Introduction to Genetic Algorithms

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Dealing with Hard Problems

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Computer programs are hard to write, but counting bugs is easy.

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- **Mutation:** X-ray them.

Applications I Have Known

Choosing among 1,500 features for OCR. (My first GA!)
Scheduling the Chili, NY, annual soccer invitational.
Scheduling my wife's golf league.
Designing LED lenses.
Programming a synchronizing cellular automaton.
Designing halftone screens for laser printers.
N Queens, Coloring Graphs, Routing Salesmen, etc., etc.

Subsetting 1,500 OCR Features

The polynet OCR engine trains and executes rapidly.

Performance was competitive.

We wanted to embed it in hardware, but it used 1,500 features.

We could deal with 300 features.

So, we bred high-performance feature subsets.

Soccer Scheduling

Bill Gustafson's MS Project, May, 1998

The Chili Soccer Association hosts an annual soccer tournament.

131 teams, 209 games, 14 fields, 17 game times.

a long weekend for a group of schedulers,

. . . . . and then some teams back out. . .

Soccer Scheduling Hard Constraints

A field can have one game at a time.
A team can only play one game at a time.
Teams must play on appropriate size fields.
Late games must be played on lighted fields.
A team must rest one game period (two is better) between games.
Teams can only play when they can be there (some can't come Friday)

Soccer Scheduling Soft Constraints

A team's games should be distributed evenly over the playing days.
Teams should play in at most two playing areas.
Each team should play at least once in the main playing area.
Teams should play in areas where they have a preference.
Games should finish as early as possible on Sunday.
Etc...

GAs Use Selective Breeding to . . .

discover a really good bit string

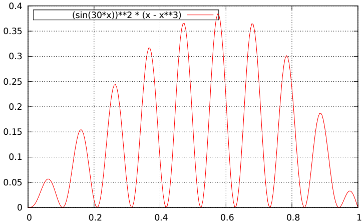
CS Dogma: Bit Strings Represent Everything

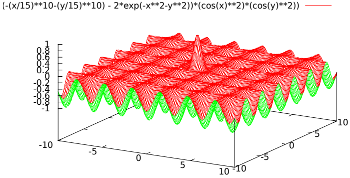
$$B = \{b_1, b_2, \ldots, b_n\}$$

1. A subset of an *n*-set (where the 1's are)
2. A number x in $[0,1)$: $x = \sum_1^n b_k 2^{-k}$
3. A pair (x, y) in $[0,1)^2$: $x = \sum_1^{n/2} b_k 2^{-k} \quad y = \sum_{n/2+1}^{n} b_k 2^{-k}$

Examples

1. Set searching
   1. Search for the biggest subset possible (maximize 1's count)
   2. Knapsack, bin packing
   3. Maximum independent set, map coloring
2. Maximize $f(x)$
3. Maximize $f(x, y)$





How to Search for Good Bit Stings

1. Enumerate all possibilities (but 2^n gets big)
2. Random search – “explore”
3. Hill climb – “exploit”
4. Genetic algorithm
5. Simulated annealing
6. Firefly algorithm

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5. Elimination of low fit individuals – more selection.

My Algorithm

See Octave code.

Parameters: Exploration vs. Exploitation

1. Population size

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2. Mutation rate

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1. Population size
2. Mutation rate
3. Tournament size

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4. Bizarre: pick and sort three individuals, $X > Y > Z$
   if $X_i == Y_i$, then $\text{child}_i := X_i$
   else $\text{child}_i := \textit{not}\ Z_i$

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2. Test a large number of times.
   Report the *median*.

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3. Parallelize: use islands of populations.
   Occasionally allow immigration.
4. Iteratively: Remove worst half of population.
   Randomly line up the survivors.
   For every adjacent pair, create and mutate a child.

Upcoming

- Programming cellular automata
- Permutation-based GA