Evolutionary Computation

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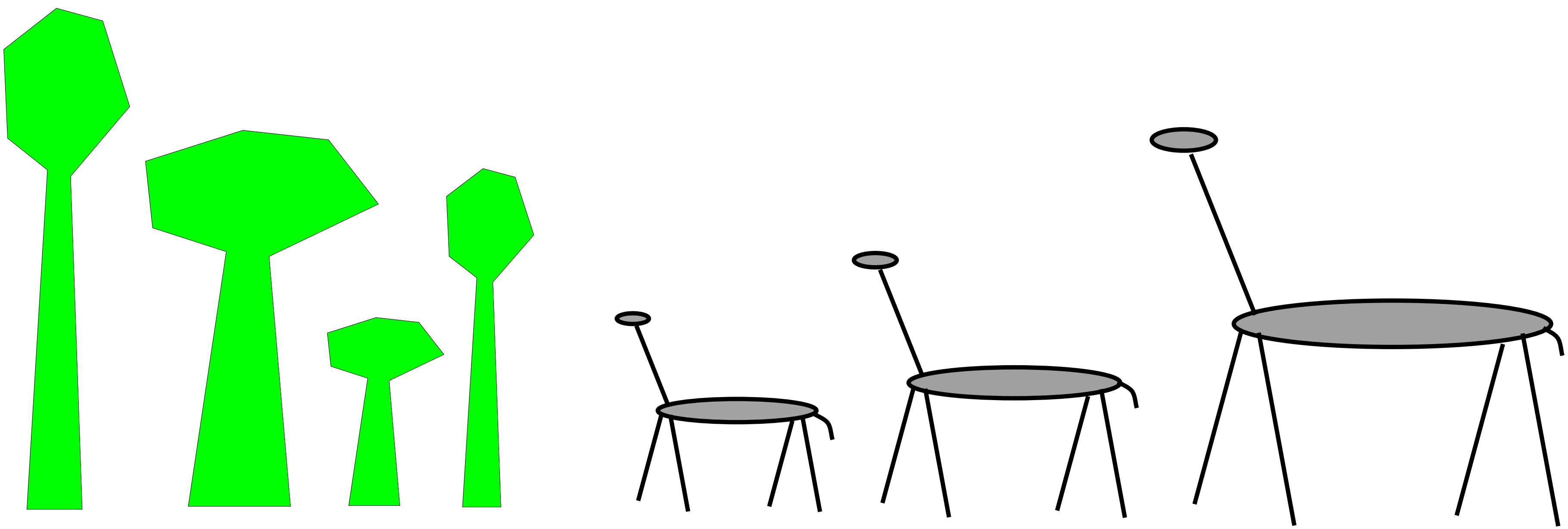
Presentation outline

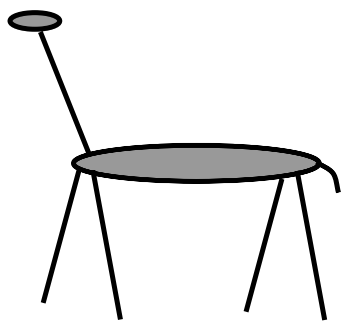
- Genetic algorithms
- Genetic programming
- Evolution strategies
- Classifier systems
- Evolution programming
- Conclusion

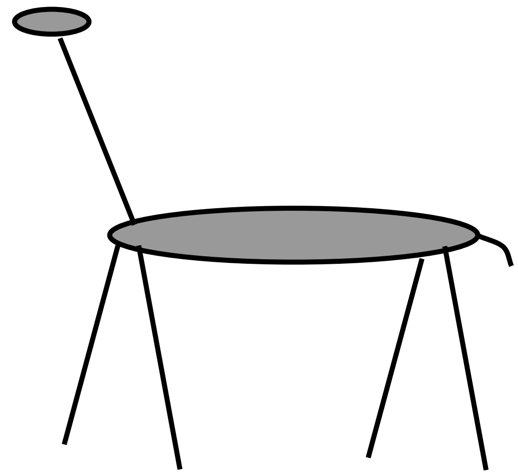
In the forest

- Fitness = Height
- Survival of the fittest



Reproduction

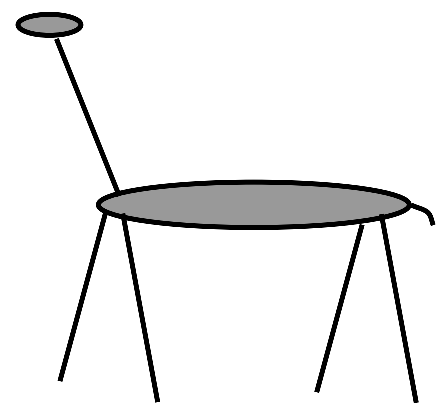




Genome: ATTGCGCCATGAT ATTAAACCATAGT

Crossover:

ATTG	CGCCATGAT
ATTA	AACCATAGT
ATTG	AACCATAGT



Mutation:

ATTGAACCATAGT

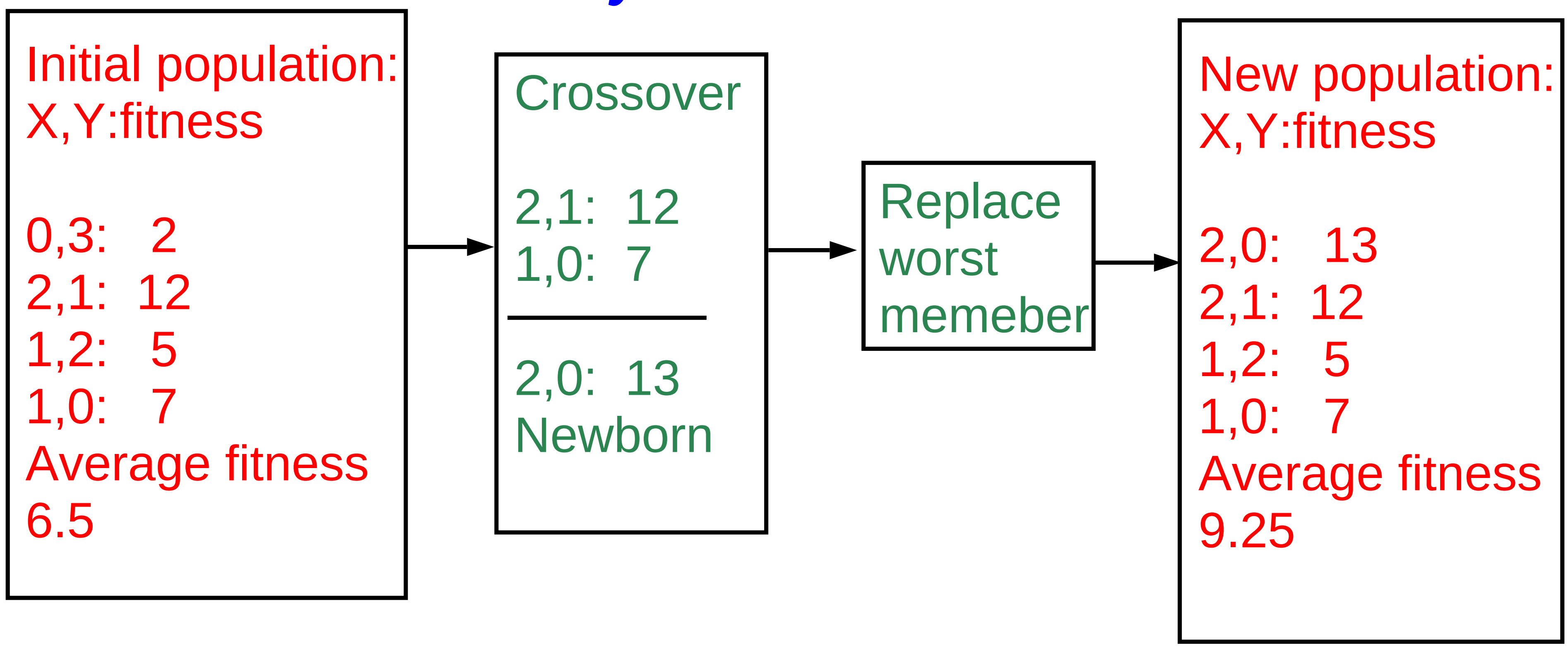
ATTGAAGCATAGT

Genetic Algorithms

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

Example: numerical optimization

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



Example with binary representation

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

Initial population:
X,Y:fitness

0011:   2
1001: 12
0110:   5
0100:   7
Average fitness
6.5

Crossover

1001: 12
0100: 7

1100: 23
Newborn

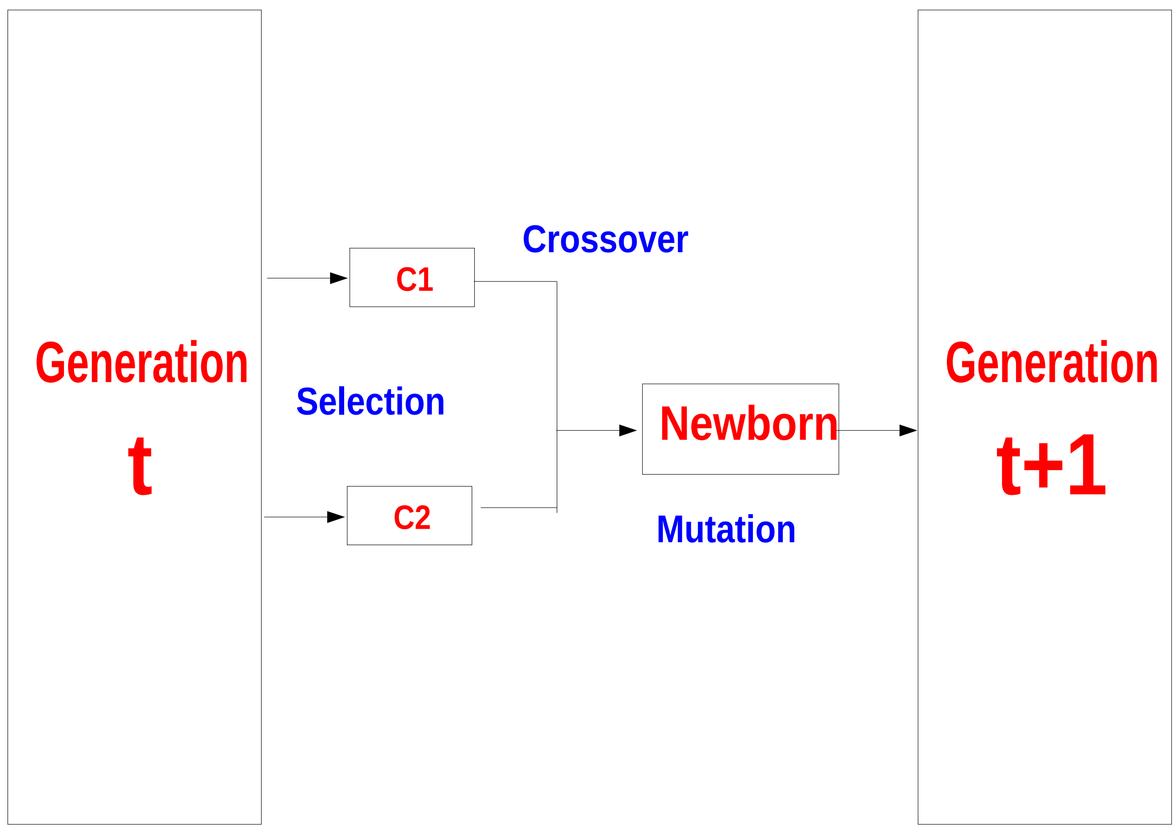
Replace
worst
memeber

New population:
X,Y:fitness

1100:   23
1001: 12
0110:   5
0100:   7
Average fitness
11.75

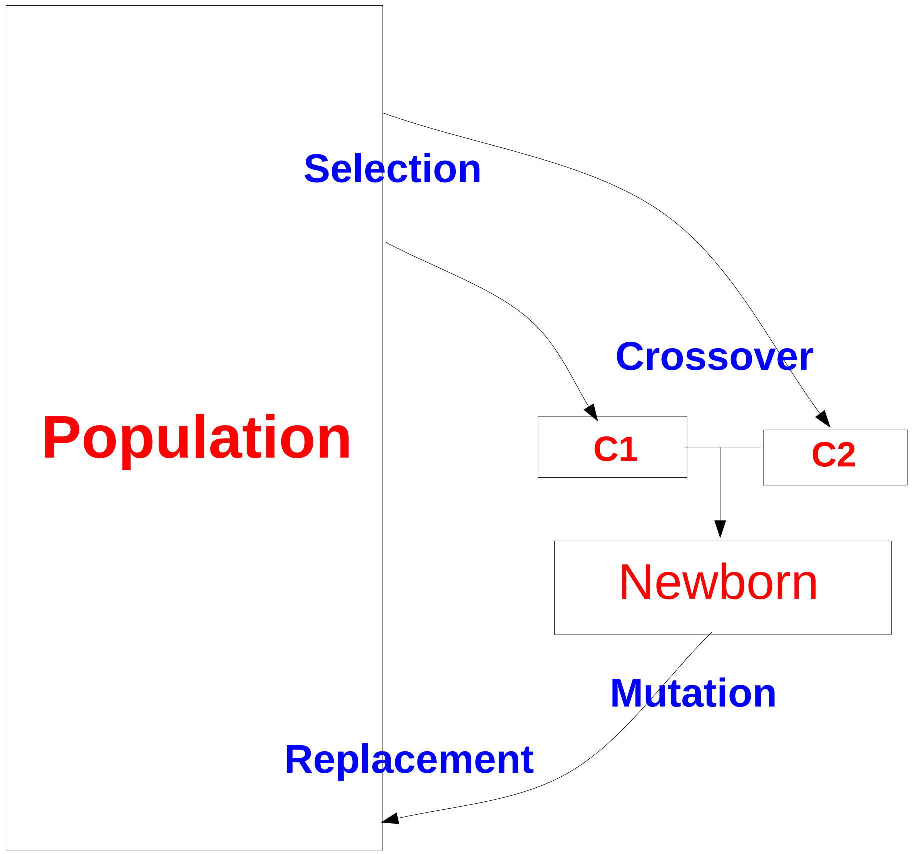
Elements of a generational genetic algorithm

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



Elements of a steady state genetic algorithm

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



Selection strategies

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

Crossover Operators

- **Point crossover (classical)**
  - Parent1=x1,x2,x3,x4,x5,x6
  - Parent2=y1,y2,y3,y4,y5,y6
  - Child =x1,x2,x3,x4,y5,y6
- **Random crossover**
  - Parent1=x1,x2,x3,x4,x5,x6
  - Parent2=y1,y2,y3,y4,y5,y6
  - Child =x1,x2,y3,x4,y5,y6
- **Arithmetic crossover**
  - Parent1=x1,x2,x3
  - Parent2=y1,y2,y3
  - Child =(x1+y1)/2,(x2+y2)/2,(x3+y3)/2

Mutation Operators

- **change one or more components**
- **Let Child=x1,x2,P,x3,x4...**
- **Gaussian mutation:**
  - $P \leftarrow P \pm \Delta p$
  - Δp: (small) random normal value
- **Uniform mutation:**
  - $P \leftarrow P\ new$
  - $p\ new$: random uniform value
- **boundary mutation:**
  - $P \leftarrow Pmin\ OR\ Pmax$
- **Binary mutation=bit flip**

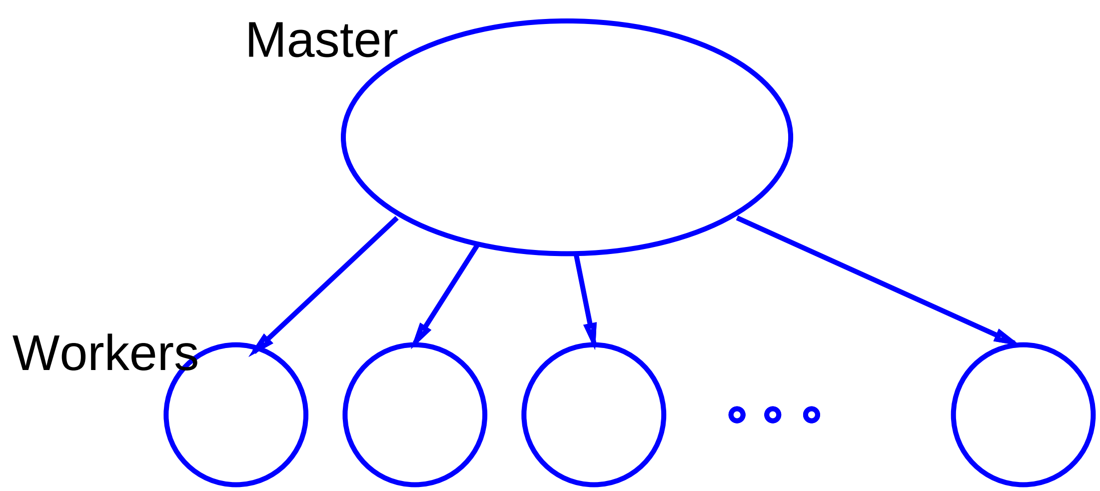
Advantages of Genetic-Algorithm based optimization

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

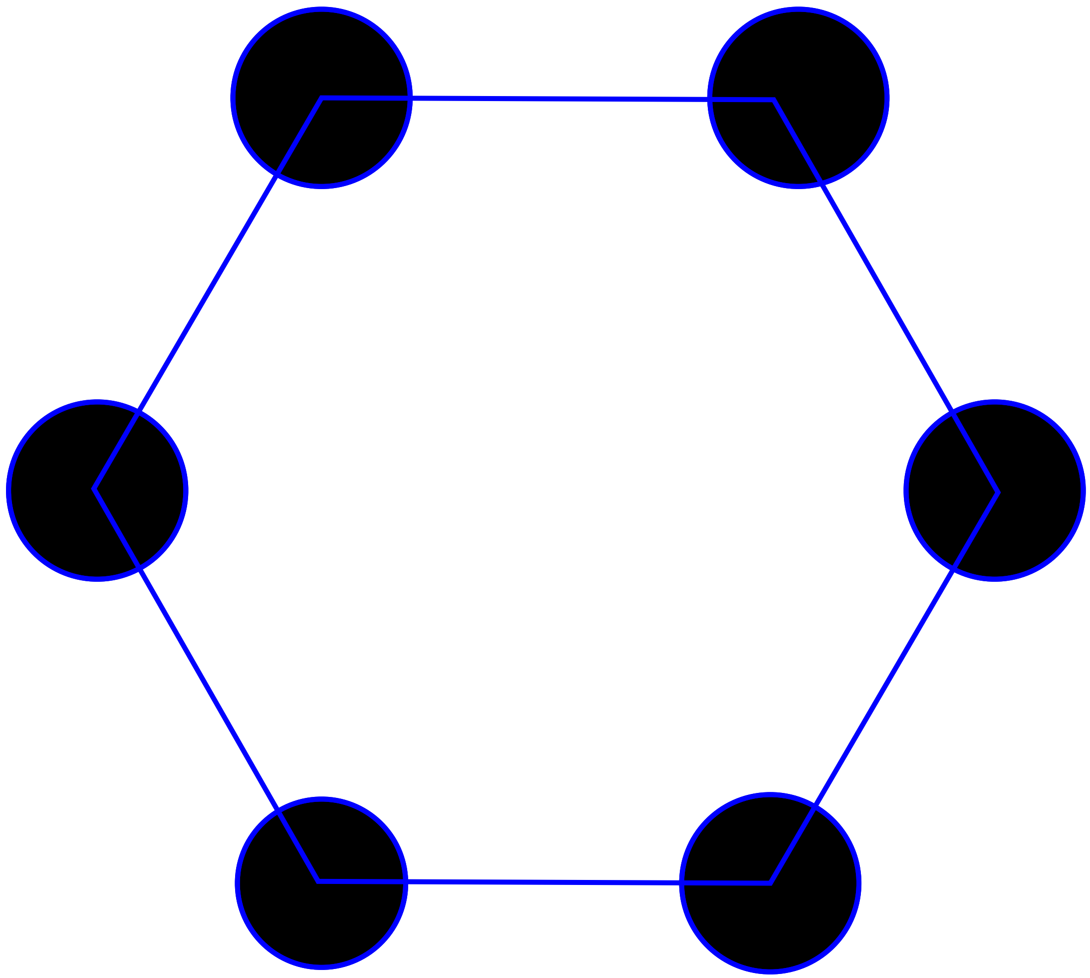
Disadvantages of Genetic-Algorithm based optimization

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

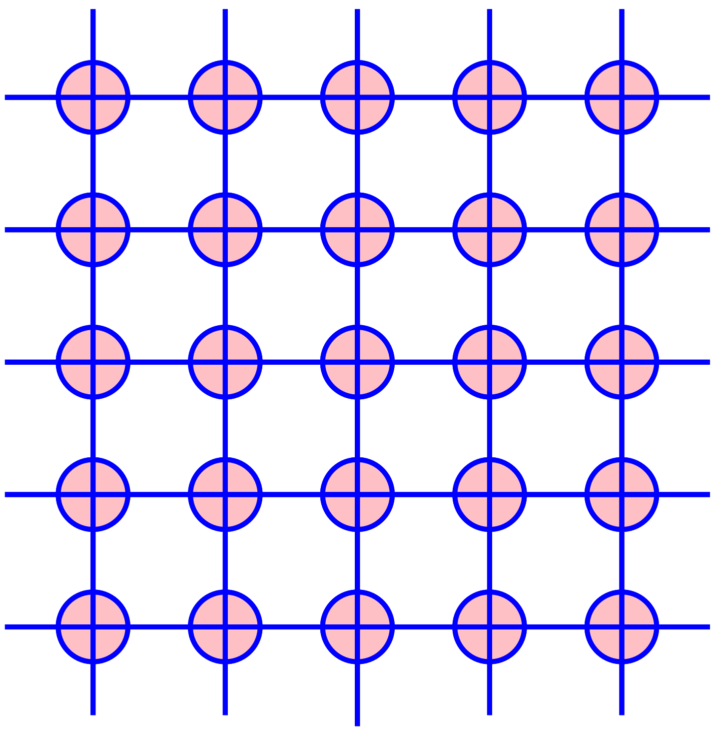
Global parallel GA



Coarse-grained parallel GA

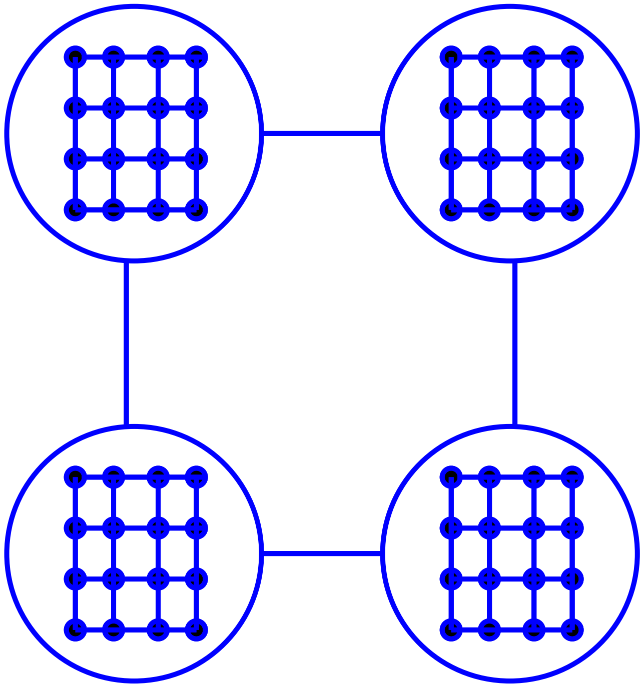


Fine-grained parallel GA



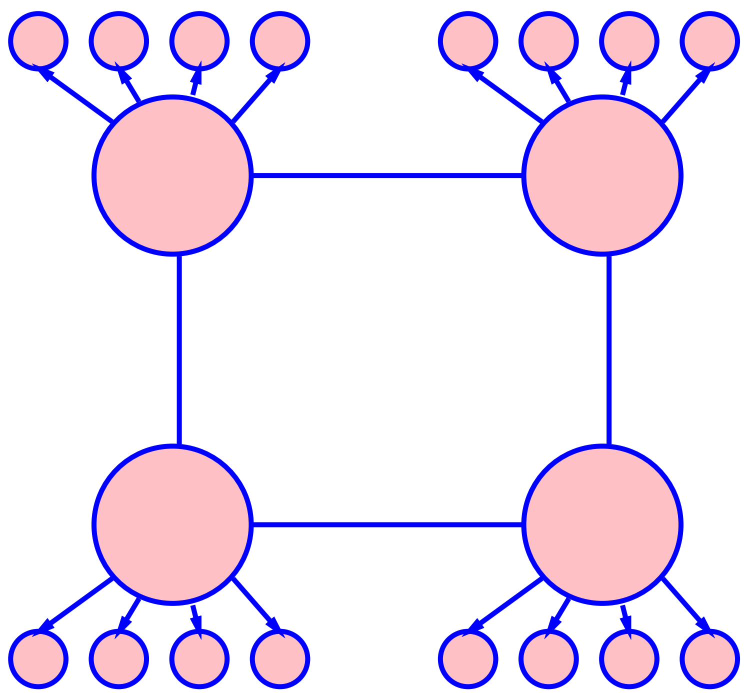
Hybrid parallel GA

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



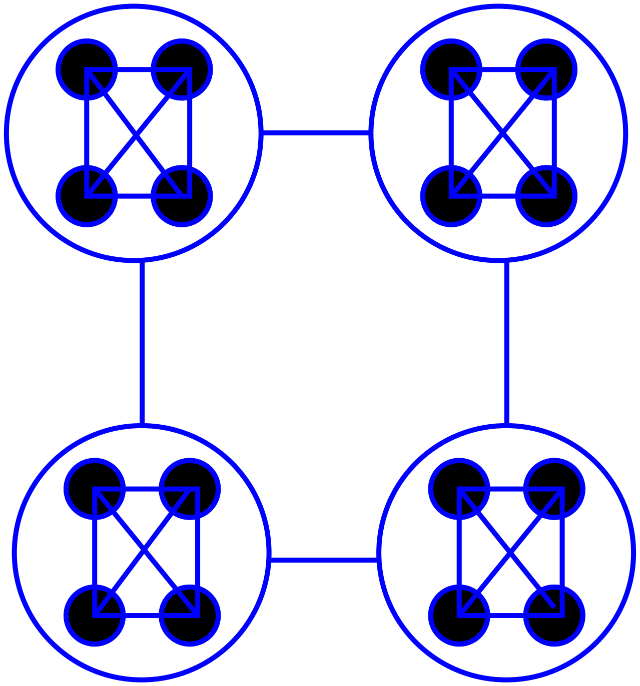
Hybrid parallel GA

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



Hybrid parallel GA

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



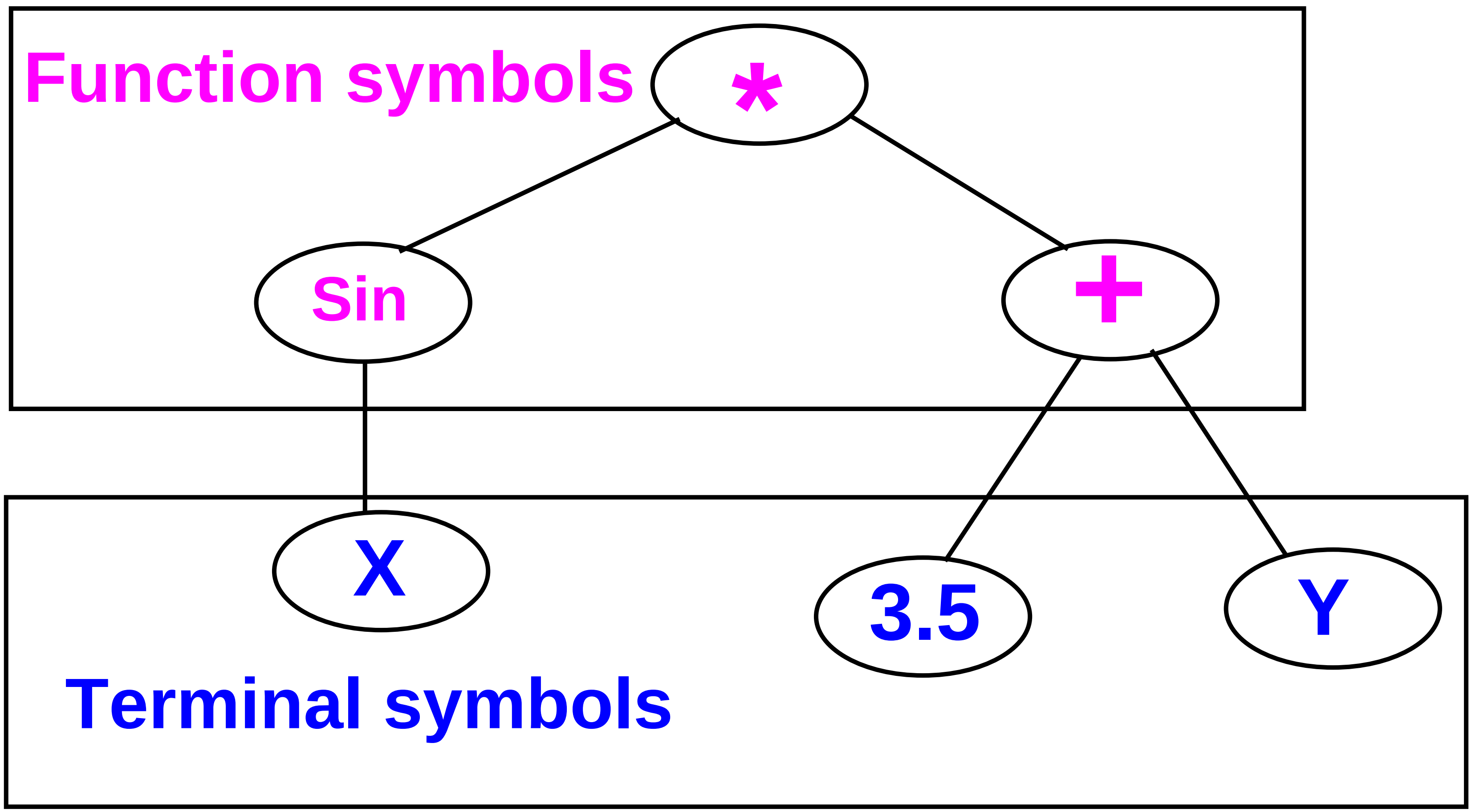
Genetic Programming (GP)

- 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 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())

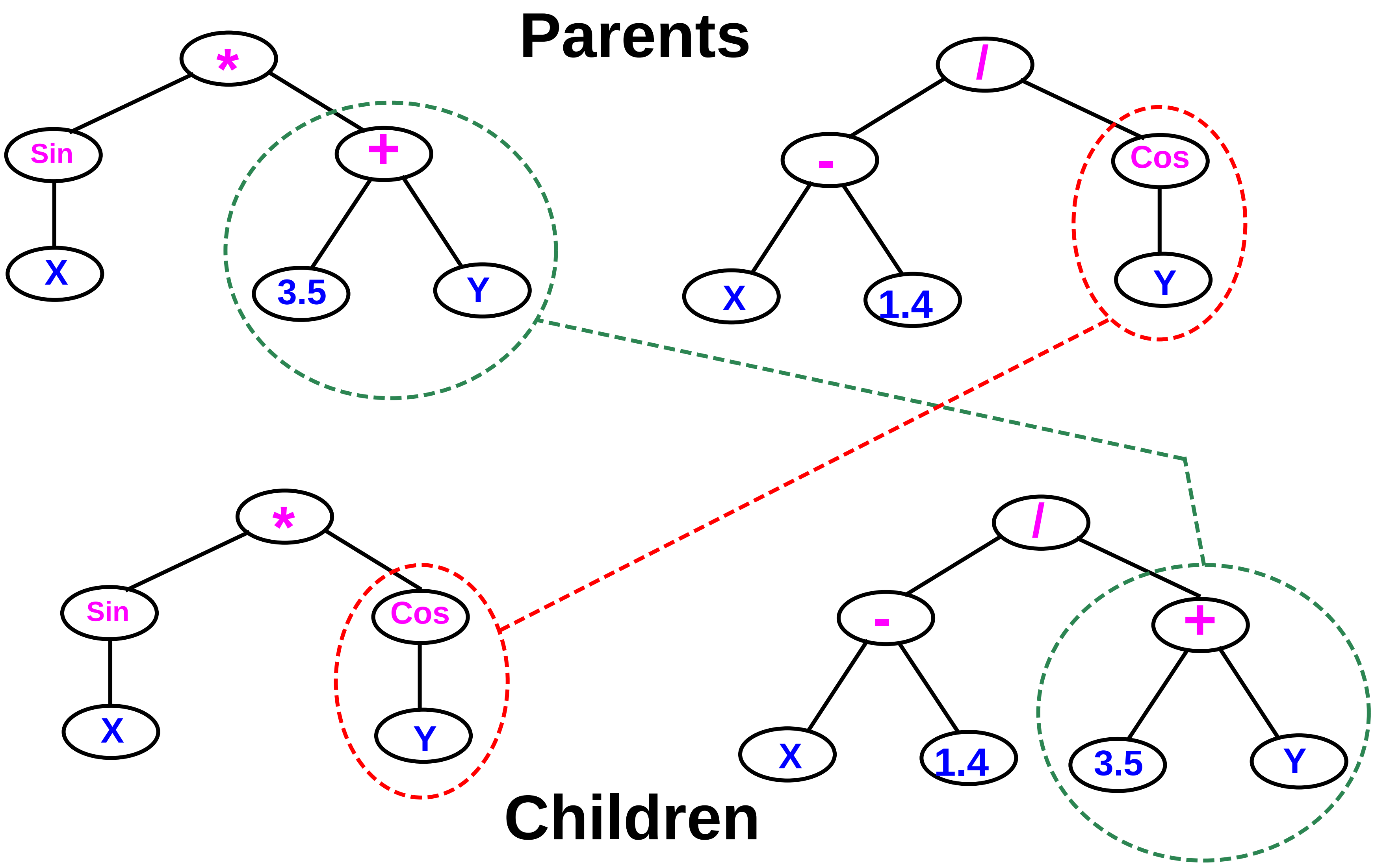
Example: GP individual



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 crossover



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.

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!

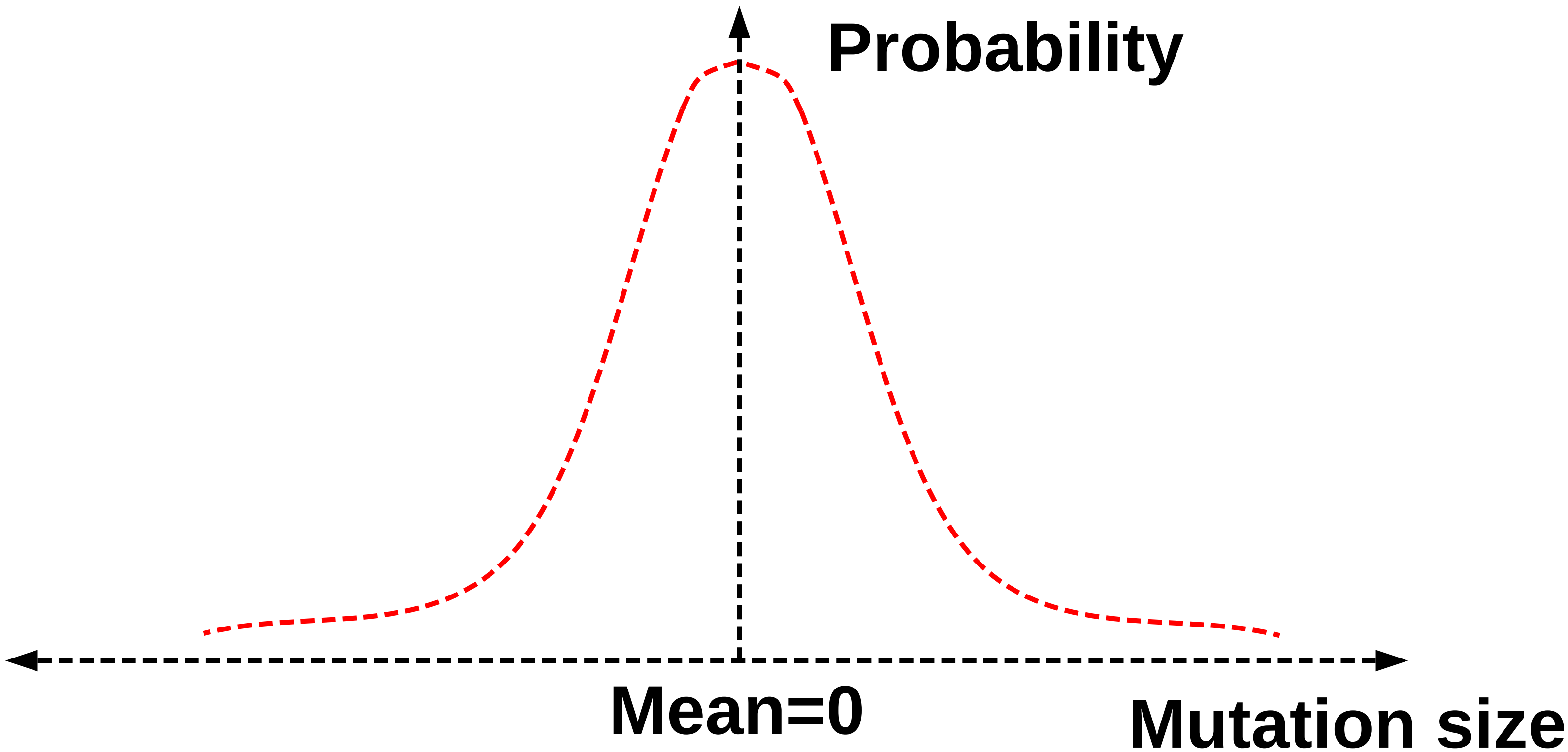
Recent Trends

- **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)

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 (μ+1) strategy which incorporated crossover**

Normal (Gaussian) mutation



Modern evolution strategies

- Schwefel introduced the multimembered ESs now denoted by $(\mu+\lambda)$ and (μ,λ)
- (μ,λ) 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

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

Machine learning and evolutionary computation

- 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.

Elements of a classifier system

- **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, existance taxes)
- **Genetic algorithm**
  - evolves a population of rules or a population of entire rule systems

The Michigan approach: population of rules

- **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?

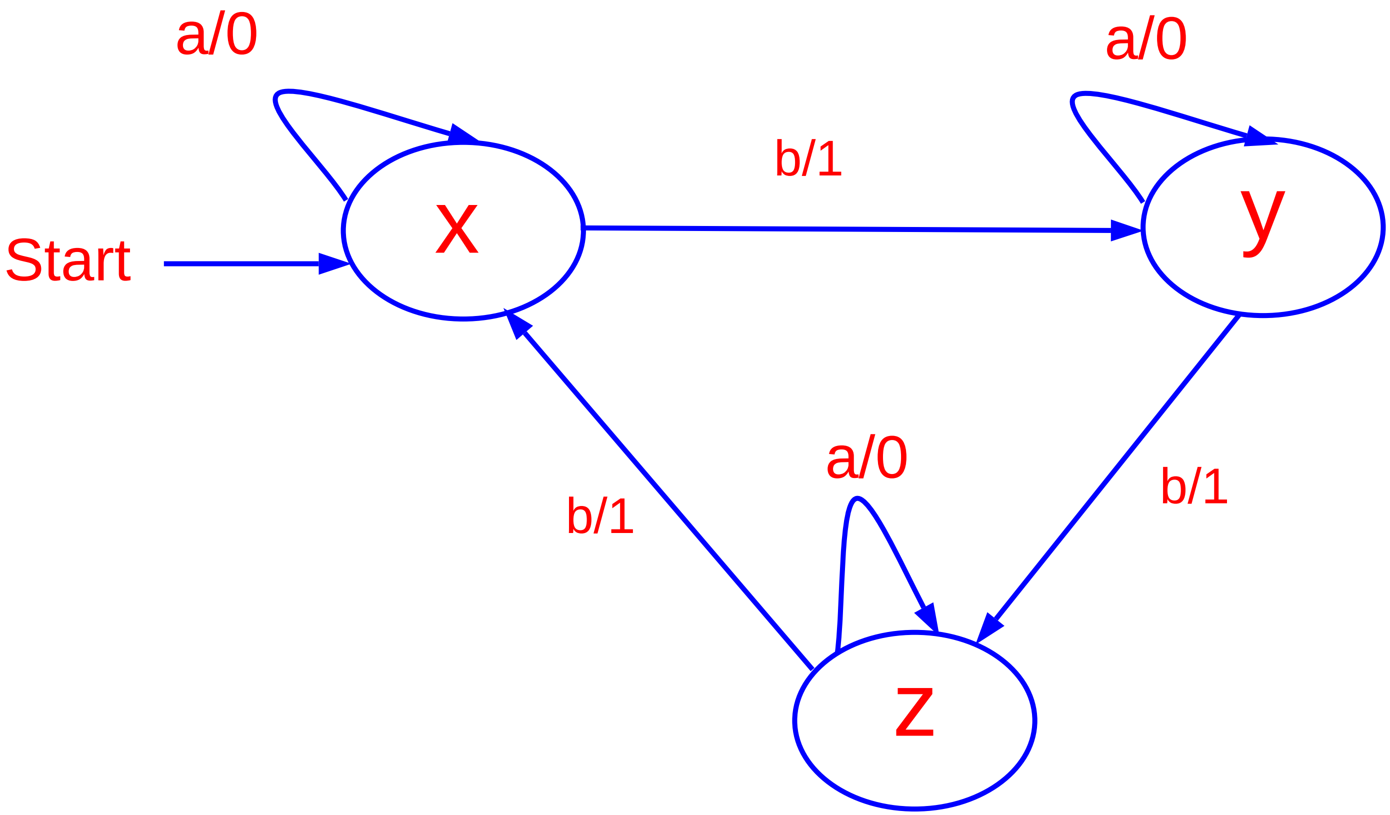
The Pitt approach

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

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

EP individual



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

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

Related Topics

- **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

The bigger picture

- **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

EC journals

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

EC conferences

- 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 ...