

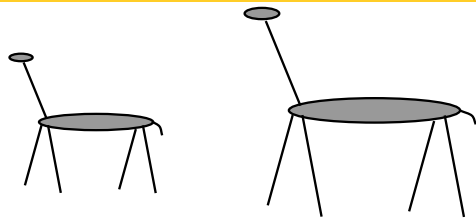
# Evolutionary Computation

## Presentation outline

- Genetic algorithms
- Genetic programming
- Evolution strategies
- Classifier systems
- Evolution programming
- Conclusion

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## Reproduction



Genome: ATTGCGCCATGAT

ATTAAACCATAGT

Crossover:

ATTG	CGCCATGAT
ATTA	AACCATAGT
ATTG	AACCATAGT

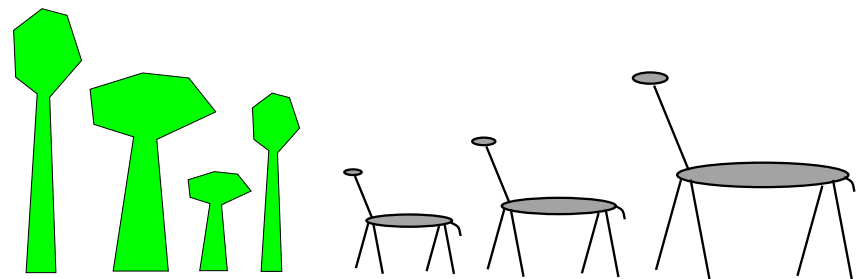
Mutation:

ATTGAA	C	CATAGT
ATTGAA	G	CATAGT



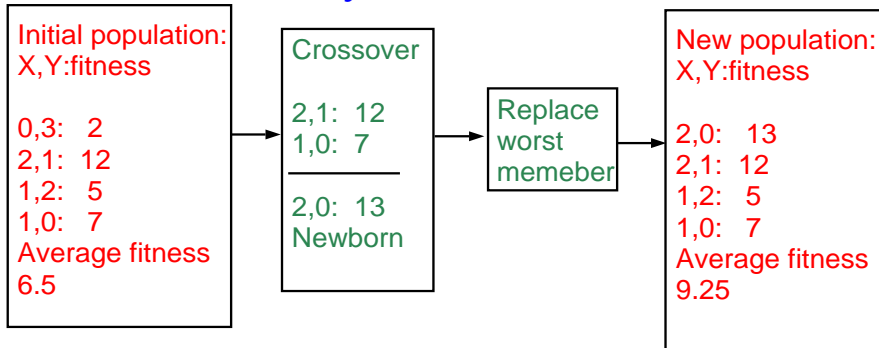
## In the forest

- Fitness = Height
- Survival of the fittest



## Example: numerical optimization

- maximize  $2X^2 - y + 5$  where  $X:[0,3], Y:[0,3]$

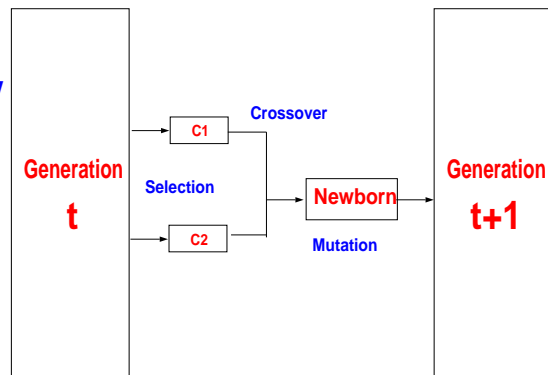


## Genetic Algorithms

- Maintain population of potential solutions
- New solutions are generated by combining and modifying existing solutions
  - Crossover
  - Mutation
- Objective function = "Fitness function"

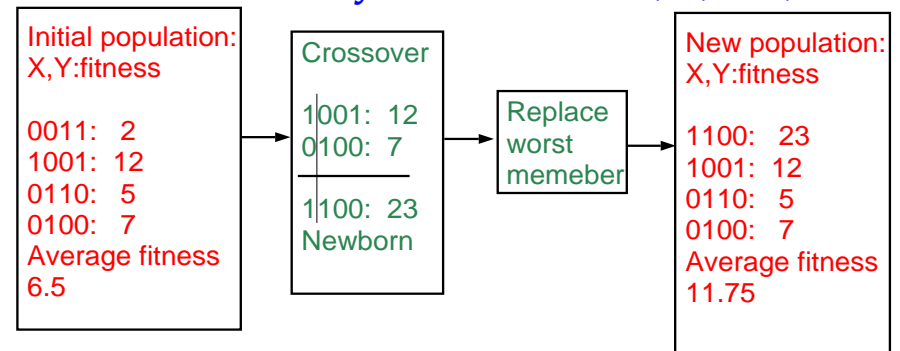
## Elements of a generational genetic algorithm

- Representation
- Fitness function
- Initialization strategy
- Selection strategy
- Crossover operators
- Mutation operators



## Example with binary representation

- maximize  $2X^2 - y + 5$  where  $X:[0,3], Y:[0,3]$

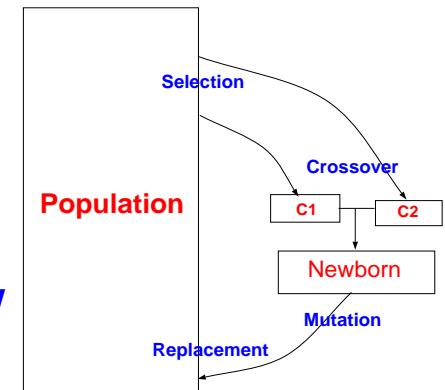


## Selection strategies

- **Proportional selection (roulette wheel)**
  - selection probability of individual =  $\text{fitness} / \text{sum of fitnesses}$
- **Rank based selection**
  - Example: decreasing arithmetic/geometric series
  - better when fitness range is very large

## Elements of a steady state genetic algorithm

- **Representation**
- **Fitness function**
- **Initialization strategy**
- **Selection strategy**
- **Crossover operators**
- **Mutation operators**
- **Replacement strategy**



## Mutation Operators

- **change one or more components**
- **Let Child =  $x_1, x_2, P, x_3, x_4, \dots$**
- **Gaussian mutation:**
  - $P \leftarrow P \pm \Delta p$
  - $\Delta p$ : random normal value
- **Uniform mutation:**
  - $P \leftarrow P_{new}$
  - $p_{new}$ : random normal value
- **boundary mutation:**
  - $P \leftarrow P_{min} \text{ OR } P_{max}$
- **Binary mutation = bit flip**

## Crossover Operators

- **Point crossover (classical)**
  - Parent1 =  $x_1, x_2, x_3, x_4, x_5, x_6$
  - Parent2 =  $y_1, y_2, y_3, y_4, y_5, y_6$
  - Child =  $x_1, x_2, x_3, x_4, y_5, y_6$
- **Random crossover**
  - Parent1 =  $x_1, x_2, x_3, x_4, x_5, x_6$
  - Parent2 =  $y_1, y_2, y_3, y_4, y_5, y_6$
  - Child =  $x_1, x_2, y_3, x_4, y_5, y_6$
- **Arithmetic crossover**
  - Parent1 =  $x_1, x_2, x_3$
  - Parent2 =  $y_1, y_2, y_3$
  - Child =  $(x_1 + y_1)/2, (x_2 + y_2)/2, (x_3 + y_3)/2$

## Disadvantages of Genetic-Algorithm based optimization

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- Relatively slower than other methods (not suitable for easy problems)
- Theory lags behind applications

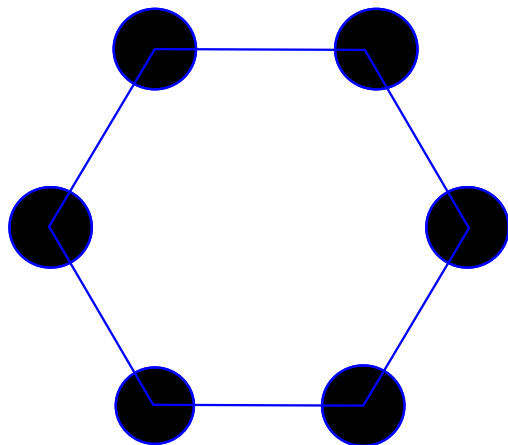
## Advantages of Genetic-Algorithm based optimization

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- Finds global optima
- Can handle discrete, continuous and mixed variable spaces
- Easy to use (short programs)
- Robust (less sensitive to noise, ill conditions)

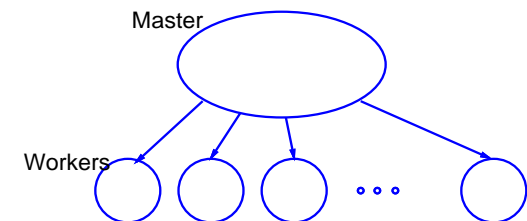
## Coarse-grained parallel GA

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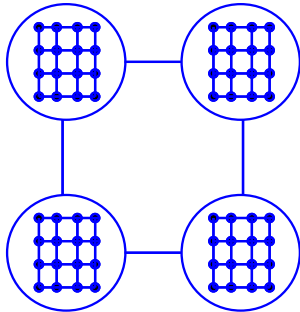
## Global parallel GA

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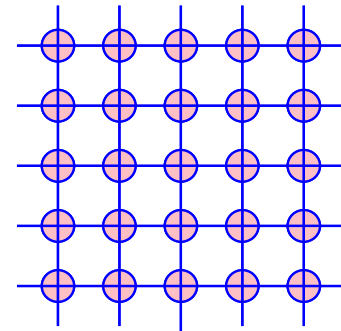


## Hybrid parallel GA

- Coarse-grained GA at high level
- Fine-grained GA at low level

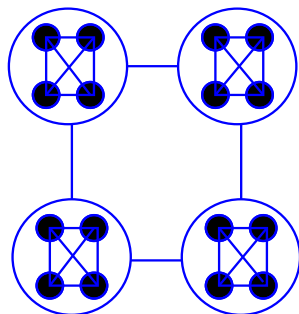


## Fine-grained parallel GA



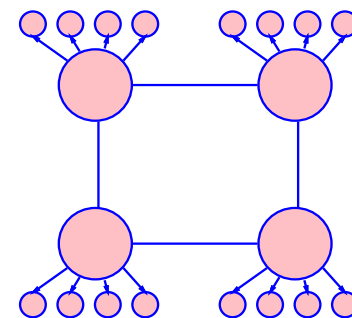
## Hybrid parallel GA

- Coarse-grained GA at high level
- Coarse-grained GA at low level



## Hybrid parallel GA

- Coarse-grained GA at high level
- Global parallel GA at low level



## GP individuals

- A population of trees representing programs
- The programs are composed of elements from the FUNCTION SET and the TERMINAL SET
- These sets are usually fixed sets of symbols
- The function set forms "non-leaf" nodes. (e.g. +, -, \*, sin, cos)
- The terminal set forms leaf nodes. (e.g. x, 3.7, random())

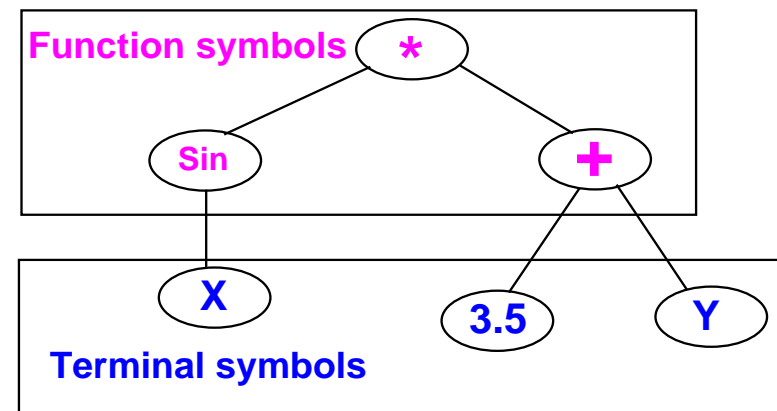
## Genetic Programming (GP)

- Introduced (officially) by John Koza in his book (genetic programming, 1992)
- Early attempts date back to the 50s (evolving populations of binary object codes)
- Idea is to evolve computer programs
- Declarative programming languages usually used (Lisp)
- Programs are represented as trees

## GP operation

- Fitness is usually based on I/O traces
- Crossover is implemented by randomly swapping subtrees between individuals
- GP usually does not extensively rely on mutation (random nodes or subtrees)
- GPs are usually generational with a generation gap
- GP usually uses huge populations (1M individuals)

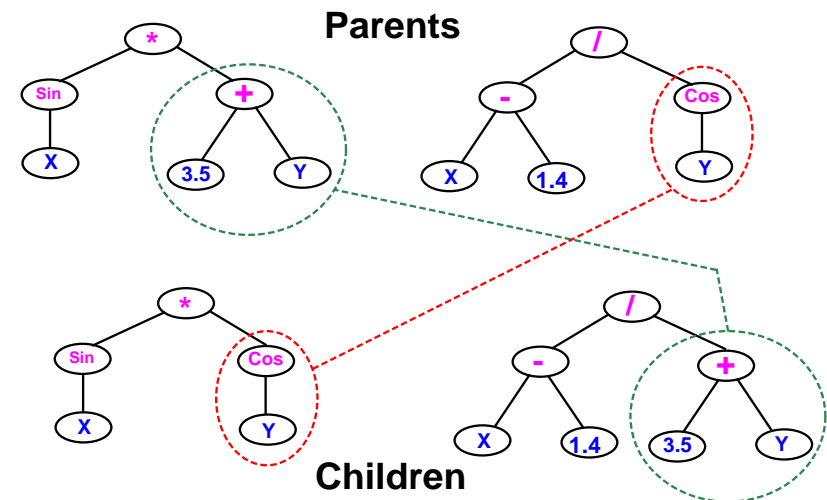
## Example: GP individual



## Advantages of GP over GAs

- More flexible representation
- Greater application spectrum
- If tractable, evolving a way to do things is more useful than evolving the things.
- Example: evolving a learning rule for neural networks (Amr Radi, GP98) vs. evolving the weights of a particular NN.

## Example: GP crossover



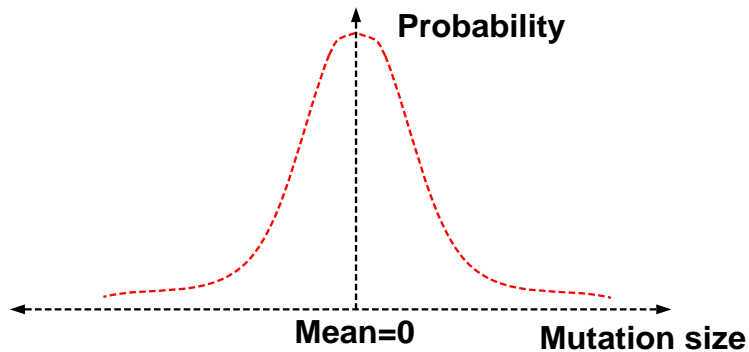
## Recent Trends

- Genetic programming with linear genomes (Wolfgang Banzaf)
  - Kind of going back to the evolution of binary program codes
- Hybrids of GP and other methods that better handle numbers:
  - Least squares methods
  - Gradient based optimizers
  - Genetic algorithms, other evolutionary computation methods
- Evolving things other than programs
  - Example: electric circuits represented as trees (Koza, AI in design 1996)

## Disadvantages of Genetic Programming

- Extremely slow
- Very poor handling of numbers
- Very large populations needed
- Criticism from classical GA community: no schema theory or any theory!

## Normal (Gaussian) mutation



## Evolution Strategies (ES)

- Were invented to solve numerical optimization problems
- Originated in Europe in the 1960s
- Initially: two-membered or (1+1) ES:
  - one PARENT generates one OFFSPRING per GENERATION
  - by applying normally distributed (Gaussian) mutations
  - until offspring is better and replaces parent
  - This simple structure allowed theoretical results to be obtained (speed of convergence, mutation size)
- Later: enhanced to a ( $\mu$ +1) strategy which incorporated crossover

## ES individuals

- Real valued vectors consisting of two parts:
  - Object variable: just like real-valued GA individual
  - Strategy variable: a set of standard deviations for the Gaussian mutation
- This structure allows for "Self-adaptation" of the mutation size
  - Excellent feature for dynamically changing fitness landscape

## Modern evolution strategies

- Schwefel introduced the multimembered ESs now denoted by ( $\mu$ + $\lambda$ ) and ( $\mu$ , $\lambda$ )
- ( $\mu$ , $\lambda$ ) ES: The parent generation is disjoint from the child generation
- ( $\mu$ + $\lambda$ ) ES: Some of the parents may be selected to "propagate" to the child generation



## Elements of a classifier system

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- **Rule and message system**
  - if <condition> then <action>
- **Apportionment of credit system**
  - Based on a set of training examples
  - Credit (fitness) given to rules that match the example
  - Example: Bucket brigade (auctions for examples, winner takes all, existence taxes)
- **Genetic algorithm**
  - evolves a population of rules or a population of entire rule systems

## Machine learning and evolutionary computation

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- In machine learning we seek a good hypothesis
- The hypothesis may be a rule, a neural network, a program ... etc.
- GAs and other EC methods can evolve rules, NNs, programs ...etc.
- Classifier systems (CFS) are the most explicit GA based machine learning tool.

## The Pitt approach

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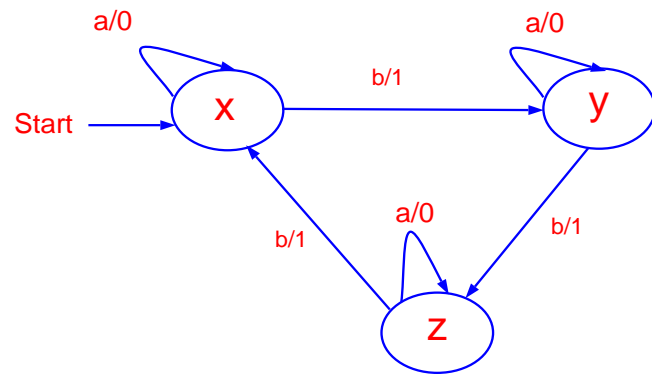
- Each individual is a complete set of rules or complete solution
- Avoids the hard credit assignment problem
- Slow because of complexity of space

## The Michigan approach: population of rules

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- Evolves a population of rules, the final population is used as the rule and message system
- Diversity maintenance among rules is hard
- If done well converges faster
- Need to specify how to use the rules to classify
  - what if multiple rules match example?
  - exact matching only or inexact matching allowed?

## EP individual



## Evolution programming (EP)

- Evolves finite state machines (or similar structures)
- Relies on mutation (recently crossover also)
- Fitness based on training sequence(s)
- Uses rank based selection
- Good for sequence problems (DNA) and prediction in time series

## Other evolutionary computation "ways"

- Variable complexity representations (Peter Gage, AI in design 96)
- Representations based on description of transformations
  - instead of enumerating the parameters of the individual, describe how to change another (nominal) individual to be it.
  - Good for dimension reduction, at the expense of optimality
- Response surface methods (alvarez, GP 98)
  - Good when objective function is very expensive
  - fit a surface to some points and optimize the surface

## EP mutation operators

- Add a state (with random transitions)
- Delete a state (reassign state transitions)
- Change an output symbol
- Change a state transition
- Change the start state

## The bigger picture

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- All evolutionary computation models are getting closer to each other
- The choice of method is important for success
- EC provides a very flexible architecture
  - easy to combine with other paradigms
  - easy to inject domain knowledge

## Related Topics

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- **Artificial life**
  - An individual's fitness depends on genes + lifetime experience
  - An individual can pass the experience to offspring
- **Co-evolution**
  - Several populations of different types of individuals co-evolve
  - Interaction between populations changes fitness measures

## EC conferences

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- Genetic and evolutionary computation conference (GECCO)
- Congress on evolutionary computation (CEC)
- evolutionary programming (EP)
- Parallel problem solving from nature (PPSN)
- other: AI in design, IJCAI, AAAI ...

## EC journals

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- Evolutionary Computation
- IEEE transactions on evolutionary computation
- Genetic programming
- other: AIEDAM, AIENG ...