The Cassowary Linear Arithmetic Constraint Solving Algorithm: Interface and Implementation

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Abstract

Linear equality and inequality constraints arise naturally in specifying many aspects of user interfaces, such as requiring that one window be to the left of another, requiring that a pane occupy the leftmost 1/3 of a window, or preferring that an object be contained within a rectangle if possible. Current constraint solvers designed for UI applications cannot efficiently handle simultaneous linear equations and inequalities. This is a major limitation. We describe Cassowary—an incremental algorithm based on the dual simplex method that can solve such systems of constraints efficiently.

This informal technical report describes the latest version of the Cassowary algorithm. It is derived from the paper "Solving Linear Arithmetic Constraints for User Interface Applications" by Alan Borning, Kim Marriott, Peter Stuckey, and Yi Xiao [7], published in the UIST'97 Proceedings. The UIST paper also contains a description of QOCA, a closely related solver that finds least-squares solutions to linear constraints. This technical report, which is intended to be self-contained, includes material on Cassowary from the UIST paper, plus a description of the Java, C++, and Smalltalk implementations and their interfaces, along with additional details, corrections, and clarifications.

An earlier technical report also discussed QOCA and the similarities between Cassowary and that algorithm [6].

1 Introduction

Linear equality and inequality constraints arise naturally in specifying many aspects of user interfaces, in particular layout and other geometric relations. Inequality constraints, in particular, are needed to express relationships such as "inside," "above," "below," "left-of," "right-of," and "overlaps." For example, if we are designing a Web document we can express the requirement that figure1 be to the left of figure2 as the constraint figure1.rightSide $\leq$ figure2.leftSide.

It is important to be able to express preferences as well as requirements in a constraint system. One use is to express a desire for stability when moving parts of an image: things should stay where they were unless there is some reason for them to move. A second use is to process potentially invalid user inputs in a graceful way. For example, if the user tries to move a figure outside of its bounding window, it is reasonable for the figure just to bump up against the side of the window and stop, rather than giving an error. A third use is to balance conflicting desires, for example in laying out a graph.

Efficient techniques are available for solving such constraints if the constraint network is acyclic. However, in trying to apply constraint solvers to real-world problems, we found that the collection of constraints was often cyclic. This sometimes arose when the programmer added redundant constraints — the cycles *could* have been avoided by careful analysis. However, this is an added burden on the programmer. Further, it is clearly contrary to the spirit of the whole enterprise to require programmers to be constantly on guard to avoid cycles and redundant constraints; after all, one of the goals in providing constraints is to allow programmers to state what relations they want to hold in a declarative fashion, leaving it to the underlying system to enforce these relations. For other applications, such as complex layout problems with conflicting goals, cycles seem unavoidable.

1.1 Constraint Hierarchies and Comparators

Since we want to be able to express preferences as well as requirements in the constraint system, we need a specification for how conflicting preferences are to be traded off. *Constraint hierarchies* [4] provide a general theory for this. In a constraint hierarchy each constraint has a strength. The required strength is special, in that required constraints must be satisfied. The other strengths all label non-required constraints. A constraint of a given strength completely dominates any constraint with a weaker strength. In the theory, a *comparator* is used to compare different possible solutions to the constraints and select among them.

Within this framework a number of variations are possible. One decision is whether we only compare solutions on a constraint-by-constraint basis (a *local* comparator), or whether we take some aggregate measure of the unsatisfied constraints of a given strength (a *global* comparator). A second choice is whether we are concerned only whether a constraint is satisfied or not (a *predicate* comparator), or whether we also want to know how nearly satisfied it is (a *metric* comparator. (Constraints whose domain is a metric space, for example the reals, can have an associated error function. The error in satisfying a constraint *cn* is 0 if and only if the constraint is satisfied, and becomes larger the less nearly satisfied is the constraint.)

As recognized for the Indigo solver [2], for inequality constraints it is important to use a metric rather than a predicate comparator. Thus, plausible comparators for use with linear equality and inequality constraints are *locally-error-better*, *weighted-sum-better*, and *least-squares-better*. For a given collection of constraints, Cassowary finds a locally-error-better or a weighted-sum-better solution. (In contrast, QOCA finds a least-squares-better solution. The least-squares-better comparator strongly penalizes outlying values when trading off constraints of the same strength. It is particularly suited to tasks such as laying out a tree, a graph, or a collection of windows, where there are inherently conflicting preferences [6].) Locally-error-better is a more permissive comparator, in that it admits more solutions to the constraints. (In fact any least-squares-better or weighted-sum-better solution is also a locally-error-better solution [4].) It is thus easier to implement algorithms to find a locally-error-better solution, and in particular to design hybrid algorithms that include sub-solvers for simultaneous equations and inequalities and also sub-solvers for non-numeric constraints [3].

1.2 Adapting the Simplex Algorithm

Linear programming is concerned with solving the following problem. Consider a collection of n real-valued variables $x_1, \ldots, x_n$, each of which is constrained to be non-negative: $x_i \geq 0$ for $1 \leq i \leq n$. There are m linear equality or inequality constraints over the x_i, each of the form:

$a_1x_1 + \ldots + a_nx_n = b$,
$a_1x_1 + \ldots + a_nx_n \leq b$, or
$a_1x_1 + \ldots + a_nx_n \geq b$.

Given these constraints, we wish to find values for the x_i that minimizes (or maximizes) the value of the *objective function*

$c + d_1x_1 + \ldots + d_nx_n$.

This problem has been heavily studied for the past 50 years. The most commonly used algorithm for solving it is the simplex algorithm, developed by Dantzig in the 1940s, and there are now numerous variations of it. Unfortunately, existing implementations of the simplex are not really suitable for UI applications.

The principal issue is incrementality. For interactive graphical applications, we need to solve similar problems repeatedly, rather than solving a single problem once. To achieve interactive response times, very fast incremental algorithms are needed. There are two cases. First, when moving an object with a mouse or other input device, we typically represent this interaction as a one-way constraint relating the mouse position to the desired x and y coordinates of a part of the figure. For this case we must re-satisfy the same collection of constraints, differing only in the mouse location, each time the screen is refreshed. Second, when editing an object we may add or remove constraints and other parts, and we would like to make these operations fast, by reusing as much of the previous solution as possible. The performance requirements are considerably more stringent for the first case than for the second.

Another issue is defining a suitable objective function. The objective function in the standard simplex algorithm must be a linear expression; but the objective functions for the locally-error-better, weighted-sum-better, and least-squares-better comparators are all non-linear. Fortunately techniques have been developed in the operations research community for handling these cases, which we adopt here. For the first two comparators, the objective functions are "almost linear," while the third comparator gives rise to a quadratic optimization problem.

Finally, a third issue is accommodating variables that may take on both positive and negative values, which in general is the case in UI applications. (The standard simplex algorithm requires all variables to be non-negative.) Here we adopt efficient techniques developed for implementing constraint logic programming languages.

1.3 Overview

We present algorithms for incrementally solving linear equality and inequality constraints for the three different comparators described above. In Section 2.1 we give algorithms for incrementally adding and deleting required constraints with restricted and unrestricted variables from a system of constraints kept in *augmented simplex form*, a type of solved form. In Section 3.1 we explain the Cassowary algorithm, based on the dual simplex method, for incrementally solving hierarchies of constraints using the locally-error-better or weighted-sum-better comparators when a constraint is added or an object is moved.

Cassowary has been implemented in Smalltalk, C++, and Java. It performs surprisingly well, and a summary of our results is given in Section 5. The algorithm is straightforward, and a re-implementation based on this paper is more reasonable, given a knowledge of the simplex algorithm. The various implementations with example applications are available from the authors.

1.4 Related Work

There is a long history of using constraints in user interfaces and interactive systems, beginning with Ivan Sutherland's pioneering Sketchpad system [18]. Most of the current systems use one-way constraints (e.g., [11, 15]), or local propagation algorithms for acyclic collections of multi-way constraints (e.g., [17, 19]). Indigo [2] handles acyclic collections of inequality constraints, but not cycles (simultaneous equations and inequalities). UI systems that handle simultaneous linear equations include DETAIL [10] and Ultraviolet [3]. A number of researchers (including the second author) have experimented with a straightforward use of a simplex package in a UI constraint solver, but the speed was not satisfactory for interactive use.

Baraff [1] describes a quadratic optimization algorithm for solving linear constraints that arise in modeling physical systems. Finally, much of the work on constraint solvers has been in the logic programming and constraint logic programming communities. Current constraint logic programming languages such as CLP($\mathcal{R}$) [13] include efficient solvers for linear equalities and inequalities. (See [14] for a survey.) However, these solvers use a refinement model of computation, in which the values determined for variables are successively refined as the computation progresses, but there is no notion as such of state and change. As a result, these systems are not so well suited for building interactive graphical applications.

Borning, Marriot, Stuckey, and Xiao discuss both the original version of Cassowary and the related QOCA algorithm [7, 6]. QOCA uses the same solving technique as Cassowary, but uses a least-squares-better comparator during the optimization from basic feasible solved form. An earlier version of QOCA is described in references [8] and [9]. These earlier descriptions, however, do not give any details of the algorithm, although the incremental deletion algorithm is described in [12].

2 Incremental Simplex

> As you see, the subject of linear programming is surrounded by notational and terminological thickets. Both of these thorny defenses are lovingly cultivated by a coterie of stern acolytes who have devoted themselves to the field. Actually, the basic ideas of linear programming are quite simple. – *Numerical Recipes*, [16, page 424]

We now describe an incremental version of the simplex algorithm, adapted to the task at hand. In the description we use a running example, illustrated by the diagram in Figure 1.

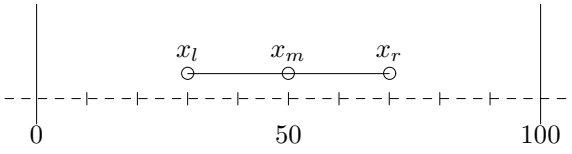

Figure 1: Simple constrained picture

The constraints on the variables in Figure 1 are as follows: x_m is constrained to be the midpoint of the line from x_l to x_r, and x_l is constrained to be at least 10 to the left of x_r. All variables must lie in the range 0 to 100. (To keep the presentation manageable, we deal only with the x coordinates. Adding analogous constraints on the y coordinates would be simple but would double the number of the constraints in our example.) Since $x_l < x_m < x_r$ in any solution, we simplify the problem by removing the redundant bounds constraints. However, even with these simplifications the resulting constraints have a cyclic constraint graph, and cannot be handled by methods such as Indigo.

We can represent this using the constraints

$$\begin{aligned} 2x_m &= x_l + x_r \\ x_l + 10 &\leq x_r \\ x_r &\leq 100 \\ 0 &\leq x_l \end{aligned}$$

Now suppose we wish to minimize the distance between x_m and x_l or in other words, minimize $x_m - x_l$.

2.1 Augmented Simplex Form

An optimization problem is in *augmented simplex form* if constraint C has the form $C_U \wedge C_S \wedge C_I$ where C_U and C_S are conjunctions of linear arithmetic equations and C_I is $\bigwedge\{x \geq 0 \mid x \in vars(C_S)\}$ and the objective function f is a linear expression over variables in C_S. The simplex algorithm does not itself handle variables that may take negative values (so-called *unrestricted variables*), and imposes a constraint $x \geq 0$ on all variables occurring in its equations. Augmented simplex form allows us to handle unrestricted variables efficiently and simply; it was developed for implementing constraint logic programming languages [14], and we have adopted it here. Essentially it uses *two* tableaux rather than one. All of the unrestricted variables will be placed in C_U, the unrestricted variable tableau. C_S, the simplex tableau, contains only variables constrained to be non-negative. The simplex algorithm is used to determine an optimal solution for the equations in the simplex tableau, ignoring the unrestricted variable tableau for purposes of optimization. The equations in the unrestricted variable tableau are then used to determine values for its variables.

Implementation Note. In the paper we describe C_U and C_S as two separate tableaux. In the implementation, however, it turns out to be simpler to have just one tableau, since most operations are applied to both C_U and C_S. Unrestricted and restricted variables are instances of different classes, and in the code we differentiate when necessary by sending the isRestricted message to the variable for each row. See Section 4.

It is not difficult to write an arbitrary optimization problem over linear real equations and inequalities into augmented simplex form. The first step is to convert inequalities to equations. Each inequality of the form $e \leq r$, where e is a linear real expression and r is a number, can be replaced with $e + s = r \wedge s \geq 0$ where s is a new non-negative *slack* variable.

For example, the constraints for Figure 1 can be written as

minimize $x_m - x_l$ subject to

$$\begin{aligned} 2x_m &= x_l + x_r \\ x_l + 10 + s_1 &= x_r \\ x_r + s_2 &= 100 \\ 0 &\leq x_l, s_1, s_2 \end{aligned}$$

We now separate the equalities into C_U and C_S. Initially all equations are in C_S. We separate out the unrestricted variables into C_U using Gauss-Jordan elimination. To do this, we select an equation in C_S containing an unrestricted variable u and remove the equation from C_S. We then solve the equation for u, yielding a new equation $u = e$ for some expression e. We then substitute e for all remaining occurrences of u in C_S, C_U, and f, and place the equation $u = e$ in C_U. The process is repeated until there are no more unrestricted variables in C_S. In our example the third equation can be used to substitute $100 - s_2$ for x_r obtaining

minimize $x_m - x_l$ subject to

$$\begin{array}{rcl} x_r & = & 100 - s_2 \\ \hline 2x_m & = & x_l + 100 - s_2 \\ x_l + 10 + s_1 & = & 100 - s_2 \\ 0 & \leq & x_l, s_1, s_2 \end{array}$$

Next, and the first equation can be used to substitute $50 + \frac{1}{2}x_l - \frac{1}{2}s_2$ for x_m, giving

minimize $50 - \frac{1}{2}x_l - \frac{1}{2}s_2$ subject to

$$\begin{array}{rcl} x_m & = & 50 + \frac{1}{2}x_l - \frac{1}{2}s_2 \\ x_r & = & 100 - s_2 \\ \hline x_l + 10 + s_1 & = & 100 - s_2 \\ 0 & \leq & x_l, s_1, s_2 \end{array}$$

The tableau shows C_U above the horizontal line, and C_S and C_I below the horizontal line. From now on C_I will be omitted — any variable occurring below the horizontal line is implicitly constrained to be non-negative. The simplex method works by taking an optimization problem in "basic feasible solved form" (a type of normal form) and repeatedly applying matrix operations to obtain new basic feasible solved forms. Once we have split the equations into C_U and C_S we can ignore C_U for purposes of optimization.

One Detail. The example includes the constraint $x_l \geq 0$. To simplify the example, we just make x_l be a restricted variable to capture this constraint. In the Cassowary implementation, however, all variables that may be accessed from outside the solver as well as within it are unrestricted. Only error or slack variables are represented as restricted variables, and these variables occur only within the solver. See Section 4. The primary benefit of this is that the programmer using the solver always uses just the one kind of variable. A minor benefit is that only the external, unrestricted variables actually store their values as a field in the variable object; the values of restricted variables are just given by the tableau. A minor drawback is that the constraint $v \geq 0$ must be represented explicitly. (For any other constant $c \neq 0$, $v \geq c$ must be represented explicitly in any event.)

Another Detail. The operations are shown as modifying C_U as well as C_S. It would be possible to modify just C_S and leave C_U unchanged, using C_U only to define values for the variables on the left hand side of its equations. This would speed up pivoting but it would make the incremental updates of the constants in edit constraints slower; and since this is a much more frequent operation, in the implementation we do actually modify both C_U and C_S.

An augmented simplex form optimization problem is in *basic feasible solved form* if the equations are of the form

$$x_0 = c + a_1x_1 + \ldots + a_nx_n$$

where the variable x_0 does not occur in any other equation or in the objective function. If the equation is in C_S, c must be non-negative. However, there is no such restriction on the constants for the equations in C_U. In either case the variable x_0 is said to be *basic* and the other variables in the

equation are *parameters*. A problem in basic feasible solved form defines a *basic feasible solution*, which is obtained by setting each parametric variable to 0 and each basic variable to the value of the constant in the right-hand side.

For instance, the following constraint is in basic feasible solved form and is equivalent to the problem above.

minimize $50 - \frac{1}{2}x_l - \frac{1}{2}s_2$ subject to

$$\begin{array}{rcrrr} x_m & = & 50 & +\frac{1}{2}x_l & -\frac{1}{2}s_2 \\ x_r & = & 100 & & -s_2 \\ \hline s_1 & = & 90 & -x_l & -s_2 \end{array}$$

The basic feasible solution corresponding to this basic feasible solved form is

$$\{x_m \mapsto 50, x_r \mapsto 100, s_1 \mapsto 90, x_l \mapsto 0, s_2 \mapsto 0\}.$$

The value of the objective function with this solution is 50.

2.2 Simplex Optimization

We now describe how to find an optimum solution to a constraint in basic feasible solved form. Except for the operations on the additional unrestricted variable tableau C_U, the material presented in this subsection is simply Phase II of the standard two-phase simplex algorithm.

The simplex algorithm finds the optimum by repeatedly looking for an "adjacent" basic feasible solved form whose basic feasible solution decreases the value of the objective function. When no such adjacent basic feasible solved form can be found, the optimum has been found. The underlying operation is called *pivoting*, and involves exchanging a basic and a parametric variable using matrix operations. Thus by "adjacent" we mean the new basic feasible solved form can be reached by performing a single pivot.

In our example, increasing x_l from 0 will decrease the value of the objective function. We must be careful as we cannot increase the value of x_l indefinitely as this may cause the value of some other basic non-negative variable to become negative. We must examine the equations in C_S. The equation $s_1 = 90 - x_l - s_2$ allows x_l to take at most a value of 90, as if x_l becomes larger than this, then s_1 would become negative. The equations above the horizontal line do not restrict x_l, since whatever value x_l takes the unrestricted variables x_m and x_r can take a value to satisfy the equation. In general, we choose the most restrictive equation in C_S, and use it to eliminate x_l. In the case of ties we arbitrarily break the tie. In this example the most restrictive equation is $s_1 = 90 - x_l - s_2$. Writing x_l as the subject we obtain $x_l = 90 - s_1 - s_2$. We replace x_l everywhere by $90 - s_1 - s_2$ and obtain

minimize $5 + \frac{1}{2}s_1$ subject to

$$\begin{array}{rcrrr} x_m & = & 95 & -\frac{1}{2}s_1 & -s_2 \\ x_r & = & 100 & & -s_2 \\ \hline x_l & = & 90 & -s_1 & -s_2 \end{array}$$

We have just performed a pivot, having moved s_1 out of the set of basic variables and replaced it by x_l.

We continue this process. Increasing the value of s_1 will increase the objective (that we are trying to minimize). Note that decreasing s_1 will also decrease the objective function value, but as s_1

```
simplex_opt(C_S,f)
    repeat
        % Choose variable y_J to become basic
        if for each j ∈ {1,...,m} d_j ≥ 0 then
            return % an optimal solution has been found
        endif
        choose J ∈ {1,...,m} such that d_J < 0
        % Choose variable x_I to become non-basic
        choose I ∈ {1,...,n} such that
            −c_I/a_IJ = min_{i∈{1,...,n}}{−c_i/a_iJ | a_iJ < 0}
        e := (x_I − c_I − Σ_{j=1,j≠J}^{m} a_Ij y_j)/a_IJ
        C_S[I] := (Y_J = e)
        replace Y_J by e in f
        for each i ∈ {1,...,n}
            if i ≠ I then replace Y_J by e in C_S[I] endif
        endfor
    endrepeat
```

Figure 2: Simplex optimization

is constrained to be non-negative, it already takes its minimum value of 0 in the associated basic feasible solution. Hence we are at an optimal solution.

(If we were to have an unrestricted variable in the objective function, the optimization would be unbounded. This is not an issue for our algorithm since the objective function in those cases always only contains restricted variables, i.e., variables implicitly constrained to be non-negative.)

In general, the simplex algorithm applied to C_S is described as follows. We are given a problem in basic feasible solved form in which the variables $x_1, \ldots, x_n$ are basic and the variables $y_1, \ldots, y_m$ are parameters.

$$\text{minimize } e + \textstyle\sum_{j=1}^{m} d_j y_j \quad \text{subject to}$$

$$\textstyle\bigwedge_{i=1}^{n} x_i \;=\; c_i + \sum_{j=1}^{m} a_{ij} y_j \;\wedge\; \bigwedge_{i=1}^{n} x_i \geq 0 \wedge \bigwedge_{j=1}^{m} y_j \geq 0.$$

Select an entry variable y_J such that $d_J < 0$. (An entry variable is one that will enter the basis, i.e., it is currently parametric and we want to make it basic.) Pivoting on such a variable can only decrease the value of the objective function. If no such variable exists, the optimum has been reached. Now determine the exit variable x_I. We must choose this variable so that it maintains basic feasible solved form by ensuring that the new c_i's are still positive after pivoting. That is, we must choose an x_I so that $-c_I/a_{IJ}$ is a minimum element of the set

$$\{-c_i/a_{iJ} \mid a_{iJ} < 0 \text{ and } 1 \leq i \leq n\}.$$

If there were no i for which $a_{iJ} < 0$ then we could stop since the optimization problem would be unbounded, and so would not have a minimum. This is because we could choose y_J to take an arbitrarily large value, and so make the objective function arbitrarily small. However, this is not an issue in our context since our optimization problems will always have a lower bound of 0.

We proceed to choose x_I, and pivot x_I out and replace it with y_J to obtain the new basic feasible solution. We continue this process until an optimum is reached. The algorithm is specified in Figure 2, and takes as inputs the simplex tableau C_S and the objective function f.

2.3 Incrementality: Adding a Constraint

We now describe how to add the equation for a new constraint incrementally. This technique is also used in our implementations to find an initial basic feasible solved form for the original simplex problem, by starting from an empty constraint set and adding the constraints one at a time.

As an example, suppose we wish to ensure that the midpoint sits in the center of the screen. This is represented by the constraint $x_m = 50$. If we substitute for each of the basic variables (only x_m) in this constraint we obtain the equation $45 - \frac{1}{2}s_1 - s_2 = 0$. In order to add this constraint straightforwardly to the tableau we create a new non-negative variable a called an *artificial variable*. (This is simply an incremental version of the operation used in Phase I of the two-phase simplex algorithm.) We let $a = 45 - \frac{1}{2}s_1 - s_2$ be added to the tableau (clearly this gives a tableau in basic feasible solved form) and then minimize the value of a. If a takes the value 0 then we have obtained a solution to the problem with the added constraint, and we can then eliminate the artificial variable altogether since it is a parameter (and hence takes the value 0). This is the case for our example; the resulting tableau is

$$\begin{array}{rcrr} x_m & = & 50 & \\ x_r & = & 100 & -s_2 \\ \hline x_l & = & 0 & +s_2 \\ s_1 & = & 90 & -2s_2 \end{array}$$

In general, to add a new required constraint to the tableau we first convert it to an augmented simplex form equation by adding slack variables if it is an inequality. Next, we use the current tableau to substitute out all the basic variables. This gives an equation $e = c$ where e is a linear expression. If c is negative, we multiply both sides by -1 so that the constant becomes non-negative. If e contains an unrestricted variable we use it to substitute for that variable and add the equation to the tableau above the line (i.e., to C_U). Otherwise we create a restricted artificial variable a and add the equation $a = c - e$ to the tableau below the line (i.e., to C_S), and minimize $c - e$. If the resulting minimum is not zero then the constraints are unsatisfiable. Otherwise a is either parametric or basic. If a is parametric, the column for it can be simply removed from the tableau. If it is basic, the row must have constant 0 (since we were able to achieve a value of 0 for our objective function, which is equal to a). If the row is just $a = 0$, it can be removed. Otherwise, $a = 0 + bx + e$ where $b \neq 0$. We can then pivot x into the basis using this row and remove the column for a.

Implementation Note. In some cases we can add an equation to the tableau without using an artificial variable, even when the equation contains only restricted variables, and for efficiency should do so when it is easy to detect that this can be done. See Section 4.3.2.

2.4 Incrementality: Removing a Constraint

We also want a method for incrementally removing a constraint from the tableaux. After a series of pivots have been performed, the information represented by the constraint may not be contained in a single row, so we need a way to identify the constraint's influence in the tableaux. To do this, we use a "marker" variable that is originally present only in the equation representing the constraint. We can then identify the constraint's effect on the tableaux by looking for occurrences of that marker variable. For inequality constraints, the slack variable s added to make it an equality serves as the marker, since s will originally occur only in that equation. The equation representing a non-required equality constraint will have an error variable that can serve as a marker — see Section 2.5. For required equality constraints, we add a "dummy" restricted variable to the original equation to serve

as a marker, which we never allow to enter the basis (so that it always has value 0). In our running example, then, to allow the constraint $2x_m = x_l + x_r$ to be deleted incrementally we would add a dummy variable d_3, resulting in $2x_m = x_l + x_r + d_3$. The simplex optimization routine checks for these dummy variables in choosing an entry variable, and does not allow one to be selected. (We did not include this variable in the tableaux presented earlier to keep things simpler.)

(Note: these dummy variables must be restricted, not unrestricted, since we might need to have some of them in the equations for restricted basic variables.)

Consider removing the constraint that x_l is 10 to the left of x_r. The slack variable s_1, which we added to the inequality to make it an equation, records exactly how this equation has been used to modify the tableau. We can remove the inequality by pivoting the tableau until s_1 is basic and then simply drop the row in which it is basic.

In the tableau above s_1 is already basic, and so removing it simply means dropping the row in which it is basic, obtaining

$$\begin{array}{rcrl} x_m & = & 50 & \\ x_r & = & 100 & -s_2 \\ \hline x_l & = & 0 & +s_2 \end{array}$$

If we wanted to remove this constraint from the tableau before adding $x_m = 50$ (i.e., the final tableau given in Section 2.2), s_1 is a parameter. We make s_1 basic by treating it as an entry variable and (as usual) determining the most restrictive equation and using that to pivot s_1 into the basis, and then remove the row.

There is such a restrictive equation in this example. However, if no equation restricts the size of the marker variable, that is, its coefficients are all non-negative, then either the marker variable has a positive coefficient in all equations, or it only occurs in equations for unrestricted variables. If it does occur in an equation for a restricted variable, pick the equation that gives the smallest ratio. (The row with the marker variable will become infeasible, but all the other rows will still be feasible, and we will be dropping the row with the marker variable. In effect we are removing the non-negativity restriction on the marker variable.) Finally, if it only occurs in equations for unrestricted variables, we can choose any equation in which it occurs.

In the case above, the row $x_l = 90 - s_1 - s_2$ is the most constraining equation. Pivoting to let s_1 enter the basis, and then removing the row in which it is basic, we obtain

$$\begin{array}{rcrll} x_m & = & 50 & +\frac{1}{2}x_l & -\frac{1}{2}s_2 \\ \hline x_r & = & 100 & & -s_2 \end{array}$$

In the preceding example the marker variable had a negative coefficient. Here is an example in which it just has positive coefficients. The original constraints are:

$$\begin{array}{rcl} x & \geq & 10 \\ x & \geq & 20 \\ x & \geq & 30 \end{array}$$

In basic feasible solved form this is:

$$\begin{array}{rcrr} x & = & 30 & +d_3 \\ \hline s_1 & = & 20 & +d_3 \\ s_2 & = & 10 & +d_3 \end{array}$$

where s_1, s_2, and d_3 are the marker variables for $x \geq 10$, $x \geq 20$, and $x \geq 30$ respectively.

Suppose we want to remove the $x \geq 30$ constraint. We need to pivot to make d_3 basic. The equation that gives the smallest ratio is $s_2 = 10 + d_3$, so the entry variable is d_3 and the exit variable is s_2, giving:

$$\begin{array}{rcrr} x & = & 20 & +s_2 \\ \hline s_1 & = & 10 & +s_2 \\ d_3 & = & -10 & +s_2 \end{array}$$

This is now infeasible, but we drop the row with d_3 giving

$$\begin{array}{rcrr} x & = & 20 & +s_2 \\ \hline s_1 & = & 10 & +s_2 \end{array}$$

which is of course feasible.

As another fine point, note that there is no problem with redundant constraints. Consider:

$$\begin{array}{rcl} x & \geq & 10 \\ x & \geq & 10 \end{array}$$

When converted to basic feasible solved form, each $x \geq 10$ constraint gets a separate slack variable, which is used as the marker variable for that constraint.

$$\begin{array}{rcrr} x & = & 10 & +s_1 \\ \hline s_2 & = & 0 & +s_1 \end{array}$$

To delete the second $x \geq 10$ constraint we would simply drop the $s_2 = 0 + s_1$ row. To delete the first $x \geq 10$ constraint we would pivot, making s_1 basic and s_2 parametric:

$$\begin{array}{rcrr} x & = & 10 & +s_2 \\ \hline s_1 & = & 0 & +s_2 \end{array}$$

and then drop the $s_1 = 0 + s_2$ row.

A consequence of this is that if there are two redundant constraints, both of them must be removed to eliminate their effect. (This seems to be a more desirable behaviour for the solver than removing redundant constraints automatically, although if the latter were desired the solver could be modified to do this.) Another consequence is that when adding a new constraint, we would never decide that it was redundant and not add it to the tableau. (If there were no dummy marker variables, we *would* do this for redundant required equality constraints.)

2.5 Handling Non-Required Constraints

Suppose the user wishes to edit x_m in the diagram and have x_l and x_r weakly stay where they are. This adds the non-required constraints *edit* x_m, *stay* x_l, and *stay* x_r . Suppose further that we are trying to move x_m to position 50, and that x_l and x_r are currently at 30 and 60 respectively. We are thus imposing the constraints strong $x_m = 50$, weak $x_l = 30$, and weak $x_r = 60$. There are two possible translations of these non-required constraints to an objective function, depending on the comparator used.

For locally-error-better or weighted-sum-better, we can simply add the errors of the each constraint to form an objective function. Consider the constraint $x_m = 50$. We define the error as $|x_m - 50|$. We need to combine the errors for each non-required constraint with a weight so we obtain the objective function

$$s|x_m - 50| + w|x_l - 30| + w|x_r - 60|$$

where s and w are weights so that the strong constraint is always strictly more important than solving any combination of weak constraints, so that we find a locally-error-better or weighted-sum-better solution. For the least-squares-better comparator the objective function is

$$s(x_m - 50)^2 + w(x_l - 30)^2 + w(x_r - 60)^2.$$

In the presentation, we will use $s = 1000$ and $w = 1$.

Cassowary actually uses symbolic weights and a lexicographic ordering, which ensures that strong constraints are always satisfied in preference to weak ones (see Section 4).

Unfortunately neither of these objective functions is linear and hence the simplex method is not applicable directly. We now show how we can solve the problem using *quasi-linear optimization*.

3 Cassowary's Quasi-linear Optimization

Cassowary finds either locally-error-better or weighted-sum-better solutions. Since every weighted-sum-better solution is also a locally-error-better solution [4], the weighted-sum part of the optimization comes automatically from the manner in which the objective function is constructed.

Both the edit and the stay constraints will be represented as equations of the form

$$v = \alpha + \delta_v^+ - \delta_v^-$$

where δ_v^+ and δ_v^- are non-negative variables representing the deviation of v from the desired value α. If the constraint is satisfied both δ_v^+ and δ_v^- will be 0. Otherwise δ_v^+ will be positive and δ_v^- will be 0 if v is too big, or vice versa if v is too small. Since we want δ_v^+ and δ_v^- to be 0 if possible, we make them part of the objective function, with larger coefficients for the error variables for stronger constraints. (We need to use the pair of variables to satisfy simplex's non-negativity restriction, since these variables δ_v^+ and δ_v^- will be part of the objective function.)

Translating the constraints strong $x_m = 50$, weak $x_l = 30$, and weak $x_r = 60$ which arise from the edit and stay constraints we obtain:

$$\begin{aligned} x_m &= 50 + \delta_{x_m}^+ - \delta_{x_m}^- \\ x_l &= 30 + \delta_{x_l}^+ - \delta_{x_l}^- \\ x_r &= 60 + \delta_{x_r}^+ - \delta_{x_r}^- \\ 0 &\leq \delta_{x_m}^+, \delta_{x_m}^-, \delta_{x_l}^+, \delta_{x_l}^-, \delta_{x_r}^+, \delta_{x_r}^- \end{aligned}$$

The objective function to satisfy the non-required constraints can now be restated as

minimize $1000\delta^+_{x_m} + 1000\delta^-_{x_m} + \delta^+_{x_l} + \delta^-_{x_l} + \delta^+_{x_r} + \delta^-_{x_r}$.

An optimal solution of this problem can be found using the simplex algorithm, and results in a tableau

minimize $10 + 1002\delta^+_{x_m} + 998\delta^-_{x_m} + 2\delta^-_{x_l} + 2\delta^-_{x_r}$ subject to

$$\begin{array}{rcl|lllll}
x_m & = & 50 & +\delta^+_{x_m} & -\delta^-_{x_m} & & & \\
x_r & = & 70 & +2\delta^+_{x_m} & -2\delta^-_{x_m} & -\delta^+_{x_l} & +\delta^-_{x_l} & \\
\hline
x_l & = & 30 & & & +\delta^+_{x_l} & -\delta^-_{x_l} & \\
s_1 & = & 30 & +2\delta^+_{x_m} & -2\delta^-_{x_m} & -2\delta^+_{x_l} & +2\delta^-_{x_l} & \\
s_2 & = & 30 & -2\delta^+_{x_m} & +2\delta^-_{x_m} & +\delta^+_{x_l} & -\delta^-_{x_l} & \\
\delta^+_{x_r} & = & 10 & +2\delta^+_{x_m} & -2\delta^-_{x_m} & -\delta^+_{x_l} & +\delta^-_{x_l} & +\delta^-_{x_r}
\end{array}$$

This corresponds to the solution $\{x_m \mapsto 50, x_l \mapsto 30, x_r \mapsto 70\}$ illustrated in Figure 1. Notice that the weak stay constraint on x_r is not satisfied ($\delta^+_{x_r}$ is non-zero, read directly from last line of the above tableau).

3.1 Incrementality: Resolving the Optimization Problem

Now suppose the user moves the mouse (which is editing x_m) to $x = 60$. We wish to solve a new problem, with constraints strong $x_m = 60$, and weak $x_l = 30$ and weak $x_r = 70$ (so that x_l and x_r should stay where they are if possible).

There are two steps. First, we modify the tableau to reflect the new constraints we wish to solve. Second, we resolve the optimization problem for this modified tableau.

Let us first examine how to modify the tableau to reflect the new values of the stay constraints. This will not require re-optimizing the tableau, since we know that the new stay constraints are satisfied exactly. Suppose the previous stay value for variable v was α, and in the current solution v takes value β. The current tableau contains the information that

$$v = \alpha + \delta^+_v - \delta^-_v$$

and we need to modify this so that instead

$$v = \beta + \delta^+_v - \delta^-_v$$

There are two cases to consider: (a) both δ^+_v and δ^-_v are parameters, or (b) one of them is basic.

In case (a) v must take the value α in the current solution since both δ^+_v and δ^-_v take the value 0 and

$$v = \alpha + \delta^+_v - \delta^-_v$$

Hence $\beta = \alpha$ and no changes need to be made.

In case (b) assume without loss of generality that δ^+_v is basic. In the original equation representing the stay constraint, the coefficient for δ^+_v is the negative of the coefficient for δ^-_v. Since these variables occur in no other constraints, this relation between the coefficients will continue to hold as we perform pivots. In other words, δ^+_v and δ^-_v come in pairs: any equation that contains δ^+_v will also contain δ^-_v and vice versa. Since δ^+_v is assumed to be basic, it occurs exactly once in an equation

with constant c, and further this equation also contains the only occurrence of δ_v^-. In the current solution

$$\{v \mapsto \beta, \delta_v^+ \mapsto c, \delta_v^- \mapsto 0\}$$

and since the equation

$$v = \alpha + \delta_v^+ - \delta_v^-$$

holds, $\beta = \alpha + c$. To replace the equation

$$v = \alpha + \delta_v^+ - \delta_v^-$$

by

$$v = \beta + \delta_v^+ - \delta_v^-$$

we simply need to replace the constant c in the row for δ_v^+ by 0. Since there are no other occurrences of δ_v^+ and δ_v^- we have replaced the old equation with the new.

For our example, to update the tableau for the new values for the stay constraints on x_l and x_r we simply set the constant of last equation (the equation for $\delta_{x_r}^+$) to 0.

Now let us consider the edit constraints. Suppose the previous edit value for v was α, and the new edit value for v is β. The current tableau contains the information that

$$v = \alpha + \delta_v^+ - \delta_v^-$$

and again we need to modify this so that instead

$$v = \beta + \delta_v^+ - \delta_v^-$$

To do so we must replace every occurrence of

$$\delta_v^+ - \delta_v^-$$

by

$$\beta - \alpha + \delta_v^+ - \delta_v^-$$

taking proper account of the coefficients of δ_v^+ and δ_v^-. (Again, remember that δ_v^+ and δ_v^- come in pairs.)

If either of δ_v^+ and δ_v^- is basic, this simply involves appropriately modifying the equation in which they are basic. Otherwise, if both are non-basic, then we need to change every equation of the form

$$x_i = c_i + a'_v\delta_v^+ - a'_v\delta_v^- + e$$

to

$$x_i = c_i + a'_v(\beta - \alpha) + a'_v\delta_v^+ - a'_v\delta_v^- + e$$

Hence modifying the tableau to reflect the new values of edit and stay constraints involves only changing the constant values in some equations. The modifications for stay constraints always result in a tableau in basic feasible solved form, since it never makes a constant become negative. In contrast the modifications for edit constraints may not.

To return to our example, suppose we pick up x_m with the mouse and move it to 60. Then we have that $\alpha = 50$ and $\beta = 60$, so we need to add 10 times the coefficient of $\delta_{x_m}^+$ to the constant part of every row. The modified tableau, after the updates for both the stays and edits, is

minimize $20 + 1002\delta^+_{x_m} + 998\delta^-_{x_m} + 2\delta^-_{x_l} + 2\delta^-_{x_r}$ subject to

$$\begin{array}{rcrrrrrr}
x_m & = & 60 & +\delta^+_{x_m} & -\delta^-_{x_m} & & & \\
x_r & = & 90 & +2\delta^+_{x_m} & -2\delta^-_{x_m} & -\delta^+_{x_l} & +\delta^-_{x_l} & \\
\hline
x_l & = & 30 & & & +\delta^+_{x_l} & -\delta^-_{x_l} & \\
s_1 & = & 50 & +2\delta^+_{x_m} & -2\delta^-_{x_m} & -2\delta^+_{x_l} & +2\delta^-_{x_l} & \\
s_2 & = & 10 & -2\delta^+_{x_m} & +2\delta^-_{x_m} & +\delta^+_{x_l} & -\delta^-_{x_l} & \\
\delta^+_{x_r} & = & 20 & +2\delta^+_{x_m} & -2\delta^-_{x_m} & -\delta^+_{x_l} & +\delta^-_{x_l} & +\delta^-_{x_r}
\end{array}$$

Clearly it is feasible and already in optimal form, and so we have incrementally resolved the problem by simply modifying constants in the tableaux. The new tableaux give the solution $\{x_m \mapsto 60, x_l \mapsto 30, x_r \mapsto 90\}$. So sliding the midpoint rightwards has caused the right point to slide rightwards as well, but twice as far. The resulting diagram is shown at the top of Figure 3.

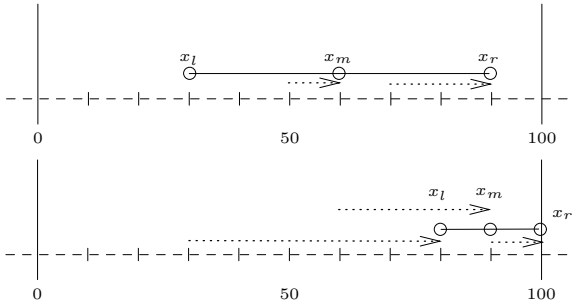

Figure 3: Resolving the constraints

Suppose we now move x_m from 60 to 90. The modified tableau is

minimize $60 + 1002\delta^+_{x_m} + 998\delta^-_{x_m} + 2\delta^-_{x_l} + 2\delta^-_{x_r}$ subject to

$$\begin{array}{rcrrrrrr}
x_m & = & 90 & +\delta^+_{x_m} & -\delta^-_{x_m} & & & \\
x_r & = & 150 & +2\delta^+_{x_m} & -2\delta^-_{x_m} & -\delta^+_{x_l} & +\delta^-_{x_l} & \\
\hline
x_l & = & 30 & & & +\delta^+_{x_l} & -\delta^-_{x_l} & \\
s_1 & = & 110 & +2\delta^+_{x_m} & -2\delta^-_{x_m} & -2\delta^+_{x_l} & +2\delta^-_{x_l} & \\
s_2 & = & -50 & -2\delta^+_{x_m} & +2\delta^-_{x_m} & +\delta^+_{x_l} & -\delta^-_{x_l} & \\
\delta^+_{x_r} & = & 60 & +2\delta^+_{x_m} & -2\delta^-_{x_m} & -\delta^+_{x_l} & +\delta^-_{x_l} & +\delta^-_{x_r}
\end{array}$$

The tableau is no longer in basic feasible solved form, since the constant of the row for s_2 is negative, even though s_2 is supposed to be non-negative.

Thus, in general, after updating the constants for the edit constraints, the simplex tableau C_S may no longer be in basic feasible solved form, since some of the constants may be negative. However, the tableau is still in basic form, so we can still read a solution directly from it as before. And since no coefficient has changed, in particular in the optimization function, the resulting tableau reflects an optimal but not feasible solution.

We need to find a feasible and optimal solution. We could do so by adding artificial variables (as we did when adding a constraint), optimizing the sum of the artificial variables to find an initial feasible solution, and then re-optimizing the original problem.

But we can do much better. The process of moving from an optimal and infeasible solution to an optimal and feasible solution is exactly the dual of normal simplex algorithm, where we progress from a feasible and non-optimal solution to feasible and optimal solution. Hence we can use the *dual simplex algorithm* to find a feasible solution while staying optimal.

Solving the dual optimization problem starts from an infeasible optimal tableau of the form

$$\text{minimize } e + \Sigma_{j=1}^{m} d_j y_j \quad \text{subject to}$$

$$\bigwedge_{i=1}^{n} x_i = c_i + \Sigma_{j=i}^{m} a_{ij} y_j$$

where some c_i may be negative for rows with non-negative basic variables (infeasibility) and each d_j is non-negative (optimality).

The dual simplex algorithm selects an exit variable by finding a row I with non-negative basic variable x_I and negative constant c_I. The entry variable is the variable y_J such that the ratio d_J/a_{IJ} is the minimum of all d_j/a_{Ij} where a_{Ij} is positive. This ensures that when pivoting we stay at an optimal solution. The pivot replaces y_j by

$$-1/a_{Ij}(-x_I + c_I + \Sigma_{j=1, j\neq J}^{m} a_{Ij} y_j)$$

and is performed as in the (primal) simplex algorithm. The algorithm is shown in Figure 4.

Continuing the example above we select the exit variable s_2, the only non-negative basic variable for a row with negative constant. We find that $\delta_{x_l}^+$ has the minimum ratio since its coefficient in the optimization function is 0, so it will be the entry variable. Replacing $\delta_{x_l}^+$ everywhere by $50 + s_2 + 2\delta_{x_m}^+ - 2\delta_{x_m}^- + \delta_{x_l}^+$ we obtain the tableau

$$\text{minimize } 30060 + 1002\delta_{x_m}^+ + 998\delta_{x_m}^- + 2\delta_{x_l}^- + 2\delta_{x_r}^- \quad \text{subject to}$$

$$\begin{array}{rcrrrrrr}
x_m & = & 90 & & +\delta_{x_m}^+ & -\delta_{x_m}^- & & \\
x_r & = & 100 & -s_2 & & & & \\
\hline
x_l & = & 80 & +s_2 & +2\delta_{x_m}^+ & -2\delta_{x_m}^- & & \\
s_1 & = & 110 & -2s_2 & +2\delta_{x_m}^+ & -2\delta_{x_m}^- & & \\
\delta_{x_l}^+ & = & 50 & +s_2 & +2\delta_{x_m}^+ & -2\delta_{x_m}^- & +\delta_{x_l}^- & \\
\delta_{x_r}^+ & = & 40 & -s_2 & & & & +\delta_{x_r}^-
\end{array}$$

The tableau is feasible (and of course still optimal) and represents the solution $\{x_m \mapsto 90, x_r \mapsto 100, x_l \mapsto 80\}$. So by sliding the midpoint further right, the rightmost point hits the wall and the left point slides right to satisfy the constraints. The resulting diagram is shown at the bottom of Figure 3.

To summarize, incrementally finding a new solution for new input variables involves updating the constants in the tableaux to reflect the updated stay constraints, then updating the constants to reflect the updated edit constraints, and finally re-optimizing if needed. In an interactive graphical application, when using the dual optimization method typically a pivot is only required when one part first hits a barrier, or first moves away from a barrier. The intuition behind this is that when a constraint first becomes unsatisfied, the value of one of its error variables will become non-zero, and hence the variable will have to enter the basis; when a constraint first becomes satisfied, we can move one of its error variables out of the basis.

In the example, pivoting occurred when the right point x_r came up against a barrier. Thus, if we picked up the midpoint x_m with the mouse and smoothly slid it rightwards, 1 pixel every screen refresh, only one pivot would be required in moving from 50 to 95. This illustrates why the dual optimization is well suited to this problem and leads to efficient resolving of the hierarchical constraints.

```
re_optimize(C_S,f)
    foreach stay : v ∈ C
        if δ_v^+ or δ_v^- is basic in row i then c_i := 0 endif
    endfor
    foreach edit : v ∈ C
        let α and β be the previous and current edit values for v
        let δ_v^+ be y_j
        foreach i ∈ {1,...,n}
            c_i := c_i + a_ij(β − α)
        endfor
    endfor
    repeat
        % Choose variable x_I to become non-basic
        choose I where c_I < 0
        if there is no such I
            return true
        endif
        % Choose variable y_J to become basic
        if for each j ∈ {1,...,m} a_Ij ≤ 0 then
            return false
        endif
        choose J ∈ {1,...,m} such that
            d_J/a_IJ = min_{j∈{1,...,m}}{d_j/a_Ij | a_Ij > 0}
        e := (x_I − c_I − Σ_{j=1,j≠J}^{m} a_Ij y_j)/a_IJ
        replace y_J by e in f
        for each i ∈ {1,...,n}
            if i ≠ I then replace y_J by e in row i endif
        endfor
        replace the I^th row by y_J = e
    until false
```

Figure 4: Dual Simplex Re-optimization

4 Implementation Details

This section explains the details of the various Cassowary implementations. There is also a subsection on some fine points regarding the comparator.

4.1 Solver Protocol

The solver itself is represented as an instance of ClSimplexSolver. The public message protocol is as follows.

addConstraint(ClConstraint cn)
: Incrementally add the linear constraint cn to the tableau. The constraint object contains its strength.

removeConstraint(ClConstraint cn)
: Remove the constraint cn from the tableau. Also remove any error variables associated with cn from the objective function.

addEditVar(ClVariable v, ClStrength s)
: Add an edit constraint of strength s on variable v to the tableau so that suggestValue (see below) can be used on that variable after a beginEdit().

removeEditVar(ClVariable v)
: Remove the previously added edit constraint on variable v. The endEdit message automatically removes all the edit variables as part of terminating an edit manipulation.

beginEdit()
: Prepare the tableau for new values to be given to the currently-edited variables. The addEditVar message should be used before calling beginEdit, and suggestValue and resolve should be used only after beginEdit has been invoked, but before the required matching endEdit.

suggestValue(ClVariable v, double n)
: Specify a new desired value, n, for the variable v. Before this call, v needs to have been added as a variable of an edit constraint (either by addConstraint of a hand-built EditConstraint object or more simply using addEditVar).

endEdit()
: Denote the end of an edit manipulation, thus removing all edit constraints from the tableau. Each beginEdit call must be matched with a corresponding endEdit invocation.

resolve()
: Try to re-solve the tableau given the newly specified desired values. Calls to resolve should be sandwiched between a beginEdit() and a endEdit(), and should occur after new values for edit variables are set using suggestValue.

addPointStays(Vector points)
: This is a bit of a kludge, and addresses the desire to satisfy the stays on both the x and y components of a given point rather than on the x component of one point and the y component of another. points is an array of points, whose x and y components are constrainable variables. This method adds a weak stay constraint to the x and y variables of each point. The weights for the x and y components of a given point are the same. However, the weights for successive points are each smaller than those for the previous point (1/2 of the previous weight). The effect of this is to encourage the solver to satisfy the stays on both the x and y of a given point rather than the x stay on one point and the y stay on another. See Subsection 4.5 for more on this issue.

setAutoSolve(boolean f)
: Choose whether the solver should automatically optimize and set external variable values after each addConstraint or removeConstraint. By default, auto-solving is on, but passing false to this method will turn it off (until later turned back on by passing true to this method). When auto-solving is off, solve (below) or resolve must be invoked to see changes to the ClVariables contained in the tableau.

FIsAutoSolving() **returns** boolean
: Return true if and only if the solver is auto-solving, false otherwise.

solve()
: Optimize the tableau and set the external ClVariables contained in the tableau to their new values. This method need only be invoked if auto-solving has been turned off. It never needs to be called after a resolve method invocation.

reset()
: Re-initialize the solver from the original constraints, thus getting rid of any accumulated numerical problems. (It is not yet clear how often such problems arise, but here is the method anyway.)

4.1.1 Possible Revisions to Solver Protocol

One thing that might be worth changing is the way that stay constraints are handled. Currently, each variable that is to stay at an old value needs an explicit stay constraint. These stay constraints need to be added before any other constraints, since otherwise the variable's value is likely to be changed inappropriately to satisfy the other constraints while initially building the tableau.

Instead, stay constraints could be implicit for each variable, and thus be in effect added before any other constraints.

4.2 Principal Classes

Here is a listing of the principal classes. (In the current implementations all the classes start with "ClI".) All of the classes are of course direct or indirect subclasses of ClObject for the Smalltalk and Java implementations.

- ClObject
  - ClAbstractVariable
    - ClDummyVariable
    - ClObjectiveVariable
    - ClSlackVariable
    - ClVariable
  - ClConstraint
    - ClEditOrStayConstraint
      - ClEditConstraint
      - ClStayConstraint
    - ClLinearConstraint
      - ClLinearEqualityConstraint
      - ClLinearInequalityConstraint
  - ClLinearExpression
  - ClTableau
    - ClSimplexSolver
  - ClStrength
  - ClSymbolicWeight

Following is a description of the classes. Some of these classes make use of the Dictionary abstract data type: dictionaries have keys and values and permit efficiently finding the value for a given key, and adding or deleting key/value pairs. One can also iterate through all keys, all values, or all key/value pairs.

The solver itself is represented as an instance of ClSimplexSolver, with public message protocol as described above. There is more on the implementation of this class in Subsection 4.3.

4.2.1 Variables

ClAbstractVariable and its subclasses represent various kinds of constrained variables. ClAbstractVariable is an abstract class, that is, it is just used as a superclass of other classes; one does not make instances of ClAbstractVariable itself. ClAbstractVariable defines the message protocol for constrainable variables. Its only instance variable is name, which is a string name for the variable. (This is used for debugging and constraint understanding tasks.)

Instances of the concrete ClVariable subclass of ClAbstractVariable are what the user of the solver sees (hence it was given a nicer class name). This class has an instance variable value that holds the value of this variable. Users of the solver can send one of these variables the message value to get its value.

The other subclasses of ClAbstractVariable are used only within the solver. They do not hold their own values — rather, the value is just given by the current tableau. None of them have any additional instance variables.

Instances of ClSlackVariable are restricted to be non-negative. They are used as the slack variable when converting an inequality constraint to an equation, and for the error variables to represent non-required constraints.

Instances of ClDummyVariable is used as a marker variable to allow required equality constraints to be deleted. (For inequalities or non-required constraints, the slack or error variable is used as the marker.) These dummy variables are never pivoted into the basis.

An instance of ClObjectiveVariable is used to index the objective row in the tableau. (Conventionally this variable is named z.) This kind of variable is just for convenience — the tableau is represented as a dictionary (with some additional cross-references). Each row is represented as an entry in the dictionary; the key is a basic variable and the value is an expression. So an instance of ClObjectiveVariable is the key for the objective row. The objective row is unique in that the coefficients of its expression are ClSymbolicWeights, not just ordinary real numbers. (The current C++ and Java implementations convert ClSymbolicWeights to real numbers to avoid dealing with ClLinearExpressions parameterized on the type of the coefficient. See Section 4.2.5 for more details.)

All variables understand the following messages: isDummy, isExternal, isPivotable, and isRestricted. They also understand messages to get and set the variable's name.

Class	isDummy	isExternal	isPivotable	isRestricted
ClDummyVariable	True	False	False	True
ClVariable	False	True	False	False
ClSlackVariable	False	False	True	True
ClObjectiveVariable	False	False	False	False

Figure 5: Subclasses of ClAbstractVariable

For isDummy, instances of ClDummyVariable return true and everyone else returns false. The solver uses this message to test for dummy variables. It will not choose a dummy variable as the subject for a new equation, unless all the variables in the equation are dummy variables. (The solver also will not pivot on dummy variables, but this is handled by the isPivotable message.)

For isExternal, instances of ClVariable return true and everyone else returns false. If a variable responds true to this message, it means that it is known outside the solver, and so the solver needs to give it a value after solving is complete.

For isPivotable, instances of ClSlackVariable returns true and everyone else returns false. The solver uses this message to decide whether it can pivot on a variable.

For isRestricted, instances of ClSlackVariable and of ClDummyVariable return true, and instances of ClVariable and ClObjectiveVariable return false. Returning true means that this variable is restricted to being non-negative.

So variables do not hold state, except for a name for debugging, and a value for instances of ClVariable — mostly their significance is just their identity. The only other messages that variables understand are some messages to ClVariable for creating constraints — see Subsection 4.2.4.

4.2.2 Linear Expressions

Instances of the class ClLinearExpression hold a linear expression, and are used in building and representing constraints, and in representing the tableau. A linear expression holds a dictionary of variables and coefficients (the keys are variables and the values are the corresponding coefficients). Only variables with non-zero coefficients are included in the dictionary; if a variable is not in this dictionary its coefficient is assumed to be zero. The other instance variable is a constant. So to represent the linear expression $a_1x_1 + \cdots + a_nx_n + c$, the dictionary would hold the key x_1 with value a_1, etc., and the constant c.

Linear expressions understand a large number of messages. Some of these are for constraint creation (see Section 4.2.4). The others are to substitute an expression for a variable in the constraint, to add an expression, to find the coefficient for a variable, and so forth.

4.2.3 Constraints

There is an abstract class ClConstraint that serves as the superclass for other concrete classes. It defines two instance variables: strength and weight. The variable strength is the strength of this constraint in the constraint hierarchy (and should be an instance of ClStrength), while weight is a float indicating the weight of the constraint, or nil/null if it does not have a weight. (Weights are only relevant for weighted-sum-better comparators, not for locally-error-better ones.)

Constraints understand various message that return true or false regarding some aspect of the constraint, such as isRequired, isEditConstraint, isStayConstraint, and isInequality.

ClLinearConstraint is an abstract subclass of ClConstraint. It adds an instance variable expression, which holds an instance of ClLinearExpression. It has two concrete subclasses. An instance of ClLinearEquation represents the linear equality constraint

expression = 0.

An instance of ClLinearInequality represents the constraint

expression $\geq$ 0.

The other part of the hierarchy is for edit and stay constraints (both of which are represented explicitly in the current implementation). ClEditOrStayConstraint has an instance field variable, which is the ClVariable with the edit or stay. Otherwise all they do is respond appropriately to the messages isEditConstraint and isStayConstraint.

This constraint hierarchy is also intended to allow extension to include local propagation constraints (which would be another subclass of ClConstraint) — otherwise we could have made everything be

a linear constraint, and eliminated the abstract class ClConstraint entirely.

4.2.4 Constraint Creation

This subsection describes a mechanism to allow constraints to be defined easily by programmers. The convenience afforded by Cassowary varies among languages. Smalltalk's dynamic nature makes it the most expressive. C++'s operator overloading still permits using natural infix notation. Java, however, requires using regular methods, and leaves us with the single option of prefix expressions when building constraints.

In Smalltalk, the messages +, -, *, and / are defined for ClVariable and ClLinearExpression to allow convenient creation of constraints by programmers. Also, ClVariable and ClLinearExpression, as well as Number, define cnEqual:, cnGEQ:, and cnLEQ: to return linear equality or inequality constraints. Thus, the Smalltalk expression

```
3*x+5 cnLEQ: y
```

returns an instance of ClLinearEquality representing the constraint $3x+5 \leq y$. This works as follows. The number 3 gets the message * x. Since x is not a number, 3 sends the message * 3 to x. x is an instance of ClVariable, which understands * to return a new linear expression with a single term, namely itself times the argument. (If the argument is not a number it raises an exception that the expression is non-linear.) The linear expression representing $3x$ gets the message + with the argument 5, and returns a new linear expression representing $3x+5$. This linear expression gets the message cnLEQ: with the argument y. It computes a new linear expression representing $y-3x-5$, and then returns an instance of ClLinearInequality with this expression.

(It is tempting to make this nicer by using the =, <=, and >= messages, so that one could write

```
3*x+5 <= y
```

instead but since the rest of Smalltalk expects =, <=, and >= to perform a test and return a boolean, rather than to return a constraint, this would not be a good idea.)

Similarly, in C++ the arithmetic operators are overloaded to build ClLinearExpressions from ClVariables and other ClLinearExpressions. Actual constraints are built using various constructors for ClLinearEquation or ClLinearInequality. An enumeration defines the symbolic constants cnLEQ and cnGEQ to approximate the Smalltalk interface. For example:

```
ClLinearInequality cn(3*x+5, cnLEQ, y);       // C++
```

build the constraint cn representing $3x+5 \leq y$.

In Java, the same constraint would be built as follows:

```
ClLinearInequality cn = new ClLinearInequality(CL.Plus(CL.Times(x,3),5), CL.LEQ, y);
```

Though the Java implementation makes it difficult to express hard-coded constraints, use of the implementation in conjunction with a user interface for specifying the constraints has shown that the inconvenience is relatively unimportant.

4.2.5 Symbolic Weights and Strengths

The constraint hierarchy theory allows an arbitrary (although finite) number of strengths of constraint. In practice, however, programmers use a small number of strengths in a stylized way. The

current implementation therefore includes a small number of pre-defined strengths, and the maximum number of strengths is defined as a constant. (This constant can be changed — see below — but we would not expect to do so frequently.)

The strengths are currently defined as follows.

required Required constraints must be satisfied. This strength is used for most programmer-defined constraints.

strong This strength is used for edit constraints.

medium Currently unused.

weak This strength is used for stay constraints.

These are represented as four instances of ClStrength.

The other relevant class is ClSymbolicWeight. As mentioned in Section 2.5, the objective function is formed as the weighted sum of the positive and negative errors for the non-required constraints. The weights should be such that the stronger constraints totally dominate the weaker ones. In general to pick a real number for the weight we need to know how big the values of the variables can be. To avoid this problem altogether, rather than real numbers as weights we use symbolic weights and a lexicographic ordering, which ensures that strong constraints are always satisfied in preference to weak ones.

Instances of ClSymbolicWeight are used to represent these symbolic weights. These instances have an array of floating point numbers, whose length is the number of non-required strengths (so 3 at the moment). Each element of the array represents the value at that strength, so $(1.0, 0.0, 10.0)$ represents a weight of 1.0 strong, 0.0 medium, and 10.0 weak. (In Smalltalk ClSymbolicWeight is a variable length subclass; we could have had an instance variable with an array of length 3 instead.) Symbolic weights understand various arithmetic messages, as follows (in C++, these are implemented using operator overloading):

+ w
w is also a symbolic weight. Return the result of adding self/this to w.

– w
w is also a symbolic weight. Return the result of subtracting w from self/this.

* n
n is a number. Return the result of multiplying self/this by n.

/ n
n is a number. Return the result of dividing self/this by n.

<= n, >= n, < n, > n, = n
w is a symbolic weight. Return true if self is related to n as the operator normally queries.

negative
Return true if this symbolic weight is negative (i.e., it does not consist of all zeros and the first non-zero number is negative).

Instances of ClStrength represent a strength in the constraint hierarchy. The instance variables are name (for printing purposes) and symbolicWeight, which is the unit symbolic weight for this strength. Thus, with the 3 strengths as above, strong is $(1.0, 0.0, 0.0)$, medium is $(0.0, 1.0, 0.0)$, and weak is $(0.0, 0.0, 1.0)$.

The above arithmetic messages let the Smalltalk implementation of the solver use symbolic weights just like numbers in expressions. This is important because the objective row in the tableau has coefficients which are ClSymbolicWeights but are subject to the same manipulation as the other tableau rows whose expressions have coefficients which are just real numbers.

In both C++ and Java, an additional message asDouble() is understood by ClSymbolicWeights. This converts the representation to a real number that approximates the total ordering suggested by the more general vector of real numbers. It is these real numbers that are used as the coefficients in the objective row of the tableau instead of ClSymbolicWeights (which the coefficients conceptually are). This kludge avoids the complexities that such genericity introduces to the static type systems of C++ and Java. (An improved C++ implementation using templates is underway.)

Also, since Java lacks operator overloading, the above operations are invoked using suggestive alphabetic method names such as add, subtract, times, and lessThan.

4.3 ClSimplexSolver Implementation

Here are the instance variables of ClSimplexSolver (some fields are inherited from ClTableau, the base class of ClSimplexSolver which provides the basic sparse-matrix interface — see section 4.3.1).

rows
: A dictionary with keys ClAbstractVariable and values ClLinearExpression. This holds the tableau. Note that the keys can be either restricted or unrestricted variables, i.e., both C_U and C_S are actually merged into one tableau. This simplified the code considerably, since many operations are applied to both restricted and unrestricted rows.

columns
: A dictionary with keys ClAbstractVariable and values Set of ClAbstractVariable. These are the column cross-indices. Each parametric variable p should be a key in this dictionary. The corresponding set should include exactly those basic variables whose linear expression includes p (p will of course have a non-zero coefficient). The keys can be either unrestricted or restricted variables.

objective
: Return an instance of ClObjectiveVariable (named z) that is the key for the objective row in the tableau.

infeasibleRows
: Return a set of basic variables that have infeasible rows. (This is used when re-optimizing with the dual simplex method.)

prevEditConstants
: An array of constants (floats) for the edit constraints on the previous iteration. The elements in this array must be in the same order as editPlusErrorVars and editMinusErrorVars, and the argument to the public resolve: message.

stayPlusErrorVars
: An array of plus error variables (instances of ClSlackVariable) for the stay constraints. The corresponding negative error variable must have the same index in stayMinusErrorVars.

stayMinusErrorVars
: See stayPlusErrorVars.

editPlusErrorVars
: An array of plus error variables (instances of ClSlackVariable) for the edit constraints. The corresponding negative error variable must have the same index in editMinusErrorVars.

editMinusErrorVars
: See editPlusErrorVars.

markerVars
: A dictionary whose keys are constraints and whose values are instances of a subclass of ClAbstractVariable. This dictionary is used to find the marker variable for a constraint when deleting that constraint. A secondary use is that iterating through the keys will give all of the original constraints (useful for reset).

errorVars
: A dictionary whose keys are constraints and whose values are arrays of ClSlackVariable. This dictionary gives the error variable (or variables) for a given non-required constraint. We need this if the constraint is deleted, since the corresponding error variables must be deleted from the objective function.

slackCounter
: Used for debugging. An integer used to generate names for slack variables, which are useful when printing out expressions. (Thus we get slack variables named s1, s2, etc.)

artificialCounter
: Similar to slackCounter but for artificial variables.

dummyCounter
: Similar to slackCounter but for dummy variables (i.e., marker variables for required equality constraints).

4.3.1 ClTableau (Sparse Matrix) Operations

The basic requirements for the tableau representation are that one should be able to perform the following operations efficiently:

- determine whether a variable is basic
- determine whether a variable is parametric
- find the corresponding expression for a basic variable
- iterate through all the parametric variables with non-zero coefficients in a given row
- find all the rows that contain a given parametric variable with a non-zero coefficient
- add a row
- remove a row
- remove a parametric variable
- substitute out a variable (i.e., replace all occurrences of a variable with an expression, updating the tableau as appropriate).

The representation of the tableau as a dictionary of rows, with column cross-indices, supports these operations. Keeping the cross indices up-to-date is a bit tricky, and so the solver actually accesses the rows and columns only via the below interface of ClTableau, to avoid getting the two representations out of sync.

addRow(ClAbstractVariable var, ClLinearExpression expr)
: Add the constraint var=expr to the tableau. var will become a basic variable. Update the column cross indices.

noteAddedVariable(ClAbstractVariable var, ClAbstractVariable subject)
: Variable var has been added to the linear expression for subject. Update the column cross indices.

noteRemovedVariable(ClAbstractVariable var, ClAbstractVariable subject)
: Variable var has been removed from the linear expression for subject. Update the column cross indices.

removeColumn(ClAbstractVariable var)
: Remove the parametric variable var from the tableau. This involves removing the column cross index for var and removing var from every expression in rows in which it occurs.

removeRow(ClAbstractVariable var)
: Remove the basic variable var from the tableau. Since var is basic, there should be a row var=expr. Remove this row, and also update the column cross indices.

substituteOut(ClAbstractVariable var, ClLinearExpression expr)
: Replace all occurrences of var with expr and update the column cross indices.

4.3.2 Adding a Constraint

Section 2.3 discussed how to add constraints incrementally. If the equation contains any unrestricted variables, we can not use an artificial variable because we can not put an equation in C_S that contains an unrestricted variable. In some other cases we can avoid using an artificial variable for efficiency. We can avoid using an artificial variable if we can choose a subject for the equation from among its current variables. Here are the rules for choosing a subject. (These are to be used after replacing any basic variables with their defining expressions.)

We start with an expression expr (which is an instance of ClLinearExpression). If necessary, normalize expr by multiplying by -1 so that its constant part is non-negative. We are adding the constraint expr=0 to the tableau. To do this we want to pick a variable in expr to be the subject of an equation, so that we can add the row var=expr2, where expr2 is the result of solving expr=0 for var.

- If expr contains any unrestricted variables, we must choose an unrestricted variable as the subject.
- If the subject is new to the solver, we will not have to do any substitutions, so we prefer new variables to ones that are currently noted as parametric.
- If expr contains only restricted variables, if there is a (restricted) variable in expr that has a negative coefficient and that is new to the solver, we can pick that variable as the subject.
- Otherwise use an artificial variable.

A consequence of these rules is that we can always add a non-required constraint to the tableau without using an artificial variable, since the equation will contain a positive and a negative error or slack variable, both of which are new to the solver, and which occur with opposite signs. (Constraints that are originally equations will have a positive and a negative error variable, while constraints that are originally inequalities will have one error variable and one slack variable, with opposite signs.) This is good because a common operation is adding a non-required edit.

4.3.3 Removing a Constraint

Here are a few additional remarks in addition to the material presented in Section 2.4.

First, before we remove the constraint, there may be some stay constraints that were unsatisfied previously — if we just removed the constraint these could come into play. Instead, reset all of the stays so that all variables are constrained to stay at their current values.

Also, if the constraint being removed is not required we need to remove the error variables for it from the objective function. To do this we add the following to the expression for the objective function:

$$-1 \times e \times s \times w$$

where e is the error variable if it is parametric, or else e is its defining expression if it is basic, s is the unit symbolic weight for the constraint's strength, and w is its weight. (s is an instance of ClSymbolicWeight and w is a float.)

If we allow non-required constraints other than stays and edits, we also need to re-optimize after deleting a constraint, since a non-required constraint might have become satisfiable (or more nearly satisfiable).

4.4 Omissions

The solver should implement Bland's anti-cycling rule [14], but it does not at the moment. Adding this should be straightforward.

4.5 Comparator Details

Our implementation of Cassowary favors solutions that satisfies some of the constraints completely, rather than ones that, for example, partially satisfy each of two conflicting equalities. These are still legitimate locally-error-better solutions. Cassowary's behaviour is analogous to that of the simplex algorithm, which always finds solutions at a vertex of the polytope even if all the solutions on an edge or face are equally good. (And of course Cassowary behaves this way because simplex does.)

Such solutions are also produced by greedy constraint satisfaction algorithms, including local propagation algorithms such as DeltaBlue [17] and Indigo [2], since these algorithms try to satisfy constraints one at a time, and in effect the constraints considered first are given a stronger strength than those considered later.

However, there is an issue regarding comparators and Cassowary, which has not yet been resolved in an entirely clean way. One of the public methods for Cassowary is addPointStays: points, as

discussed in Subsection 4.1. This method addresses the desire to satisfy the stays on both the x and y components of a given point rather than on the x component of one point and the y component of another.

As an example of why this is useful, consider a line with endpoints p1 and p2 and a midpoint m. There are constraints (p1.x+p2.x)/2 = m.x and (p1.y+p2.y)/2 = m.y. Suppose we are editing m. It would look strange to satisfy the stay constraints on p1.x and p2.y, rather than both stays on p1 or both stays on p2. (This claim has been verified empirically — in earlier implementations of Cassowary this happened, and indeed it looked strange.)

The current implementation of addPointStays: points uses different weights for the stay constraints for successive elements of points, which is a kludge but which seems to work well in practice.

We had some trouble coming up with an example where it would give a bad answer — here is a contrived one. Suppose we have a line with endpoints p1 and p2 and a midpoint m. Suppose also we have constraints p2.x = 2*p3.x and p2.y = 2*p3.y. (This is a bit strange since here we are using p3 as a distance from the origin rather than as a location — otherwise multiplying it by 2 is problematic.) If we give these points to addPointStays: in the order p1, p2, and p3, then the stays on p1 will have weight 1, those on p2 will have weight 0.5, and those on p3 will have weight 0.25. Then, a one legitimate WSB solution would satisfy the stays on p1.x and p1.y, but another legitimate WSB solution would satisfy the stays on p1.x, p2.y, and p3.y.

Here is a cleaner way to handle this situation. We first introduce a new comparator with the dubious name of *tilted-locally-error-better*. The set of TLEB solutions can be defined by taking a given hierarchy, forming all possible hierarchies by breaking strength ties in all possible ways to form a totally ordered set of constraints, and taking the union of the sets of solutions to each of these totally ordered hierarchies.

For example, consider the two constraints weak $x = 0$ and weak $x = 10$. The set of LEB solutions is the infinite set of mappings from x to each number in $[0, 10]$. Assuming equal weights on the constraints, the (single) least-squares solution is $\{x \mapsto 5\}$. The TLEB solutions are defined by producing all the totally ordered hierarchies and taking the union of their solutions. In this case the two possible total orderings are:

weak $x = 0$, slightly_weaker $x = 10$
slightly_weaker $x = 0$, weak $x = 10$

These have solutions $\{x \mapsto 0\}$ and $\{x \mapsto 10\}$ respectively, so the set of TLEB solutions to the original hierarchy is $\{\{x \mapsto 0\}, \{x \mapsto 10\}\}$.

As an aside, we hypothesize that the only psychologically plausible solutions to the example are $\{x \mapsto 0\}$, $\{x \mapsto 5\}$, and $\{x \mapsto 10\}$, but not, for example, $\{x \mapsto 3.8\}$. (This hypothesis has not been tested.) Another relevant question is whether users prefer any of these solutions over others (for a given application domain).

Next, we introduce a notion of a *compound constraint*, a conjunction of primitive constraints, in this case linear equalities or inequalities. For compound constraints, when we break the strength ties in defining the set of tilted-locally-error-better solutions, we insist on mapping each linear equality or inequality in a compound constraint to an adjacent strength. (We have been a bit imprecise in the use of the term "constraint" in this paper, sometimes using it to denote a primitive constraint and sometimes to denote a conjunction of primitive constraints. For the present definition, however, we need to distinguish compound constraints that have been specifically identified as such by the user from conjunctions of primitive constraints more generally, such as the constraints C_S and C_U discussed in Section 2.1.)

Now, to define addPointStays: in a more clean way, we could make each point stay a compound constraint. To illustrate why this works, consider the midpoint example again. We have two endpoints p1 and p2, and a midpoint m. There are constraints (p1.x+p2.x)/2 = m.x and (p1.y+p2.y)/2 = m.y, and we are editing m. Then the stays on p1 and p2 will each be compound constraints:

weak (*stay* $p1.x$ & *stay* $p1.y$)
weak (*stay* $p2.x$ & *stay* $p2.y$)

In defining the set of tilted-locally-error-better solutions, the total orderings of these constraints that we will consider have the stays on $p1.x$ and $p1.y$ both stronger than those on $p2.x$ and $p2.y$, or both weaker. This produces the desired result.

Note that it is not sufficient just to define a notion of "compound constraint" without adding the notion of tilting — otherwise if we were using locally-error-better, we would just sum the errors of the primitive constraints, which would allow us to trade off the errors arbitrarily and hence satisfy the stay on the x component of one point and the y component of another.

Note also that none of these difficulties is a problem for least-squares-better comparators such as the one that the QOCA algorithm uses — that comparator distributes the error to the x and y components of all the points with stays of the same strength [6].

5 Empirical Evaluation

Cassowary has been implemented in Smalltalk, C++, and Java. We ran some simple benchmarks using test problems which tried to add 300 randomly-generated constraints using 300 variables, and 900 randomly-generated constraints using 900 variables.

When running the Smalltalk implementation of Cassowary on the 300-constraint benchmark problem, adding a constraint takes on average 38 msec (including the initial solve), deleting a constraint 46 msec, and resolving as the point moves 15 msec. (Stay and edit constraints are represented explicitly in this implementation, so there were also stay constraints on each variable, plus two edit constraints, for a total of 602 constraints minus the constraints that, if added, would have resulted in an unsatisfiable system.) For the 900 constraint problem, adding a constraint takes on average 98 msec, deleting a constraint 151 msec, and resolving as the point moves 45 msec. These tests were run using an implementation in OTI Smalltalk Version 4.0 running on a IBM Thinkpad 760EL laptop computer.

For the C++ implementation on the problem with 900 constraints and variables, adding a constraint takes 40 msec, deleting a constraint 8 msec, and resolving as the point moves 8 msec. The Java implementation under the basic Sun JDK 1.1.3 (no JIT compiler) is about 6 to 10 times slower than the C++ implementation. These tests were run on a Pentium 200 running Linux 2.0.29.

The various implementations of Cassowary are being used actively. The first author is currently embedding the C++ implementation in a X11 system window manager based on a Scheme configuration language. A demonstration Constraint Drawing Application using the Java implementation was written by Michael Noth and is available from the authors. A third Cassowary application currently being developed using a different Java implementation is a web authoring tool [5], in which the appearance of a page is determined by the combination of constraints from both the web author and the viewer.

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