. “delete-worst”
  - From Whitley’s original Steady-State algorithm (he also used linear ranking for parent selection)
  - Rapid takeover: use with large populations or “no duplicates” policy
- Round-robin tournament
  - P(t): μ parents, P’(t): μ offspring
  - Pairwise competitions in round-robin format:
    - Each solution x from $P(t) \cup P'(t)$ is evaluated against q other randomly chosen solutions
    - For each comparison, a "win" is assigned if x is better than its opponent
    - The μ solutions with the greatest number of wins are retained to be parents of the next generation
  - Parameter q allows tuning selection pressure
  - Typically $q = 10$

Fitness-based replacement (2/2)

- (μ,λ)-selection
  - based on the set of children only ($\lambda > \mu$)
  - choose best μ
- $(\mu+\lambda)$-selection
  - based on the set of parents and children
  - choose best μ

- Often (μ,λ)-selection is preferred for:
  - Better in leaving local optima
  - Better in following moving optima
  - Using the + strategy bad σ values can survive in $\langle x,\sigma\rangle$ too long if their host x is very fit
- $\lambda \approx 7 \cdot \mu$ is a traditionally good setting (decreasing over the last couple of years, $\lambda \approx 3 \cdot \mu$ seems more popular lately)

Selection Pressure

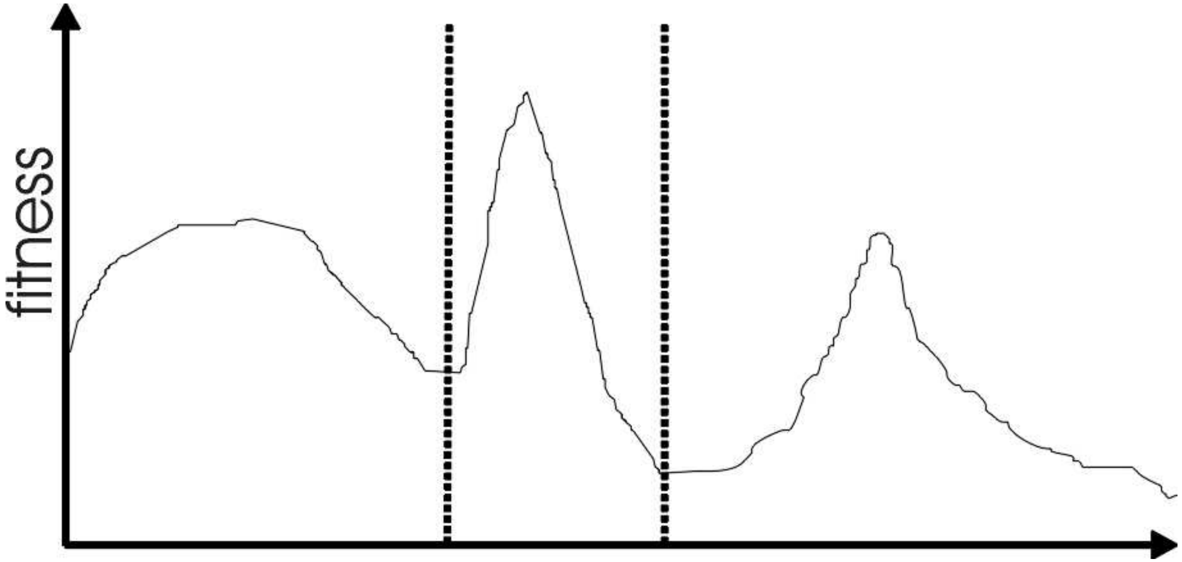
- Takeover time τ^* is a measure to quantify the selection pressure
- The number of generations it takes until the application of selection completely fills the population with copies of the best individual
- Goldberg and Deb showed:

$$\tau^* = \frac{\ln \lambda}{\ln(\lambda / \mu)}$$

- For proportional selection in a genetic algorithm the takeover time is $\lambda \ln(\lambda)$

Multimodality

Most interesting problems have more than one locally optimal solution.



Multimodality: Genetic Drift

- Finite population with global mixing and selection eventually convergence around one optimum
- Why?
- Often might want to identify several possible peaks
- Sub-optimum can be more attractive

Approaches for Preserving Diversity: Introduction (1/2)

- Explicit vs implicit
- Implicit approaches:
  - Impose an equivalent of geographical separation
  - Impose an equivalent of speciation
- Explicit approaches
  - Make similar individuals compete for resources (fitness)
  - Make similar individuals compete with each other for survival

Approaches for Preserving Diversity: Introduction (1/2)

Different spaces:

- Genotype space
  - Set of representable solutions
- Phenotype space
  - The end result
  - Neighbourhood structure may bear little relation with genotype space
- Algorithmic space
  - Equivalent of the geographical space on which life on earth has evolved
  - Structuring the population of candidate solutions

Explicit Approaches for Preserving Diversity: Fitness Sharing (1/2)

- Restricts the number of individuals within a given niche by "sharing" their fitness, so as to allocate individuals to niches in proportion to the niche fitness
- need to set the size of the niche σ_{share} in either genotype or phenotype space
- run EA as normal but after each generation set

$$f'(i) = \frac{f(i)}{\sum_{j=1}^{\mu} sh(d(i,j))} \qquad sh(d) = \begin{cases} 1 - d/\sigma & d \leq \sigma \\ 0 & otherwise \end{cases}$$

Explicit Approaches for Preserving Diversity: Fitness Sharing (2/2)

- Note: if we used $sh(d) = 1$ for $d < \sigma_{share}$ then the sum that reduces the fitness would simply count the number of neighbours, i.e., individuals closer than σ_{share}
- This creates an advantage of being alone in the neighbourhood
- Using $1 – d/ \sigma_{share}$ instead of 1 implies that we count distant neighbours less

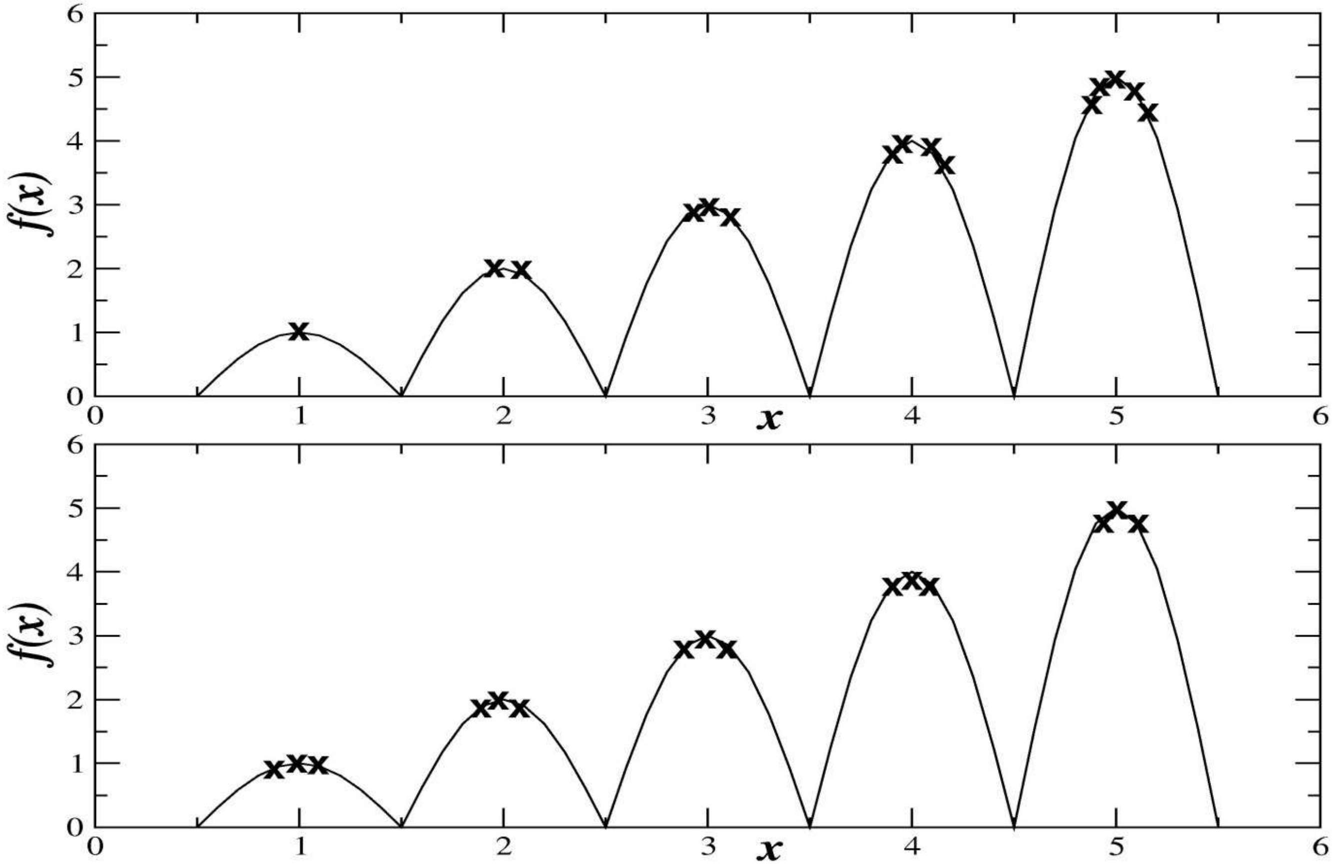
Explicit Approaches for Preserving Diversity: Crowding (1/2)

- Attempts to distribute individuals evenly amongst niches
- relies on the assumption that offspring will tend to be close to parents
- uses a distance metric in ph/genotype space
- randomly shuffle and pair parents, produce 2 offspring
- set up the parent vs. child tournaments such that the intertournament distances are minimal

Explicit Approaches for Preserving Diversity: Crowding (2/2)

- That is, number the two p's (parents)and the two o's (offspring) such that
- $d(p_1,o_1) + d(p_2,o_2) < d(p_1,o_2) + d(p_2,o_1)$
- and let o_1 compete with p_1 and o_2 compete with p_2

Explicit Approaches for Preserving Diversity: Crowding or Fitness sharing?

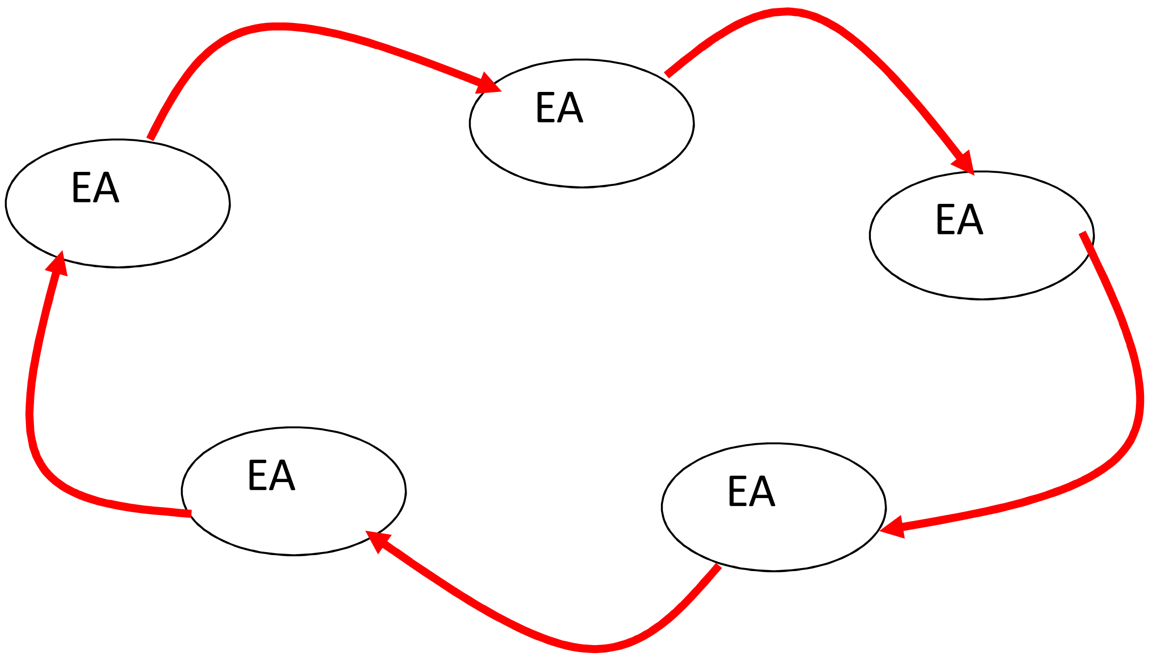


Observe the number of individuals per niche

Implicit Approaches for Preserving Diversity: Automatic Speciation

- Either only mate with genotypically / phenotypically similar members or
- Add bits (tags) to problem representation
  - that are initially randomly set
  - subject to recombination and mutation
  - when selecting partner for recombination, only pick members with a good match

Implicit Approaches for Preserving Diversity: "Island" Model Parallel EAs (1/4)



Periodic migration of individual solutions between populations

Implicit Approaches for Preserving Diversity: "Island" Model Parallel EAs (2/4)

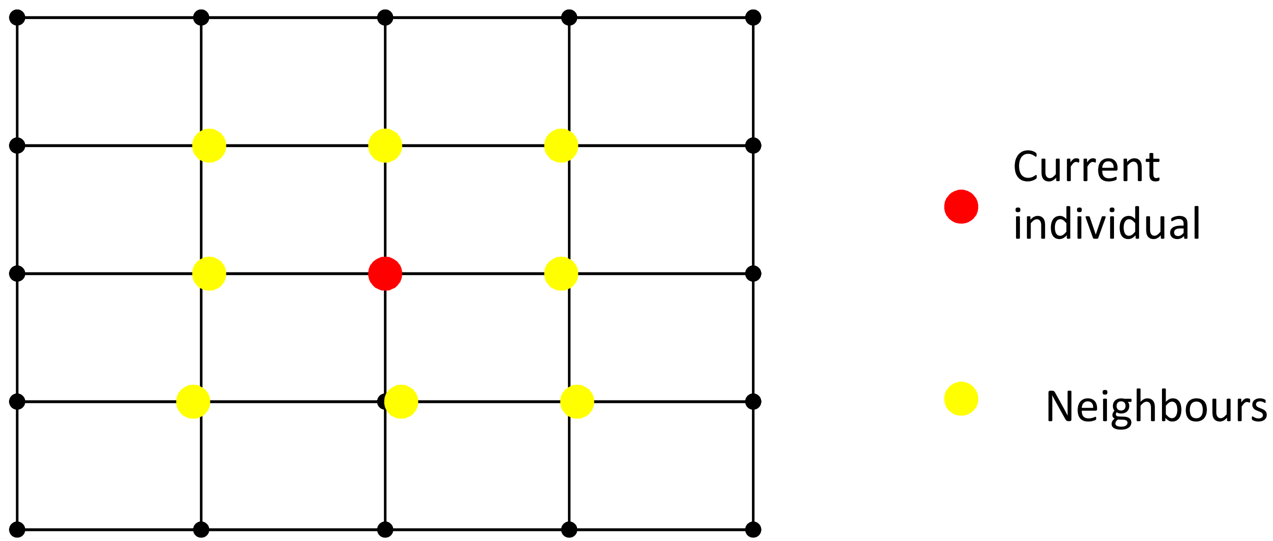
- Run multiple populations in parallel
- After a (usually fixed) number of generations (an ***Epoch***), exchange individuals with neighbours
- Repeat until ending criteria met
- Partially inspired by parallel/clustered systems

Island Model: Parameters

- How often to exchange individuals ?
  - too quick and all sub-populations converge to same solution
  - too slow and waste time
  - most authors use range~ 25-150 generations
  - can do it adaptively (stop each pop when no improvement for (say) 25 generations)
- How many, which individuals to exchange ?
  - usually ~2-5, but depends on population size.
  - Copied vs moved
  - Martin et al found that better to exchange randomly selected individuals than best
- Operators can differ between the sub-populations

Implicit Approaches for Preserving Diversity: Cellular EAs (1/3)

- Impose spatial structure (usually grid) in 1 pop



Implicit Approaches for Preserving Diversity: Cellular EAs (2/3)

- Consider each individual to exist on a point on a (usually rectangular toroid) grid
- Selection (hence recombination) and replacement happen using concept of a neighbourhood a.k.a. ***deme***
- Leads to different parts of grid searching different parts of space, good solutions diffuse across grid over a number of gens

Implicit Approaches for Preserving Diversity: Cellular EAs (3/3)

- Assume rectangular grid so each individual has 8 immediate neighbours
- Equivalent of 1 generation is:
  - pick individual in pop at random
  - pick one of its neighbours using roulette wheel
  - crossover to produce 1 child, mutate
  - replace individual if fitter
  - circle through population until done