A0M33EOA
Genetic Programming

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Contents

Genetic Programming (GP)

GP shares with GA

- the philosophy of survival and reproduction of the fittest and
- the analogy of naturally occurring genetic operators.

GP differs from GA in

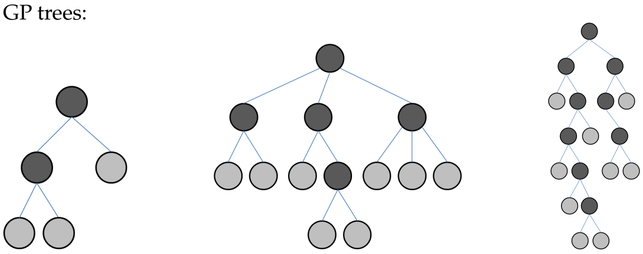
- a representation,
- genetic operators and
- the scope of applications.

Structures evolved in GP are (usually trees) dynamically **varying in size and shape**, representing an algorithm/computer program.

GA chromosome of fixed length:

v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8	v_9	v_{10}

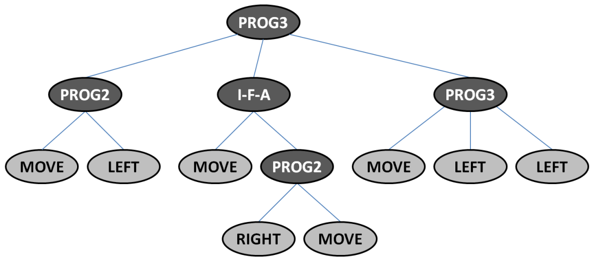
GP trees:



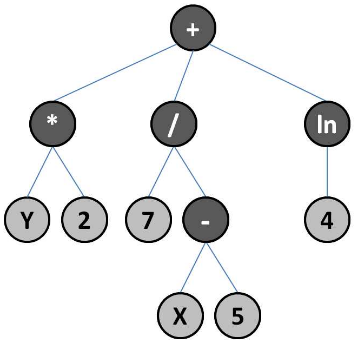
Genetic Programming (GP): Application Domains

Applications

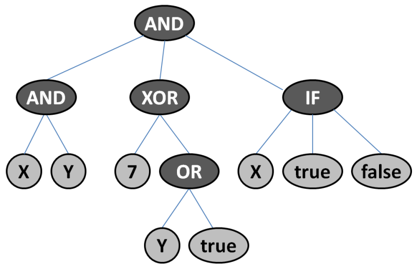
- learning programs,
- learning decision trees,
- learning rules,
- learning strategies,
- ...



Strategy for artificial ant



Arithmetic expression



Logic expression

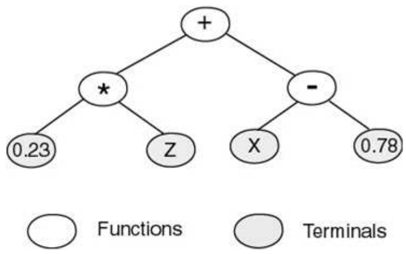
GP: Representation

Many possible representations; here we focus on **trees** composed of

- **terminals**:
  - inputs to the program (independent variables),
  - real, integer or logical constants,
  - actions, ...

  and
- **functions**:
  - arithmetic operators (+, -, *, /),
  - algebraic functions (sin, cos, exp, log),
  - logical functions (AND, OR, NOT),
  - conditional operators (If-Then-Else, cond ? true : false),
  - ...

Example: Tree representation of a LISP S-expression
$0.23 * Z + X - 0.78$

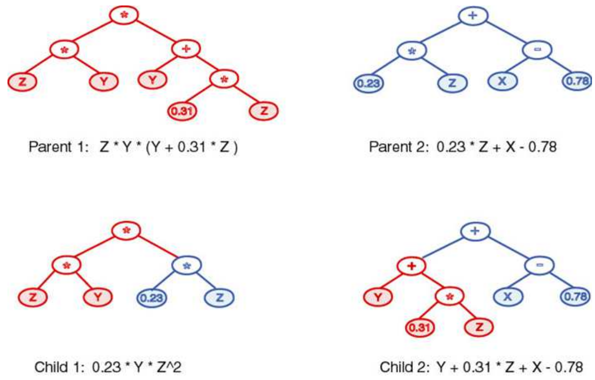


Closure property: each of the functions should be able to accept, as its argument, any value that may be returned by any function and any terminal.

GP: Crossover

Subtree crossover

1. Randomly select a node (crossover point) in each parent tree.
2. Create offspring by exchanging the subtrees rooted at the crossover nodes.



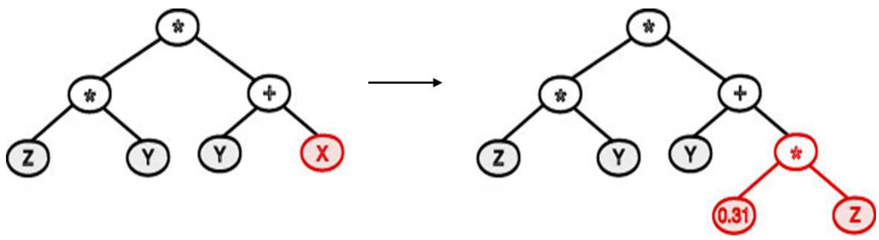
Crossover points do not have to be selected with uniform probability

- Typically, the majority of nodes in the trees are leaves, because the average branching factor (the number of children of each node) is ≥ 2.
- To avoid swapping leave nodes most of the time, the widely used crossover scenario chooses function nodes 90% of the time and leaves 10% of the time.

GP: Mutation

Subtree mutation

1. Randomly select a mutation point from the set of all nodes in the parent tree.
2. Replace the subtree rooted at the chosen node with a new randomly generated subtree.



Point mutation

1. Randomly select a mutation point from the set of all nodes in the parent tree.
2. Replace the primitive stored in the selected node with a different primitive of the same arity taken from the primitive set.

GP: Constant Creation

In many problems exact real-valued constants are required to be present in the correct solution (evolved program tree) $\Longrightarrow$ GP must have the ability to create arbitrary real-valued constants.

Ephemeral random constant (ERC) $\mathfrak{R}$ is a special terminal.

- Initialization:
  - Whenever an ERC is chosen for any endpoint of the tree during the initialization, a random number of a specified data type in a specified range is generated and attached to the tree at that point.
  - Each occurrence of this terminal symbol invokes a generation of a unique value.
- After initialization:
  - Many different constants can be found in the trees.
  - These constants remain fixed during evolution.
  - Other constants can be evolved by mixing the existing subtrees, being driven by the goal of improving the overall fitness.
  - The pressure of fitness function determines both the directions and the magnitudes of the adjustments in numerical constants.

GP: Trigonometric Identity

Task: find an expression equivalent to $\cos(2x)$.

GP setup:

- **Terminal set:** $T = \{x, 1\}$.
- **Function set:** $F = \{+, -, *, \%, \sin\}$.
- **Training cases:** 20 pairs (x_i, y_i), where x_i are values evenly distributed in interval $(0, 2\pi)$.
- **Fitness:** Sum of absolute differences between desired y_i and the values returned by generated expressions.
- **Stopping criterion:** A solution found that gives the error less than 0.01.

Example of GP in Action: Trigonometric Identity

Run 1, 13^{th} **generation**

```
(- (- 1 (* (sin x) (sin x))) (* (sin x) (sin x)))
```

which equals (after editing) to $1 - 2\sin^2 x$.

Run 2, 34^{th} **generation**

```
(- 1 (* (* (sin x) (sin x)) 2))
```

which is another way of writing the same expression.

Run 3, 30^{th} **generation**

```
(sin (- (- 2 (* x 2))
        (sin (sin (sin (sin (sin (sin (* (sin (sin 1))
                                         (sin (sin 1)))))))))))
```

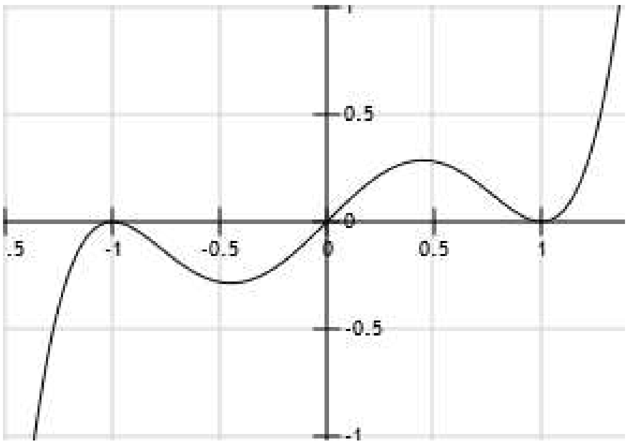
- The subtree `sin(sin(...` evaluates to 0.433.
- The expression is thus $\sin(2 - 2x - 0.433)$.
- $2 - 0.433 \doteq \frac{\pi}{2}$.
- The discovered identity is $\cos(2x) = \sin(\frac{\pi}{2} - 2x)$.

GP: Symbolic Regression

Task: find a function that fits the training data evenly sampled from interval $\langle -1.0, 1.0 \rangle$, $f(x) = x^5 - 2x^3 + x$.

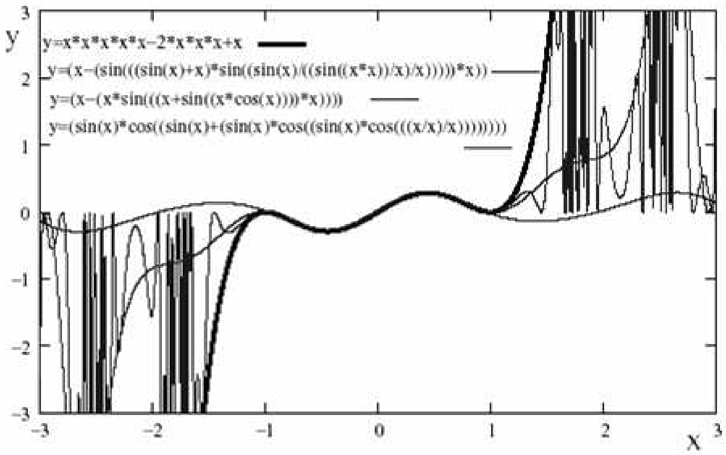
GP setup:

- **Terminal set** $T = \{x\}$.
- **Function set** $F = \{+, -, *, \%, \sin, \cos\}$.
- **Training cases**: 20 pairs (x_i, y_i), where x_i are values evenly distributed in interval $\langle -1, 1 \rangle$.
- **Fitness**: Sum of errors calculated over all (x_i, y_i) pairs.
- **Stopping criterion**: A solution found that gives the error less than 0.01.



Besides the desired function other three were found

- with a very strange behavior outside the interval of training data,
- though optimal with respect to the defined fitness.



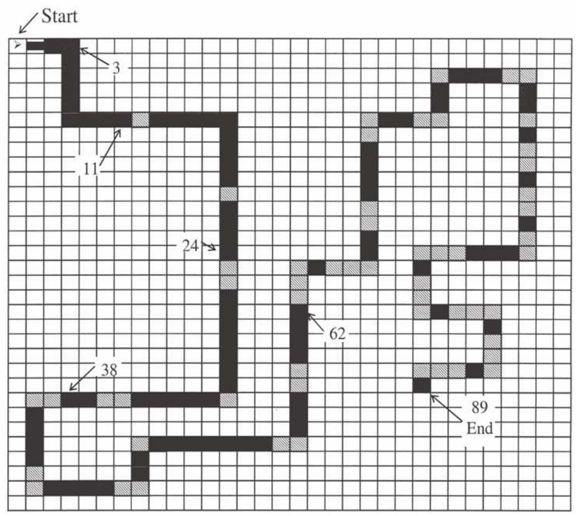
Artificial Ant Problem

Santa Fe trail

- 32×32 **grid** with 89 food pieces.
- **Obstacles**
  - $1\times, 2\times$ strait,
  - $1\times, 2\times, 3\times$ right/left.

Ant capabilities

- **detects** the food right in front of him in direction he faces.
- **actions** observable from outside
  - MOVE: makes a step and eats a food piece if there is some,
  - LEFT: turns left,
  - RIGHT: turns right,
  - NO-OP: no operation.



Goal: find a strategy that navigates an ant through the grid so that it finds all the food pieces in the given time (600 time steps).

Artificial Ant Problem: GP Approach

Terminals (ant actions):

- T = {`MOVE`, `LEFT`, `RIGHT`}.

Functions:

- conditional `IF-FOOD-AHEAD`: food detection, 2 arguments,
- unconditional `PROG2`, `PROG3`: sequence of 2/3 actions.

Ant repeats the program until time runs out (600 time steps) or all the food has been eaten.

Typical solutions in the initial population:

- `(PROG2 (RIGHT) (LEFT))`
  completely fails to fin and eat any food.
- `(IF-FOOD-AHEAD (LEFT) (RIGHT))`
  does nothing useful either.
- `(PROG2 (MOVE) (MOVE))`
  finds a few pieces of food by chance.

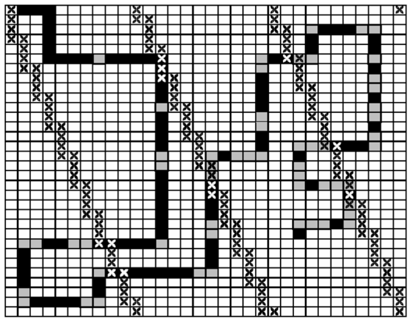
Artificial Ant Problem: GP Approach (cont.)

More interesting solutions from the initial population:

- **Quilter** performs systematic exploration of the grid:

```
(PROG3 (RIGHT)
       (PROG3 (MOVE) (MOVE) (MOVE))
       (PROG2 (LEFT) (MOVE)))
```

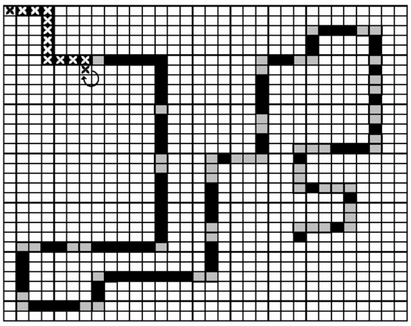
Quilter performance



- **Tracker** perfectly tracks the food until the first obstacle occurs, then it gets trapped in an infinite loop.

```
(IF-FOOD-AHEAD (MOVE) (RIGHT))
```

Tracker performance

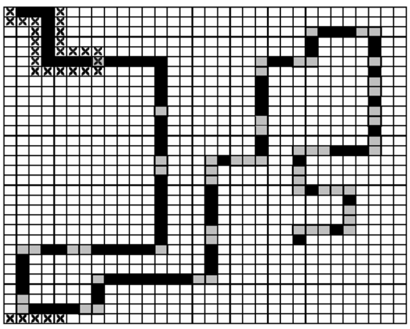


Artificial Ant Problem: GP Approach (cont.)

- **Avoider** perfectly avoids food!!!

```
(I-F-A (RIGHT)
       (I-F-A (RIGHT)
              (PROG2 (MOVE) (LEFT))))
```

Avoider performance



Average fitness in the initial population is 3.5.

Artificial Ant Problem: GP result

In generation 21, the following solution was found:

```
(IF-FOOD-AHEAD (MOVE)
             (PROG3 (LEFT)
                   (PROG2 (IF-FOOD-AHEAD (MOVE)
                                        (RIGHT))
                         (PROG2 (RIGHT)
                               (PROG2 (LEFT)
                                     (RIGHT))))
                   (PROG2 (IF-FOOD-AHEAD (MOVE)
                                        (LEFT))
                         (MOVE))))
```

- It navigates the ant so that it eats all 89 food pieces in the given time.
- The program solves every trail with obstacles of the same type as occur in Santa Fe trail.

Compare the computational complexity with the GA approach!!!

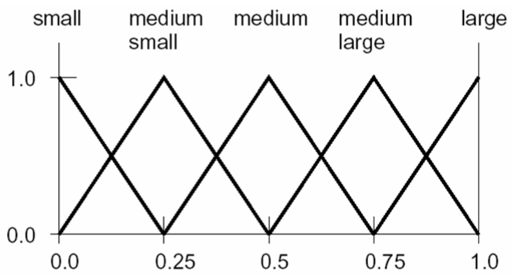
GA approach: $65.536 \times 200 = 13 \times 10^6$ trials.
GP approach: $500 \times 21 = 10.500$ trials.

Syntax-preserving GP: Evolving Fuzzy-rule based Classifier

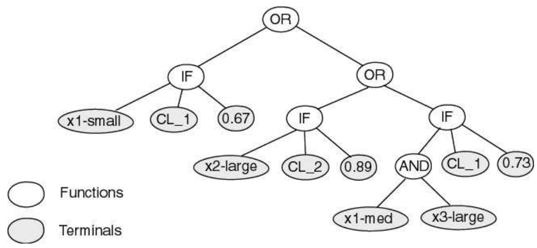
Classifier consists of fuzzy if-then rules of type

If ($x1$ is *medium*) and ($x3$ is *large*) then *class* = 1 with cf = 0.73

- **Linguistic terms:** small, medium small, medium, medium large, large.
- **Fuzzy membership functions:** approximate the confidence in that the crisp value is represented by the linguistic term.

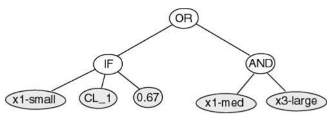


Three rules connected by `OR`



Blind *crossover and mutation operators can produce incorrect trees* that do not represent valid rule base.

- Obviously due to the fact that the **closure** property does not hold here.
- **What can we do?**



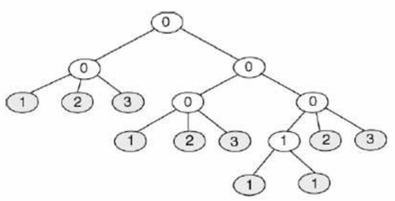
Syntax-preserving GP: Strongly Typed GP

Strongly typed GP: crossover and mutation explicitly use the *type* information:

- every terminal has a type,
- every function has types for each of its arguments and a type for its return value,
- the genetic operators are implemented so that they do not violate the type constraints $\Longrightarrow$ only type correct solutions are generated.

Example: Given the representation as specified below, consider that we chose `IS` node (with return type 1) as a crossing point in the first parent. Then, the crossing point in the second parent must be either `IF` or `AND` node.

F / T	Output	Input
OR	0	0, 0
IF	0	1, 2, 3
AND	1	1, 1
IS	1	None
CLASS	2	None
CF	3	None



STGP can be extended to more complex type systems – multi-level and polymorphic higher-order type systems.

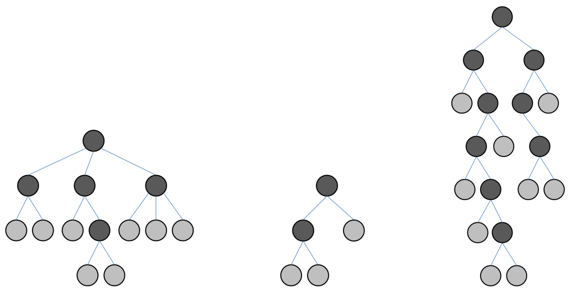
GP Initialisation: Requirements

GP needs a good tree-creation algorithm to create

- trees for the initial population and
- subtrees for subtree mutation.

Required characteristics:

- Computationally light; optimally linear in tree size.
- User control over expected tree size.
- User control over specific node appearance in trees.

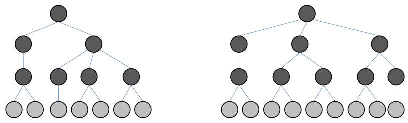


GP Initialisation: Simple Methods

D is the maximum initial depth of trees, typically between 2 to 6.

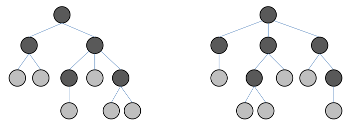
Full method:

- Each branch has depth $d = D$.
- Nodes at depth $d < D$ randomly chosen from function set F.
- Nodes at depth $d = D$ randomly chosen from terminal set T.



Grow method:

- Each branch has depth $d \leq D$.
- Nodes at depth $d < D$ randomly chosen from $F \cup T$.
- Nodes at depth $d = D$ randomly chosen from T.



Ramped half-and-half:

- Grow & full method each deliver half of the initial population.
- A range of depth limits is used to ensure that trees of various sizes and shapes are generated.

GP Initialisation: Simple Methods

Characteristics of **Grow** and **Full** methods:

- No size parameter: they do not allow the user to create a population with a desired size distribution.
- No way to define the expected probabilities of certain nodes appearing in trees.
- They do not give the user much control over the tree shapes generated.

GP Initialization: Probabilistic Tree-Creation Method

Probabilistic tree-creation method:

- An expected desired tree size can be defined.
- Probabilities of occurrence of individual functions and terminals within the generated trees can be defined.
- Fast – running in time near-linear in tree size.

Notation:

- **T** denotes a newly generated tree.
- D is the maximal depth of a tree.
- E_{tree} is the expected tree size of **T**.
- F is a function set divided into terminals T and nonterminals N.
- p is the probability that an algorithm will pick a nonterminal.
- b is the expected number of children to nonterminal nodes from N.
- g is the expected number of children to a newly generated node in **T**.

$$g = pb + (1-p)(0) = pb$$

GP Initialization: Probabilistic Tree-Creation Method 1

PTC1 is a modification of Grow that

- allows the user to define probabilities of appearance of functions within the tree,
- gives user a control over expected desired tree size, and guarantees that, on average, trees will be of that size,
- does not give the user any control over the variance in tree sizes.

Given

- maximum depth bound D,
- function set F consisting of N and T,
- expected tree size, E_{tree},
- probabilities q_t and q_n for each $t \in T$ and $n \in N$,
- arities b_n of all nonterminals $n \in N$,

the probability, p, of choosing a nonterminal over a terminal according to

$$p = \frac{1 - \frac{1}{E_{tree}}}{\sum_{n \in N} q_n b_n}$$

PTC1(depth d)

```
Returns: a tree of depth d ≤ D
if (d = D) return a terminal from T
  (by q_t probabilities)
else if (rand < p)
  choose a nonterminal n from N
    (by q_n probabilities)
    for each argument a of n
      fill a with PTC1(d + 1)
    return n
else return a terminal from T
  (by q_t probabilities)
```

Probabilistic Tree-Creation Method PTC1: Proof of p

- The expected number of nodes at depth d is $E_d = g^d$ for $g \geq 0$ (the expected number of children to a newly generated node).
- E_{tree} is the sum of E_d over all levels of the tree, that is

$$E_{tree} = \sum_{d=0}^{\infty} E_d = \sum_{d=0}^{\infty} g^d$$

  From the geometric series, for $g \geq 0$

$$E_{tree} = \begin{cases} \frac{1}{1-g}, & \text{if } g < 1 \\ \infty, & \text{if } g \geq 1. \end{cases}$$

  The expected tree size E_{tree} (we are interested in the case that E_{tree} is finite) is determined solely by g, the expected number of children of a newly generated node.
- Since $g = pb$, given a constant, nonzero b (the expected number of children of a nonterminal node from N), a p can be picked to produce any desired g.

  Thus, a proper value of g (and hence the value of p) can be picked to determine any desired E_{tree}.

Probabilistic Tree-Creation Method PTC1: Proof of p

- From

$$E_{tree} = \frac{1}{1 - pb}$$

  we get

$$p = \frac{1 - \frac{1}{E_{tree}}}{b}$$

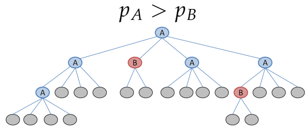
  After substituting $\sum_{n \in N} q_n b_n$ for b we get

$$p = \frac{1 - \frac{1}{E_{tree}}}{\sum_{n \in N} q_n b_n}.$$

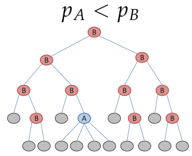
- User can bias typical bushiness of a tree by adjusting the occurrence probabilities of nonterminals with large fan-outs and small fan-outs, respectively.

  Example: Nonterminal A has four children branches, nonterminal B has two children branches.

$p_A > p_B$



$p_A < p_B$



GP: Selection

Fitness-proportionate roulette wheel selection or tournament selection are commonly used.

Greedy over-selection:

- Recommended for complex problems that require large populations (> 1000).
- Increases the selection probability of the fitter individuals in the population.
- Algorithm:
  - Rank population by fitness and divide it into two groups:
    - group I: the fittest individuals that together account for x% of the sum of fitness values in the population,
    - group II: remaining less fit individuals.
  - 80% of the time an individual is selected from group I in proportion to its fitness; 20% of the time, an individual is selected from group II.
- For population size = 1000, 2000, 4000, 8000, $x = 32\%, 16\%, 8\%, 4\%$.
  (%'s come from a rule of thumb.)

Example: Effect of greedy over-selection for the 6-multiplexer problem

Population size	I(M,i,z) without over-selection	I(M,i,z) with over-selection
1,000	343,000	33,000
2,000	294,000	18,000
4,000	160,000	24,000

GP: Crossover Operators

Standard crossover operators used in GP (subtree crossover) are designed to ensure **just the syntactic closure property**.

- On the one hand, they produce syntactically valid children from syntactically valid parents.
- On the other hand, the only semantic guidance of the search is from the fitness measured by the difference of behavior of evolving programs and the target programs.

  This is very different from real programmers' practice where any change to a program should pay heavy attention to the change in semantics of the program.

To remedy this deficiency in GP, genetic operators making use of the semantic information has been introduced:

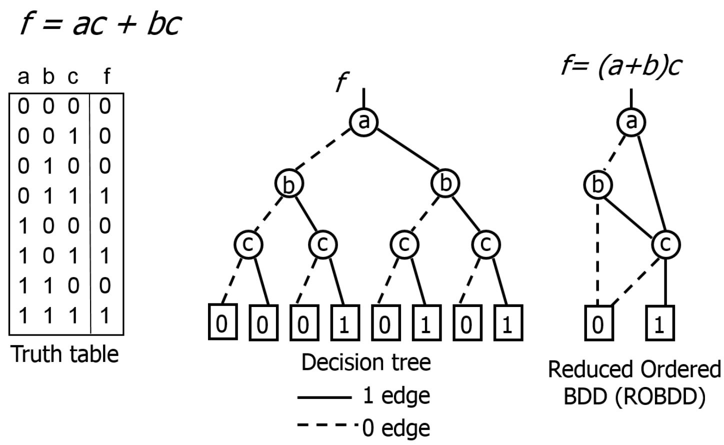
- **Semantically Driven Crossover (SDC)** [BJ08]
- **Semantic Aware Crossover (SAC)** [UHO09]

[BJ08] Lawrence Beadle and Colin Johnson. Semantically driven crossover in genetic programming. In Jun Wang, editor, *Proceedings of the IEEE World Congress on Computational Intelligence, CEC 2008*, pages 111–116, Hong Kong, 2008. IEEE Computational Intelligence Society, IEEE Press.

[UHO09] Nguyen Quang Uy, Nguyen Xuan Hoai, and Michael O'Neill. Semantic aware crossover for genetic programming: The case for real-valued function regression. In *EuroGP*, volume 5481 of *Lecture Notes in Computer Science*, pages 292–302. Springer, 2009.

GP: Semantically Driven Crossover

- Applied to **Boolean domains**.
- The semantic equivalence between parents and their children is checked by transforming the trees to **reduced ordered binary decision diagrams** (ROBDDs).
  Trees are considered semantically equivalent if and only if they reduce to the same ROBDDs.



This **eliminates** two types of **introns** (code that does not contribute to the fitness of the program):

- Unreachable code: `(IF A1 D0 (IF A1 (AND D0 D1) D1))`
- Redundant code: `AND A1 A1`

GP: Semantically Driven Crossover (cont.)

Ensuring semantic diversity:

- If the children are semantically equivalent to their parents w.r.t. their ROBDD representation then the crossover is repeated until semantically non-equivalent children are produced.

SDC was reported useful in increasing GP performance as well as reducing code bloat (compared to GP with standard subtree crossover):

- **SDC significantly reduces the depth of programs** (smaller programs).
- **SDC yields better results** - an average maximum score and the standard deviation of score are significantly higher than the standard GP; SDC is performing wider search.

GP: Semantic Aware Crossover

- Applied to **real-valued domains**.
- Determining semantic equivalence between two real-valued expressions is NP-hard.
- **Approximate semantics are calculated:**
  - Compared expressions are measured against a random set of points sampled from the domain.
  - Two trees, T1 and T2, are considered *semantically equivalent* if the output of the two trees on the random sample set S are close enough, subject to a parameter ε called *semantic sensitivity*, i.e., if

$$\sum_{x \in S} |T1(x) - T2(x)| < \varepsilon.$$

- Equivalence checking is used both for individual trees and subtrees.
- **Constraint crossover: encourage exchanging subtrees with different semantics**.
  - While the two subtrees chosen for exchange are semantically equivalent, the operator tries to choose different subtrees.

GP: Semantic Aware Crossover

Effects of semantic guidance on the crossover (SAC):

- **SAC is more semantic exploratory** than standard GP. It carries out much fewer semantically equivalent crossover events than standard GP crossover.
- **SAC is more fitness constructive** than standard GP: the percentage of crossover events generating a better child from its parents is significantly higher in SAC.
- SAC increases the number of successful runs in solving a class of real-valued symbolic regression problem.
- SAC increases the semantic diversity of population.

Automatically Defined Functions: Motivation

Hierarchical problem-solving (”divide and conquer”):

- The solution to an overall problem may be found by decomposing it into smaller and more tractable subproblems such that
- the solutions of subproblems are reused many times in assembling the solution to the overall problem.

Automatically Defined Functions [Koz94]: idea similar to reusable code represented by subroutines in programming languages.

- The reuse eliminates the need to ”reinvent the wheel” on each occasion when a particular sequence of steps may be useful.
- Subroutines are reused with different instantiation of dummy variables.
- The reuse makes it possible to exploit a problem’s modularities, symmetries and regularities.
- Code encapsulation – protection from crossover and mutation.
- Simplification – less complex code, easier to evolve.
- Efficiency – acceleration of the problem-solving process (i.e., the evolution).

[Koz94] John R. Koza. *Genetic Programming II: Automatic Discovery of Reusable Programs*. MIT Press, Cambridge, MA, USA, 1994.

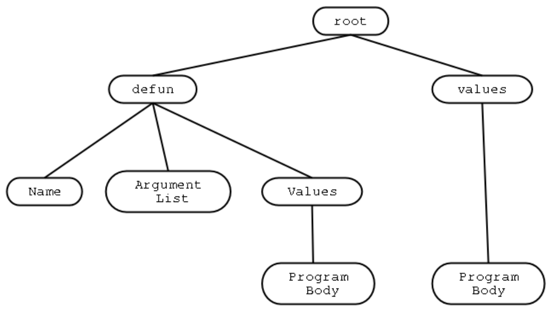
Automatically Defined Functions: Structure of Programs with ADFs

Function defining branches (ADFs): each ADF resides in a separate function-defining branch.

Each ADF

- can have zero, one or more formal parameters (dummy variables),
- belongs to a particular individual (program) in the population,
- may be called by the program’s result-producing branch(es) or other ADFs.

Typically, the ADFs are invoked with different instantiations of their dummy variables.

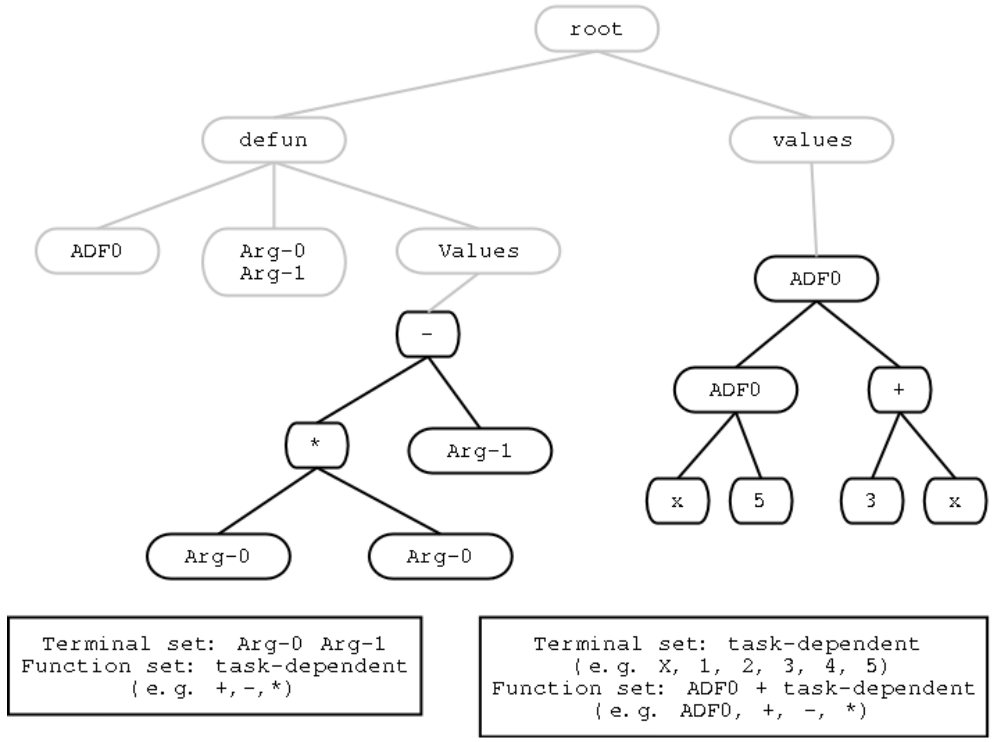


Result-producing branch (RPB): the ”main” program (can be one or more).

Remarks:

- The RPBs and ADFs can have different function and terminal sets.
- ADFs as well as RPBs undergo the evolution through the crossover and mutation operations.

ADF: Tree Example for Symb. Regression of Real-valued Functions



ADF: Symbolic Regression of Even-Parity Functions

Even-n-parity function of n Boolean arguments:

- Return `true` if the number of `true` arguments is even; return `false` otherwise.
- The function is uniquely specified by the value of the function for each of the 2^n possible combinations of its n arguments.

Exmaple: Even-3-parity: the truth table has $2^3 = 8$ rows.

	D2	D1	D0	Output
0	0	0	0	1
1	0	0	1	0
2	0	1	0	0
3	0	1	1	1
4	1	0	0	0
5	1	0	1	1
6	1	1	0	1
7	1	1	1	0

Even-3-Parity Function: Blind Search vs. Simple GP

Experimental setup:

- Function set: F = {AND, OR, NAND, NOR}
- The number of internal nodes fixed to 20.
- Blind search – randomly samples 10,000,000 trees
- GP without ADFs
  - Population size $M = 50$.
  - A run is terminated as soon as it produces a correct solution.
  - Total number of trees generated 10,000,000.

Results: number of times the correct function appeared in 10,000,000 generated trees:

Blind search	0
GP without ADFs	2

Effect of using larger populations in GP:

Population size	50	100	200	500	1000
Ind. processed per solution	999,750	665,923	379,876	122,754	20,285

The performance advantage of GP over blind search increases with population size; it demonstrates the importance of a proper choice of the population size.

Observed GP Performance Parameters

Performance measures:

- $P(M, i)$: cumulative probability of success for all the generations between generation 0 and i, where M is the population size.
- $I(M, i, z)$: number of individuals that need to be processed in order to yield a solution with probability z (here $z = 99\%$).

  For the desired probability z of finding a solution by generation i at least once in R runs the following holds

  $$z = 1 - [1 - P(M, i)]^R.$$

  Thus, the number $R(z)$ of independent runs required to satisfy the success predicate by generation i with probability $z = 1 - \varepsilon$ is

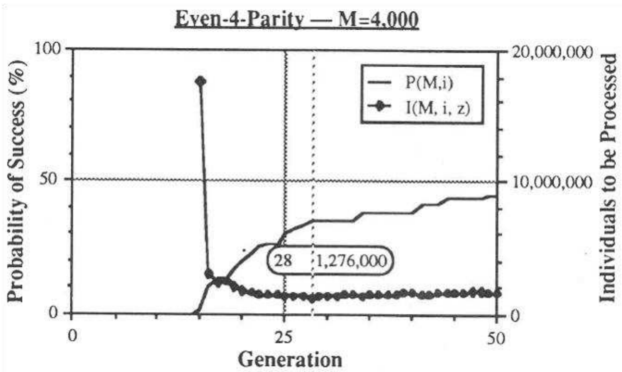
  $$R(M, z, i) = \left(\frac{\log \varepsilon}{\log(1 - P(M, i))} \right).$$

  And

  $$I(M, i, z) = M \cdot i \cdot R(M, z, i).$$

GP without ADFs: Even-4-Parity Function

GP without ADFs on even-4-parity problem (based on 60 independent runs)



- Cumulative probability of success, $P(M, i)$, is 35% and 45% by generation 28 and 50, respectively.
- The most efficient is to run GP up to the generation 28 – if the problem is run through to generation 28, processing a total of

  $$4,000 \times 29 \text{ generations} \times 11 \text{ runs} = 1,276,000$$

  individuals is sufficient to yield a solution with 99% probability.

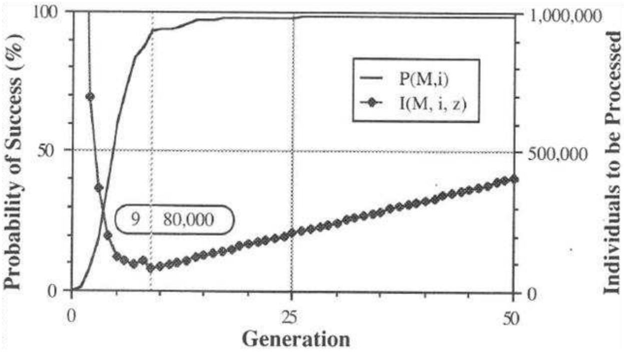
GP without ADFs: Even-4-Parity Function

An example of solution with 149 nodes.

```
(AND (OR (OR (OR (NOR D0 (NOR D2 D1)) (NAND (OR (NOR (AND
D3 D0) D2) (NAND D0 (NOR D2 (AND D1 (OR D3 D2))))) D3))
(AND (AND D1 D2) D0)) (NAND (NAND (NAND D3 (OR (NOR D0
(NOR (OR D3 D2) D2)) (NAND (AND (AND (AND D3 D2) D3) D2)
D3))) (NAND (OR (NAND (OR D0 (OR D0 D1)) (NAND D0 D1))
D3) (NAND D1 D3))) D3)) (OR (OR (NOR (NOR (AND (OR (NOR
D3 D0) (NOR (NOR D3 (NAND (OR (NAND D2 D2) D2) D2)) (AND
D3 D2))) D1) (AND D3 D0)) (NOR D3 (OR D0 D2))) (NOR D1
(AND (OR (NOR (AND D3 D3) D2) (NAND D0 (NOR D2 (AND D1
D0)))) (OR (OR D0 D3) (NOR D0 (NAND (OR (NAND D2 D2) D2)
D2)))))) (AND (AND D2 (NAND D1 (NAND (AND D3 (NAND D1
D3)) (AND D1 D1)))) (OR D3 (OR D0 (OR D0 D1)))))).
```

GP with ADFs: Even-4-Parity Function

GP with ADFs on even-4-parity problem (based on 168 independent runs)



- Cumulative probability of success, $P(M, i)$, is 93% and 99% by generation 9 and 50, respectively.
- If the problem is run through to generation 9, processing a total of
  4,000 $\times$ 10 gener $\times$ 2 runs = 80,000
  individuals is sufficient to yield a solution with 99% probability.

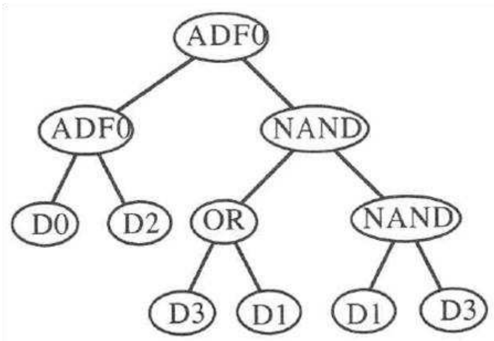
This is a considerable improvement in performance compared to the performance of GP without ADFs.

GP with ADFs: Even-4-Parity Function

An example of solution with 74 nodes.

```
(LIST3 (NAND (OR (AND (NOR ARG0 ARG1) (NOR (AND ARG1
           ARG1) ARG1)) (NOR (NAND ARG0 ARG0) (NAND ARG1
           ARG1))) (NAND (NOR (NOR ARG1 ARG1) (AND (OR
           (NAND ARG0 ARG0) (NOR ARG1 ARG0)) ARG0)) (AND
           (OR ARG0 ARG0) (NOR (OR (AND (NOR ARG0 ARG1)
           (NAND ARG1 ARG1)) (NOR (NAND ARG0 ARG0) (NAND
           ARG1 ARG1))) ARG1))))
       (OR (AND ARG2 (NAND ARG0 ARG2)) (NOR ARG1 ARG1))
       (ADF0 (ADF0 D0 D2) (NAND (OR D3 D1) (NAND D1
           D3)))).
```

- ADF0 defined in the first branch implements two-argument XOR function (odd-2-parity function).
- Second branch defines three-argument ADF1. It has no effect on the performance of the program since it is not called by the value-producing branch.
- VPB implements a function equivalent to
  ADF0 (ADF0 D0 D2) (EQV D3 D1)



GP with Hierarchical ADFs

Hierarchical form of ADFs: any function can call upon any other already-defined function.

- Hierarchy of function definitions where any function can be defined in terms of any combination of already-defined functions.
- All ADFs have the same number of dummy arguments. Not all of them have to be used in a particular function definition.
- VPB has access to all of the already defined functions.

Setup of the GP with hierarchical ADFs:

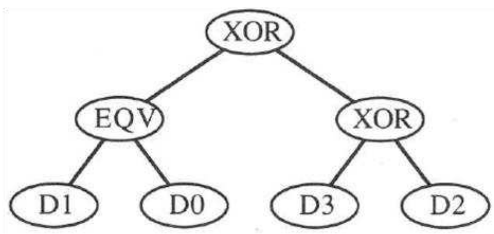
- ADF0 branch
  Functions: F={AND, OR, NAND, NOR}
  Terminals: A2 = {ARG0, ARG1, ARG2}
- ADF1 branch
  Functions: F = {AND, OR, NAND, NOR, ADF0}
  Terminals: A3 = {ARG0, ARG1, ARG2}
- Value-producing branch
  Functions: F={AND, OR, NAND, NOR, ADF0, ADF1}
  Terminals: T4 = {D0, D1, D2, D3}

GP with Hierarchical ADFs: Even-4-Parity Function

An example of solution with 45 nodes.

```
(LIST3 (NOR (NOR ARG2 ARG0) (AND ARG0 ARG2))
       (NAND (ADF0 ARG2 ARG2 ARG0)
             (NAND (ADF0 ARG2 ARG1 ARG2)
                   (ADF0 (OR ARG2 ARG1)
                         (NOR ARG0 ARG1)
                         (ADF0 ARG1 ARG0 ARG2))))
       (ADF0 (ADF1 D1 D3 D0)
             (NOR (OR D2 D3) (AND D3 D3))
             (ADF0 D3 D3 D2))).
```

- ADF0 defines a two-argument XOR function of variables ARG0 and ARG2 (it ignores ARG1).
- ADF1 defines a three-argument function that reduces to the two-argument equivalence function of the form (NOT (ADF0 ARG2 ARG0))
- VPB reduces to (ADF0 (ADF1 D1 D0) (ADF0 D3 D2))



Value-producing branch

Learning outcomes

After this lecture, a student shall be able to

- explain the main differences between GA and GP, and name typical application areas for GP;
- describe the representation that GP uses, including the associated crossover and mutation operators;
- explain how GP deals with real-valued constants in evolved solutions;
- explain two different ways how GP deals with the possibility that a crossover or mutation operator results in an invalid offspring;
- describe solution initialization methods used in GP (full, grow, ramped half-n-half, PTC);
- explain greedy over-selection operator and why it was invented;
- motivate and describe the semantic crossover operators;
- explain ”automatically defined functions” and motivate them;

Reading

[Koz94] John R. Koza. *Genetic Programming II: Automatic Discovery of Reusable Programs*. MIT Press, Cambridge, MA, USA, 1994.

[PLM08] Riccardo Poli, William B. Langdon, and Nicholas F. Mcphee. *A Field Guide to Genetic Programming*. Lulu Enterprises, UK Ltd, March 2008.