LANGUAGE THEORY with APPLICATIONS 2011

Cartesian Genetic Programming

Author: Michaela Šikulová

Genetic Programming

Evolutionary computation

- Non-deterministic search algorithms
- Based on aspects of Darwin's theory of evolution
- 1970s

Alan Turing (1948)

Idea of artificial evolution

Genetic programming (GP)

- Automatic evolution of computer programs
- Generating random programs (initial population)
- Evaluation of each program in population (determining fitness)
- Creating of new generation (using recombination, mutation)
- Till searched program is found

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Variants of GP

Tree-Based GP

- LISP expressions
- Unique path between any pair of nodes

Gramatical evolution (GE)

Grammar defined using Backus-Naur form (BNF)

Push GP

Lee Spector – stack-based computer language Push

Cartesian Graph-Based GP

• Graphs allow more than one path between any pair of nodes

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Cartesian Genetic Programming

Grew from a method of evolving digital circuits (Miller et al., 1997)

Programs represented as directed acyclic graphs

Applications:

- Self-modiffying digital circuits
- Evolution of Electronic Circuits
- Image processing
- Artificial art and creativity
- Medical applications

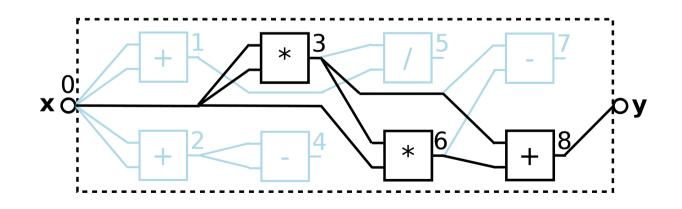
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Directed acyclic graph

 More general than tree - two directed paths from a single starting node meet back at the same ending node

Two-dimensional grid of computation nodes

- Coding nodes, non-coding nodes
- Similar to digital circuits



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A cartesian program is a 9-tuple

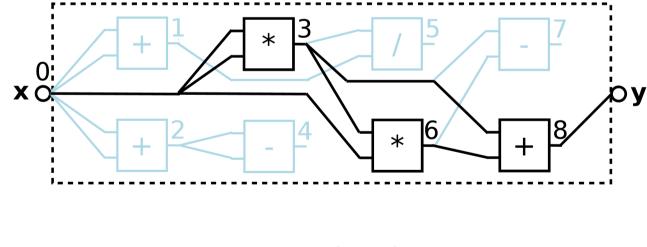
$$P = (G, n_{i'}, n_{o'}, n_{n'}, F, n_{f'}, n_{r'}, n_{c'}, I)$$

where

- *G* represents genotype as a sequence of integers
- n_i number of program inputs
- *n* number of program outputs
- *n*_n number of node input connections
- *F* set of node functions
- n_{r} number of node functions
- n_r number of rows
- *n*_c number of columns
- I levels back parameter (how many columns of cells may have their outputs connected to a node in current column)

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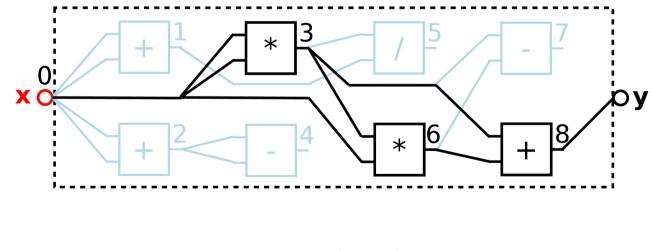
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 $G = (0, 0, 1, 0, 0, 1, 0, 0, 3, 2, 2, 2, 3, 1, 4, 3, 0, 3, 3, 6, 2, 3, 6, 1, 8),$
 $n_i = 1, n_o = 1, n_n = 2, F = \{+, -, *, /\}, n_f = 4, n_r = 2, n_c = 4, I = 4:$



 $y = \chi^2 + \chi^3$

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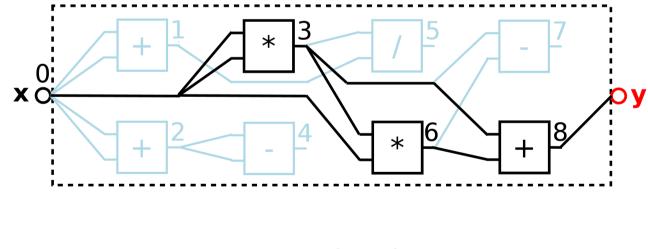
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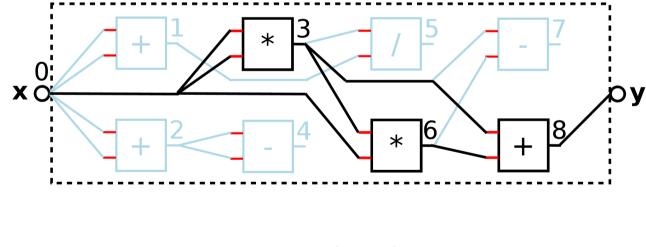
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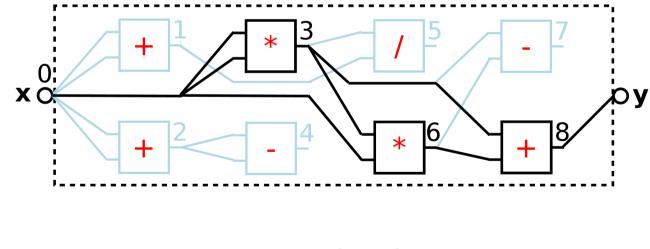
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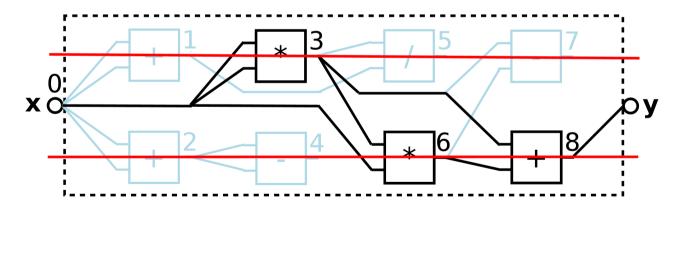
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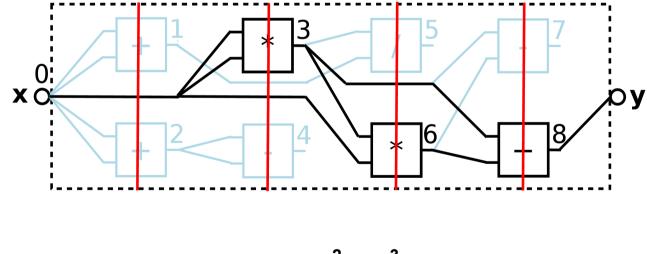
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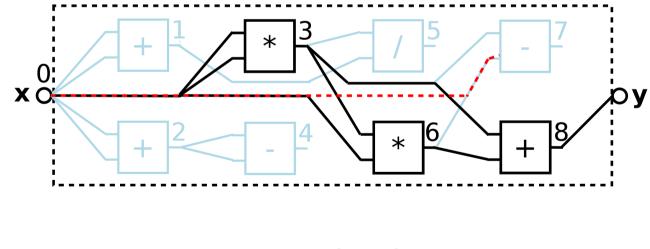
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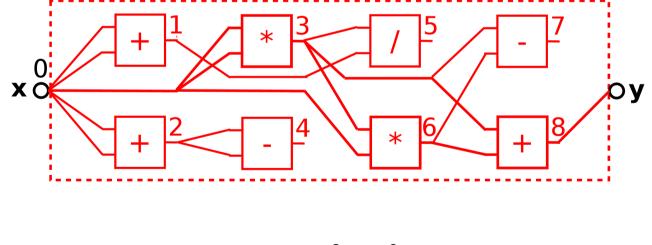
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 $y = x^2 + x^3$

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Cartesian Genetic Programming

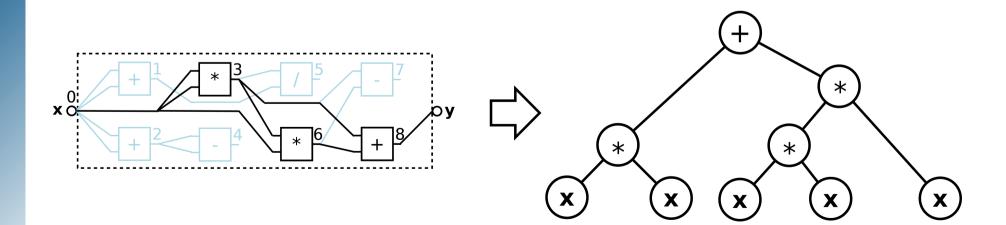
Training data set

- CGP training data set (TDS) is a set of n-tuples, where $n = n_i + n_o$.
- Cardinality of TDS in CGP typically goes from tens to ten thousands in dependence on application domain.
- A one-bit full adder TDS has 8 5-tuples
- Symbolic regression f(x) with 200 training data points has 200 2tuples

CP fitness evaluation

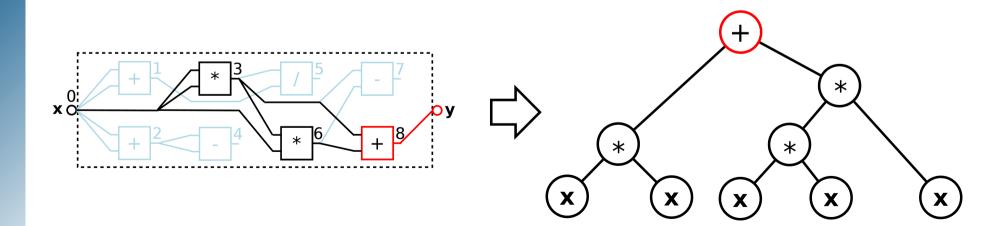
- A fitness evaluation is an assessment used to determine current fitness level of CP.
- CP fitness evaluation includes runing CP for every n-tuple in TDS (interpretation of CP).

- Similar to tree representation
- + Only use active nodes (phenotype)
- nodes can be evaluated many times



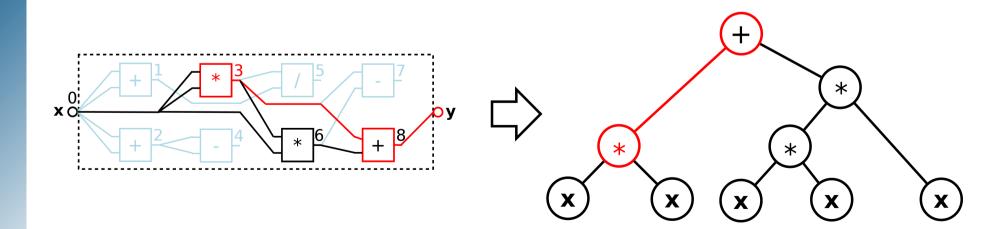
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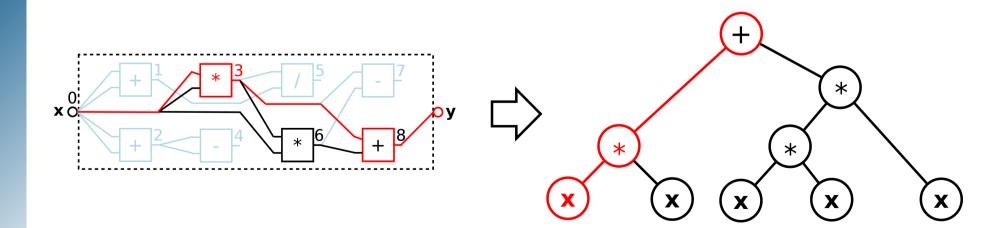
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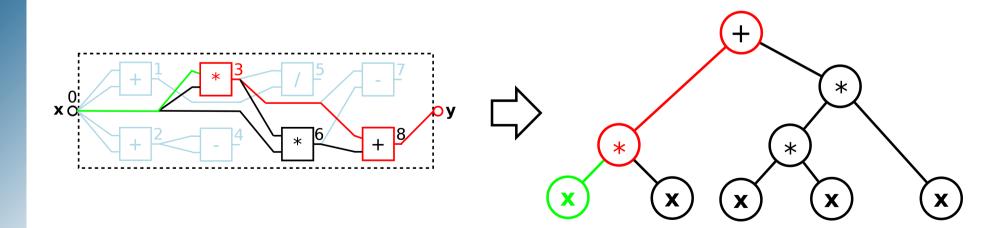
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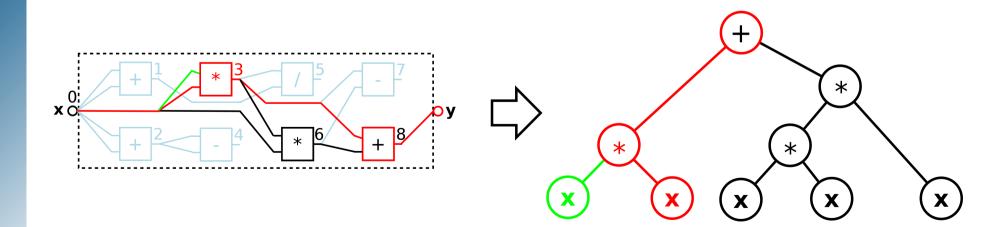
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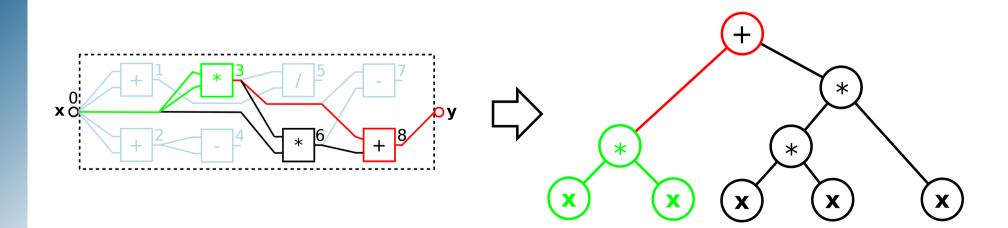
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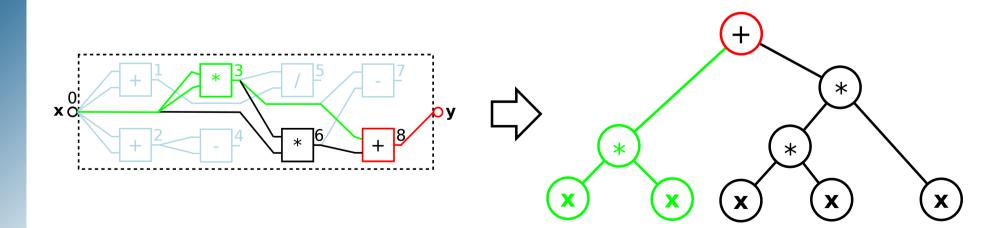
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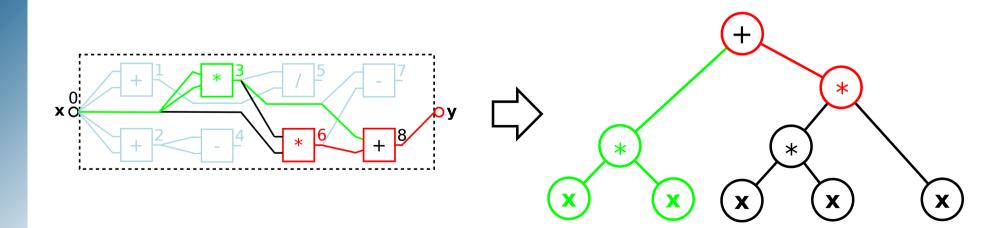
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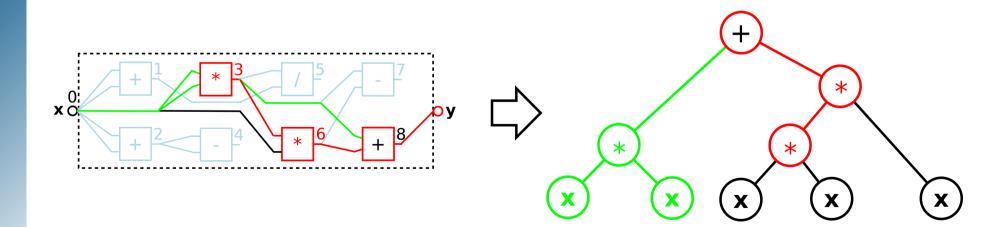
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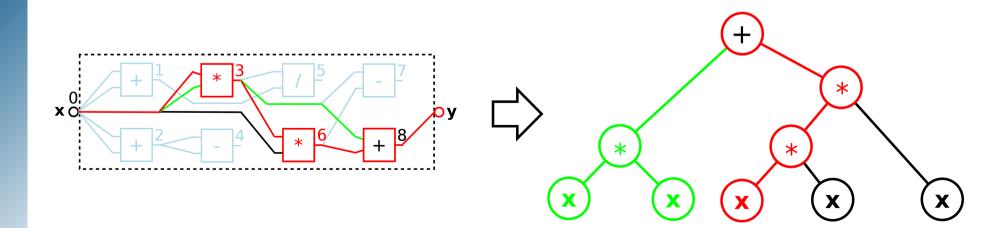
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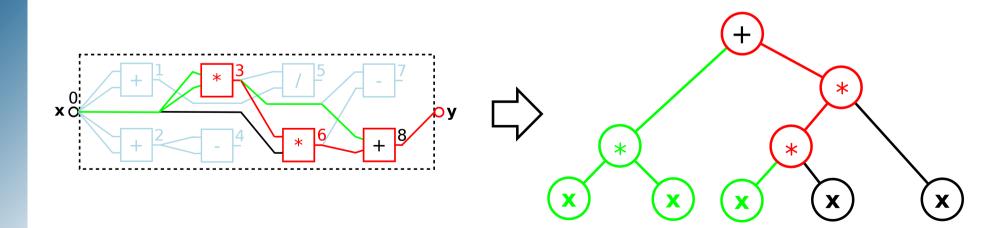
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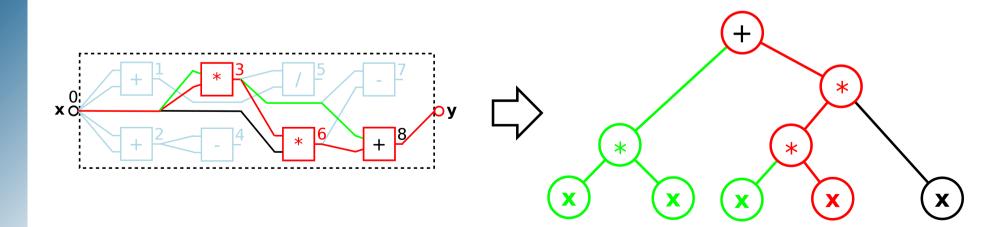
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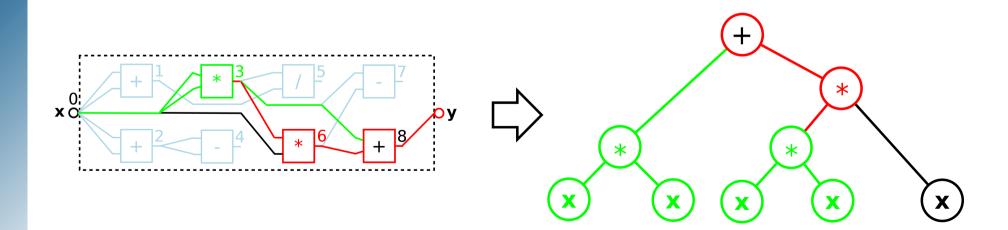
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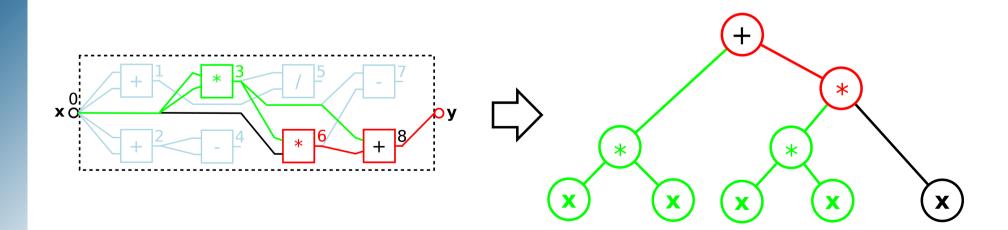
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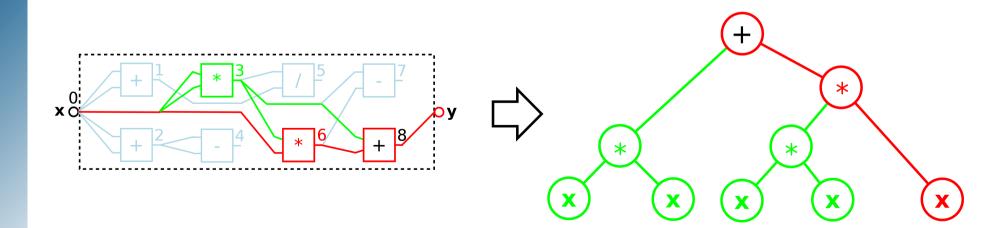
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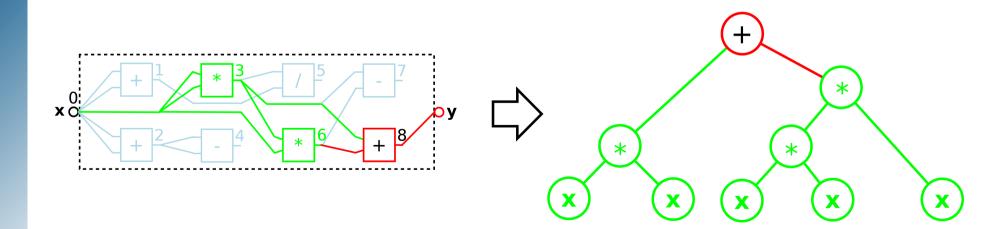
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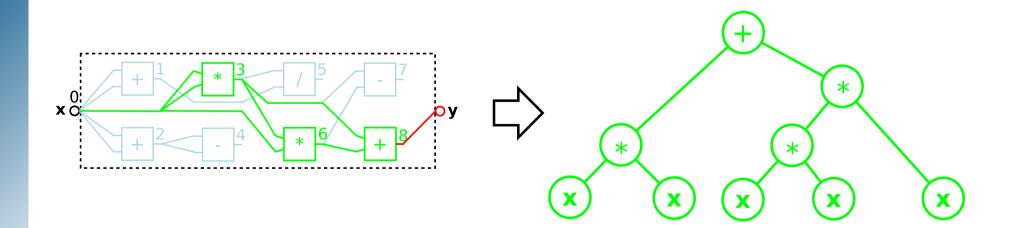
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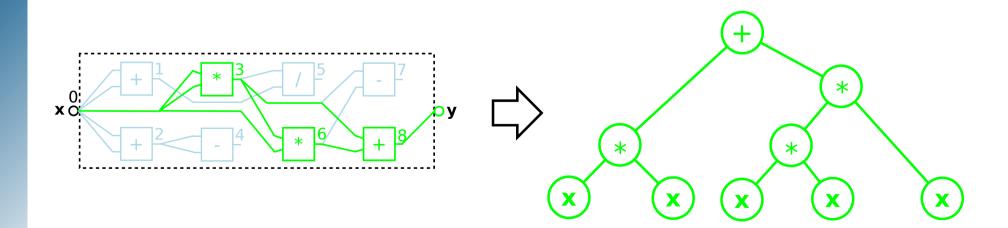
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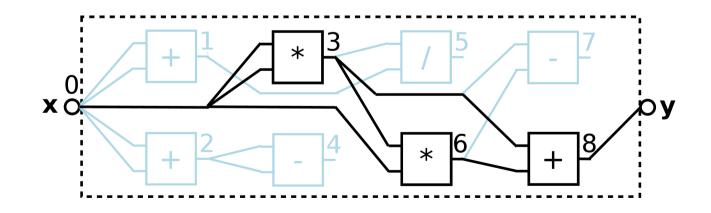
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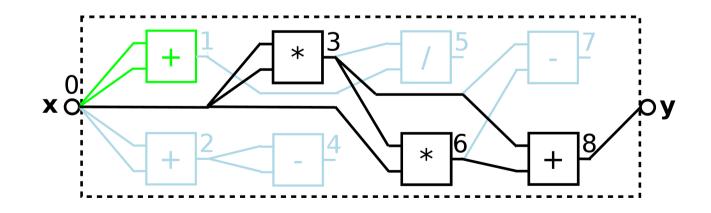
CP – Sequential Interpretation

- Similar to logical circuit evaluation
- + every node is evaluated exactly once
- inactive nodes are evaluated (Miller has shown, that most efficient percentage of inactive nodes is about 95%)



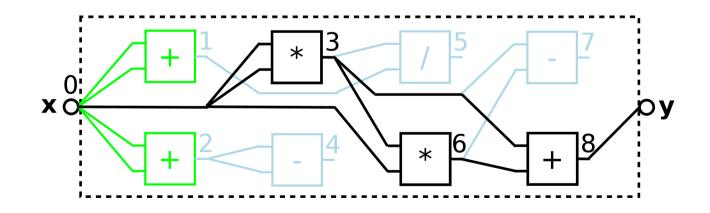
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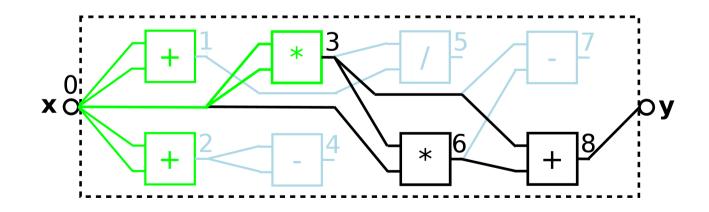
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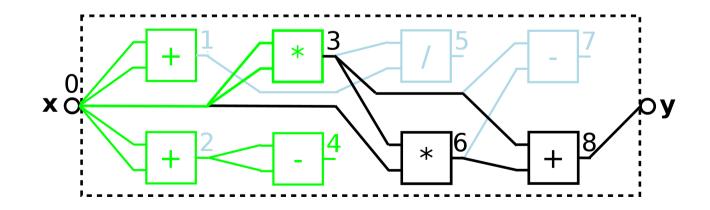
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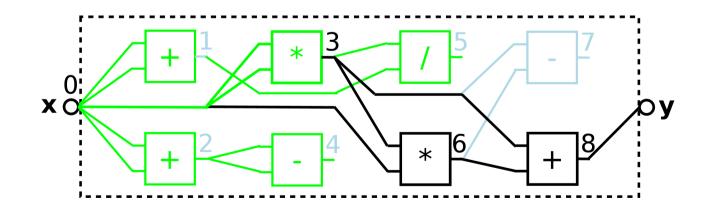
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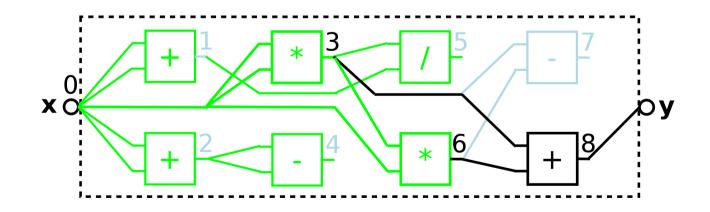
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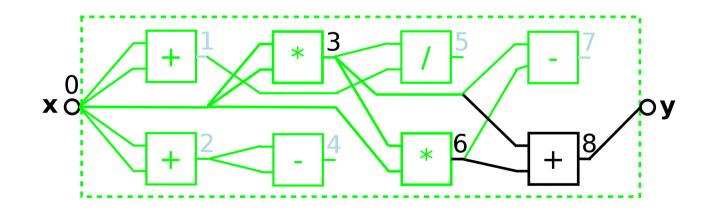
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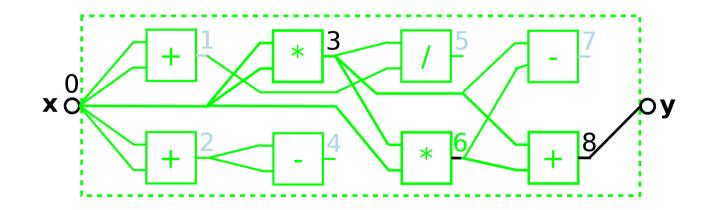
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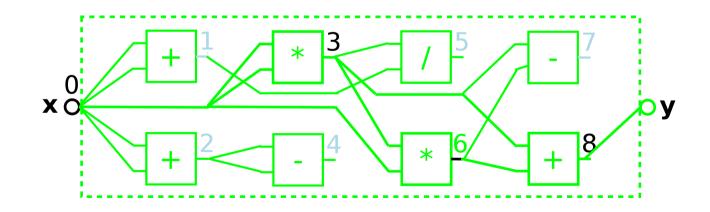
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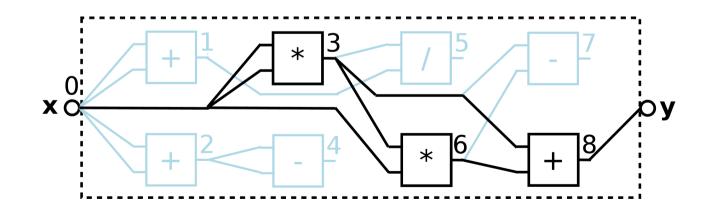
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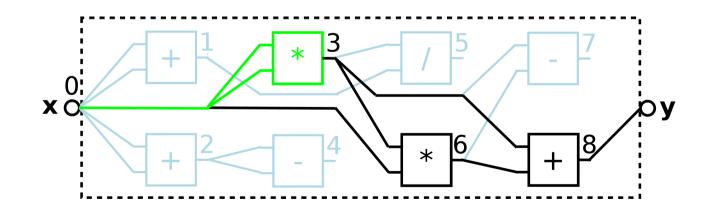
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- Active nodes selected using recursive descent
- CP sequentially interpreted for every element in TDS, but only active nodes
- + every active node is evaluated exactly once
- + inactive nodes are not evaluated
- additional active nodes selection



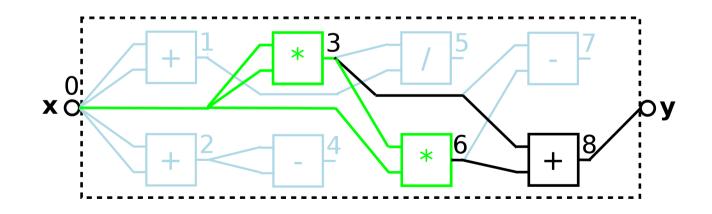
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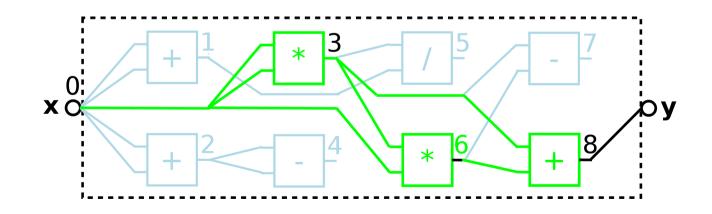
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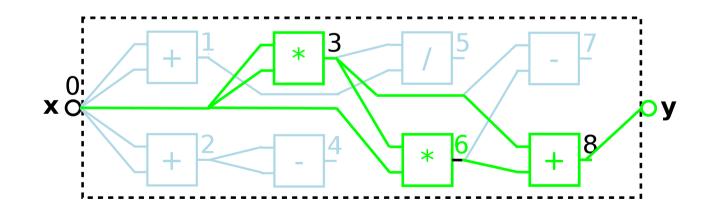
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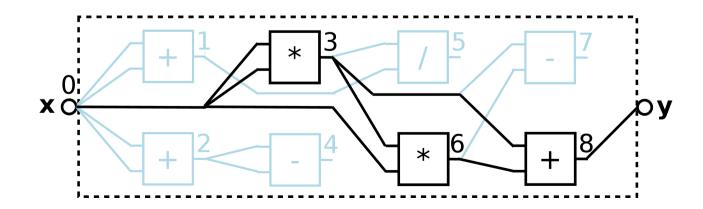
Evolution of CGP genotypes - Mutation

Mutation

- one-point mutation
- an allele at randomly chosen gene is changed to another valid random value
- mutation rate μ_r is a percentage of total number of genes L_g in the genotype. Number of mutations per genotype is then defined

$$\mu_{g} = \mu_{r} L_{g}$$

• μ_r is usually 4 %



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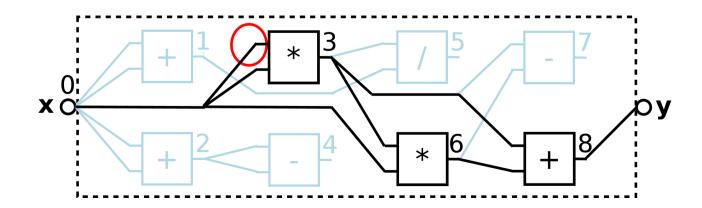
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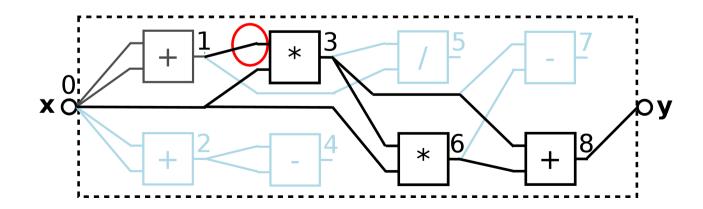
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Evolution of CGP genotypes

- 1) Randomly generate CPs in initial population
- 2) Select the fittest individual (parent) in population
- 3) Mutate the parent and generate offsprings (next generation)
- If solution is not found or the generation limit is not reached continue with 2)

References

- Miller, J. F.; Thomson, P.: Cartesian Genetic Programming. In Proc. of the Third European Conference on Genetic Programming (EuroGP2000), LNCS 1820, Springer, 2000: s. 121-132.
- Miller, J.F.: Cartesian Genetic Programming. Springer-Verlag (2011)
- Poli, R., Langdon, W.B., McPhee, N.F.: A field guide to genetic programming. Published via http://lulu.com and freely available at http://www.gp-field-guide.org.uk. (2008)

Thank you for your attention

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