On the Specification of Search Tree Ordering Heuristics by Pattern Matching in a Rule-Based Modeling Language

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Abstract. In this paper, we show that in a rule-based modeling language, search tree ordering heuristics can be specified declaratively by pattern matching on left-hand sides of rule definitions. As opposed to other modeling languages able to express search heuristics, such as OPL and Comet, heuristics are expressed here purely declaratively. That eliminates the need of changing data structures or introducing intermediary objects. The price to pay for this ease of modeling is in the compilation process which we describe here with a formal system. We analyze the complexity of the transformation and present some performance figures on the compilation process and on the generated constraint programming code.

1 Introduction

Constraint programming is a programming paradigm which relies on two components: a constraint component which manages posting and checking satisfiability and entailment of constraints over some fixed computational domain, and a programming component which assembles the constraints of a given problem and expresses search procedures. To make constraint programming easier to use by non-programmers, a lot of work has been devoted to the design of front-end modeling languages using logical and algebraic notations instead of programming constructs for assembling constraints, e.g. OPL [10, 6], Zinc [8, 2], Essence [5] and Rules2CP [3, 4]. For efficiency reasons however, the search procedure needs be controlled and this part of programming can hardly be eliminated.

For instance, let us consider the following Comet model of the Bridge disjunctive scheduling problem [10] p. 209:

(...) tuple Disjunction {Task first; Task second;} int maxDuration = sum(t in Task) duration[t]; Scheduler <CP> cp(maxDuration); Activity<CP> a[t in Task](cp, duration[t]); UnaryResource<CP> tool[Resource](cp);
minimize<cp>
a[stop].start()
subject to {
  forall(t in precedences)
    a[t.before].precedes(a[t.after]);
  forall(t in max_nf)
    cp.post(a[t.before].end() + t.dist >= a[t.after].start());
  forall(t in max_ef)
    cp.post(a[t.before].end() + t.dist >= a[t.after].end());
  forall(t in min_af)
    cp.post(a[t.before].start() + t.dist <= a[t.after].start());
  forall(t in min_sf)
    cp.post(a[t.before].start() + t.dist >= a[t.after].end());
  forall(t in min_nf)
    cp.post(a[t.before].end() + t.dist <= a[t.after].start());
  forall(r in Resource)
    forall(t in res[r])
      a[t].requires(tool[r]);
}
using {
  forall(r in Resource)
    tool[r].rank();
  label(a[stop]);
}

The general strategy is to post first the (deterministic) precedence, distance and resource requirement constraints, and then to rank each unary resource by finding (non-deterministically) a total ordering of all tasks requiring the resource. Once the resources are ranked, the minimal starting dates of the activities provide a solution. Choosing which resource or task to rank next may be important for the size of the explored search tree and hence the efficiency of the search procedure. For instance, we may want to select the tasks by decreasing durations and discriminate equalities by preferring pairs of tasks which have the least domain lower bounds. To achieve that in Comet, some form of programming involving creation of intermediate arrays or sets, or changes of data-structures, is necessary:

using {
  forall(d in make_disjunct(res)) by (-duration[d.first] - duration[d.second],
    a[d.first].start().getMin() +
    a[d.second].start().getMin()) {
    try<cp>
      { a[d.first].precedes(a[d.second]); } ||
      { a[d.second].precedes(a[d.first]); }
    }
  label(cp);
}

function set{Disjunction} make_disjunct(set{Task}[] res) {
    set{Disjunction} disj = {};
    forall(r in Resource)
        forall(t1 in res[r])
            forall(t2 in res[r]: t1 < t2)
                disj.insert(Disjunction(t1, t2));
    return disj;
}

We show that in a rule-based modeling language, search tree ordering heuristics can be specified declaratively by ordering criteria using pattern matching on the tree structure. These criteria apply to conjunctions and disjunctions of constraints involved in the search tree.

In the particular case of labeling, criteria on conjunctions encode variable ordering (e.g., first-fail: among the operands of a conjunction, choose the variable with the smallest domain first) and criteria on disjunction encode value ordering (e.g., middle-out: among the operands of a disjunction of assignments, choose the most centered value first). Ordering heuristics are generalized here to search trees with arbitrary nesting of conjunctions and disjunctions. Heuristics are driven by criteria to estimate which node to consider first. Every rule definition is of the form \( p(x) = e \), associating the left-hand side \( p(x) \) to the right-hand side \( e \). Patterns guarding criteria are matched against \( p(x) \) which gives the scores used to reorder the subtree.

We consider a new version of the Rules2CP modeling language [3], called Cream (Constraints with Rules to EAse Modeling). The previous example can be written in Cream as follows:

\[
\begin{align*}
\text{end}(T) &= T: \text{start} + T: \text{duration}, \\
\text{maxDuration} &= \text{sum}(\text{map}(T \text{ in tasks}, T: \text{duration})). \\
\text{tasks_domain} &= \text{domain}(\text{tasks}, 0, \text{maxDuration}). \\
\text{precedes}(T1, T2) &= \text{end}(T1) \leq T2: \text{start}. \\
\text{disjuncts}(T1, T2) &= \text{precedes}(T1, T2) \text{ or } \text{precedes}(T2, T1). \\
\text{precedences} &= \\
    \forall (\text{TaskPair} \text{ in precedences_list}, \\
        \text{precedes}(\text{nth}(1, \text{TaskPair}), \text{nth}(2, \text{TaskPair}))). \\
\text{distances} &= \\
    \forall (T \text{ in max_nf_list}, \text{max_nf}(\text{nth}(1, T), \text{nth}(2, T), \text{nth}(3, T))) \text{ and} \\
    \forall (T \text{ in min_sf_list}, \text{min_sf}(\text{nth}(1, T), \text{nth}(2, T), \text{nth}(3, T))) \text{ and} \\
    \forall (T \text{ in max_ef_list}, \text{max_ef}(\text{nth}(1, T), \text{nth}(2, T), \text{nth}(3, T))) \text{ and} \\
    \forall (T \text{ in min_nf_list}, \text{min_nf}(\text{nth}(1, T), \text{nth}(2, T), \text{nth}(3, T))) \text{ and} \\
    \forall (T \text{ in min_af_list}, \text{min_af}(\text{nth}(1, T), \text{nth}(2, T), \text{nth}(3, T))). \\
\text{disjunctives} &= \\
    \forall (T \text{ in resource}, \\
        \forall (T1 \text{ in Task}, \\
            \forall (T2 \text{ in Task}, \\
                T1: \text{uid} < T2: \text{uid} \implies \text{disjuncts}(T1, T2))).
\end{align*}
\]
In Cream, heuristics on conjunctive or disjunctive formulae are stated declaratively by a vector of criteria:

\[
\langle \text{order}_1(\text{expression}_1 \text{ for } \text{pattern}_1), \ldots, \text{order}_n(\text{expression}_n \text{ for } \text{pattern}_n) \rangle
\]

where \(\forall i \in \{1, \ldots, n\}, \text{order}_i \in \{\text{least, greatest}\}, \text{expression}_i\) is any Cream expression evaluating to an integer with variables bound to the arguments of \(\text{pattern}_i\). Criteria give a vector of scores for each node of the search tree and every conjunction or disjunction group occurring in the search tree is reordered lexicographically according to these scores. Given a node \(v\) in the search tree, criteria are evaluated as follows: if \(v\) results from a call to a rule whose left-hand side can be matched against \(\text{pattern}_i\), then the \(i\)th component of the associated vector of scores is given by \(\text{expression}_i\). Otherwise, the \(i\)th component is assigned to the lowest possible value. As opposed to Rules2CP, Cream handles dynamic ordering criteria, \(i.e.\) criteria involving finite domain variables. In the above example, the second conjunctive criterion involves the domain lower bound of task starting date. Assume now that we want also to order disjunctions, for instance by trying to schedule the task with the greatest duration first. That composition of ordering heuristics would be difficult to program in Comet but simply consists in Cream in stating a disjunctive criterion as follows:

\[
\text{disjunct_ordering}(\langle \text{greatest}(\text{T1:duration for precedes(T1, T2))} \rangle)
\]

Whereas \textit{ad-hoc} data structures have to be explicited by the user in other modeling languages, the rule-based nature of Cream implicitly gives a structure to the search tree and allows the user to express directly heuristics by pattern matching.

Cream’s rules are similar to Zinc’s definitions and the pattern-matching language we define here to specify search tree ordering heuristics should be applicable to Zinc as well.

The price to pay for this ease of modeling is in the compilation process which we describe here with a formal system. We analyze the complexity of the transformation and present some performance figures on the compilation process and on the generated constraint programming code.

The rest of the paper is organized as follows. The next section defines the syntax of Cream. Section 3 presents the transformation of Cream models in constraint programs using a formal system to prove the correctness of the transformation. Section 4 evaluates the performances of our Cream compiler and of the generated code on a benchmark of scheduling and bin packing problems.
2 Cream Syntax

The language defined in this section covers the whole set of constructions for search trees and heuristics specifications in Cream. In the actual implementation, a layer of syntactic sugar offers facilities such as the separation between heuristic specifications and search tree constructions so as to let the programmer reuse heuristics throughout searches.

We suppose an infinite set $\mathcal{N}$ of labels for record fields, an infinite set $\mathcal{F}$ of predicates for user-defined rules, and a set $\mathcal{C}$ of predicates for constraints (which should map the underlying constraint theory).

A Cream program is a sequence of definitions ended by a query. $X^*$ denotes a possibly empty sequence of $X$, delimited by commas.

$$
P ::= \emptyset \mid D P \mid Q \\
D ::= \mathcal{F}(V^*) = E. \\
Q ::= ? E.
$$

The central elements of the syntax are expressions $E$, which cover definition calls, constraints, values $T$ and search-tree directives $S$ over an infinite set of variables $V$. Operators follow usual priority rules.

$$
E ::= V \mid T \mid \mathcal{F}(E^*) \mid \mathcal{C}(E^*) \mid S \\
| E \text{ and } E \mid E \text{ or } E \mid E \text{ implies } E \\
| \text{let}(V = E \text{ in } E) \mid \text{minimize}(V \text{ in } E)
$$

Cream values are numbers, lists and records. Numbers come with basic arithmetics and operators for indexicals over finite domains. $\text{bottom}$ is $-\infty$. Lists are either constructed by extension, concatenation or as discrete interval between two numerical expressions. Lists can be reversed or projected to an element at a given position. Records can be projected to any fixed field.

$$
T ::= \langle \text{number} \rangle \mid E \langle \text{arithop} \rangle E \text{ where } \langle \text{arithop} \rangle \in \{+, -, *, /\} \\
| \text{bottom} \mid \text{dsize}(E) \mid \text{dmin}(E) \mid \text{dmax}(E) \\
| [E^*] \mid E \cdot E \mid E \ldots E \mid \text{nth}(E, E) \\
| \{N=E\} \mid E : \mathcal{N}
$$

Search strategies are defined through criteria, with respect to which search trees are reordered. Search trees are either constructed in extension (boolean operators of $E$ give the $\land$ and $\lor$ nodes), or in intension by iterating over list values with fold. The parameters of a fold are respectively: a binary associative operator (which can be any user-defined predicate, with some fixed initial arguments), the neutral element of this operator, a variable, a list giving the values for the
variable, and an expression depending on the variable.

\[
S ::= \text{search}(E, \text{disjunct}(O^*)\text{, conjunct}(O^*)) \quad (\text{search})
\]

\[
| \text{fold}(F(V^*), E, V \text{ in } E, E) \quad (\text{search})
\]

Each criterion applies on the sub-nodes of a definition distinguished by its left-hand side predicate. The score associated to the criterion is an arithmetic expression which possibly depends on the arguments of the definition. In the concrete Cream syntax, greater or least operators modify the sign of the expression.

\[
O ::= E \text{ for } F(V^*) \quad (\text{criterion})
\]

Constraints \( C \) are plunged into values through reification. Reciprocally, values 1 and 0 are interpreted as the constraints true and false respectively. The use of other values as constraints is rejected.

Cream comes with a standard library of rule definitions. Here is an excerpt of those definitions:

\[
domain(X, Lo, Hi) = Lo \leq X \text{ and } X \leq Hi.
\]

\[
\text{for}(E, A) = E \text{ and } A.
\]

\[
\text{or}(E, A) = E \text{ or } A.
\]

\[
\text{exists}(X \text{ in } L, E) \equiv \text{fold}(\text{or}, \text{false}, X \text{ in } L, E)
\]

\[
\text{forall}(X \text{ in } L, E) \equiv \text{fold}(\text{and}, \text{true}, X \text{ in } L, E)
\]

\[
\text{map}(X \text{ in } L, E) \equiv \text{fold}(\text{cons}, [], X \text{ in } L, E)
\]

To illustrate Cream compilation, we will consider two rule definitions that constrain the shape of objects for a simple two-dimensional placement problem of thin sticks which can be either short (from 1 to 5 units), normal (from 11 to 15 units) or long (from 21 to 25 units). A stick is a 1-unit wide rectangle which can be either horizontal or vertical.

\[
\text{shape\_constraint}(O) = \text{exists}(S, [1, 11, 21], \text{shape\_stick}(O, S, S + 4)).
\]

\[
\text{shape\_stick}(O, \text{Min}, \text{Max}) = \text{domain}(O:w, \text{Min}, \text{Max}) \text{ and } O:h = 1
\]

\[
\text{or domain}(O:h, \text{Min}, \text{Max}) \text{ and } O:w = 1.
\]

The compilation scheme for \text{fold} described in the next section transforms the expression \text{shape\_constraint}(S) into a code computing the same answers as the following unfolded expression:

\[
((1 \leq S:w \text{ and } S:w \leq 1+4) \text{ and } S:h=1) \text{ or } ((1 \leq S:h \text{ and } S:h \leq 1+4) \text{ and } S:w=1)
\]

\[
\text{or } (((11 \leq S:w \text{ and } S:w \leq 11+4) \text{ and } S:h=1) \text{ or } ((11 \leq S:h \text{ and } S:h \leq 11+4) \text{ and } S:w=1))
\]

\[
\text{or } (((21 \leq S:w \text{ and } S:w \leq 21+4) \text{ and } S:h=1) \text{ or } ((21 \leq S:h \text{ and } S:h \leq 21+4) \text{ and } S:w=1) \text{ or false})).
\]

(1)
Recursion is prohibited in Cream: there should exist a topological order for dependency among rule definitions. A definition $d$ depends on another definition $e$ if $d$ explicitly calls $e$ (construction $\mathcal{F}(E)$ ) or if $e$ is used as a fold operator in $d$.

### 3 Cream Compilation

Compilation is defined as two transformations which produce intermediary code: $\llbracket \cdot \rrbracket^d$ expands a query to the deterministic code which adds the constraints and make calls to dynamic search parts. These search parts are transformed by $\llbracket \cdot \rrbracket^*$ to the non-deterministic code which handles reordering and searching. Intermediary code follows the syntax of Cream programs, but without the recursion restriction. In the intermediary code, there is no search-tree directives $S$ (they are reformulated by $\llbracket \cdot \rrbracket^*$), operators or represent either reified $\lor$-constraints the deterministic code, or choice-points in the non-deterministic code. The syntactic construction $\text{delay}(p(X))$ is introduced in intermediary code to denote the symbolic term $p(X)$ (as opposed to a call to the definition $p(X)$ ). Such an intermediary code is then straightforward to translate to a Prolog or Java program.

#### 3.1 Transformation of the query to deterministic code

$\llbracket \cdot \rrbracket^d(V)$ reformulates search directives inductively over the structure of Cream expressions as follows. $V$ is supposed to contain all the free variables appearing in the expression: $V$ is used to pass the context to auxiliary definitions introduced by the translation.

Each definition $p(X) = e$ is translated in the intermediary code to the definition: $p_d(X) = \llbracket e \rrbracket^d(fv(e))$. The translation of calls follows then directly: $\llbracket p(X) \rrbracket ^d(V) = p_d(X)$.

Search directives rely on the search transformation (defined in the section 3.2).

$\llbracket \text{search}(e, \text{disjunct}(o_\lor), \text{conjunct}(o_\land)) \rrbracket ^d(V) = \llbracket e \rrbracket^*\left[ o_\land, o_\lor \right](V)$

Recursive predicates iterating on lists are generated for each fold:

$\llbracket \text{fold}(p(e_i), n, X \in l, e) \rrbracket ^d(V) = q(\llbracket e \rrbracket^d(V), \llbracket e_i \rrbracket^d(V), V)$

with $q$ a new predicate symbol described by the following definitions, where all variables are fresh with respect to $V$:

$q(\emptyset, \overrightarrow{E_i}, V) = \llbracket n \rrbracket^d(V).$

$q(\mathbb{H} \mid \mathbb{T}, \overrightarrow{E_i}, V) = p_d(\overrightarrow{E_i}, \llbracket e \mathbb{H} / X \rrbracket^d(V), q(\mathbb{T}, \overrightarrow{E_i}, V)).$

Other cases for $\llbracket \cdot \rrbracket^d$ are defined homomorphically with respect to sub-expressions, taking care of scopes and name clashes: e.g.,

$\llbracket \text{let}(v = e \ in \ e') \rrbracket^d(V) = \text{let}(X = \llbracket e \rrbracket^d(V) \ in \ \llbracket e'[X/v] \rrbracket^d(V \cdot X))$

where $X$ is a fresh variable.
3.2 Transformation of the search to non-deterministic code

Search-strategy compilation relies on the notion of $O$-layers of $\land/\lor$-trees: for $O \in \{\land, \lor\}$, we call $O$-layer of an $\land/\lor$-tree any maximal tree sub-graph with either only $\land$-nodes or only $\lor$-nodes. It is worth noticing that an $O$-layer is a tree but not necessarily a sub-tree of the considered $\land/\lor$-tree: branches are cut on operator changes.

The following $\land/\lor$-tree corresponds to the expression (1) given in the previous section, where layers have been circled:

The definition of $O$-layers is generalized for Cream expression syntax trees by letting layers go through let-bindings, definition calls, in the right-hand side of implies and through the tree intentionally constructed by fold. The children of a layer are children of a node in the layer without being themselves in the layer. The root $O$-layer is the $O$-layer containing the root node if it is not the dual of $O$, or the empty layer otherwise. By convention, the root node is the (only) child of the empty layer. Tree reordering is applied between all child nodes of each $O$-layer: criteria defined for $O \in \{\land, \lor\}$ associate a vector of scores to each child, and children are reordered according to their scores lexicographically (the score returned by the first criterion for $O$ is considered first, then, in case of equality, the score of the second criterion for $O$, and so on).

Neither the tree (due to fold over arbitrary lists) nor the scores (due to indexicals) are supposed to be completely known at compile-time. Therefore, the transformation generates code for computing the reordering at execution-time rather than computing the reordering statically.

For a fixed pair of criteria $(o_\land, o_\lor)$, $J^*(c_\land, c_\lor, V)$ produces code which reorders the root $O$-layer of the tree and explores its children sequentially. $c_\land$ and $c_\lor$ are current score vectors (they have the same dimension than $o_\land$ and
Definitions and calls For each definition \( p(X) = e \), the compilation produces two definitions in the intermediary code, one for each kind of layer:

\[
\begin{align*}
p_{\land}(C_{\land}, C_{\lor}, V) &= \llbracket e \rrbracket_{\land}^{\mathcal{O}}(u(C_{\land}, o_{\land}, p(X)), C_{\lor}, \text{fv}(e)) \\
p_{\lor}(C_{\land}, C_{\lor}, V) &= \llbracket e \rrbracket_{\lor}^{\mathcal{O}}(C_{\land}, u(C_{\lor}, o_{\lor}, p(X)), \text{fv}(e))
\end{align*}
\]

where the function \( u(c, o, p(X)) \) calculates the score vector \( c' \), where components corresponding to criteria matching \( p(X) \) are updated:

\[
u(c_i', e_i \text{ for } p_i(X_i'), p(X)) = c_i'
\]

where:

\[
c_i' = \begin{cases} 
\sigma(e_i) & \text{if } \exists \sigma, \sigma(p_i(X_i)) = p(X) \\
\sigma \end{cases}
\]

Calls select one of these two definitions, depending on the kind of the current layer.

\[
\llbracket p(X) \rrbracket^{\mathcal{O}}_{\land}(c_{\land}, c_{\lor}, V) = p_{\mathcal{O}}(c_{\land}, c_{\lor}, X)
\]

Boolean operators \( \llbracket \rrbracket_{\land} \) aggregates lists in the root \( \land \)-layer. A new predicate \( q \) is introduced for each child node of the \( \land \)-layer.

\[
\begin{align*}
\llbracket e \land e' \rrbracket_{\land}(c_{\land}, c_{\lor}, V) &= \llbracket e \rrbracket_{\land}(c_{\land}, c_{\lor}, V) \cdot \llbracket e' \rrbracket_{\land}(c_{\land}, c_{\lor}, V) \\
\llbracket e \lor e' \rrbracket_{\land}(c_{\land}, c_{\lor}, V) &= \\
[ \{ \text{scores} = c_{\land}, \text{predicate} = \text{delay}(q(c_{\land}, c_{\lor}, V)) \} ]
\end{align*}
\]

where \( q \) applies the transformation recursively to the sub-\( \lor \)-layer (all variables are fresh with respect to \( V \)).

\[
q(C_{\land}, C_{\lor}, V) = \llbracket e \lor e' \rrbracket_{\lor}(C_{\land}, C_{\lor}, V).
\]

Dual definitions hold for \( \llbracket \rrbracket_{\lor}^{\mathcal{O}} \).
Filtering

\[ [e \implies e']_O(c_\land, c_\lor, V) = \text{filter}(c_O, [e]_d(V), [e']_O(c_\land, c_\lor, V)) \]

where, \( \text{filter}(c, e, e') \) is an internal function which returns \( e' \) if \( e \) is true, and returns the singleton list \([\{\text{scores = c, predicate = delay(true)}\}]\) otherwise.

Let-binding

\[ [\text{let}(X = e \text{ in } e')]_O(c_\land, c_\lor, V) = \]
\[ \text{let}(Y = [e]_d(V), [e'[Y/X]]_O(c_\land, c_\lor, V \cdot Y)) \]

where \( Y \) is a fresh variable.

Aggregators

Aggregators use a special source symbol, \( \text{rec} \), to handle recursion.

\( \text{fold} \) is translated to a call to a recursive predicate:

\[ [\text{fold}(p(c_i), n, X \text{ in } e, e')]_O(c_\land, c_\lor, V) = q_O([e]_d, [e_i]_d, c_\land, c_\lor, V) \]

where \( q_\land \) and \( q_\lor \) are new predicate symbols described by the following definitions (all variables are fresh with respect to \( V \)):

\[ q_O(\emptyset, \bar{E_i}, C_\land, C_\lor, V) = [n]_O(C_\land, C_\lor, V). \]
\[ q_O([H | T], \bar{E_i}, C_\land, C_\lor, V) = \]
\[ [p_O(\bar{E_i}, \text{rec}(q, T, \bar{E_i}, V), e'[H/X])]_O(C_\land, C_\lor, V \cdot H). \]

and \( \text{rec} \) is translated to a recursive call to \( q \):

\[ [\text{rec}(q, T, \bar{E_i}, V)]_O(c_\land, c_\lor, V) = q_O(T, \bar{E_i}, c_\land, c_\lor, V) \]

Constraints and sub-search directives

Constraints and sub-search directives are children of the layer, therefore the transformation produces singleton lists associating their score to a fresh predicate \( q \).

\[ [e]_O(c_\land, c_\lor, V) = [\{\text{scores = c_O, predicate = delay(q(V))}\}] \]

where \( q \) applies the transformation recursively (all variables are fresh with respect to \( V \)):

\[ q(V) = [e]_d. \]

Property 1 There are \( O(d \cdot s) \) \( p_\land \)-, \( p_\lor \)- and \( p_\land \)-definitions in intermediary code, where \( d \) is the number of definitions in the Cream code and \( s \) is the number of search clauses. Each definition in the intermediary code, including auxiliary definitions for \( \text{fold} \) and sub-layers, has a size linear in the size of the original Cream definition. In particular, if there is one search clause, the intermediary code has a size linear in the size of the original Cream code. The complexity of the transformation is linear in the size of the generated code.
Proof. $[\cdot]^d$ and $[\cdot]^l$ are inductive transformations where each step linearly composes results of sub-transformations, either in auxiliary definitions or in-place expressions. Therefore, there exists a multiplicative constant factor between the size of the generated definitions and the size of the original Cream definition. For each Cream definition $p(X)$, there is one definition $p_d$ in the intermediary code, plus two definitions $p_v$ and $p_\wedge$ by search clauses.

This complexity result contrasts with Rules2CP transformation complexity[3] where definition unfolding leads to exponential code size in the worst case.

4 Evaluation

We report here performances comparisons of the Rules2CP and Cream compilers and generated constraint programs as well as a brief explanation for observed differences. Performances are measured on the Bridge Scheduling, Open-Shop Scheduling and Optimal Rectangle Packing problems.

The Bridge problem consists in finding a schedule, involving 46 tasks subject to precedence, distance and resource requirement constraints, that minimizes the time to build a five-segment bridge [10] p. 209.

The Open-Shop problem consists in finding the non-preemptive schedule with minimal completion time of a set $J$ of $n$ jobs, consisting each of $m$ tasks, on a set $M$ of $m$ machines. The processing times are given by a $m \times n$-matrix $P$, in which $p_{ij} \geq 0$ is the processing time of task $T_{ij}$ of job $J_j$ to be done on machine $M_i$. The tasks of a job can be processed in any order, but only one at a time. Similarly, a machine can process only one task at a time. Here, the j6-4 ($n = m = 6$) and j7-1 ($n = m = 7$) Open-Shop problem instances (Brucker et al. [1]) are considered.

The Rectangle Packing problem consists in finding the smallest rectangle containing $n$ squares of sizes $S_i = i$ for $1 \leq i \leq n$. The model is based on the proposal of Simonis and O’Sullivan [9] implemented in SICStus Prolog. They tackled the Korf’s benchmark [7] and improved best known runtimes up to a factor of 300. We consider here for evaluation the $n = 22$ instance of the problem.

<table>
<thead>
<tr>
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<th>Rules2CP</th>
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<tr>
<td></td>
<td>Compilation</td>
<td>Solving</td>
</tr>
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<td>Bridge</td>
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<td>0.150</td>
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<tr>
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<td>Open-Shop j7-1</td>
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<td>Rectangle-Packing n22</td>
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Table 1. Rules2CP and Cream programs runtimes in seconds.

Table 1 compares the compilation and execution runtimes in seconds in Cream with those obtained in Rules2CP. In all scheduling problem instances,
the same heuristics on disjunctive formulae with static criterion “schedule first
the task that has the greatest duration” was used. The implementation of the
Cream compiler is a proof of concept of the transformations presented in Sec. 3,
and no effort has been made yet to improve performances.

On the one hand, Cream yields structured constraint programs including
(recursive) clauses as a programmer would have written the model in Prolog.
On the other hand, Rules2CP produces optimized flatten constraint programs by
complete expansion of definitions and record projections with partial evaluation.

In the Rectangle Packing model, there is no heuristics stated, thus the same
runtimes between Rules2CP and Cream.

When heuristics on formulae are involved, that is in the scheduling prob-
lems, the compilation in Cream is about twice faster than in Rules2CP because
ordering is delayed to execution time and partial evaluation does not occur.

Solving runtimes of constraint programs generated by Cream are twice slower
than those generated by Rules2CP. This overhead is explained by the following
reasons: (a) in both Rules2CP and Cream, finite domain variables are global
variables. But in constraint programs generated with Cream, they are handled
by a backtrackable table associating names with actual variables. Whereas pro-
grams generated by Rules2CP does not need such a mechanism because of the
complete expansion scheme; (b) In Rules2CP, partial evaluation at compile-time
avoids the need of Prolog tests for handling logical implication as it is the case
in programs generated with Cream; (c) record projections, finite domain arith-
metic expressions computation, and goal calls in general are yet other sources of
overhead. As we considered optimization problems, this aggregation of overheads
for one call of the search goal is to multiply by the number of iterations of the
branch and bound algorithm; (d) finally, priority queues could advantageously
substitute for lists of pairs to enumerate children of layers.

It is worth noticing that these points are mainly implementation details and
should be avoided in future work by an optimizing compiler.

5 Conclusion

A rule-based modeling language provides interesting features for specifying search
tree and labeling ordering heuristics declaratively by pattern matching on rule
left-hand sides’ derivation. We have described our experience with Cream and
Rules2CP modeling languages. While in Rules2CP the static expansion of the
goals [3] was combined with calls to the Rules2CP interpreter for expressions de-
dpending on variable domains that can only be evaluated at runtime, in Cream,
models are compiled in constraint programs that select the continuation for
search according to the heuristic criteria, at runtime.

We have described the transformation of Cream models to constraint pro-
grams with a formal system and showed with a benchmark of examples that
in the static case, the Cream overhead at runtime was limited w.r.t. the static
expansion of Rules2CP.
This approach to specifying ordering heuristics by pattern matching should be applicable to other modeling languages that use definitions, such as Zinc [8, 2] for instance. A natural extension for future work is the specification of search procedures which are currently limited in Cream to depth-first backtracking and branch and bound search.

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References