Session : Genetic Programming

Course Title: Computational Intelligence
Course Code: 19CSE422A

Course Leader:
Dr. Vaishali R. Kulkarni
Assistant Professor, Department of Computer Science and Engineering
Faculty of Engineering and Technology
Ramaiah University of Applied Sciences, Bengaluru
Email: vaishali.cs.et@msruas.ac.in
Tel: +91-804-906-5555 Ext:2325
Website: www.msruas.ac.in/staff/fet_cse#Vaishali

Objectives of this Session

I wish to introduce:

1. Genetic Programming (GP)
2. Tree-based chromosome representation in GP
3. Fitness function evaluation in GP
4. Common crossover operators in GP
5. Common mutation operators in GP
6. Building block GP (BGP) and
7. Applications of GP

Intended Outcomes of this Session

At the end of this session, the student will be able to:

1. Distinguish GP from a GA
2. Represent a program code or a decision tree using a tree
3. Judge root and leaf nodes of a tree
4. Evaluate the fitness of a tree
5. Perform crossover and mutation on trees
6. Distinguish standard GP from BGP and
7. Summarize the application potential of GP

Recommended Resources for this Session

1. Engelbrecht, A. P. (2007). *Computational intelligence: An introduction*. Chichester, England, John Wiley & Sons.

2. De Jong, K. A. (2012). *Evolutionary Computation: A Unified Approach*. New York, USA, Bradford Books.

3. Konar, A. (2005). *Computational Intelligence: Principles, Techniques and Applications*. Secaucus, NJ, USA, Springer-Verlag New York, Inc.

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- **Domain-specific grammar:** A grammar accurately reflects the problem to be solved. The defined grammar should be good enough to represent any possible solution

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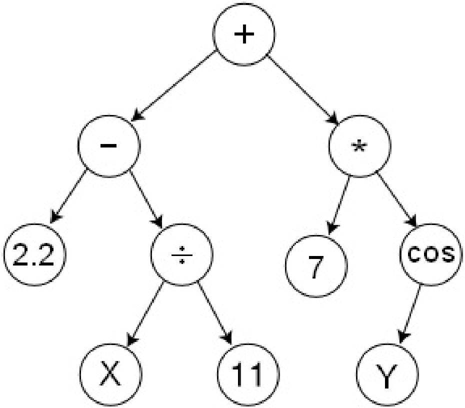

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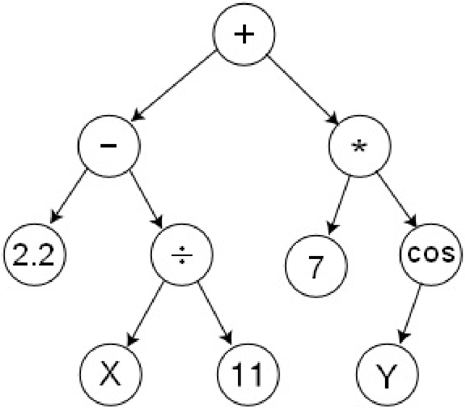

$$\left(2.2 - \frac{X}{11}\right) + \left(7 \times \cos Y\right)$$

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- In some applications, individuals represents a decision tree. The fitness of individuals is calculated as the classification accuracy of the corresponding decision tree

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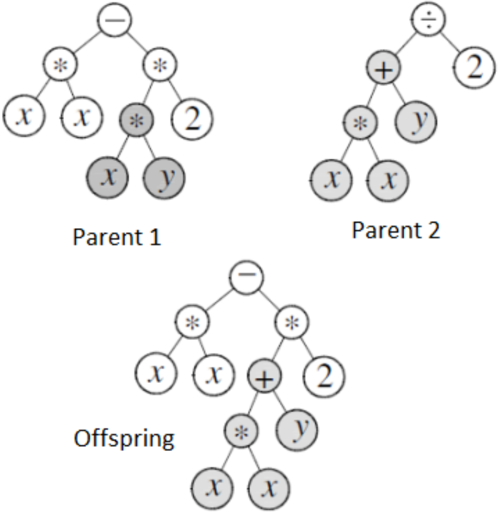
- **Generating one offspring:** A random node is selected within each of the parents. Crossover then replaces the corresponding subtree in the one parent by that of the other parent
- **Generating two offspring:** A random node is selected in each of the two parents. The corresponding subtrees are swapped to create two offspring

One-Offspring Crossover



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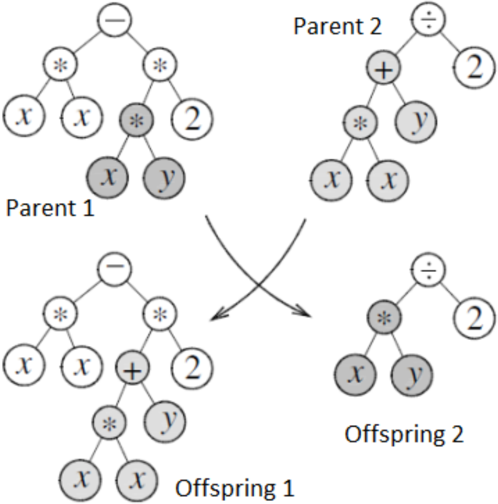

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- **Trunc mutation:** A function node is randomly selected and replaced by a random terminal node

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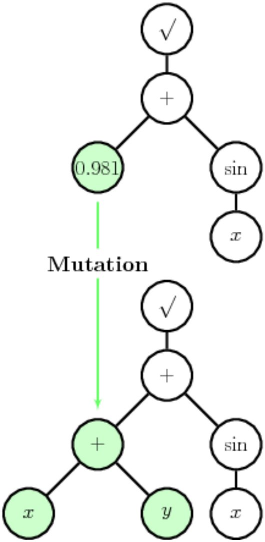

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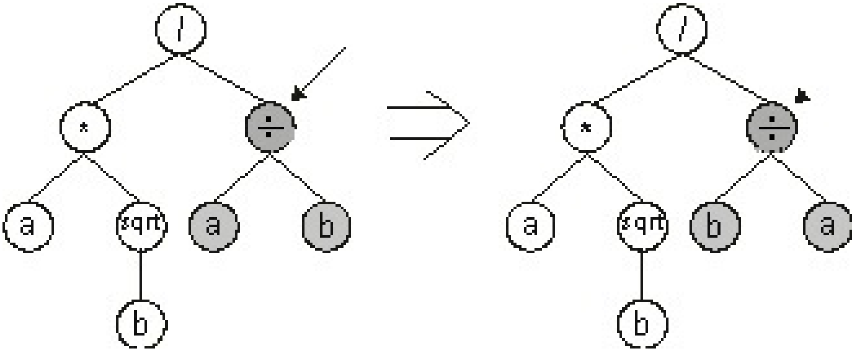

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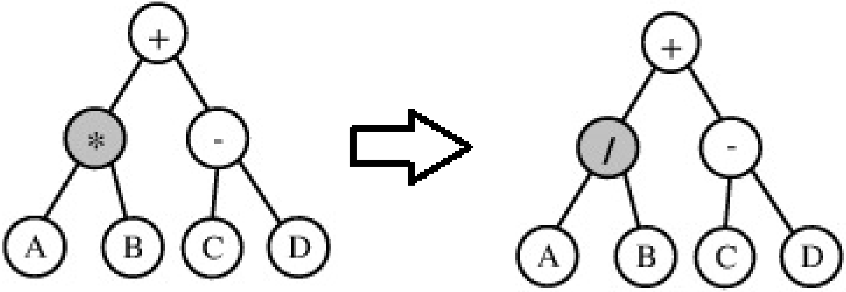

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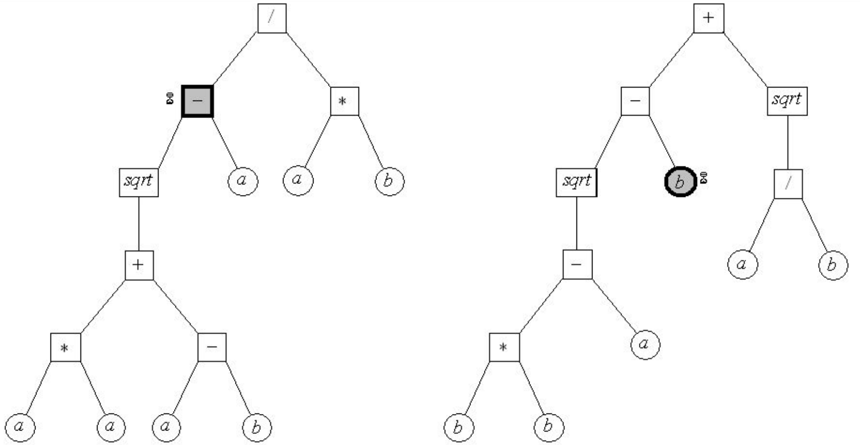

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- Bioinformatics
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5. Applications of GPs include the following: Decision trees, Game-playing, Bioinformatics, Data mining and Robotics

Any Questions?

Thank You