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# Genetic Programming: Syntax & Semantics

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## Overview

### Genetic Programming: Syntax & Semantics

#### 1. Setting the Stage

- ▶ What is Natural Computing?
- ▶ What is Evolutionary Computation?
- ▶ An Introduction to Genetic Programming (GP)

#### 2. Grammar-based GP

#### 3. Semantic methods & Open Issues in GP



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Natural Computing  
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## Semantic Methods & Open Issues in GP



## Semantic Methods

- ▶ Over dependence on fitness (single point)
- ▶ Credit Assignment
- ▶ Semantic analysis of evolving populations
- ▶ Semantic-aware program construction
- ▶ Semantic-aware search operators

# Attribute Grammars - Adding Semantics to Solution Construction

$$\text{maximise } \sum_{j=1}^n p_j x_j \quad (1)$$

$$\text{subject to } \sum_{j=1}^n w_{ij} x_j \leq c_i, \quad i = 1 \dots m \quad (2)$$

$$x_j \in \{0, 1\}, \quad j = 1 \dots n \quad (3)$$

1

$S \rightarrow K$   $\text{lim}(K) = \text{lim}(S)$

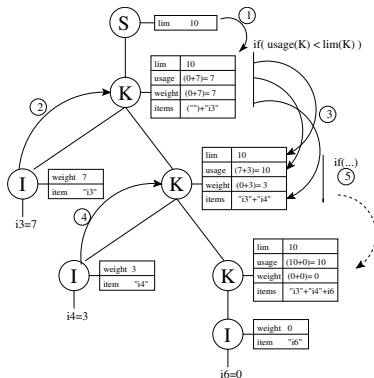
$K \rightarrow I$   $\text{weight}(K) = \text{weight}(K) + \text{weight}(I)$   
**Condition:**  $\text{if}(\text{usage}(K) + \text{weight}(I) \leq \text{lim}(K))$   
 $\text{items}(K) = \text{items}(K) + \text{item}(I)$

$K_1 \rightarrow IK_2$   $\text{weight}(K_1) = \text{weight}(K_1) + \text{weight}(I)$   
 $\text{items}(K_1) = \text{items}(K_1) + \text{item}(I)$   
 $\text{usage}(K_1) = \text{usage}(K_1) + \text{weight}(I)$   
**Condition:**  $\text{if}(\text{usage}(K_1) < \text{lim}(K_1))$   
 $\text{lim}(K_2) = \text{lim}(K_1)$   
 $\text{usage}(K_2) = \text{usage}(K_1)$   
 $\text{items}(K_2) = \text{items}(K_1)$

$I \rightarrow i_1$   $\text{item}(I) = "i_1"$   
**Condition:**  $\text{if}(\text{notin knapsack?}(i_1))$   
 $\text{weight}(I) = \text{weight}(i_1)$

⋮

$I \rightarrow i_n$   $\text{item}(I) = "i_n"$   
**Condition:**  $\text{if}(\text{notin knapsack?}(i_n))$   
 $\text{weight}(I) = \text{weight}(i_n)$



1 Where,  $p_j$  refers to the profit, or worth of item  $j$ ,  $x_j$  refers to the item  $j$ ,  $w_{ij}$  refers to the relative-weight of item  $j$ , with respect to knapsack  $i$ , and  $c_i$  refers to the capacity, or weight-constraint of knapsack  $i$ . There are present  $j = 1 \dots n$  items, and  $i = 1 \dots m$  knapsacks.



## Semantic-aware search operators

- ▶ Crossover
- ▶ Mutation
- ▶ Semantic Locality & Diversity

## Semantic Similarity Crossover

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### Algorithm 1: Semantic Similarity based Crossover

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```

select Parent 1  $P_1$ ;
select Parent 2  $P_2$ ;
Count=0;
while  $Count < Max\_Trial$  do
    choose a random crossover point  $Subtree_1$  in  $P_1$ ;
    choose a random crossover point  $Subtree_2$  in  $P_2$ ;
    generate a number of random points ( $P$ ) on the problem domain;
    calculate the SSD between  $Subtree_1$  and  $Subtree_2$  on  $P$ 
    if  $Subtree_1$  is similar to  $Subtree_2$  then
        execute crossover;
        add the children to the new population;
        return true;
    else
        Count=Count+1;
if  $Count = Max\_Trail$  then
    choose a random crossover point  $Subtree_1$  in  $P_1$ ;
    choose a random crossover point  $Subtree_2$  in  $P_2$ ;
    execute crossover;
    return true;

```

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## Sampling Semantic Distance

Based on SS, we define a *Sampling Semantic Distance* (SSD) between two subtrees. It differs from that in [24] in using the mean absolute difference in SS values, rather than (as before) the sum of absolute differences. Let  $U = (u_1, u_2, \dots, u_N)$  and  $V = (v_1, v_2, \dots, v_N)$  represent the SSs of two subtrees,  $S_1$  and  $S_2$ ; then the SSD between  $S_1$  and  $S_2$  is defined in equation 1:

$$\text{SSD}(S_1, S_2) = \frac{\sum_{i=1}^N |u_i - v_i|}{N} \quad (1)$$

We follow [24] in defining a semantic relationship, *Semantic Similarity* (SSi), on the basis that the exchange of subtrees is most likely to be beneficial if they are not semantically identical, but also not too different. Two subtrees are semantically similar if their SSD lies within a positive interval. The formal definition of SSi between subtrees  $S_1$  and  $S_2$  is given in the following equation:

$$\text{SSi}(S_1, S_2) = \text{TruthValue}(\alpha < \text{SSD}(S_1, S_2) < \beta)$$

where  $\alpha$  and  $\beta$  are two predefined constants, the *lower* and *upper* bounds for semantics sensitivity. In general, the best values for these semantic sensitivity bounds are problem dependent. In this work we set  $\alpha = 10^{-4}$  and several values of  $\beta$  were tested.

Functions	Training Data	Testing Data
$F_1 = x^4 + x^3 + x^2 + x$	20 random points $\subseteq [-1, 1]$	30 points $\subseteq [0:0.05:1.5]$
$F_2 = x^3 - x^2 - x - 1$	20 random points $\subseteq [-1, 1]$	30 points $\subseteq [0:0.05:1.5]$
$F_3 = \arcsin(x)$	20 random points $\subseteq [-1, 0]$	30 points $\subseteq [-1:0.67:1]$
$F_4 = \sqrt{x}$	20 random points $\subseteq [0, 2]$	30 points $\subseteq [0:0.1:3]$
$F_5 = 0.3\sin(2\pi x)$	20 random points $\subseteq [-1, 1]$	30 points $\subseteq [0:0.05:1.5]$
$F_6 = \cos(3x)$	20 random points $\subseteq [-1, 1]$	30 points $\subseteq [0:0.05:1.5]$

## Semantic vs. Syntactic Locality

**Table 3.** Comparison of the effects of SC, SSC and SySC on GP performance (mean of the best fitness). The values are scaled by  $10^2$ .

Xovers	$F_1$	$F_2$	$F_3$	$F_4$	$F_5$	$F_6$
SC	1.51	3.07	0.37	0.96	4.36	1.48
SySC6	1.63	3.20	0.46	1.06	4.42	1.46
SySC8	1.49	3.50	0.43	0.99	4.36	1.98
SySC10	1.56	3.08	0.39	1.18	4.41	2.04
SSC04	0.78	1.30	0.20	0.58	3.36	0.67
SSC05	0.85	1.40	0.21	0.61	3.28	0.81
SSC06	0.87	1.70	0.22	0.38	3.44	0.92



## Open Issues

1. Identifying appropriate representations for GP
2. Fitness landscapes & problem difficulty in GP
3. Static vs. Dynamic Problems
4. The influence of biology on GP
5. Open-ended evolution in GP
6. Generalisation in GP
7. GP Benchmarks
8. GP and Modularity
9. The Complexity of GP



## Open Issues

### 10 Miscellaneous issues:

- ▶ The Halting Problem
- ▶ How much Domain Knowledge?
- ▶ GP Theory
- ▶ Constants in GP
- ▶ Bloat
- ▶ Distributed GP
- ▶ The Elephant in the Room!



## Sample Literature

### Semantic Methods & Open Issues

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- ▶ Krawiec K (2011) Semantically embedded genetic programming: automated design of abstract program representations. In: Proceedings of the 13th annual conference on Genetic and evolutionary computation (GECCO 2011), pp 1379-1386, ACM Press
- ▶ Krawiec K, Lichocki P (2009) Approximating geometric crossover in semantic space. In: Proceedings of the 11th Annual conference on Genetic and evolutionary computation (GECCO 2009), pp 987-994, ACM Press

## Sample Literature (continued)

### Semantic Methods & Open Issues

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- ▶ Nguyen Q U (2011) Examining Semantic Diversity and Semantic Locality of Operators in Genetic Programming. PhD Thesis. University College Dublin
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- ▶ Moraglio A., Krawiec K., Johnson C. (2012) Geometric Semantic Genetic Programming. In *PPSN 2012*, p21-31. Springer.
- ▶ D. R. White et al., (2013). "Better GP benchmarks: community survey results and proposals," *Genetic Programming and Evolvable Machines*, 14(1):3–29.
- ▶ O'Neill M., Vanneschi L., Gustafson S., Banzhaf W. (2010). Open Issues in Genetic Programming. *Genetic Programming & Evolvable Machines*. 11(3-4):339-363.



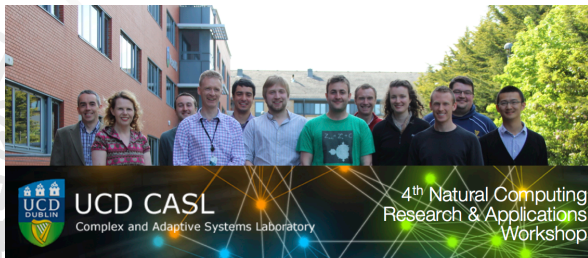
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Thank You



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