

The SDMLib solution to the Class Responsibility Assignment Case for TTC2016

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This paper describes the SDMLib solution to the Class Responsibility Assignment Case for TTC2016. SDMLib provides reachability graph computation ala Groove. Thus, the simple idea was to provide rules for possible clustering operations and then use the reachability graph computation to generate all possible clusterings. Then, we apply the CRAIndex computation to each generated clustering and identify the best clustering. Of course, this runs into scalability problems, very soon. Thus, we extended our reachability graph computation to do an A* based search space exploration. Therefore, we passed the CRAIndex computation as a metric to our reachability graph computation and in each step, we consider the set of not yet expanded graphs and choose the one, that has the best metric value for expansion. The paper reports about the results we achieved with this approach.

1 Introduction

This paper describes the SDMLib solution to the Class Responsibility Assignment Case for TTC2016 [1]. SDMLib provides reachability graph computation ala Groove [2]. For a given start graph and a given set of rules, the reachability graph computation generates all graphs that may be derived from the start graph by applying all rules at all possible matches as often as possible in all possible orders. Each time a new graph is computed, we search through the set of already computed graphs for an already known isomorphic graph. As proposed by [2], SDMLib computes node and graph certificates which are then used as hash keys to access potentially isomorphic graphs, efficiently. The node certificates then also help to do the actual isomorphism test. If a new graph has been generated, we create a so-called reachable state node and we connect the reachable state node of the predecessor graph with the reachable state node for the new graph via a rule application edge labeled with the name of the rule used. In addition, a root node of the graph is attached to the reachable state node. Altogether, the generated reachability graph has a top layer consisting of reachable state nodes connected via rule application edges and each reachable state node refers to the corresponding application graph via a `graphRoot` link. In SDMLib, this whole structure is again a graph, and graph rules may be applied to it in order to find e.g. reachable states with a maximal metric value for the attached application graph or to find states where all successor states have lower metric values or to find the shortest path leading to the best state. Actually, any graph related algorithm may be deployed.

The Class Responsibility Assignment Case challenges the rule orchestration mechanisms provided by the different model transformation approaches. Thus, our solution uses the SDMLib reachability graph computation for rule orchestration. This is a very simple way to apply all rules in all possible ways and in addition we are able to investigate all intermediate results in order to identify which paths through the search space are the most interesting ones. The drawback of this approach is that it wastes a lot of runtime and memory space for copying the whole class model graph each time a rule is applied and for the search of already known isomorphic copies of the generated graphs. As shown in the case description, the number

of possible clusterings grows with the Bell number, i.e. for larger examples a complete enumeration of all possible clustering is not possible in a meaningful time. As only a small fraction of the search space can be explored, it might be helpful to be able to investigate all intermediate states to identify the most promising spots for further expansion. Thus, we hope that the flexibility provided by the SDMLib reachability graphs to investigate different intermediate states pays off, at the end.

As it is usually not possible to generate the whole reachability graph for a given example, our reachability graph computation may be restricted to a maximum number of reachable states to be considered. Next, we have extended our reachability graph computation with an A* like search space exploration that takes a metric as parameter and at each step chooses the state with the best metric value for expansion. We have developed two variants of this A* algorithm which will be discussed below.

The next section introduces the rules we use to solve the Class Responsibility Assignment Case and then Section 3 shows the different search strategies we use in this example. Finally, 4 shows our performance measurements. In the last section we sum up our results.

2 The Model Transformation Rules

Our feature clustering approach uses three SDMLib model transformation rules. In the preparation phase we use the rule shown in Figure 1 to create one class for each feature in our class model.

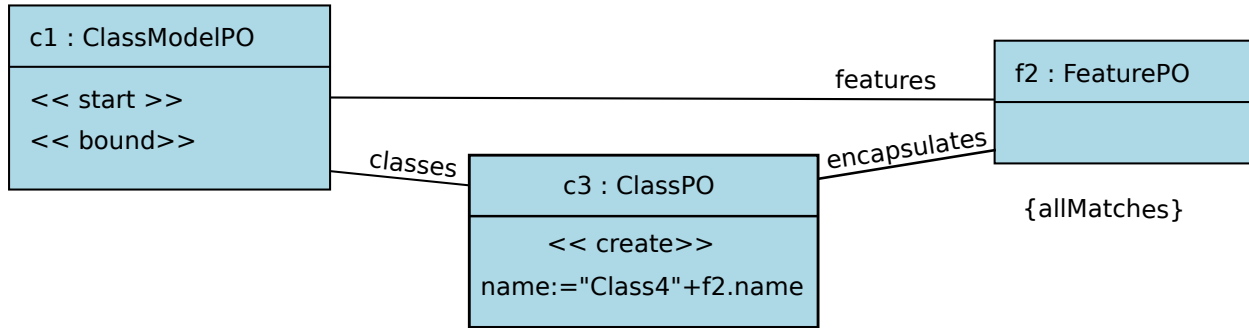


Figure 1: Rule adding initial classes

This rule starts by matching the pattern object `c1` to the `ClassModel` object passed as parameter. Then, `f2` is matched to a `Feature` object attached to this `ClassModel` object. The `{allMatches}` constraint causes the rule to be applied to all possible matches. Thus, for each `Feature` object in our current `ClassModel`, the `<<create>>` stereotype on pattern object `c3` causes the creation of a new `Class` object. In addition the new `Class` object is attached to the `ClassModel` via a `classes` link and to the `Feature` object via an `encapsulates` link. Finally, the new `Class` object's name attribute gets assigned the concatenation of the prefix "Class4" and the name of the current `Feature`. Thus, after the execution of this rule, each feature has its own class containing just this feature. This class model is then used as starting point for the repetitive application of our clustering rules.

We use two different clustering rules, one for clustering along attribute dependencies and one for clustering along method dependencies. Figure 2 shows the attribute dependency clustering rule:

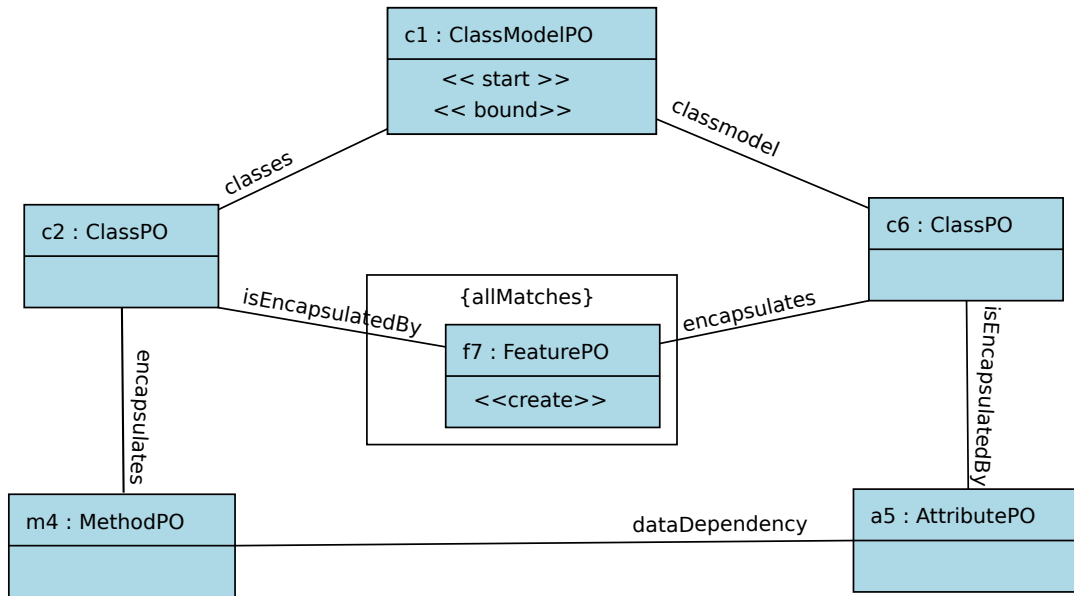


Figure 2: Merging Classes via Attribute Dependencies

3 The Search Space Expansion Mechanisms

```

1  ReachabilityGraph::explore(depth) {
2      todo = new ArrayList();
3      todo.add(this.startState);
4      states.put(certificate(this.startState), startState);
5      while (! todo.isEmpty() && states.size() <= depth) {
6          current = todo.get(0); todo.remove(0);
7          for(Rule r : this.rules) {
8              while (r.findMatch()) {
9                  newState = current.clone().apply(r);
10                 isoOldState = find(states, newState);
11                 if (isoOldState == null){
12                     states.put(certificate(newState), newState);
13                     addEdge(current, r, newState);
14                     todo.add(newState);
15                 } else {
16                     addEdge(current, r, isoOldState);
17                 }
18             }
19         }
20     }
  
```

```
21 }
```

Listing 1: General Reachability Graph Computation

4 Performance Results

5 Summary

References

- [1] M. Fleck, J. Troya, and M. Wimmer. TTC2016 The Class Responsibility Assignment Case. <https://github.com/martin-fleck/cra-ttc2016>, 2016.
- [2] A. Rensink. The GROOVE simulator: A tool for state space generation. In *Applications of Graph Transformations with Industrial Relevance*, pages 479–485. Springer, 2003.