Evolutionary Computation

Evolutionary Computation

- Evolutionary algorithms
- Genetic algorithms
- Genetic programming
- Artificial life ("alife")

Historical

- 1966, Fogel, Owens, and Walsh, *Artificial Intelligence through Simulated Evolution*, John Wiley & Sons
- Looked at derivation of
  - finite-state machines
  - controllers
  - data reduction

  through successive mutations

Historical

- 1975, John H. Holland *Adaptation in natural and artificial systems*, MIT Press
  - Focus was on natural systems, simulation
  - Introduced current genetic algorithm idea
  - Mostly theory, some applications to:
    - game-playing
    - search programs

Among Dr. Holland's Opuses

- "A universal computer capable of executing an arbitrary number of programs simultaneously." In Proceedings 1959 Eastern Joint Computer Conference. IEEE. pp108-13.
- See http://www.pscs.umich.edu/jhhfest/jhh-pub.html for more.

Holland's Progeny

- David Goldberg
- Stephanie Forrest
- Kenneth DeJong
- Melanie Mitchell
- John Koza
- many others
- See http://www.pscs.umich.edu/jhhfest/schedule-closed.html for Festschrift papers.

Genetic Algorithms

- An approach to difficult optimization problems (TSP, etc.)
- Heuristic, not guaranteed to find true optima
- Finds good approximations fast

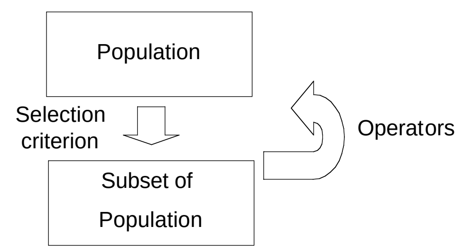
GA Applications

- Hundreds, if not thousands
- All manner of optimization problems in engineering, science, finance, etc.
- Application to neural networks:
  - Evolve the structure and/or weights of a neural network, rather than train it.

Principles of Natural Selection

- Concentrate on **population** rather than a single individual
- Individuals that are fit enough to survive will reproduce
- Create new individuals from existing ones
  - Crossover
  - Mutation

Genetic Flow Diagram



until an individual exists satisfying performance criterion or resources are exhausted

Common Operators

- **Copy** (aka Reproduce): An individual from the current generation is copied into the next generation.
- **Crossover**: Two (or more) individuals from the current generation are used to form an individual in the next generation.
- **Mutate**: A single individual from the current generation is mutated to form an individual in the next generation.

Individuals

- Individuals are represented by their genome, or genotype.
- The genotype may be the “program” for the actual individual, or “phenotype”.

Genetic Algorithm Example

- Consider the “subset sum” problem:
  - Given a set of integers S and a target value T, find a subset of S that the maximum sum without exceeding T.

Genetic Algorithm Example

- Consider the “subset sum” problem:
  - Given a set of integers S and a target value T, find a subset of S that the maximum sum without exceeding T.
- This is an *optimization* problem. The related *decision* problem, find whether there is a subset summing to exactly T, is known to be NP-complete.
- The related problem arises in cryptography.

Genetic Approach

- As the genome, use a bit-vector.
- There is one bit for each element in the set S.
- The bit is 1 iff the element is in the subset.

Example

- S = {19, 23, 35, 52, 61, 68, 76, 84, 92}
- T = 200
- Genome is an element of $\{0, 1\}^9$
- Possible individuals:
  010001001, sum{23, 68 , 92} = 183
  101000010, sum{19, 35, 84} = 138

What can we try to produce more fit individuals?

- **Mutation**: change a random bit:
  101000010, sum{19, 35, 84} = 138
  ⇩
  111100010, sum{19, 23, 35, 84} = 161

Fatal Mutations

- Note that a mutation could be “fatal”, resulting in a totally unfit individual. The “carcass” of this individual could still be in the next generation, however.

What can we try to produce more fit individuals?

- **Crossover**: Combine two individuals
  001|110000, sum{35, 52, 61} = 148
  100|000110, sum{19, 76, 84} = 179
  crossover point selected at random
- New genomes:
  001000110, sum{35, 76, 84} = 195 ⇐ better
  100110000, sum{19, 52, 61} = 132

Crossover Variations

- Sometimes two crossover points are chosen, rather than one, and the sub-sequences between them are swapped.

Sample GA Program

- The program /cs/cs152/ga/subsum/subsum.java carries out the genetic algorithm on this problem.

Main Loop of the Subset Sum GA Program (1)

```
public void evolve(int generations)
  {
  for( generation = 0; generation < generations; generation++ )
    {
     retain();              // retain the more fit individuals
     crossover();           // perform crossover on those retained
     mutate();              // mutate the resulting population
     sort();                // sort by fitness
    }
  }
```

Sample Run of subsum (1)

```
Subset sum problem
generations = 100
population size = 10
retain size = 5
immutable = 5
mutation rate = 0.1

target = 200.0
values = (19 23 35 52 61 68 76 84 92)
```

Sample Run of subsum (1)

```
generation 0, average fitness = 33.7:
181/200 (r 19) 000111000 52 61 68  } only two fit
164/200 (r 36) 100010010 19 61 84  } individuals
-1/200 (r 201) 000011110 61 68 76 84
-1/200 (r 201) 010111000 23 52 61 68
-1/200 (r 201) 000010110 61 76 84
-1/200 (r 201) 000111100 52 61 68 76
-1/200 (r 201) 101101101 19 35 52 68 76 92
-1/200 (r 201) 000011110 61 68 76 84
-1/200 (r 201) 101101101 19 35 52 68 76 92
-1/200 (r 201) 001100101 35 52 76 92
```

Sample Run of subsum (2)

```
generation 1, average fitness = 64.4:
181/200 (r 19) 000111000 52 61 68
164/200 (r 36) 100010010 19 61 84
160/200 (r 40) 000000110 76 84
145/200 (r 55) 000010010 61 84
-1/200 (r 201) 001100101 35 52 76 92
-1/200 (r 201) 000011110 61 68 76 84
-1/200 (r 201) 010111000 23 52 61 68
-1/200 (r 201) 000011110 61 68 76 84
-1/200 (r 201) 100011110 19 61 68 76 84
-1/200 (r 201) 000010110 61 76 84
```

four fit individuals

Sample Run of subsum (3)

```
generation 2, average fitness = 114.3:
197/200 (r 3) 000110010 52 61 84
181/200 (r 19) 000111000 52 61 68
164/200 (r 36) 100010010 19 61 84
160/200 (r 40) 000000110 76 84
148/200 (r 52) 100011000 19 61 68
145/200 (r 55) 000010010 61 84
96/200 (r 104) 001010000 35 61
54/200 (r 146) 101000000 19 35
-1/200 (r 201) 000110011 52 61 84 92
-1/200 (r 201) 001100101 35 52 76 92
```

eight fit individuals

Sample Run of subsum (4)

```
generation 5, average fitness = 157.7:
200/200 (r 0) 100111000 19 52 61 68
197/200 (r 3) 000110010 52 61 84
197/200 (r 3) 000110010 52 61 84
181/200 (r 19) 000111000 52 61 68
181/200 (r 19) 000111000 52 61 68
179/200 (r 21) 001100001 35 52 92
164/200 (r 36) 100010010 19 61 84
164/200 (r 36) 100010010 19 61 84
115/200 (r 85) 101010000 19 35 61
-1/200 (r 201) 000111010 52 61 68 84
best possible fit reached in generation 5
```

perfect individual

Complexity Considerations

- All possible subsets of n values can be **enumerated** in 2^n steps.
- For low n (say in the 20's or less), this might be feasible.
- For larger n, it is not (2^{32} = about 5 billion).
- For large n, the genetic algorithm can produce good, if not optimal, answers in much less time than enumeration.

Fatal Crossovers

- Just as with mutation, crossover could produce one or more individuals that are totally unfit.

Other Genomes

- A bit vectors is not the only way, or necessarily the best way, to represent a genome.
- Other possibilities:
  - A list or matrix of integers or floats

Challenges in representing Genomes: Traveling Salesperson Problem

- Not every optimization problem has a genome encoding that will allow naïve mutations and crossovers.
- Consider the TSP:
  - An instinctive way to represent a genome is as a **permutation** of the cities on a tour.

Crossing two Permutations

- [1, 3, | 2, 6, 5, | 4]
  [2, 3, | 4, 1, 6, | 5]

  crossover points selected at random
- Result of naïve crossing:
  [1, 3, 4, 1, 6, 5]
  [2, 3, 2, 6, 5, 4]
- Unfortunately, these sequences are **not** permutations.

Reinterpreting permutation crossings

- [1, 3, | 2, 6, 5, | 4]
  [2, 3, | 4, 1, 6, | 5]

  crossover points selected at random
- Interpret as:
  - Insert 2,6,5 in the second genome at the first crossover point and remove those elements from wherever they occurred in the second genome.

Reinterpreting permutation crossings

- [1, 3, | 2, 6, 5, | 4]
  [2, 3, | 4, 1, 6, | 5]

  crossover points selected at random
- [1, 3, 2, 6, 5, 4]
  [2, 3, 4, 1, 6, 5]

  insert
  remove

  [3, 2, 6, 5, 4, 1]

Similarly, to produce the second new genome

- [1, 3, | 2, 6, 5, | 4]
  [2, 3, | 4, 1, 6, | 5]
- [1, 3, 2, 6, 5, 4]
  [2, 3, 4, 1, 6, 5]

  remove
  insert

  [3, 4, 1, 6, 2, 5]

Net effect of Crossover

- [1, 3, | 2, 6, 5, | 4]
  [2, 3, | 4, 1, 6, | 5]
- [3, 4, 1, 6, 2, 5]
  [3, 2, 6, 5, 4, 1]
- The results share some of the structure of both parents, which is desirable.

Keller's TSP GA

- /cs/cs152/ga/tsp
- Uses same overall loop as the subset sum algorithm.
- The genome is now a permutation vector.
- Crossover is as described.
- Mutation consists of swapping two random elements of the permutation.

TSP GA in operation (1)

Traveling Salesperson Problem
generations = 1000
population size = 50
retain size = 25
immutable = 15
mutation rate = 0.1

TSP GA in operation (2)

```
Costs:
0.0  1.0  2.0  4.0  9.0  8.0  3.0  2.0  1.0  5.0  7.0  1.0  2.0  9.0  3.0
1.0  0.0  5.0  3.0  7.0  2.0  5.0  1.0  3.0  4.0  6.0  6.0  6.0  1.0  9.0
2.0  5.0  0.0  6.0  1.0  4.0  7.0  7.0  1.0  6.0  5.0  9.0  1.0  3.0  4.0
4.0  3.0  6.0  0.0  5.0  2.0  1.0  6.0  5.0  4.0  2.0  1.0  2.0  1.0  3.0
9.0  7.0  1.0  5.0  0.0  9.0  1.0  1.0  2.0  1.0  3.0  6.0  8.0  2.0  5.0
8.0  2.0  4.0  2.0  9.0  0.0  3.0  5.0  4.0  7.0  8.0  3.0  1.0  2.0  5.0
3.0  5.0  7.0  1.0  1.0  3.0  0.0  2.0  6.0  1.0  7.0  9.0  5.0  1.0  4.0
2.0  1.0  7.0  6.0  1.0  5.0  2.0  0.0  9.0  4.0  2.0  1.0  1.0  7.0  8.0
1.0  3.0  1.0  5.0  2.0  4.0  6.0  9.0  0.0  3.0  3.0  5.0  1.0  6.0  4.0
5.0  4.0  6.0  4.0  1.0  7.0  1.0  4.0  3.0  0.0  9.0  1.0  8.0  5.0  2.0
7.0  6.0  5.0  2.0  3.0  8.0  7.0  2.0  3.0  9.0  0.0  2.0  1.0  8.0  1.0
1.0  6.0  9.0  1.0  6.0  3.0  9.0  1.0  5.0  1.0  2.0  0.0  5.0  4.0  3.0
2.0  6.0  1.0  2.0  8.0  1.0  5.0  1.0  1.0  8.0  1.0  5.0  0.0  9.0  6.0
9.0  1.0  3.0  1.0  2.0  2.0  1.0  7.0  6.0  5.0  8.0  4.0  9.0  0.0  7.0
3.0  9.0  4.0  3.0  5.0  5.0  4.0  8.0  4.0  2.0  1.0  3.0  6.0  7.0  0.0
```

TSP GA in operation (3)

Improvement in generation 1: 25: 4 6 10 14 9 11 7 12 3 5 13 1 0 8 2
Improvement in generation 9: 22: 4 6 14 9 11 7 12 10 3 5 13 1 0 8 2
Improvement in generation 10: 20: 4 6 9 14 10 11 7 12 3 5 13 1 0 8 2
Improvement in generation 30: 18: 4 6 9 14 10 12 7 11 3 5 13 1 0 8 2
Improvement in generation 317: 17: 4 6 9 14 10 12 5 13 3 11 7 1 0 8 2

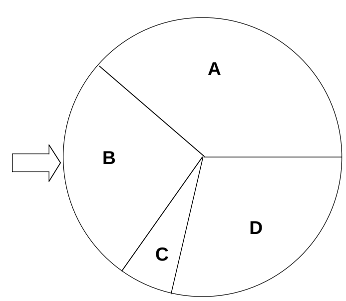
best after 1000 generations, 17: 4 6 9 14 10 12 5 13 3 11 7 1 0 8 2

verification: 4 (1.0) 6 (1.0) 9 (2.0) 14 (1.0) 10 (1.0) 12 (1.0) 5 (2.0) 13 (1.0) 3 (1.0) 11 (1.0) 7 (1.0) 1 (1.0) 0 (1.0) 8 (1.0) 2 (1.0) 4

Roulette-Wheel Optimization

- Rather than keep n copies of the same individual, record the individual once, along with its % of the population.
- Then during selection, choose individuals by spinning a "roulette wheel" biased with the given % toward the individual.

Roulette-Wheel Optimization



GA Perspective

- Like gradient descent, GA's can also get stuck in local fitness extrema.
- The space is different; for GA's, a stuck point corresponds to a population from which crossover does not yield any better individuals.
- Mutation is one hope for leaving such an extremum. Other possibilities are simulated annealing, random restarts.

Evolution Options

- Since we are simulating using a computer, not actually evolving species, there is no reason why **Lamarckian**, rather than **Darwinian**, evolution could not be used.
- Most results to date are Darwinian.
- Lamarckian could integrate other learning models to breed new species from individuals that have learned.

Lamarckian Leads

- Grefenstette, J. 1991. *Lamarckian learning in multi-agent environments*. In Proceedings of the Fourth International Conference of Genetic Algorithms, 303-310. Morgan Kaufmann.
- Houck, C., Joines, J., and Kay, M., Utilizing Lamarckian Evolution and the Baldwin Effect in Hybrid Genetic Algorithms, NCSU-IE TR 96-01, 1996.

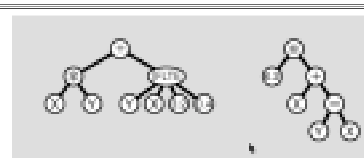
Genetic Programming

- Genetic programming is the GA idea applied to evolving ***programs*** (as opposed to just numbers).
- The prime mover of this field is John R. Koza.

Reference

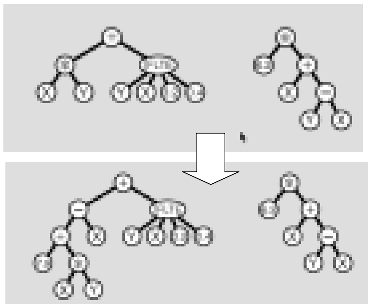
John R. Koza
Genetic Programming :
On the Programming
of Computers
by Means of Natural Selection
MIT Press, 1996

Genetic Programming Genomes = Syntax Trees

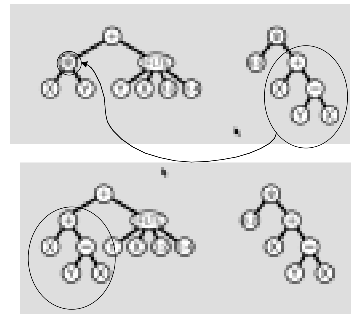


For animated tutorial, please see:
http://www.genetic-programming.com/gpanimatedtutorial.html

Mutation of a Progam

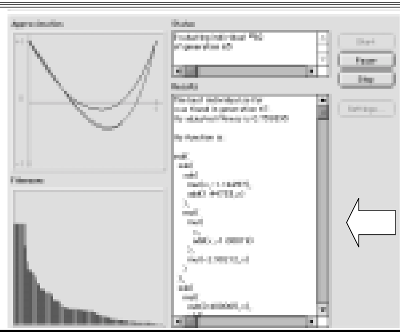


Crossover of Two Programs



Genetic Programming Demo: Symbolic Regression

(http://www.ifh.ee.ethz.ch/~gerber/approx/default.html)

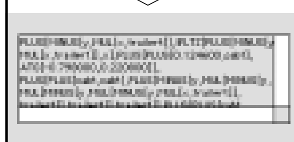


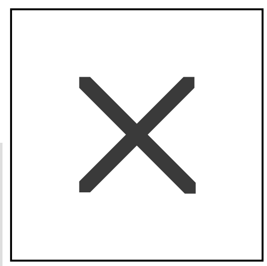
The evolved program

Truck-Backer using GP

http://www.handshake.de/user/blickle/Truck/index.html

The evolved program





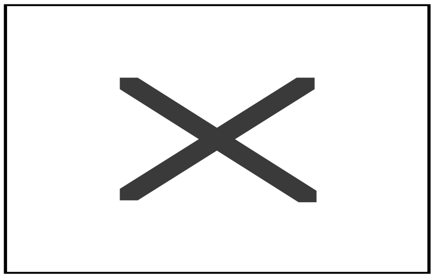
GP Caution

- Typically fitness of genetically-evolved programs is established by working on a large number of test cases.
- We know this is not completely sound.
- A possible fruitful area is to evolve a proof of correctness along with the program itself. I know of no work in this area.

Engineering Applications: Evolving Hardware (Analog & Digital)

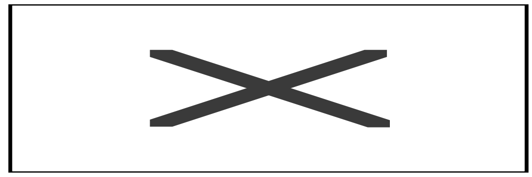
- The evolved program is a *list of instructions* for constructing the circuit, rather than the graph of the circuit itself.
- This approach has also been used to construct neural networks.
- The results for circuit design are competitive with, or superior to, human engineering.
- Numerous patents have been reinvented using GP.

Generating Analog Circuits

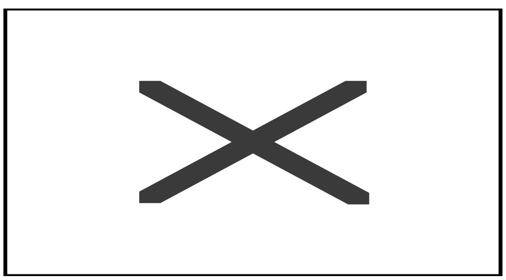


http://www.genetic-programming.com/published/eetimes060396.html

An analog filter generated by genetic programming

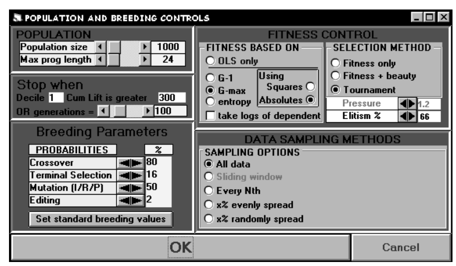


A Genetically-Evolved Amplifier



Commercial Applications: Marketing Projections

gmax-dm™ SALFORD SYSTEMS



http://www.statsoft.com/textbook/stcluan.html#h

Other Opportunities

- Parallelism in Computation (local work of Beda & Margileth, and others)
- Parallelism optimizing transformations
- Music
- Robotics