

CSE/ECE 848

Introduction to

Evolutionary Computation

Module 4, Lecture 18, Part 1b
Combinatorial Optimization

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Example Operators for Permutation-Based Representations: Order Crossover:

- $A = 9\ 8\ 4 \mid 5\ 6\ 7 \mid 1\ 3\ 2\ 10$ (segment A and B)
- $B = 8\ 7\ 1 \mid 2\ 3\ 10 \mid 9\ 5\ 4\ 6$
- $\Rightarrow B^* = 8\ H\ 1 \mid 2\ 3\ 10 \mid 9\ H\ 4\ H$ (in B, repl. 5 6 7 with H's)
- $\Rightarrow B^{**} = 2\ 3\ 10 \mid H\ H\ H \mid 9\ 4\ 8\ 1$ (move middle segment from B to left, gather H's, append rest, with wrap-around)
- $\Rightarrow B' = 2\ 3\ 10 \mid 5\ 6\ 7 \mid 9\ 4\ 8\ 1$
- Similarly, $A' = 5\ 6\ 7 \mid 2\ 3\ 10 \mid 1\ 9\ 8\ 4$
- Order crossover preserves more information about RELATIVE ORDER than does PMX, but less about ABSOLUTE POSITION of each “city” (for TSP example).

Example Operators for Permutation-Based Representations:

Cycle Crossover:

- Cycle crossover forces the city in each position to come from that same position on one of the two parents:
- $C = 9\ 8\ 2\ 1\ 7\ 4\ 5\ 10\ 6\ 3$
- $D = 1\ 2\ 3\ 4\ 5\ 6\ 7\ 8\ 9\ 10$
- $\quad 9\ \text{-----}$
- $\Rightarrow 9\ \text{--}\ 1\ \text{-----}$
- $\Rightarrow 9\ \text{--}\ 1\ \text{--}\ 4\ \text{--}\ 6\ \text{--}$, which completes 1st cycle; then (depending on whose cycle crossover you choose), (i) start from first unassigned position in D and perform another cycle, or (ii) just fill in the rest of the numbers from chromosome D:
- (i) yields $\Rightarrow 9\ 2\ \text{--}\ 1\ \text{--}\ 4\ \text{--}\ 8\ 6\ 10$
- $\Rightarrow 9\ 2\ 3\ 1\ \text{--}\ 4\ \text{--}\ 8\ 6\ 10$
- $\Rightarrow C' = 9\ 2\ 3\ 1\ 7\ 4\ 5\ 8\ 6\ 10$ D' is done similarly.
- (ii) yields $\Rightarrow C' = 9\ 2\ 3\ 1\ 5\ 4\ 7\ 8\ 6\ 10$. D' is done similarly.

Example Operators for Permutation-Based Representations:

Uniform Order-Based Crossover:

- (< Lawrence Davis, Handbook of Genetic Algorithms)
- Analogous to *uniform* crossover for ordinary parameter-based chromosomes. Effectively acts as if many one- or two-point crossovers were performed at once on a pair of chromosomes, combining parents' genes on a locus-by-locus basis, so is quite disruptive of longer schemata. (I don't like it much, but it works quite well for some problems.)
- A = 1 2 3 4 5 6 7 8
- B = 8 6 4 2 7 5 3 1
- Binary Template: 0 1 1 0 1 1 0 0 (random)
- ==> - 2 3 - 5 6 - -
- (then, reordering rest of A's nodes to the order THEY appear in B)
- ==> A' = 8 2 3 4 5 6 7 1
- (and similarly for B', ==> 8 4 5 2 6 7 3 1

Alternative Approach to Permutation Problems: Change the *Representation*, Not the *Operators*

Random Key GA (Bean, 1994) Is commonly used:

- Each locus represents one of the items to be sequenced (a city to visit, for example)
- Each locus is initialized as a random real in (0,1)
- The phenotype is determined by sorting the real numbers, remembering that their locus numbers represent the items to be sequenced: for example

(1, 2, 3, 4, 5, 6)

(.423, .623, .154, .334, .988, .744) translates to:

3→4→1→2→6→5

Random Key GA, cont.

- Crossover can now be 1-pt, 2-pt, uniform, etc., WITHOUT fear of generating ANY illegal tours: that is, sorting will always produce a legal sequence
- Bean used a biased uniform crossover: 70% probability that each allele comes from first parent, 30% from second (this tends to make an offspring be more similar to one parent, which they found empirically to be effective)
- Original RKGA generated 1% new random individuals instead of locus-wise mutation, to maintain diversity
- Elitist selection kept fittest 20% unchanged, crossed others to make 79% of new population

Random Key GA, cont.

- Of course, like any other GA that keeps introducing new individuals, RKGA *converges asymptotically with probability 1*, but so do enumeration and random search in a combinatorial domain
- What ACTUALLY matters is the typical RATE of convergence
- RKGA does well APPROXIMATING optimal solutions, rather than in “fine tuning” of solutions, so is useful for many real-world problems where fast, close-to-optimal solutions are valuable
- But how does it scale? Fast sort for each individual in a problem with K “cities” is $O(K \log K)$, so for population size N , requires $O(NK \log K)$ per generation just for sorting, which can be a significant cost. (Many other techniques sort at most N individuals per generation, so $O(N \log N)$).

Other Types of Combinatorial Problems (OTHER than Sequencing)

- Knapsack-like subset selection problems
 - For N items, if N not huge, fixed length binary representation often used:
 - Locus i is 1 if item i is INCLUDED
 - Locus i is 0 otherwise
 - Or if multiple knapsacks, integer index of a knapsack for each item
 - Items may be differently weighted/sized/valued, with various types of capacity constraints and cost functions

Other Types of Combinatorial Problems (OTHER than Sequencing)(cont.)

- Knapsack-like subset selection problems
 - Otherwise, sometimes use variable length chromosome, where index of items to include is listed
 - Must then “repair” any duplications that operators introduce—just need rules for what to do, and they may be problem-specific
- In general, *find* a representation and operators that make sense for YOUR problem, given what you know about handling of building blocks (schemata)