Genetic Algorithms

Inspired by biological processes that produce genetic change in populations of individuals.

Genetic algorithms (GAs) are adaptive search procedures that usually include three basic elements:

1. A Darwinian notion of fitness: the most fit individuals have the best chance of survival and reproduction.
2. Mating operators: individuals contribute their genetic material to their children.
3. Mutation: individuals are subject to random changes in their genetic material.

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Learning through populations

- Many learning algorithms commit to a single hypothesis at any one point in time.
- Genetic algorithms maintain a population of hypotheses.
- Each hypothesis is evaluated using a **fitness function**. The fitness scores force individuals to compete for the privilege of survival and reproduction.
- Genetic algorithms are typically performance-oriented. The fitness of a hypothesis is often measured by the performance of the hypothesis on a set of tasks.

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Genetic algorithms as search

- Genetic algorithms are local heurisitc search algorithms.
- "Weak" (i.e. general-purpose) method.
- Especially good for problems that have large and poorly understood search spaces.
- Genetic algorithms use a randomized parallel beam search to explore the hypothesis space.
- You must be able to define a good fitness function, and of course, a good hypothesis representation.

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Binary string representations

- Hypotheses are usually represented using bit strings.
- Hypotheses represented can be arbitrarily complex.
- E.g. each attribute is allocated a specific portion of the string, which encodes the attribute values that are acceptable.
- Each bit encodes whether a single attribute value is acceptable or not. So you need N bits to represent N attribute values.
- Why not use binary-valued encoding (e.g., 2 bits could represent 4 values)?
- Bit string representation allows crossover operation to change multiple values. Crossover and mutation can also

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produce previously unseen values.

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Representing Hypotheses

Bit sequences can also represent conjunctions of constraints on attribute values. For example:

$$(Outlook = Overcast \vee Rain) \wedge (Wind = Strong)$$

$$\Rightarrow \begin{array}{cc} Outlook & Wind \\ 011 & 10 \end{array}$$

Bit sequences can also represent rules, or more complicated structures. For example:

$$\text{IF} \;\; Wind = Strong \;\;\; \text{THEN} \;\; Ski? = yes$$

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	$Outlook$	$Wind$	$Ski?$
$\Rightarrow$	011	10	1

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GA$(Fitness, Fitness\_threshold, p, r, m)$

- $P \leftarrow$ randomly generate p hypotheses
- For each h in P, compute $Fitness(h)$
- While $[\max_h Fitness(h)] < Fitness\_threshold$
  1. Probabilistically **select** $(1-r)p$ members of P to add to P_S.
  2. Probabilistically choose $\frac{r \cdot p}{2}$ pairs of hypotheses from P. For each pair, $\langle h_1, h_2 \rangle$, apply **crossover** and add the offspring to P_s
  3. **Mutate** $m \cdot p$ random members of P_s
  4. $P \leftarrow P_s$
  5. For each h in P, compute $Fitness(h)$
- Return the hypothesis in P with the highest fitness.

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Selecting Most Fit Hypotheses

Hypotheses are chosen probabilistically for survival and crossover based on **fitness proportionate selection**:

$$\Pr(h) = \frac{Fitness(h)}{\sum_{j=1}^{p} Fitness(h_j)}$$

Other selection methods include:

- **Tournament Selection:** 2 hypotheses selected at random. With probability p, the most fit is selected. With probability $(1 - p)$, the less fit is selected.

- **Rank Selection:** The hypotheses are sorted by fitness and the probability of selecting a hypothesis is proportional to its rank in the list.

Crossover Operators

Single-point crossover:

Parent A:	**1**	**0**	**0**	**1**	**0**	**1**	**1**	**1**	**0**	**1**
Parent B:	0	1	0	1	1	1	0	1	1	0
Child AB:	**1**	**0**	**0**	**1**	**0**	1	0	1	1	0
Child BA:	0	1	0	1	1	**1**	**1**	**1**	**0**	**1**

Two-point crossover:

Parent A:	**1**	**0**	**0**	**1**	**0**	**1**	**1**	**1**	**0**	**1**
Parent B:	0	1	0	1	1	1	0	1	1	0
Child AB:	**1**	**0**	**0**	**1**	1	1	0	**1**	**0**	**1**
Child BA:	0	1	0	1	**0**	**1**	**1**	1	1	0

Uniform Crossover

Uniform crossover:

Parent A:	**1**	**0**	**0**	**1**	**0**	**1**	**1**	**1**	**0**	**1**
Parent B:	0	1	0	1	1	1	0	1	1	0
Child AB:	**1**	1	**0**	**1**	1	1	**1**	1	**0**	**1**
Child BA:	0	**0**	0	1	**0**	**1**	0	**1**	1	0

Mutation

Mutation: randomly toggle one bit

Individual A:	1	0	0	1	0	1	1	1	0	1
Individual A':	1	0	0	**0**	0	1	1	1	0	1

Mutation

- The **mutation** operator introduces random variations, allowing hypotheses to jump to different parts of the search space.
- What happens if the mutation rate is too low?
- What happens if the mutation rate is too high?
- A common strategy is to use a high mutation rate when learning begins but to decrease the mutation rate as learning progresses.

Learning illegal structures

Consider the traveling salesman problem, where an individual represents a potential solution. The standard crossover operator can produce illegal children:

Parent A:	ITH	Pitt	Chicago	Denver	Boise
Parent B:	Boise	Chicago	ITH	Phila	Pitt
Child AB:	ITH	Pitt	Chicago	Phila	Pitt
Child BA:	Boise	Chicago	ITH	Denver	Boise

Two solutions:

1. define special genetic operators that only produce syntactically and semantically legal hypotheses.
2. ensure that the fitness function returns extremely low fitness values to illegal hypotheses.

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Applications: Parameter Optimization

- Parameter optimization problems are well-suited for GAs. Each individual represents a set of parameter values and the GA tries to find the set of parameter values that achieves the best performance.
- The crossover operator creates new combinations of parameter values and, using a binary representation, both the crossover and mutation operators can produce new values.
- Many learning systems can be recast as parameter optimization problems. For example, most neural networks use a fixed architecture so learning consists entirely of adjusting weights and thresholds.

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GABIL [DeJong et al. 1993]

Learn disjunctive set of propositional rules **Fitness:**

$$Fitness(h) = (correct(h))^2$$

Representation:

$$\text{IF } a_1 = T \wedge a_2 = F \text{ THEN } c = T; \;\; \text{IF } a_2 = T \text{ THEN } c = F$$

represented by

a_1	a_2	c	a_1	a_2	c
10	01	1	11	10	0

Genetic operators: ???

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Crossover with Variable-Length Bitstrings

Start with

	a_1	a_2	c	a_1	a_2	c
h_1 :	10	01	1	11	10	0
h_2 :	01	11	0	10	01	0

1. choose crossover points for h_1, e.g., after bits 1, 8
2. now restrict points in h_2 to those that produce bitstrings with well-defined semantics, e.g., $\langle 1, 3\rangle$, $\langle 1, 8\rangle$, $\langle 6, 8\rangle$.

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if we choose $\langle 1, 3 \rangle$, result is

	a_1	a_2	c
h_3 :	11	10	0

	a_1	a_2	c	a_1	a_2	c	a_1	a_2	c
h_4 :	00	01	1	11	11	0	10	01	0

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GABIL Extensions

Add new genetic operators, also applied probabilistically:

1. *AddAlternative*: generalize constraint on a_i by changing a 0 to 1
2. *DropCondition*: generalize constraint on a_i by changing every 0 to 1

And, add new field to bitstring to determine whether to allow these

a_1	a_2	c	a_1	a_2	c	AA	DC
01	11	0	10	01	0	1	0

So now the learning strategy also evolves!

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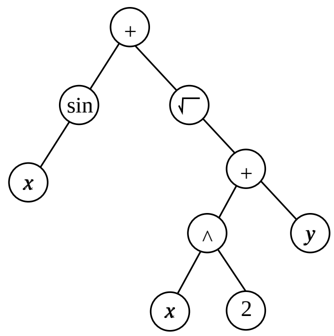
Genetic Programming

In **Genetic Programming**, programs are evolved instead of bit strings. Programs are often represented by trees. For example:

$$\sin(x) + \sqrt{x^2 + y}$$



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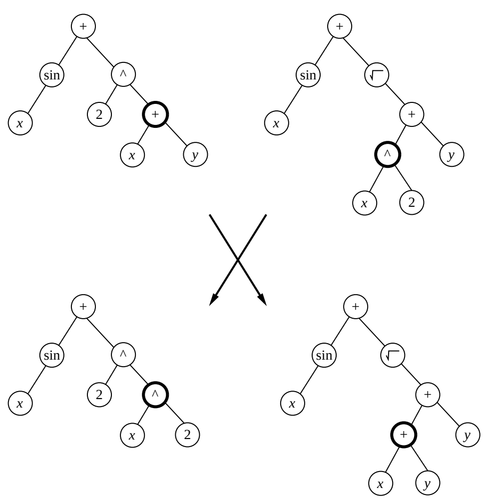
Crossover in genetic programming



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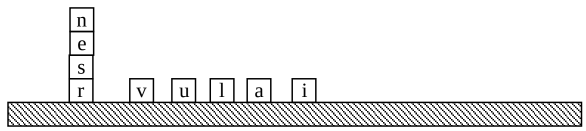
Block Problem



Goal: spell UNIVERSAL

Terminals:

- CS ("current stack") = name of the top block on stack, or F.
- TB ("top correct block") = name of topmost correct block on stack
- NN ("next necessary") = name of the next block needed above TB in the stack

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Primitive functions:

- (MS x): ("move to stack"), if block x is on the table, moves x to the top of the stack and returns the value T. Otherwise, does nothing and returns the value F.
- (MT x): ("move to table"), if block x is somewhere in the stack, moves the block at the top of the stack to the table and returns the value T. Otherwise, returns F.
- (EQ x y): ("equal"), returns T if x equals y, and returns F otherwise.
- (NOT x): returns T if $x = F$, else returns F
- (DU x y): ("do until") executes the expression x repeatedly until expression y returns the value T

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Learned Program

Trained to fit 166 test problems

Using population of 300 programs, found this after 10 generations:

(EQ (DU (MT CS)(NOT CS)) (DU (MS NN)(NOT NN)))

Genetic Programming

More interesting example: design electronic filter circuits

- Individuals are programs that transform begining circuit to final circuit, by adding/subtracting components and connections
- Use population of 640,000, run on 64 node parallel processor
- Discovers circuits competitive with best human designs

Biological Evolution

Lamarck (19th century)

- Believed individual genetic makeup was altered by lifetime experience
- But current evidence contradicts this view

What is the impact of individual learning on population evolution?

Baldwin Effect

Assume

- Individual learning has no direct influence on individual DNA
- But ability to learn reduces need to "hard wire" traits in DNA – can perform local search!

Then

- Ability of individuals to learn will support more diverse gene pool
- More diverse gene pool will support faster evolution of gene pool

→ individual learning (indirectly) increases rate of evolution

Computer Experiments on Baldwin Effect

[Hinton and Nowlan, 1987]

Evolve simple neural networks:

- Some network weights fixed during lifetime, others trainable
- Genetic makeup determines which are fixed, and their weight values

Results:

- With no individual learning, population failed to improve over time
- When individual learning allowed

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  - Early generations: population contained many individuals with many trainable weights
  - Later generations: higher fitness, while number of trainable weights decreased

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