

A GP Approach to QoS-Aware Web Service Composition including Conditional Constraints

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IEEE Congress on Evolutionary Computation, 25-28 May 2015

Introduction

Service-Oriented Architecture (SOA): Organise processes and data in reusable modules for integration into new applications.

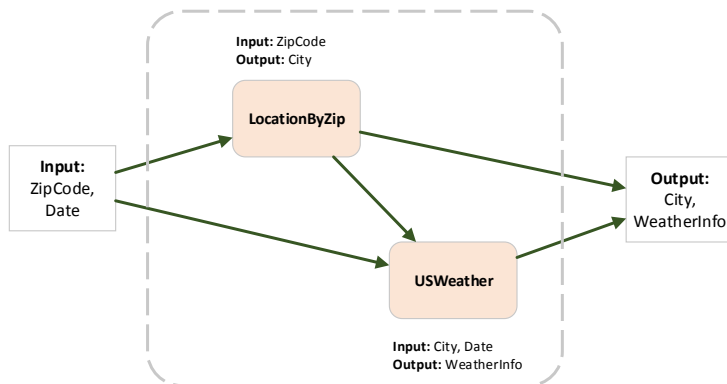


Web service

A functionality module that provides operations accessible over the network via a standard communication protocol.

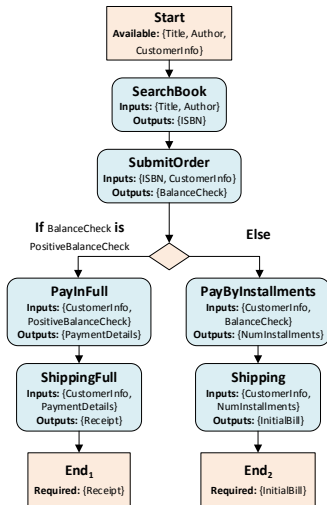
Web Service Composition

The combination of Web services to achieve a more complex task.
Fully automated scenario:



New weather by zip code service

A Composition Example with Branching



Certain compositions require alternative paths according to runtime values.

Example: Depending on balance, pay in full or pay in installments.

Composition Dimensions

- 1 Solution feasibility:** Service inputs and outputs must be properly linked (e.g. *City* → *Location*, but not *PhoneNumber* → *Location*).
- 2 Conditional constraints:** Condition leading to multiple possible execution paths (e.g. if *City* is a *NewZealandCity*, produce *WindForecast* instead of *GeneralForecast*).
- 3 Quality of Service (QoS):** The overall quality of the composition (e.g. *lowest execution time*, *lowest cost*).

Existing Approaches

AI Planning

Build a solution service by service.

Dimensions: *Solution feasibility, conditional constraints.*

Evolutionary Computation (EC)

Improve population of solutions over multiple generations.

Dimensions: *Solution feasibility, QoS.*

Hybrid Approaches

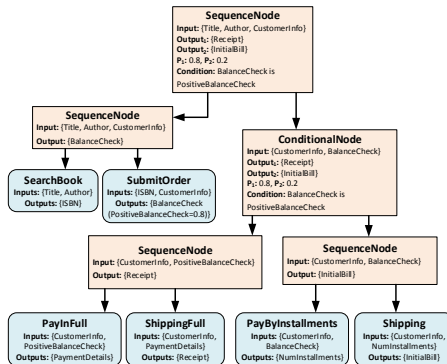
Combine AI planning and EC ideas.

Dimensions: *Solution feasibility, QoS.*

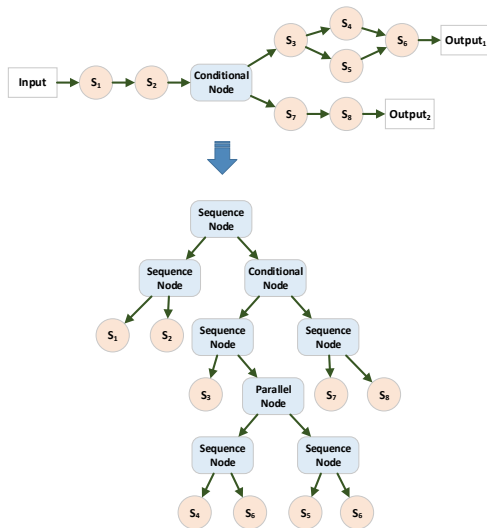
Goal

To propose a Genetic Programming (GP) composition approach that simultaneously considers all dimensions.

- 1 Trees preserve solution feasibility.
- 2 Conditions encoded in trees.
- 3 Optimisation performed on QoS.



Candidate Representation



- Tree equivalent to graph composition.
- Parallel, sequential, and conditional represented as non-terminal nodes.
- Candidate services as terminal nodes.

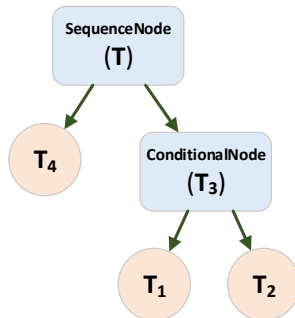
Population Initialisation

An algorithm is used to create a candidate in graph format, and then translate it into a tree representation.

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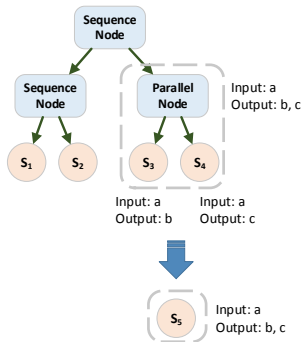
Input :  $I, O_1, O_2, C, P$ 
Output: candidate tree  $T$ 
1: if  $O_2 \neq \emptyset$  then
2:    $G_1 \leftarrow \text{createGraph}(I \cup C.\text{if}, O_1)$ ;
3:    $G_2 \leftarrow \text{createGraph}(I \cup C.\text{else}, O_2)$ ;
4:    $T_1 \leftarrow \text{toTree}(G_1.\text{input})$ ;
5:    $T_2 \leftarrow \text{toTree}(G_2.\text{input})$ ;
6:    $T_3 \leftarrow \text{new ConditionalNode}(C)$ ;
7:    $T_3.\text{leftChild} \leftarrow T_1$ ;
8:    $T_3.\text{rightChild} \leftarrow T_2$ ;
9:   if  $C \sqsubseteq I$  then
10:     $T_3.\text{prob} \leftarrow P$ ;
11:    return  $T_3$ ;
12:   else
13:     $G_4 \leftarrow \text{createGraph}(I, C.\text{else})$ ;
14:     $T_4 \leftarrow \text{toTree}(G_4.\text{input})$ ;
15:     $T_3.\text{prob} \leftarrow T_4.\text{final}.P$ ;
16:     $T \leftarrow \text{new SequenceNode}()$ ;
17:     $T.\text{leftChild} \leftarrow T_4$ ;
18:     $T.\text{rightChild} \leftarrow T_3$ ;
19:    return  $T$ ;
20:   end
21: else
22:    $G \leftarrow \text{createGraph}(I, O_1)$ ;
23:    $T \leftarrow \text{toTree}(G.\text{input})$ ;
24:   return  $T$ ;
25: end

```

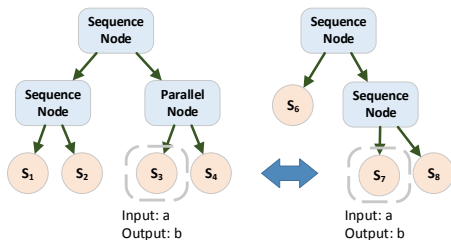


Mutation and Crossover

Mutation: Selects random node and replaces it with equivalent subtree.



Crossover: Swaps any two equivalent terminal nodes.

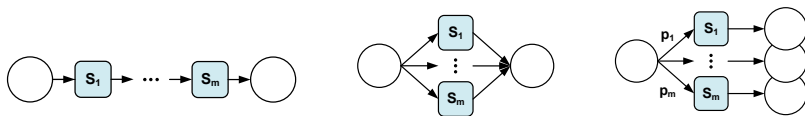


Fitness Function

Measures the overall quality of a composition candidate (minimising).

$$fitness_i = w_1(1 - A_i) + w_2(1 - R_i) + w_3 T_i + w_4 C_i$$

$$\text{where } \sum_{i=1}^4 w_i = 1$$



Experiments

- Lack of datasets supporting composition with branching.
- Lack of comparable approaches that produce solutions with multiple output possibilities.

Decision: Create datasets, execute for conditional compositions and also for each branch separately.

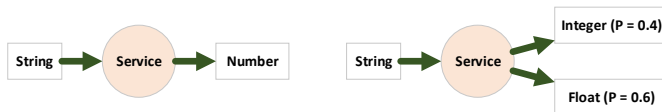
Parameters:

Independent runs	50	Elitism candidates	1
Population size	20	Tournament size	7
Crossover probability	0.9	Fitness weights	0.25 (all)
Mutation probability	0.1		

Creation of Datasets

Modified from WSC2008.

- Can be extended to contain QoS.
- Provides ontology of input and output values.



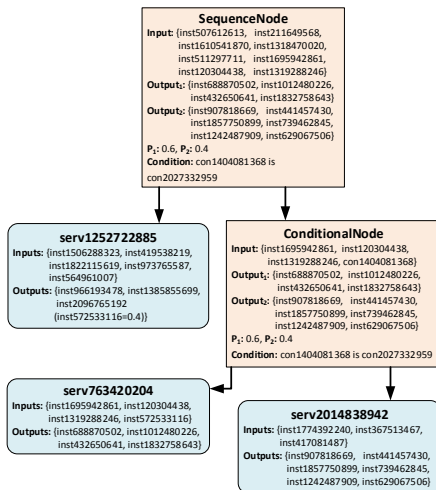
Tasks requiring branching were created.

Results

Set (size)	Conditional	
	Avg. fitness	Avg. time (s)
1 (158)	0.60 \pm 0.01	1.29 \pm 0.10
2 (558)	0.71 \pm 0.01	2.83 \pm 0.25
3 (604)	0.63 \pm 0.01	13.29 \pm 1.23
4 (1041)	0.72 \pm 0.05	6.15 \pm 0.57
5 (1090)	0.70 \pm 0.01	11.76 \pm 0.95
6 (2198)	0.66 \pm 0.02	92.39 \pm 11.35
7 (4113)	0.58 \pm 0.01	97.34 \pm 13.71
8 (8119)	0.66 \pm 0.01	326.39 \pm 37.66

Set (size)	Non-conditional			
	If branch		Else branch	
	Avg. fitness	Avg. time (s)	Avg. fitness	Avg. time (s)
1 (158)	0.51 \pm 0.00	0.56 \pm 0.14	0.59 \pm 0.04	0.72 \pm 0.08
2 (558)	0.59 \pm 0.08	1.49 \pm 0.53	0.69 \pm 0.02	1.53 \pm 0.19
3 (604)	0.37 \pm 0.00	4.39 \pm 0.77	0.79 \pm 0.00	7.10 \pm 0.91
4 (1041)	0.69 \pm 0.06	4.51 \pm 1.18	0.74 \pm 0.43	3.57 \pm 0.43
5 (1090)	0.45 \pm 0.00	5.73 \pm 0.76	0.69 \pm 0.01	6.49 \pm 0.74
6 (2198)	0.41 \pm 0.06	58.30 \pm 12.77	0.65 \pm 0.02	52.31 \pm 5.79
7 (4113)	0.36 \pm 0.00	44.84 \pm 5.93	0.69 \pm 0.03	51.73 \pm 4.26
8 (8119)	0.47 \pm 0.00	106.12 \pm 7.15	0.77 \pm 0.00	186.90 \pm 20.01

Solution Example



Conclusions

Novel approach addresses **three composition dimensions** simultaneously (fully feasible, contain branches, quality-optimised).

- Solutions found with similar performance as non-branching technique.

Future work: More than two branches, more complex branching conditions, analysis of convergence behaviour.

Thank you!

Questions?