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

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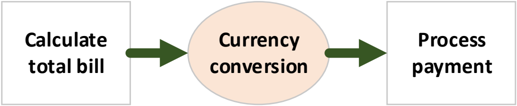
Introduction

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



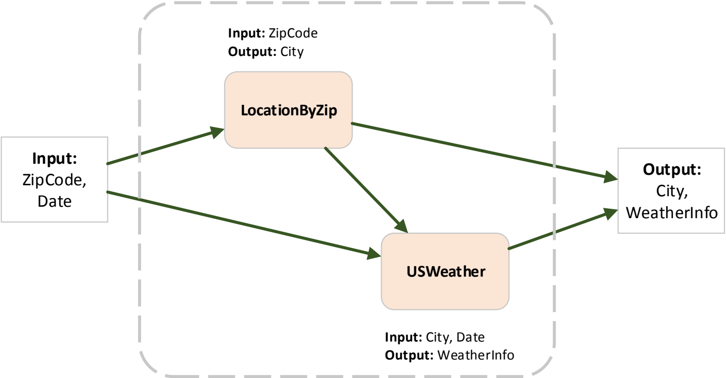
Web service

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

Web Service Composition

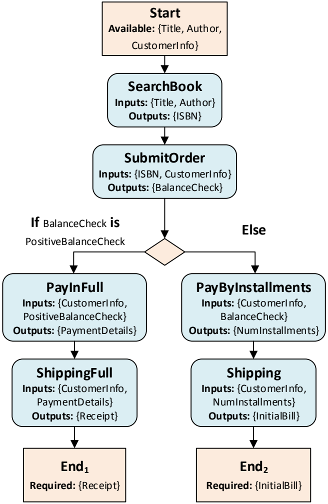
The combination of Web services to achieve a more complex task.

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. **Functional correctness:** Service inputs and outputs must be properly linked (e.g. *FourDigitNumber* → *ZipCode*, but not *FourDigitNumber* → *City*).

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: *Functional correctness, conditional constraints.*

Evolutionary Computation (EC)

Improve population of solutions over multiple generations.
Dimensions: *Functional correctness, QoS.*

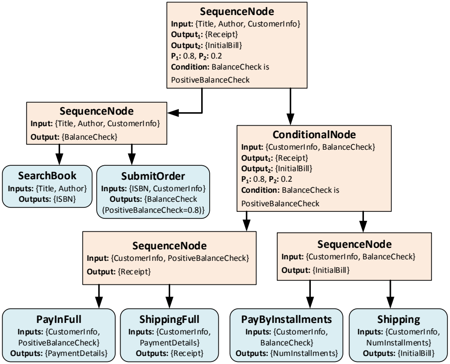
Hybrid Approaches

Combine AI planning and EC ideas.
Dimensions: *Functional correctness, QoS.*

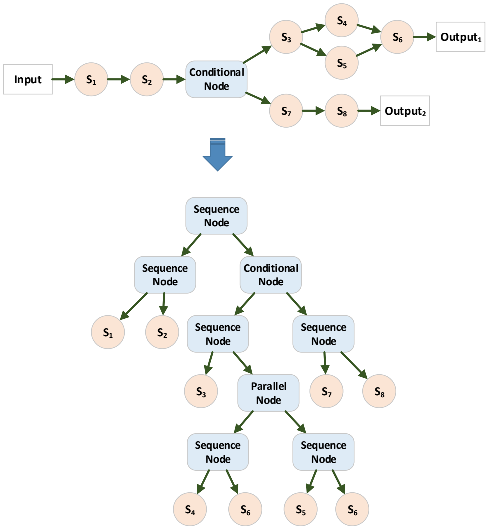
Goal

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

1. Trees preserve functional correctness.
2. Conditions encoded in trees.
3. Optimisation performed on QoS.



Candidate Representation

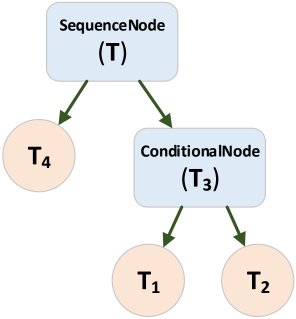


- Tree equivalent to graph composition.
- Parallel, sequential, and conditional represented as non-terminal nodes.
- Candidate services as terminal nodes.

Population Initialisation

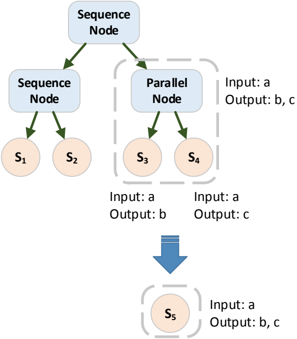
An algorithm is used to create a candidate in graph format, and then translate it into a tree representation.

```
Input  : I, O1, O2, C, P
Output: candidate tree T
if O2 ≠ ∅ then
    G1 ← createGraph(I ∪ C.if, O1);
    G2 ← createGraph(I∪C.else, O2);
    T1 ← toTree(G1.input);
    T2 ← toTree(G2.input);
    T3 ← new ConditionalNode(C);
    T3.leftChild ← T1;
    T3.rightChild ← T2;
    if C ⊑ I then
        T3.prob ← P;
        return T3;
    else
        G4 ← createGraph(I, C.else);
        T4 ← toTree(G4.input);
        T3.prob ← T4.final.P;
        T ← new SequenceNode();
        T.leftChild ← T4;
        T.rightChild ← T3;
        return T;
    end
else
    G ← createGraph(I, O1);
    T ← toTree(G.input);
    return T;
end
```

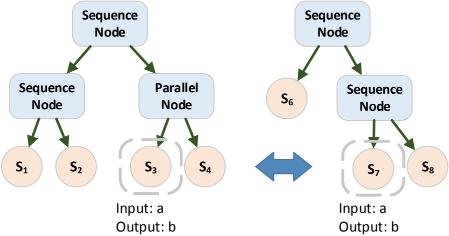


Mutation and Crossover

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



Crossover: Swaps any two equivalent terminal nodes.

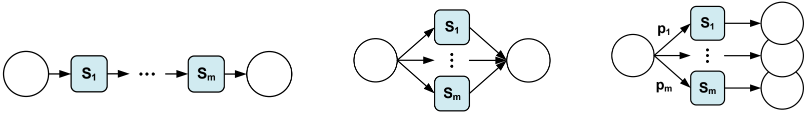


Fitness Function

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

	Conditional	
Set (size)	Avg. fitness	Avg. time (s)
1 (158)	0.601 ± 0.013	1.290 ± 0.100
2 (558)	0.712 ± 0.009	2.829 ± 0.250
3 (604)	0.631 ± 0.008	13.285 ± 1.229
4 (1041)	0.718 ± 0.048	6.146 ± 0.574
5 (1090)	0.698 ± 0.005	11.759 ± 0.948
6 (2198)	0.662 ± 0.017	92.392 ± 11.353
7 (4113)	0.578 ± 0.010	97.344 ± 13.705
8 (8119)	0.656 ± 0.005	326.387 ± 37.659

	Non-conditional			
	If branch		Else branch	
Set (size)	Avg. fitness	Avg. time (s)	Avg. fitness	Avg. time (s)
1 (158)	0.508 ± 0.000	0.563 ± 0.144	0.588 ± 0.037	0.718 ± 0.079
2 (558)	0.588 ± 0.084	1.490 ± 0.526	0.694 ± 0.016	1.527 ± 0.194
3 (604)	0.365 ± 0.000	4.387 ± 0.768	0.788 ± 0.000	7.099 ± 0.906
4 (1041)	0.689 ± 0.064	4.510 ± 1.177	0.741 ± 0.429	3.568 ± 0.429
5 (1090)	0.446 ± 0.000	5.726 ± 0.755	0.688 ± 0.011	6.491 ± 0.743
6 (2198)	0.412 ± 0.063	58.295 ± 12.765	0.645 ± 0.024	52.308 ± 5.785
7 (4113)	0.363 ± 0.000	44.838 ± 5.926	0.688 ± 0.032	51.725 ± 4.260
8 (8119)	0.474 ± 0.000	106.119 ± 7.152	0.766 ± 0.002	186.896 ± 20.008

Conclusions

Novel approach addresses three composition dimensions simultaneously (fully functional, 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?