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Master's Thesis

# **Linear programming on Cell/BE**

by

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**Abstract**

(TODO:)



# Acknowledgements

(TODO: Natvig, Elster, Mujahed, Chris, Henrik Andersson, Marielle Christiansen, the people at Ugle)



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# List of Symbols and Abbreviations

<b>Abbreviation</b>	<b>Description</b>	<b>Definition</b>
Cell BE	Cell Broadband Engine	page 28
ILP	Integer linear programming	page 4
ILP	Instruction-level parallelism	page 28
LP	Linear programming	page 3
LS	Local Store	page 29
MFC	Memory Flow Controller	page 29
PPE	PowerPC Processor Element	page 29
PPU	PowerPC Processor Unit	page 29
SPE	Synergistic Processor Element	page 29
SPU	Synergistic Processor Unit	page 29

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# Introduction

(TODO: )

**Task description** (Natvig/Elster/Mujahed: This is the task description I entered in DAIM. Should probably be changed a bit...) The aim of the project is to implement a parallel linear solver for large sparse problems on the Cell BE using the Simplex method. Interior point methods may also be investigated.

(TODO: A paragraph about Miriam)

Therefore, we have adjusted our aims to that of producing a code base from which further development may take place, and writing a report that is rich in background material, references and advice that we hope will prove useful to those that are to continue the project.

## Outline

In Chapter 2, we give a presentation of the field of linear programming, and we describe the standard and revised simplex methods and a parallel revised simplex method called ASYNPLEX. We also explain the Cell architecture and programming model.

In Chapter 3, we describe our initial plans, the progress of our work and the decisions we had to make during the project. We also present our design of a parallel standard simplex algorithm for Cell, and our adaptations of the ASYNPLEX algorithm (which we did not get the time to fully implement).

In Chapter 4, (TODO: ) This project ended up very differently from what we had anticipated; in this chapter, we also discuss the challenges we have encountered.

In Chapter 5, we provide several timing analyses of the parallel standard simplex algorithm, in order to learn how the parallelisation, number of cores, and Cell features such as vectorisation, affect the performance. We also discuss

features we did not get the time to implement, and give several pieces of advice to the researchers that will build upon our work.

Finally, in Chapter 6, we present our conclusions and summarise our suggestions for future work.

# Chapter 2

## Background

(TODO: Chapter introduction)

### 2.1 Linear programming

(If time permits: Section introductions)

This section is primarily based on Vanderbei[37] and Cormen et al.[7].

#### 2.1.1 Problem formulation. Standard and slack forms

The term *linear programming* (LP) refers to a type of optimisation problems in which one seeks to maximise or minimise the value of a linear function of a set of variables<sup>1</sup>. The values of the variables are constrained by a set of linear equations and/or inequalities. Linear programming is a fairly general problem type, and many important problems can be cast as LP problems — for instance, shortest path problems and maximum flow problems (see [7]). However, the true virtue of linear programming stems from its ability to model a vast range of optimisation problems for which specialised algorithms do not exist, including many situations from economics and industry processes.

The following framed text is an example of a simple linear programming problem. We will use this example throughout this section to illustrate how the linear programming algorithms work.

---

<sup>1</sup>Hence, LP is not (as the name would seem to suggest) a programming technique. The name originated in the 1940s, when “program” referred to military supply plans and schedules (TODO: citation).

— Example —

A company owns a factory that makes two kinds of products based on two different raw materials. The profit the company makes per unit of product A is \$30, and the profit of product B is \$20. Producing one unit of A requires 1 unit of raw material R and 1 unit of raw material S; one unit of B requires 2 units of R and 1 unit of S. The company possesses 40 units of R and 50 units of S. We make the simplifying assumptions that all prices are constant and cannot be affected by the company, and that the company is capable of selling everything it produces. The company's goal is to maximise the profit, which can be described as  $30x_1 + 20x_2$ , where  $x_1$  is the number of units of product A and  $x_2$  is the number of units of product B. The following constraints are in effect:

- $x_1 + x_2 \leq 40$  (the production of A and B cannot consume more units of raw material R than the company possesses)
- $2x_1 + x_2 \leq 50$  (similarly for raw material S)
- $x_1, x_2 \geq 0$  (the company cannot produce negative amounts of its products)

Note that in regular LP problems, one cannot restrict the variables to be integers — in fact, adding this requirement produces a new kind of problem known as *integer linear programming* (ILP), which is *NP-hard*<sup>2</sup>. It is also, in general, a requirement that all variables are nonnegative. This is often the case in real-world problems that deal with physical quantities, but problems involving variables that may be negative as well as positive can still be modeled by rewriting each original variable as a difference of two nonnegative variables.

The function to be optimised is called the *objective function*. In the real world situation that gives rise to an optimisation problem, the function may contain a constant term, but it can be removed since that will affect all possible solutions in the same way. The objective function can then be written as  $\zeta = c_1x_1 + c_2x_2 + \dots + c_nx_n = \sum_{j=1}^n c_jx_j$ , where the  $c_j$  are constants. The variables in the objective function are often called *decision variables*, since our task is not only to find the optimal value of the objective function, but also which variable values that yield this function value. Throughout this report, we will consistently use  $n$  to refer to the number of decision variables and  $m$  to refer to the number of equations

<sup>2</sup>*NP-hardness* is a term from complexity theory, which deals with the relative difficulties of solving different kinds of problems. The only known algorithms for solving *NP-hard* problems require an amount of time that is exponential in the size of the problem, which renders those algorithms useless for many real life problem sizes. For further reading on complexity theory, consult Garey and Johnson[11].

and/or inequalities. The variables will typically be labelled  $x_1$  through  $x_n$ .

**Standard form** An LP problem is commonly called a *linear program*. The equations and inequalities that (together with the objective function) constitute a linear program may be represented in different forms. We shall first consider the *standard form*, in which only less-than-or-equal-to inequalities with all variables on the left hand side are allowed<sup>3</sup>. A problem containing equalities of the form  $a_{i1}x_1 + \dots + a_{in}x_n = b_i$  may be rewritten by splitting each equality into two inequalities<sup>4</sup>:  $a_{i1}x_1 + \dots + a_{in}x_n \leq b_i$  and  $-a_{i1}x_1 - \dots - a_{in}x_n \leq -b_i$ . Also, the goal must be to maximise the objective function — if the original problem is to minimize  $\zeta$ , we let our objective function be  $-\zeta$ . A linear program in standard form can be expressed as follows:

Maximise

$$\zeta = \sum_{j=1}^n c_j x_j \quad (2.1)$$

with respect to

$$\sum_{j=1}^n a_{ij} x_j \leq b_i, \quad \text{for } i = 1, \dots, m. \quad (2.2)$$

$$x_1, \dots, x_n \geq 0 \quad (2.3)$$

**Slack form** The other common representation is *slack form*, which only allows a set of equations (and a nonnegativity constraint for each variable). A slack form program should be produced by rewriting a standard form program. An inequality of the form  $a_{i1}x_1 + \dots + a_{in}x_n \leq b_i$  is converted to an equation by adding a *slack variable*  $w_i$ . Together with the condition that  $w_i \geq 0$ , the equation  $a_{i1}x_1 + \dots + a_{in}x_n + w_i = b_i$  is equivalent to the original inequality (whose difference, or “slack”, between the left and right hand sides is represented by  $w_i$ ). When the program is constructed in this manner, each slack variable only appears in exactly one equation, which is an important property that will be utilised later. A linear program in slack form can be expressed as follows:

Maximise

$$\zeta = \sum_{j=1}^n c_j x_j \quad (2.4)$$

---

<sup>3</sup>Note that strictly-less-than and strictly-greater-than inequalities are never allowed in LP problems, as they could easily cause situations in which it is impossible to achieve optimality — for instance, there is no optimal value for  $x$  with respect to  $x < 3$ ; given any value for  $x$  that is less than 3, one can always find a number between  $x$  and 3.

<sup>4</sup>The drawback of doing this is that it increases the number of equations. See Hillier[19] for another approach, called *artificial variables* — with the drawback that it increases the number of variables.

with respect to

$$w_i = b_i - \sum_{j=1}^n a_{ij}x_j, \text{ for } i = 1, \dots, m. \quad (2.5)$$

$$x_1, \dots, x_n, w_1, \dots, w_m \geq 0 \quad (2.6)$$

— *Example* —

In standard form, our example is expressed as

Maximise

$$\zeta = 30x_1 + 20x_2$$

with respect to

$$x_1 + x_2 \leq 40$$

$$2x_1 + x_2 \leq 50$$

$$x_1, x_2 \geq 0$$

In slack form, it becomes

Maximise

$$\zeta = 30x_1 + 20x_2$$

with respect to

$$w_1 = 40 - x_1 - x_2$$

$$w_2 = 50 - 2x_1 - x_2$$

$$x_1, x_2, w_1, w_2 \geq 0$$

A proposed solution vector (that is, a specification of a value for each variable) of a linear program in slack form is called:

**Feasible** if it does not violate any constraints

**Infeasible** if it violates one or more constraints (however, it is still called a “solution”)

**Basic** if it consists of setting all variables except the slack variables to zero (so that  $w_i = b_i$  for all  $i$ )

**Optimal** if it is feasible and no other feasible solutions yield a higher value for the objective function. An optimal solution vector is not necessarily unique, although the optimal objective function value of course is.

(TODO: Move this paragraph to next section? Natvig says “Ta med etter behov”.) The *linear programming theorem* (TODO: Is it actually called this? Find something to cite) states that the optimal solution of a linear program, if it exists, occurs when at least  $m$  variables are set to zero. (TODO: Combinatorics. Mention cycling here?)

### 2.1.2 The simplex method

The *simplex method*<sup>5</sup>, developed by George Dantzig[8], was the first systematic approach for solving linear programs. It requires the linear program to be in slack form. The initial coefficients and constants are written down in a *tableau* that will change as the method progresses. The nonnegativity constraints are not represented anywhere; rather, they are implicitly maintained by the method. Because the equations will undergo extensive rewriting, it will be convenient not to distinguish the slack variables from the other variables, so we will relabel  $w_i$  to  $x_{n+i-1}$  for  $i = 1, \dots, m$ . Thus, the total number of variables is  $n + m$ . Furthermore, we will use overlines over the coefficients in the tableau to denote their *current* value (which will change in each iteration of the simplex method), and the indices of the coefficients will refer to the coefficients' position within the tableau — for instance,  $-\bar{a}_{ij}$  is located in row  $i$ , column  $j$ . We also introduce a constant term  $\bar{\zeta}$  (initially zero) in the objective function, which will help us keep track of the best function value we have found so far. The topmost row and leftmost column are not really a part of the tableau; they are simply headers — the topmost row shows which variables correspond to which columns, and the leftmost column shows the slack variables for each row. The first actual tableau row (below the double line) contains the objective function coefficients  $\bar{c}_j$  and is numbered as row 0; the first actual tableau column (to the right of the double line) contains the  $\bar{b}_i$  constants and is numbered as column 0; the rest of the tableau contains the negatives of the coefficients from the equations:  $-\bar{a}_{ij}$ . Initially,  $\bar{c}_j = c_j$ ,  $\bar{b}_i = b_i$ , and  $\bar{a}_{ij} = a_{ij}$ . For instance, with  $n = 3$  and  $m = 3$ , the initial tableau will look like this:

---

<sup>5</sup>The reason for not calling it the “simplex *algorithm*” is that there exist several versions of the method, and that the general method formulation is somewhat underspecified because it does not say how to choose the pivot elements.

	$x_1$	$x_2$	$x_3$	
$\zeta$	0	$c_1$	$c_2$	$c_3$
$x_4$	$b_1$	$-a_{11}$	$-a_{12}$	$-a_{13}$
$x_5$	$b_2$	$-a_{21}$	$-a_{22}$	$-a_{23}$
$x_6$	$b_3$	$-a_{31}$	$-a_{32}$	$-a_{33}$

Note that this is essentially just a tabular version of the standard form — for instance, the last row is interpreted as the equation  $x_6 = b_3 - a_{31}x_1 - a_{32}x_2 - a_{33}x_3$ .

— Example —

In tableau form, our example becomes

	$x_1$	$x_2$	
$\zeta$	0	30	20
$x_3$	40	-1	-1
$x_4$	50	-2	-1

Note that  $w_1$  and  $w_2$  have been renamed to  $x_3$  and  $x_4$ , respectively.

The variables are partitioned into two sets. The variables in the leftmost column (at the left side of the equations) are referred to as the *basic variables*, and the variables inside the tableau are called *nonbasic variables*. At any stage of the method, the set of the indices of the basic variables is denoted  $\mathcal{B}$ , and the set of nonbasic indices is denoted  $\mathcal{N}$ . Initially,  $\mathcal{N} = \{1, \dots, n\}$ , and  $\mathcal{B} = \{n + 1, \dots, n + m\}$ . The sizes of the basic and nonbasic sets are constant, with  $|\mathcal{N}| = n$  and  $|\mathcal{B}| = m$ . The tableau will generally look like this (if, for instance,  $m = n = 3$ ):

	$\dots$	$x_{j \in \mathcal{N}}$	$\dots$	
$\zeta$	$\bar{\zeta}$	$\bar{c}_1$	$\bar{c}_2$	$\bar{c}_3$
$\vdots$	$\bar{b}_1$	$-\bar{a}_{11}$	$-\bar{a}_{12}$	$-\bar{a}_{13}$
$x_{i \in \mathcal{B}}$	$\bar{b}_2$	$-\bar{a}_{21}$	$-\bar{a}_{22}$	$-\bar{a}_{23}$
$\vdots$	$\bar{b}_3$	$-\bar{a}_{31}$	$-\bar{a}_{32}$	$-\bar{a}_{33}$

For now, let us assume that the solution that is obtained by setting all nonbasic variables to zero is feasible (which is the case only if all of the  $b_i$  are non-negative); we will remove this restriction later. This trivial solution will provide a lower bound for the value of the objective function (namely, the constant term,  $\bar{\zeta}$ ). We will now select one nonbasic variable  $x_j$  and consider what happens if we increase its value (since all nonbasic variables are currently zero, we cannot decrease any of them). Since our goal is to maximise the objective function, we should select a variable whose coefficient  $c_j$  in the objective function is positive.



If no such variables exist, we cannot increase the objective function value further, and the current solution (the one obtained by setting all nonbasic variables to zero, so that  $\zeta = \bar{\zeta}$ ) is optimal — we can be certain of this since linear functions do not have local maxima.

It seems reasonable to select the variable with the greatest coefficient (this is known as the *Dantzig criterion* (TODO: verify name); other rules are possible). Let us say that this variable is located in column  $e$ . Note that because we will soon start swapping variable positions, the indices of the leaving and entering variables will generally not correspond to their respective row and column numbers. For notational convenience, we therefore let  $x_{\bar{i}}$  denote the basic variable that is located in row  $i$ , and we let  $x_{\bar{j}}$  denote the nonbasic variable in column  $j$ . Then, our variable is labelled  $x_{\bar{e}}$ . How far can we increase this variable? Recall that each line in the tableau expresses one basic variable as a function of all the nonbasic variables; hence we can increase  $x_{\bar{e}}$  until one of the basic variables becomes zero. Let us look at row  $i$ , which is now reduced to  $x_{\bar{i}} = \bar{b}_i - \bar{a}_{ie}x_{\bar{e}}$  since all nonbasic variables except  $x_{\bar{e}}$  are zero. If  $\bar{a}_{ie}$  is positive, the value of  $x_{\bar{i}}$  will decrease as  $x_{\bar{e}}$  increases, so the largest allowable increase is limited by  $\bar{b}_i$ . Thus, by setting  $x_{\bar{e}} = \frac{\bar{b}_i}{\bar{a}_{ie}}$ ,  $x_{\bar{i}}$  becomes zero. However, other equations may impose stricter conditions. By looking at all rows where  $\bar{a}_{ie}$  is positive, we can determine an  $l$  such that  $\frac{\bar{b}_l}{\bar{a}_{le}}$  is minimal and set  $x_{\bar{e}} = \frac{\bar{b}_l}{\bar{a}_{le}}$ . This will cause  $x_{\bar{l}}$  to become zero. If all  $\bar{a}_{ie}$  are nonpositive, we can increase  $x_{\bar{e}}$  indefinitely without any  $x_{\bar{i}}$  ever becoming negative, and in that case, we have determined the linear program to be *unbounded*; the method should report this to the user and terminate.

— Example —

Recall the tableau:

	$x_1$	$x_2$	
$\zeta$	0	30	20
$x_3$	40	-1	-1
$x_4$	50	-2	-1

Since 30 is the greatest objective function coefficient, we select  $x_1$  to be increased.  $x_3$  becomes zero if  $x_1 = \frac{\bar{b}_1}{\bar{a}_{11}} = \frac{40}{1}$ , and  $x_4$  becomes zero if  $x_1 = \frac{\bar{b}_2}{\bar{a}_{12}} = \frac{50}{2}$ . The latter is the most restrictive constraint, so  $x_4$  will become zero when we increase  $x_1$ .

The next step, called *pivoting*, is an operation that exchanges a nonbasic variable and a basic variable. The purpose of pivoting is to produce a new situation in which all nonbasic variables are zero (and no  $b_i$  is negative), so that we can repeat the previous steps all over again and find a new variable whose value we can increase. The nonbasic variable that was selected to be increased,  $x_{\bar{e}}$ , is

called the *entering variable*, since it is about to enter the collection of basic variables.  $x_{\tilde{l}}$ , which becomes zero when  $x_{\hat{e}}$  is increased appropriately, is called the *leaving variable*, since it is to be removed from said collection. Keep in mind that since  $x_{\tilde{l}}$  is a basic variable, it only occurs in one equation, namely

$$x_{\tilde{l}} = \bar{b}_l - \sum_{j \in \mathcal{N}} \bar{a}_{lj} x_{\hat{j}}. \quad (2.7)$$

Note that we have retained all the nonbasic variables, as we want an equation that is valid at all times, not only when almost all nonbasic variables are zero. We can eliminate the entering variable from (and introduce the leaving variable into) the set of nonbasic variables by rewriting (2.7):

$$x_{\tilde{l}} = \bar{b}_l - \bar{a}_{le} x_{\hat{e}} - \sum_{j \in \mathcal{N} - \{\hat{e}\}} \bar{a}_{lj} x_{\hat{j}} \quad (2.8)$$

$$x_{\hat{e}} = \frac{1}{\bar{a}_{le}} \left( \bar{b}_l - x_{\tilde{l}} - \sum_{j \in \mathcal{N} - \{\hat{e}\}} \bar{a}_{lj} x_{\hat{j}} \right). \quad (2.9)$$

Now that we have an expression for  $x_{\hat{e}}$ , we can substitute it into all of the other equations — this will eliminate  $x_{\hat{e}}$  and introduce  $x_{\tilde{l}}$  into the rest of the tableau. For all  $i \in \mathcal{B} - \{\tilde{l}\}$ , we have:

$$x_{\tilde{i}} = \bar{b}_i - \sum_{j \in \mathcal{N}} \bar{a}_{ij} x_{\hat{j}} \quad (2.10)$$

$$= \bar{b}_i - \bar{a}_{ie} x_{\hat{e}} - \sum_{j \in \mathcal{N} - \{\hat{e}\}} \bar{a}_{ij} x_{\hat{j}} \quad (2.11)$$

$$= \bar{b}_i - \frac{\bar{a}_{ie}}{\bar{a}_{le}} \left( \bar{b}_l - x_{\tilde{l}} - \sum_{j \in \mathcal{N} - \{\hat{e}\}} \bar{a}_{lj} x_{\hat{j}} \right) - \sum_{j \in \mathcal{N} - \{\hat{e}\}} \bar{a}_{ij} x_{\hat{j}} \quad (2.12)$$

$$= \left( \bar{b}_i - \frac{\bar{a}_{ie} \bar{b}_l}{\bar{a}_{le}} \right) + \frac{\bar{a}_{ie}}{\bar{a}_{le}} x_{\tilde{l}} - \sum_{j \in \mathcal{N} - \{\hat{e}\}} \left( \bar{a}_{ij} - \frac{\bar{a}_{ie} \bar{a}_{lj}}{\bar{a}_{le}} \right) x_{\hat{j}}. \quad (2.13)$$

A similar result will be achieved for the expression for the objective function. Although it might look complicated, it amounts to subtracting  $\frac{\bar{a}_{ie}}{\bar{a}_{le}}$  times the tableau row  $l$  from all other tableau rows  $i$  (and adding  $\frac{\bar{c}_e}{\bar{a}_{le}}$  times row  $l$  to the objective function row), and then setting the tableau entries in column  $e$  to  $\frac{\bar{a}_{ie}}{\bar{a}_{le}}$  (and to  $-\frac{\bar{c}_e}{\bar{a}_{le}}$  in the objective function row). Note that because  $l$  was selected such that  $\bar{a}_{le}$  was positive and  $\frac{\bar{b}_l}{\bar{a}_{le}}$  was minimal, all  $\bar{b}_i$  remain nonnegative; and because  $e$  was selected such that  $\bar{c}_e$  was positive,  $\bar{z}$  cannot decrease (it will either retain its old value or increase, depending on whether  $\bar{b}_l$  was zero).

(2.9) is the new form of the tableau row that originally corresponded to the basic variable  $x_{\tilde{l}}$ . The new row, which corresponds to  $x_{\hat{e}}$ , can be easily obtained

from the old one by dividing the row by  $\bar{a}_{ie}$  and setting the coefficient of what is now  $x_{\tilde{l}}$  to  $-\frac{1}{\bar{a}_{ie}}$ .

Finally, we remove  $\tilde{l}$  from  $\mathcal{B}$  and add it to  $\mathcal{N}$ , and remove  $\hat{e}$  from  $\mathcal{N}$  and add it to  $\mathcal{B}$ , so that the leaving and entering variables swap positions in the new tableau. This completes the pivot operation — we again have a tableau in which all nonbasic variables can be set to zero and all  $b_i$  are nonnegative, and the entire process may be repeated.

A  $3 \times 3$  tableau will look like this after one pivot with  $x_2$  as the entering variable and  $x_5$  as the entering variable: (TODO: Verify!)

	$x_1$	$x_5$	$x_3$	
$\zeta$	$0 + b_2c_2/a_{22}$	$c_1 - a_{21}c_2/a_{22}$	$-c_2/a_{22}$	$c_3 - a_{23}c_2/a_{22}$
$x_4$	$b_1 - b_2a_{12}/a_{22}$	$-a_{11} + a_{21}a_{12}/a_{22}$	$a_{12}/a_{22}$	$-a_{13} + a_{23}a_{12}/a_{22}$
$x_2$	$b_2/a_{22}$	$-a_{21}/a_{22}$	$-1/a_{22}$	$-a_{23}/a_{22}$
$x_6$	$b_3 - b_2a_{32}/a_{22}$	$-a_{31} + a_{21}a_{32}/a_{22}$	$a_{32}/a_{22}$	$-a_{33} + a_{23}a_{32}/a_{22}$

— Example —

After one pivot with  $x_1$  as the entering variable and  $x_4$  as the leaving variable, we get the following tableau:

	$x_4$	$x_2$	
$\zeta$	750	-15	5
$x_3$	15	0.5	-0.5
$x_1$	25	-0.5	-0.5

For the next pivot operation, only  $x_2$  can be selected as the entering variable, which causes  $x_3$  to be selected as the leaving variable. After the pivot, the tableau looks like this:

	$x_4$	$x_3$	
$\zeta$	900	-10	-10
$x_2$	30	1	-2
$x_1$	10	-1	1

Since all objective function coefficients are now negative, we have reached an optimal solution with the value  $\zeta = \bar{\zeta} = 900$ . This solution value is obtained by setting the nonbasic variables ( $x_3$  and  $x_4$ ) to 0, in which case  $x_1 = 10$  and  $x_2 = 30$ . We can easily verify that these variable values do not violate any constraints, and by substituting the values into the original objective function, we can verify that the optimal value is indeed  $\zeta = 30x_1 + 20x_2 = 30 \cdot 10 + 20 \cdot 30 = 900$ .

### 2.1.2.1 Degeneracy and cycling

A tableau is *degenerate* if some of the  $\bar{b}_i$  are zero. Degeneracy may cause problems because a pivot on a degenerate row will not cause the objective function value to change, and we will not have gotten any closer to a solution. With severely bad luck, the algorithm may end up cycling through a number of degenerate states. This, however, rarely happens — according to Vanderbei[37, p. 32], cycling “is so rare that most efficient implementations do not take precautions against it”.

As mentioned in Footnote 5 on page 7, the general formulation of the simplex method is underspecified because it does not tell how to break ties between potential entering and leaving variables. There exist rules that guarantee that cycling will not happen; one of them, called *Bland’s rule*[37, Sec. 3.4] is to break ties by always selecting the variable with the smallest index. There are  $\binom{m+n}{m}$  possible dictionaries — each dictionary is uniquely determined by the set of basic variables, and the order of the variables is unimportant (if the rows and columns of a dictionary are permuted, it is still regarded as the same dictionary, since the same variables will be selected for pivoting). Since each step transforms one dictionary into another, the simplex method is guaranteed to terminate in at most  $\binom{m+n}{m}$  steps if precautions are taken against cycling. In practice, however, the method is usually far more efficient, and algorithms that are guaranteed to run in polynomial time are only superior for very large data sets(TODO: citation).

### 2.1.2.2 Initially infeasible problems

The method presented so far is capable of solving linear programs whose initial basic solution (the one obtained by setting all nonbasic variables to 0) is feasible. This is the case if and only if all of the  $b_i$  are nonnegative, which we cannot in general assume them to be. If we have one or more negative  $b_i$ , we get around this by introducing an *auxiliary problem* which is based on the original problem, is guaranteed to have a basic feasible solution, and whose optimal solution will provide us with a starting point for solving the original problem. The auxiliary problem is created by subtracting a new variable  $x_0$  from the left hand side of each equation of the original problem (which is assumed to be in standard form), and replacing the objective function with simply  $\zeta = -x_0$ . The purpose of  $x_0$  is that by initially setting it to a sufficiently large value, we can easily satisfy all equations (even those having negative entries in the right hand side<sup>6</sup>). Then, we can try to change variable values (through regular pivoting) and see if it is possible to make  $x_0$  equal to zero, in which case we can remove it from our equations and reinstate the original objective function, thereby having arrived

---

<sup>6</sup>Beware that “the right hand side” refers to the  $b_i$ , which are on the right hand side of the original equations — but in the tableau, they are on the *left* side.

at a problem that is equivalent to the original one. This is the purpose of our new objective function — since  $x_0$ , like all other variables, is required to be non-negative, the goal of optimising  $-x_0$  means that we are trying to make  $x_0$  zero. Fortunately, we do not need a new algorithm for this optimisation process; we can use the simplex algorithm as it has been described above. We only need to do one pivot operation before we start that algorithm: since the idea of  $x_0$  is to initially set it to a suitably large value, and since the algorithm requires a non-negative right hand side, we should make  $x_0$  a basic variable by performing one pivot operation with the row containing the most negative  $b_i$ . This will make the entire right hand side nonnegative. Solving the auxiliary problem is called *Phase I*, and solving the resulting problem (with the original objective function) is called *Phase II*. Thus, the full simplex method is a two-phase method (but of course, if the right hand side of the original problem is nonnegative, we can skip Phase I).

Another Phase I method, the one used by Vanderbei, is to first replace negative terms in the objective function by an arbitrary positive number (e.g. 1) and then run the dual simplex method (TODO: Need something on duality). This essentially transposes the entire tableau and treats the original right-hand side (which contains negative numbers, since we needed to run Phase I) as the new objective function (where negative numbers are tolerated), and the original objective function (which, after our modification, is strictly positive) as the new right-hand side. The dual method will terminate when the original right hand side only consists of nonnegative numbers, in which case we can reinstate the actual coefficients of the original objective function and proceed with Phase II.

One-phase methods also exist, such as the *parametric self-dual simplex method*, as described in [37, Sec. 7.3].

(If time permits: example)

### 2.1.2.3 Formal algorithm statement

In Algorithm 1 on the next page we present the pseudocode for an individual phase of the standard simplex method (with the first approach described in Section 2.1.2.2, the same code can be used for both Phase I and Phase II. The tableau is called  $T$  and is zero-indexed; keep in mind that row 0 is the objective function and column 0 contains the constants from the right hand sides of the inequalities. The current value of the objective function is always in row 0, column 0. We use row major indexing, so  $T[2, 3]$  is row 2, column 3. (Natvig's comment: Should ideally be recognisable in the real code; maybe reference the real code here (or the other way around?))

(TODO: Verify)

loa 1: The standard simplex method using the Dantzig criterion TODO: verify name

```

1: procedure STANDARDSIMPLEXPHASE( $m, n, a[1..m, 1..n], b[1..m], c[1..n]$ )
2:    $T[0, 0] \leftarrow 0$ 
3:    $T[i, j] \leftarrow -a[i, j]$  for  $i = 1 \dots m, j = 1 \dots n$ 
4:    $T[i, 0] \leftarrow b[i]$  for  $i = 1 \dots m$ 
5:    $T[0, j] \leftarrow c[j]$  for  $j = 1 \dots n$ 
6:    $\mathcal{N} \leftarrow \{1, \dots, n\}$ 
7:    $\mathcal{B} \leftarrow \{n + 1, \dots, n + m\}$ 
8:   loop
9:     Pick a column number  $e \geq 1$  such that  $T[0, e]$  is positive and maximal
10:    if no  $e$  is found then
11:      return  $T[0, 0]$  as the optimal solution
12:    end if
13:    Pick a row number  $l \geq 1$  such that  $T[l, e] < 0$  and  $-\frac{T[l, 0]}{T[l, e]}$  is minimal
14:    if no  $l$  is found then
15:      return "The problem is infeasible" (if this is Phase I) or "The problem is unbounded" (if this is Phase II)
16:    end if
17:     $p \leftarrow -T[l, e]$ 
18:    for  $i \leftarrow 0, m$  do
19:      if  $i \neq l$  then
20:         $f \leftarrow \frac{T[i, e]}{p}$ 
21:        Add  $f$  times row  $l$  of  $T$  to row  $i$  of  $T$ 
22:         $T[i, e] \leftarrow -f$ 
23:      end if
24:    end for
25:    Divide row  $l$  of  $T$  by  $p$ 
26:     $T[l, e] \leftarrow -\frac{1}{p}$ 
27:  end loop
28: end procedure

```

#### 2.1.2.4 Complexity and numerical instability

The complexity classes  $P$  and  $NP$  should be familiar to anyone that has taken an algorithms course:  $NP$  is the class of decision problems (problems that are in the form of a yes/no question) where, if the answer is "yes" and we are given a "certificate" that demonstrates the solution, we can validate the solution in time that is polynomial in the size of the input.  $P$  is the subset of  $NP$  that consists of those decision problems where we can also *find* the solution in polynomial time. The question of whether  $P = NP$  remains one of the most important open questions in the field of computer science, and is one of the seven Clay Mille-

nium Prize problems<sup>7</sup>. Most researchers believe that  $P \subset NP$ , and that the most difficult problems in  $NP$ , the so-called *NP-complete* ( $NP$ -complete) ( $NP$ -complete) ( $NP$ -complete) problems, cannot be solved in polynomial time. Cormen et al.[7] give a good introduction to complexity theory.

When dealing with parallel programming, another complexity class is also useful:  $NC$ , also known as *Nick's Class*. This is the class of all problems that can be solved in  $O(\lg^{k_1} n)$  steps (so-called *polylogarithmic time*) using a polynomial ( $O(n^{k_2})$ ) number of processors. Here,  $k_1$  and  $k_2$  are constants.  $NC$  is a subset of  $P$ , since any parallel algorithm requiring  $f(n)$  steps using  $p(n)$  processors can be simulated in  $p(n)f(n)$  steps on a sequential computer. Thus, any  $NC$ -algorithm will require  $O(n^{k_2} \lg^{k_1} n)$  steps on a sequential machine, and this is polynomial in  $n$ . However, there are problems in  $P$  which have not yet been proven to be in  $NC$ , and the most difficult problems among these are called *P-complete* ( $P$ -complete) ( $P$ -complete) ( $P$ -complete) — this is quite analogous to the  $NP/P/NP$  situation.

In some sense,  $NC$  captures the notion of what it means for a problem to be “parallelisable”, while the  $P$ -complete problems can be said to be “hard to parallelise”. However, it is not an all-encompassing concept — a problem may be in  $NC$  without being efficiently solvable in practice due to a prohibitive processor requirement of the algorithm (for instance  $O(n^{10})$  processors) or large constants hidden by the  $O$ -notation, and a parallel algorithms for  $P$ -complete problems may still be useful because they might be faster than their sequential counterparts (just not “much faster”).

Where does LP fit into this picture? The trivial upper bound of  $O(\binom{m+n}{m})$  given in Section 2.1.2.1 for the number of iterations in the simplex method is absolutely horrible:  $\binom{m+n}{m} \geq \left(\frac{m+n}{m}\right)^m = \left(1 + \frac{n}{m}\right)^m$ , which, if  $m = n$ , becomes  $2^m$ . Unfortunately, Klee and Minty[25] proved that it is possible to construct arbitrary-size data sets that make the method hit that bound when a certain pivoting rule is used (and no one has succeeded in finding a pivoting rule that can guarantee polynomial time). In spite of this, the method is often surprisingly efficient in practice (TODO: citation). In 1979, Khachiyan[24] discovered a different kind of algorithm that is guaranteed to run in polynomial time, and thus he proved LP to be in  $P$ .<sup>8</sup> However, LP is also  $P$ -complete, as proved by Dobkin et al.[9]. Still, for the reasons mentioned above, this should not discourage us from seeking parallel versions of LP algorithms.

Greenlaw et al.[14] give a thorough presentation of  $NC$  and other aspects of parallel complexity, and a more compact survey of the field can be found in Natvig (TODO: citation).

<sup>7</sup><http://www.claymath.org/millennium/>

<sup>8</sup>Strictly speaking, LP is a computation problem (one in which we seek a numerical answer) rather than a decision problem and thus falls outside of the  $NP/P/NC$  discussion. However, like many other computation problems, LP easily can be reformulated as a decision problem that can be solved by the same algorithms; see [14, Problem A.4.3] for more references.

### 2.1.2.5 Duality

(TODO: )

### 2.1.2.6 Warmstarting

If one has solved an LP problem and then wishes to solve a very similar problem (one that has been obtained by slightly altering the various coefficients of the original problem), it would seem reasonable to believe that the optimal solution to the original problem would be a great starting point in the search for the optimal solution to the new problem. This turns out to be the case, and the idea is known as *warmstarting*. It normally leads to a great reduction in the time required to solve the new problem, and it is also very easy to implement — the simplex method need not be changed at all; the program must simply be capable of taking a suggested starting solution as input. Note that one might have to run both phases, in case the original solution is not feasible for the new problem. Interested readers may consult Vanderbei[37, Chapter 7] for a more thorough introduction to the subject (which he refers to as *sensitivity analysis*).

Miriam employs Monte Carlo methods<sup>9</sup> that produce a number of random variations of the current state of the oil pipeline network in order to predict what will happen if anything changes. (TODO: more information) This is an important reason that they want to focus on the simplex method rather than interior point methods(Section 2.1.5) — warmstarting is possible for the latter class of methods, but it is much harder to implement. Various approaches to warmstarting interior point methods are described by e.g. Gondzio and Grothey[13] (this is actually a more general approach for quadratic programming), Yildirim and Wright[42], and Benson and Shanno[5].

## 2.1.3 The revised simplex method

The *revised simplex method* (TODO: citation) is essentially just a linear algebra reformulation of the mathematical operations of the standard simplex method. Rather than

The exposition in this section is based on [37] and [17]. Note that all vectors are column vectors unless stated otherwise.

While this may sound even more time consuming, it turns out that a few tricks will remove the need to perform inversions all of the time. Since most real life problems are sparse, the matrix computations can take that into account and save a lot of time compared to the standard simplex method (in which each iteration requires  $O(mn)$  arithmetic operations for the pivot operation).

---

<sup>9</sup>TODO: describe Monte Carlo methods



For these reasons, the revised simplex method is almost always preferred over the standard simplex method in practical implementations (see, for instance, our list of available solvers in Section 2.1.7).

We begin with expressing the slack form constraint tableau in matrix notation. An LP problem in slack form (with renaming of the slack variables) looks like the following:

Maximise

$$\zeta = \sum_{j=1}^n c_j x_j \quad (2.14)$$

with respect to

$$x_{n+i} = b_i - \sum_{j=1}^n a_{ij} x_j, \text{ for } i = 1, \dots, m. \quad (2.15)$$

$$x_1, \dots, x_{n+m} \geq 0 \quad (2.16)$$

If we let

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} & 1 & & \\ a_{21} & a_{22} & \cdots & a_{2n} & & 1 & \\ \vdots & \vdots & \ddots & \vdots & & & \ddots \\ a_{m1} & a_{m2} & \cdots & a_{mn} & & & 1 \end{bmatrix} \quad (2.17)$$

$$\mathbf{b} = [ b_1 \ \cdots \ b_m ]^\top \quad (2.18)$$

$$\mathbf{c} = [ c_1 \ \cdots \ c_n \ 0 \ \cdots \ 0 ]^\top \text{ (} m \text{ zeroes at the end)} \quad (2.19)$$

$$\mathbf{x} = [ x_1 \ \cdots \ x_n \ x_{n+1} \ \cdots \ x_{n+m} ]^\top \quad (2.20)$$

we can express the problem in a very compact manner:

Maximise

$$\zeta = \mathbf{c}\mathbf{x} \quad (2.21)$$

with respect to

$$\mathbf{A}\mathbf{x} = \mathbf{b} \quad (2.22)$$

$$\mathbf{x} \geq 0 \quad (2.23)$$

In order to be able to handle the pivot operations, we will need to split each of our matrices and vectors into two in order to reflect which entries correspond to basic variables and which ones do not. As before, we let  $\mathcal{N}$  be the collection

of nonbasic variable indices (initially  $\{1, \dots, n\}$ ), and  $\mathcal{B}$  the collection of basic variable indices (initially  $\{n + 1, \dots, n + m\}$ ). All the basic variables are put in the vector  $\mathbf{x}_{\mathcal{B}}$ , and the nonbasic variables are put in  $\mathbf{x}_{\mathcal{N}}$  — the order of the variables within these vectors do not matter, as long as the entries of the other matrices are arranged correspondingly. We split  $\mathbf{A}$  into two matrices: an  $m \times n$  matrix  $\mathbf{N}$ , containing all columns from  $\mathbf{A}$  that correspond to nonbasic variables (initially, this will be all the columns containing the  $a_{ij}$  entries), and  $\mathbf{B}$ , which is initially an  $m \times m$  identity matrix. Similarly, we split  $\mathbf{c}$  into one vector  $\mathbf{c}_{\mathcal{N}}$  for the objective function coefficients belonging to nonbasic variables (initially,  $\mathbf{c}_{\mathcal{N}} = [c_1 \ \cdots \ c_n]^\top$ ) and one vector  $\mathbf{c}_{\mathcal{B}}$  for the coefficients belonging to basic variables (initially an  $m$  element zero vector). After each pivot operation, entries of these matrices and vectors will swap *positions* according to how the collections of basic and nonbasic variables have changed, but the *values* themselves will never change during the course of the algorithm. This means that numerical stability may be significantly improved. Note that the “right hand side” vector  $\mathbf{b}$  remains a single vector that will never change. Using these “split” matrices and vectors, we can express the problem as

Maximise

$$\zeta = \mathbf{c}_{\mathcal{N}}^\top \mathbf{x}_{\mathcal{N}} + \mathbf{c}_{\mathcal{B}}^\top \mathbf{x}_{\mathcal{B}} \quad (2.24)$$

with respect to

$$\mathbf{N}\mathbf{x}_{\mathcal{N}} + \mathbf{B}\mathbf{x}_{\mathcal{B}} = \mathbf{b} \quad (2.25)$$

$$\mathbf{x} \geq 0 \quad (2.26)$$

During execution of the (standard) simplex method, it is always the case that each basic variable occurs in exactly one equation, and hence each basic variable can be written as a function of the nonbasic variables. Therefore,  $\mathbf{B}$  must be invertible, so we can multiply (2.25) by  $\mathbf{B}^{-1}$  and rearrange it to get

$$\mathbf{x}_{\mathcal{B}} = \mathbf{B}^{-1}\mathbf{b} - \mathbf{B}^{-1}\mathbf{N}\mathbf{x}_{\mathcal{N}}. \quad (2.27)$$

Combining this with (2.24), we get

$$\zeta = \mathbf{c}_{\mathcal{N}}^\top \mathbf{x}_{\mathcal{N}} + \mathbf{c}_{\mathcal{B}}^\top \mathbf{x}_{\mathcal{B}} \quad (2.28)$$

$$= \mathbf{c}_{\mathcal{N}}^\top \mathbf{x}_{\mathcal{N}} + \mathbf{c}_{\mathcal{B}}^\top (\mathbf{B}^{-1}\mathbf{b} - \mathbf{B}^{-1}\mathbf{N}\mathbf{x}_{\mathcal{N}}) \quad (2.29)$$

$$= \mathbf{c}_{\mathcal{B}}^\top \mathbf{B}^{-1}\mathbf{b} + (\mathbf{c}_{\mathcal{N}}^\top - \mathbf{c}_{\mathcal{B}}^\top \mathbf{B}^{-1}\mathbf{N})\mathbf{x}_{\mathcal{N}}. \quad (2.30)$$

This is very interesting, because it provides explicit formulas for the simplex tableau at any time given the current basic/nonbasic variable configuration. From (2.27) (which can be rewritten as  $\mathbf{B}^{-1}\mathbf{N}\mathbf{x}_{\mathcal{N}} + \mathbf{x}_{\mathcal{B}} = \mathbf{B}^{-1}\mathbf{b}$ ), we see that

the current body of the standard simplex tableau (known as  $[\bar{a}_{ij}]$  (TODO: this must match the preceding subsection)) can be expressed as  $\mathbf{B}^{-1}\mathbf{N}$ , and the right hand side of the tableau (known as  $[\bar{b}_i]$  — this is also the current values of the basic variables) is  $\mathbf{B}^{-1}\mathbf{b}$ . Similarly, we see from (2.30) that  $\mathbf{c}_B^\top \mathbf{B}^{-1}\mathbf{b}$  corresponds to the current value of the objective function (obtained by setting  $\mathbf{x}_N = 0$ ), and the current objective function coefficients (also called the *reduced costs*) from the tableau (known as  $[\bar{c}_j]$ ) are  $\mathbf{c}_N^\top - \mathbf{c}_B^\top \mathbf{B}^{-1}\mathbf{N}$ . Armed with this knowledge, we can formulate the revised simplex method, as shown in Algorithm 2.

(TODO: Show how we rearrive at the same expression for the tableau after pivoting)

(TODO: Phase I and II)

### loa 2: The revised simplex method

```

1: procedure REVISEDSIMPLEX( $m, n, \mathbf{N}, \mathbf{c}_N, \mathbf{b}$ )
2:   Let  $\mathbf{c}_B$  be an  $m$  element zero vector
3:   Let  $\mathbf{B}$  be an  $m \times m$  identity matrix
4:   Let  $\mathbf{B}^{-1}$  be an  $m \times m$  identity matrix
5:    $\mathcal{N} \leftarrow \{1, \dots, n\}$ 
6:    $\mathcal{B} \leftarrow \{n + 1, \dots, n + m\}$ 
7:   loop
8:      $\hat{\mathbf{c}}_N^\top \leftarrow \mathbf{c}_N^\top - \mathbf{c}_B^\top \mathbf{B}^{-1}\mathbf{N}$  ▷ Compute the reduced costs
9:     Search  $\hat{\mathbf{c}}_N$  for a negative number; let  $e$  be its index (the corresponding
    nonbasic variable is then  $x_{\hat{e}}$ )
10:    if no negative number found in  $\hat{\mathbf{c}}_N$  then
11:      return  $\mathbf{c}_B^\top \mathbf{B}^{-1}\mathbf{b}, \mathbf{B}^{-1}\mathbf{b}$  ▷ Optimal value and basic variable values
12:    end if
13:    Let  $\mathbf{N}_e$  be the  $e$ th column of  $\mathbf{N}$  (the one corresponding to  $x_{\hat{e}}$ )
14:     $\hat{\mathbf{a}} \leftarrow \mathbf{B}^{-1}\mathbf{N}_e$  ▷ Compute the tableau coefficients of  $x_{\hat{e}}$ 
15:     $\hat{\mathbf{b}} \leftarrow \mathbf{B}^{-1}\mathbf{b}$  ▷ Compute the basic variable values
16:    Let  $l$  be a value of  $i$  that minimises  $t = \frac{\hat{b}_i}{\hat{a}_i}$  (only perform this calculation
    for those  $i \in \mathcal{B}$  where  $\hat{a}_i$  is positive)
17:    if no value is found for  $l$  then
18:      return "The problem is unbounded"
19:    end if
20:    Exchange the  $e$ th column of  $\mathbf{N}$  with the  $l$ th column of  $\mathbf{B}$ 
21:     $\mathcal{B} \leftarrow (\mathcal{B} - \{\tilde{l}\}) \cup \{\hat{e}\}$ 
22:     $\mathcal{N} \leftarrow (\mathcal{N} - \{\hat{e}\}) \cup \{\tilde{l}\}$ 
23:    Recalculate  $\mathbf{B}^{-1}$  from  $\mathbf{B}$ 
24:  end loop
25: end procedure

```

This method, however, would seem problematic in that it seems to require  $\mathbf{B}$  to be inverted in every single iteration. However, it turns out that since only one column of  $\mathbf{B}$  changes between iterations, the new  $\mathbf{B}^{-1}$  can be calculated from

the old one by changing one column (this change can be performed by multiplying by a certain sparse matrix)(**TODO: a little bit on eta files**). This approach is described in greater detail in Section 8.3 of [37].

#### 2.1.4 ASYNPLEX

[17]

As we will describe in Section 4.1,

Since this algorithm is not a result of our own research, we will describe it briefly here. We did need to make some small changes to the algorithm, and we have described those in (**TODO: reference**).

There are essentially two ways to achieve parallelism:

**Task parallelism** can be achieved when two or more different operations can be performed in parallel.

**Data parallelism** can be achieved when the same operation is applied to several pieces of data (**TODO: reformulate**).

The extent to which the different parts of the computation are independent will greatly affect the possibilities for speedup. Computations that can be split into parts that are entirely independent are called *embarrassingly parallel* (see Section 2.3.3 for more information on this), and such computations will benefit greatly from parallelisation (unless the computation is so simple that the time spent distributing the data to the different processors exceeds the time saved on the computation). (**TODO: Amdahl's law here?**) Unfortunately, many important problems are not embarrassingly parallel because one computation may depend on an *intermediate* result from another computation (if, on the other hand, it depends on the *final* result, it cannot be said to be parallelisable). (**TODO: Comm. to comp. ratio**)

ASYNPLEX is an asynchronous algorithm for message-passing systems. The authors also describe a shared-memory version of the algorithm. (**TODO: Can we do both on cell?**)

#### Matrix inversion

In ASYNPLEX, one process, called the *invert processor*, is dedicated to performing matrix inversions. Whenever one of the other processes has decided that a certain

Section 3.4.1

#### Candidate persistence

The key observation upon which ASYNPLEX is based is a phenomenon called *candidate persistence*. A *attractive candidate* is a nonbasic variable whose objective

function coefficient is negative, so that it is possible to select it as the entering variable. According to Hall et al., (TODO: whom do they cite?), a variable that is attractive in one iteration (but remains nonbasic because some other variable is eventually selected as the entering variable) will often remain attractive in subsequent iterations. Furthermore, it can be observed that the pivot operation itself is usually very cheap (assuming that the implementation swaps matrix columns implicitly by using permutation lists to keep track of the current location of each column, while the columns themselves remain in one place) — the majority of the work in each iteration is associated with determining the entering and leaving variables and updating the solution vector. This leads to the idea of having several

one or more *iteration processes*

In addition, ASYNPLEX employs a *basis change manager* process, which is responsible for ensuring that no

and a *column selection manager* process, which keeps track of which variables are currently regarded as attractive.

The pseudocode uses some overly compact names (that probably stem from some old naming convention; Maros[29] uses them too) for each step of the algorithm; they are as follows:

**FTRAN**

**BTRAN**

**UPRHS** Update the right-hand sides

**UPDATE.BASIS**

**CHUZR** Choose row (leaving variable)

**CHUZR** Choose column (entering variable)

We now present the pseudocode for ASYNPLEX as it is given by Hall et al. in [17] (with a few notational adaptations). It is assumed that there is a separate, sequential piece of code that handles input reading and sets up the different processes. In Section 3.4.2, we describe how we have adapted the algorithm.

A short explanation of Hall's notation may be useful. Each process has a number of points where it sends or receives data to or from the other processes. Each such communication endpoint is given a short identifying tag, both on the sending and receiving end, and each send or receive operation indicates where it wishes to send to or receive from.

### 2.1.5 Interior point methods

(TODO: methods/algorithms) It is possible to interpret the simplex method in a geometric fashion: with  $n$  decision variables, the space of all feasible or infeasible

loa 3: ASYNPLEX — iteration process number  $i$  ( $0 \leq i < p$ )

```

1: procedure RUNITERATIONPROCESS( $i, p, \mathbf{N}, \mathbf{b}, \mathbf{c}$ )
2:    $k_i \leftarrow 0$ 
3:   BTRAN
4:   PRICE
5:   FTRAN — let  $q$  be the  $i$ th most attractive candidate column, or -1 if that
      does not exist
6:   repeat
7:     if received  $\leftarrow$  V2 an LU factorisation of the inverse then ▷ I1
8:       Install new inverse
9:     end if
10:    while basis changes received  $\leftarrow$  I7 are not yet applied do ▷ I2
11:      Apply basis change;  $k_i \leftarrow k_i + 1$ 
12:    end while
13:    Permute column  $\mathbf{a}_q$ 
14:    FTRAN
15:    while basis changes received  $\leftarrow$  I7 are not yet applied do ▷ I3
16:      Apply basis change
17:      FTRAN_STEP;  $k_i \leftarrow k_i + 1$ 
18:    end while
19:    if  $q = -1$  or  $\hat{c}_q > 0$  then
20:      Send  $\rightarrow$  C4 a message that the candidate is unattractive ▷ I4
21:    else
22:      Send  $\rightarrow$  R1 an offer to perform CHUZR ▷ I5
23:      Wait  $\leftarrow$  (R2 or R3) for a reply to offer ▷ I6
24:      if Offer accepted then
25:        CHUZR
26:        Send  $\rightarrow$  (I2/I3/I10 on all other iteration processes) the basis
      change and pivotal column ▷ I7
27:        Send  $\rightarrow$  (V1 and C1) basis change ▷ I8
28:        UPDATE_BASIS;  $k_i \leftarrow k_i + 1$ 
29:        BTRAN
30:        Permute  $\pi$ 
31:        PRICE
32:        FTRAN — choose a set of the most attractive candidates
33:        Send  $\rightarrow$  C2 the most attractive candidates ▷ I9
34:      else
35:        Wait  $\leftarrow$  I7 for next basis change ▷ I10
36:        goto line 15
37:      end if
38:    end if
39:    Wait  $\leftarrow$  (C3 or C5) for a new candidate column,  $q$  ▷ I11
40:  until The algorithm terminates
41: end procedure

```

## loa 4: ASYNPLEX — invert processor

```

1: procedure RUNINVERTPROCESSOR( $p, m, \mathbf{N}$ )
2:   Let  $\mathbf{B}$  be an  $m \times m$  identity matrix
3:    $k_v \leftarrow 0$ 
4:   repeat
5:     while received  $\leftarrow$  I8 a notification that  $x_l$  has left the basis and  $x_e$  has
       entered do ▷ V1
6:       Swap the corresponding columns between  $\mathbf{B}$  and  $\mathbf{N}$ 
7:        $k_v \leftarrow k_v + 1$ 
8:     end while
9:     INVERT
10:    Send  $\rightarrow$  I1 on all  $p$  iteration processes the new LU factorisation of the
       inverse for basis  $k_v$  ▷ V2
11:    until the algorithm terminates
12: end procedure

```

## loa 5: ASYNPLEX — column selection manager

```

1: procedure RUNCOLUMNSELECTIONMANAGER( $m, n$ )
2:    $k_c \leftarrow 0$ 
3:   Mark all nonbasic variables as unselected
4:   repeat
5:     if received  $\leftarrow$  I8 basis change then ▷ C1
6:       Mark the variable which has left the basis as unselected
7:     else if received  $\leftarrow$  I9:i a set of candidates corresponding to basis  $k_i$ 
       then ▷ C2
8:       if  $k_i > k_c$  then
9:         Filter out the candidates already selected and those already
           rejected after the FTRAN at a basis  $\geq k_i$ 
10:         $k_c \leftarrow k_i$ 
11:       end if
12:       Send  $\rightarrow$  I11:i the most attractive candidate to enter the basis and
           mark the candidate as selected ▷ C3
13:       else if received  $\leftarrow$  I4:i a message that its current candidate is now
           unattractive then ▷ C4
14:         Send  $\rightarrow$  I11:i the most attractive candidate to enter the basis and
           mark the candidate as selected ▷ C5
15:       end if
16:     until the algorithm terminates
17: end procedure

```

loa 6: ASYNPLEX — basis change manager

```

1: procedure RUNBASISCHANGEMANAGER
2:    $k_b \leftarrow 1$ 
3:   repeat
4:     if received  $\leftarrow$  I5: $i$  an offer to perform CHUZR for basis  $k_i$  then  $\triangleright$  R1
5:       if  $k_i = k_b$  then
6:         Send  $\rightarrow$  I6: $i$  an acceptance of the offer  $\triangleright$  R2
7:          $k_b \leftarrow k_b + 1$ 
8:       else
9:         Send  $\rightarrow$  I6: $i$  a refusal of the offer  $\triangleright$  R3
10:      end if
11:    end if
12:  until the algorithm terminates
13: end procedure

```

ble solutions (TODO: is “solutions” a good term here?) form an  $n$ -dimensional space. Each constraint can be modelled as a plane in this space — an equality constraint requires that feasible solutions lie on the plane, and an inequality constraint requires that feasible solutions lie to one of the sides of the plane. The geometrical shape known as a *simplex* — hence the name of the method. Each intermediate solution produced by the simplex method represents a point that is a vertex (an intersection between (TODO:  $n$  or more) planes). There exists another class of algorithms called *interior point methods*, whose intermediate solutions always lie in the interior of the simplex. , and interior point methods have

A distinct advantage of interior point methods over the simplex method is that they have polynomial worst-case bounds on their time consumption. The first polynomial interior point method was invented by Khachiyan[24] in 1979, and one of the most well-known methods is due to Karmarkar[22]. (Natvig/Elster/Mujahed: You or Mujahed mentioned that (dense) Cholesky factorisation had been implemented on Cell; can you send me the reference?)

In order to limit the scope of this project, interior point methods will not be taken into consideration, but we felt that no discussion of linear programming would be complete without mentioning this subject.

### 2.1.6 Use of LP to solve advanced flow problems

A *flow network* is a graph where a *flow* of some substance (expressed in e.g. litres per second) is associated with each edge. In addition, each edge may have upper and lower bounds (known as *capacities*) on the flow value, and possibly a *cost* that will be incurred per unit of flow that is sent through the edge. The goal may, for instance, be to send as much flow as possible from a designated



*source* (producer) node to a designated *sink* (consumer) node, or to send a certain flow as cheaply as possible. Other variations are also possible. If there are no lower bounds and no costs, there exist efficient algorithms for the maximum flow problem, such as the Edmonds-Karp algorithm[7]. In more complex situations, no specialised algorithms exist, but LP comes to the rescue. Cormen et al.[7] give a good overview of how to express a flow problem as an LP problem, which we summarise here (but only for the simple case of a maximum flow problem). There are two variables for each edge, expressing the amount of flow in each direction through that edge. The flow from node  $u$  (directly) to node  $v$  is denoted by  $f_{uv}$ , and it may not increase above the edge capacity  $c_{uv}$  (which may be different in each direction). The following constraints apply:

- The flow in one direction is the negative of the flow in the opposite direction:  $f_{uv} = -f_{vu}$ , for all  $u, v$ .
- The flow through an edge may not exceed the capacity for that edge in that direction:  $f_{uv} \leq c_{uv}$ , for all  $u, v$ .
- Except for the source  $s$  and the sink  $t$ , all flow entering a node must also exit the node. Due to the “negative flow” convention, this is equivalent to requiring that the flow out of a node is zero:  $\sum_v f_{uv} = 0$  for all  $u$  except  $s$  and  $t$ .

The objective is to maximise the flow out of the source (which, by the rules above, must equal the flow into the sink), which is  $\sum_v f_{sv}$ .

(TODO: Consult Miriam on this)

### 2.1.7 State of the art: sequential LP solvers

#### ILOG CPLEX

CPLEX, developed by the company ILOG, is the industry standard LP solver(Natvig/Elster/Mujahed: Who/what can I cite here?). Being proprietary closed-source software, we cannot examine its inner workings (but they are probably too complex for this project). While our department does not have a CPLEX license, we can still to some extent compare the answers from our solvers to those that CPLEX gives(TODO: as long as the solver is good enough, I guess the answers will always be correct — or?) — sites such as (TODO: citation) provide CPLEX’ answers to the `netlib` problem sets, and Miriam has a license that they can use to find the answers to their own data sets. (TODO: Something on why Miriam doesn’t just use CPLEX rather than bothering with PS3?)

#### GLPK

*Gnu Linear Programming Kit*

Unfortunately, the code base is extremely large, comprising more than (TODO: ) lines of C code distributed across nearly 100 files. While only a handful of these files contain functionality that is directly related to the simplex method, reverse engineering it still would be a daunting task — especially given that their coding conventions apparently calls for very short variable names.

GLPK is released by its authors under version 3 of the GNU General Public License.

### **Xpress**

[http://www.dashoptimization.com/home//products/products\\_optimizer.html](http://www.dashoptimization.com/home//products/products_optimizer.html)

### **OOPS**

<http://www.maths.ed.ac.uk/~gondzio/parallel/solver.html>

### **CLP**

COIN-OR Linear Program Solver (<http://www.coin-or.org/Clp/>).

### **Numerical Recipes**

(2nd and 3rd ed.)

### **SoPlex (Wunderling)**

An implementation developed as a part of Roland Wunderling's Ph.D. thesis[39], and available at <http://soplex.zib.de/>.

### **retroLP**

As opposed to virtually all other LP solvers, retroLP[40] implements the original simplex method, not the revised method. The former is advantageous for dense problems, which occur in some special applications such as “wavelet decomposition, digital filter design, text categorization, image processing and relaxations of scheduling problems.”[41] As compared to GLPK, the code is fairly short and readable — but it still consists of (TODO: ) lines.

retroLP is released by its authors under version 2 of the GNU General Public License.

### **Vanderbei's code**

Vanderbei has published a freely available implementation of the revised simplex algorithm as presented in his book[37], at <http://www.princeton.edu/>

`~rvdb/LPbook/`. While it comprises more than 9000 lines, the core parts are fairly short and well separated from the rest of the code (much of which deals with different input formats).

The code has no licence information attached to it. Anyone who wishes to commercially utilise those parts of our code that are derived from Vanderbei's code are strongly advised to contact Vanderbei.

### 2.1.8 State of the art: parallel LP solvers

#### ASYNPLEX (Hall, McKinnon)

[17]

#### Parallelisation of CPLEX' dual simplex method (Bixby, Martin)

[6]

#### Parallelisation of the revised simplex method using CUDA (Spampinato)

Compute Unified Device Architecture (CUDA) is a framework from the graphics processing unit (GPU) manufacturer nVidia. Daniele Spampinato, a student at our department, implemented the revised simplex method by using the CUBLAS linear algebra library to offload the linear algebra computations onto the GPU[36]. He reported overall speedups of 2.0–2.4 relative to a sequential implementation using ATLAS, but only for dense data sets. The only operation that (by itself) yielded the vast speedups that are theoretically possible when using GPUs (which have hundreds of cores) was the basis inversion[36, Figure 5.6 on p. 45]. Furthermore, he experienced major problems with numerical stability. Note that his implementation parallelised each linear algebra operation individually; it was not a parallel version of the simplex method itself.

#### XPRESS (Andersen, Andersen)

[3]

#### SMoPlex, DoPlex (Wunderling)

These are, respectively, shared memory and distributed memory implementations of the revised simplex method, also from Wunderling's thesis[39]. Regrettably, these implementations are not available online, and since the thesis is written in German, we have not been able to study it — but it may prove useful to someone proficient in German.([Natvig/Elster/Mujahed: Does this sound sarcastic? It's not the intention...](#)) According to slides from a presentation by Hall([TODO: link](#)), the implementation is “parallel (except for INVERT) for only two processors”, and gives “good results only for problems when  $n \gg m$ ”.

**Parallelisation of interior point algorithms (Karypis, Gupta, Kumar)**

Those interested in [23]

**retroLP**

(TODO: See above.)

**Distributed simplex algorithm (Ho, Sundarraaj)**

[20]

**2.2 Cell Broadband Engine**

The *Cell Broadband Engine* (Cell BE) is a single chip multiprocessor architecture jointly developed by IBM, Sony and Toshiba. The initial design goals was to create an architecture that would be suitable for the demands of future gaming and multimedia applications (meaning not only high computational power, but also high responsiveness to user interaction and network communications), with a performance of 100 times that of Sony PlayStation 2[21]. Several obstacles to such goals exist; in particular the infamous *brick walls*[4]:

**Memory wall** While processor speeds have grown substantially over the past few decades, the growth in memory access times has been much more modest. Because of this, the relative cost of memory accesses is now prohibitively large, and for efficient scientific computation, it is necessary to use caches and try to keep data cached for as long as possible once it has been loaded from memory.(TODO: )

**Power wall** Heat dissipation becomes a greater and greater obstacle as frequency increases (TODO: and size is reduced). (TODO: )

**ILP wall** *Instruction-level parallelism* techniques such as pipelines and speculative execution face diminishing returns as most programs have a limited amount of exploitable parallelism, and the hardware and power cost of implementing such techniques is growing.(TODO: )

The Cell BE architecture tries to solve these problems in the following ways:

- Having two different kinds of cores: one optimised for control logic and operating systems, and one optimised for computational throughput.
- Giving the programmer explicit control over data movement in the memory hierarchy, rather than having hardware-controlled caches.
- (TODO: more?)

## 2.2.1 Architecture

### Overview

The Cell BE consists of one *PowerPC Processor Element* (PPE) and eight *Synergistic Processing Elements* (SPE)

### PPE

*PowerPC Processor Unit* (PPU) Separate register files for fixed-point, floating-point, and vector. 32 SIMD registers.

### SPE

Unified register file with 128 128-bit registers

*Synergistic Processor Unit* (SPU)

### Memory bus and DMA controller

Base addresses (both in local storage and in system memory (TODO: correct?)) for all DMA transfers must be aligned on a 16-byte (quadword) border (TODO: term?), and the data to be transferred must be a multiple of 16 bytes. Performance is improved if aligned, whole cache lines (128 bytes (TODO: verify)) are transferred at a time.

*Local Store* (LS) *Memory Flow Controller* (MFC)

Another method that is available for communication between the cores is *mailboxes signals*

## 2.2.2 Programming methods

### The vector data type

### Compiler intrinsics

### Compiler directives

`__attribute__((aligned(16)))`, `spu_sel`, `__builtin_expect`, `_align_hint`, `malloc`  
loop unrolling, function inlining (watch for code size!)

**Branch prediction and avoidance** Given the deep pipeline of the SPEs (TODO: verify), branch mispredictions are very expensive. A couple of compiler directives are available to let the programmer help the compiler and the SPE:

1. `__builtin_expect (expression, expected)` will evaluate and return `expression` while informing the compiler that the programmer expects the result to be `expected`. This is typically placed in the condition of an `if/else`.

2. If the condition of an `if/else` is not easily predictable, but the `if/else` bodies are very simple, one might be better off by computing both bodies and using a special selection instruction to determine which result will be kept. `spu_sel(a, b, condition)` will return either `a` or `b` depending on the truth value of `condition`. This translates to (TODO: a single) instruction which does not involve branches.

## Overlays

(TODO:)

### 2.2.3 Tools and libraries

(Natvig's comment: Good: which libs are used in the project? Better: Which libs are relevant for the project?)

#### BlockLib

[1]

#### Cell Superscalar

(CellSs) [31]

#### RapidMind

<http://www.rapidmind.net/>

#### OpenMP for Cell

[38]

#### MPI for Cell

(TODO: Add citations: Kumar: A Buffered-Mode MPI Implementation for the Cell BE Processor; Krishna: A Synchronous Mode MPI Implementation on the Cell BE Architecture; JulCe)

*The Cell Messaging Layer (CML):* <http://www.ccs3.lanl.gov/~pakin/software/cellmessaging/>

(TODO: move) CML does have some disadvantages. First, it only supports messaging between the SPEs, not between an SPE and the PPE. Second, CML (like MPI) employs the Single Program Multiple Data (SPMD) model, which means that all processors must run the same program. This means that even if different SPEs are to perform different tasks, they must each contain the code both for its own functionality and the code for the functionality of all other SPEs.

Still, we chose to run both the column selection manager and the basis change manager on the SPEs, because their code is fairly short, their operations are fast and simple, and it is vital that they are able to respond quickly to messages from the iteration processes. For the same reasons, we merged them into one SPE thread so that the other seven SPEs would be available for iteration processes.

**(TODO: Locate a BLAS library)**

## 2.3 Miscellaneous topics

### 2.3.1 pthreads

**(TODO: )**

### 2.3.2 Representation of sparse matrices

**(TODO: )**

### 2.3.3 Amdahl's law

The following section is taken from our fall project report[10].

In 1967, Gene Amdahl argued[2] that parallel processing was *not* a good way to improve performance, based on the following observation: If we have a computation that consists of a sequence of serial steps that take a total time of  $t_s$ , and a certain percentage  $f$  of these steps can be performed in parallel using  $p$  processors<sup>10</sup>, then the total time for the sequential part of the calculation will be  $ft_s$ , and if we can distribute the remaining workload equally over the  $p$  processors, the parallel part will take the time  $(1 - f)t_s/p$ . Since the sequential part must presumably be completed before the parallel computations can begin (or the other way around), these times must be added together for a total time of  $t_p = ft_s + (1 - f)t_s/p$ , and we arrive at *Amdahl's law*<sup>11</sup> for the speedup  $S(p)$ :

$$S(p) = \frac{t_s}{t_p} = \frac{t_s}{ft_s + (1 - f)t_s/p} = \frac{1}{f + (1 - f)/p} = \frac{p}{1 + f(p - 1)} \quad (2.31)$$

The most significant aspect of this formula is that it highlights the importance of  $f$  as a severely limiting factor for the potential speedup of parallelising. Amdahl used this to claim that parallel programming was not a good idea. However, since parallelisation is currently regarded as the primary way of improving performance in high performance computing[4], the modern interpretation is that

<sup>10</sup>These are quite optimistic calculations, since we assume that the calculation can be parallelised without incurring communication penalties or extra computation steps, and that the parallel processors are as fast as the sequential one.

<sup>11</sup>Amdahl did not actually state this formula in his article, but it has been derived later (in many different forms) from his article.

speedups can come arbitrarily close to  $p$  if only we can make  $f$  small enough, and thus, one should focus on reducing  $f$  when parallelising a calculation. On the other hand, since  $f$  in most situations cannot (even approximately) become equal to zero<sup>12</sup>, Amdahl's law provides an upper bound on performance gain for a specific problem given the best nonzero  $f$  we can achieve: As  $p$  tends to infinity, the speedup converges to  $1/f$ . Again, it should be noted that these bounds are optimistic, as they are based on very simplifying assumptions.

---

<sup>12</sup>Calculations in which  $f \approx 0$  and where the assumptions about independence between the parallel parts hold are called *embarrassingly parallel*.



# Design

(TODO: Chapter introduction)

## 3.1 Overall approach

The author and his advisor agreed that we should follow a gradual, step by step approach in which we begin with solving simpler problems and (TODO: ) We decided upon the following overall plan:

1. Implement the standard simplex method on a sequential machine.
2. Parallelise the standard simplex method on Cell (if the Cell turns out to be very hard to program, we could first parallelise it on a regular multicore machine using e.g. pthreads or OpenMP (see <http://openmp.org/wp/>) to make sure our parallelisation approach is correct).
3. Implement the revised simplex method on a sequential machine.
4. Parallelise the revised simplex method on Cell. This is expected to be harder than (TODO: ) most likely by implementing an existing algorithm. For each implementation, several refinements could be investigated:(TODO: wording)
  - a) Investigating various ways of handling numerical instability that may occur when using single precision arithmetic.
  - b) Experimenting with how different representations of sparse matrices and vectors affect performance.
  - c) Figuring out how to improve performance by utilising the Cell/BE's vector operations.
  - d) Using autotuning to find good values for e.g. data transfer block sizes.

5. Investigate interior point methods and implement them if time permits.

## 3.2 Initial experiments

### 3.2.1 Arithmetic performance

(Natvig/Elster/Mujahed: Should we do this ourselves, or find someone who has already done it?)

**All data in registers**

**Single precision**

**Double precision**

**All data in LS**

**Single precision**

**Double precision**

**Double buffering of data from main storage**

(Natvig/Elster/Mujahed: Maybe we can find out that data transfer takes so much time that the DP performance loss doesn't have too much of an impact?)

**Single precision**

**Double precision**

## 3.3 Standard simplex method

In order to become familiar with programming the Cell BE, we initially implemented a few versions of the standard simplex method (which is best suited for dense problems). (Natvig's comment: This can be justified when we have a task description and "angrepsmåte") As mentioned in Section 4.1, it turned out that it is extremely hard to make the standard simplex method work reliably on even medium-sized data sets

Our Cell implementation is a fairly straightforward parallelisation of the standard simplex method (that is, it is only a parallel formulation of the same algorithm), so it gives the same results as our sequential implementation. Given that the sequential implementation normally yields a wrong answer for problems of nontrivial size, it is not particularly useful for computations, but Miriam

(who has invested in a Cell (TODO: Move this information to the introduction)) was still interested in a demonstration of how much impact the data transfers have on performance. Therefore, we provide here a description of our parallelisation strategy, and in Section 5.2.1 we provide detailed timings of some test runs.

### 3.3.1 PPE version

(TODO: Far from finished) As described in Section 2.2.1, the PPE supports SIMD instructions (also referred to as vector instructions) capable of operating on four single precision floating point values simultaneously. Since the simplex method primarily consists of row operations on the tableau, it is an excellent target for such vectorisation — the only problem is the low arithmetic intensity, which may reduce performance because a lot of data needs to be loaded into the registers, and only a very simple and fast operation is being performed on each element before it is thrown out again. (TODO: How much does this matter, given the fast LS? However, if the data is too large to fit in the LS, things will probably slow down a lot.)

(TODO: Something on why we chose C++?)

### 3.3.2 SPE version

Our approach is fairly obvious<sup>1</sup>:

1. The PPE, which initially holds the entire tableau, distributes the tableau rows evenly among the SPEs (TODO: SPE or SPU?), giving each SPE a batch of consecutive rows.
2. The first SPE analyses the objective function to determine the leaving variable and sends the column number to the PPE, which distributes this number to the other SPEs. If no leaving variable was found, the optimal solution has been found, and the SPEs are asked to send their basic variable values to the PPE and terminate. (TODO: which pivot rule?)
3. Each SPE determines the strictest bound (that is imposed by its subset of the rows) on the value of the leaving variable and sends the bound (TODO: and the corresponding row number) to the PPE.
4. The PPE determines which SPE that “wins” and requests this SPE to transfer the pivot row to main memory; afterwards, all the other SPEs are re-

---

<sup>1</sup>After having written the application, we found that [40] essentially uses the same approach, albeit for cluster computers with MPI. (Natvig/Elster/Mujahed: I’m trying to express that although it’s not difficult to come up with this approach, I *did* do it myself, before finding that paper. Is that something I should do?)

quested to receive this row (TODO: wording). If no SPEs found a finite bound, the problem is unbounded, and the SPEs are asked to terminate.

5. Each SPE performs row operations on its part of the tableau, using the pivot row, and notify the PPE upon completion. Go to step 2.

### 3.4 Revised simplex method

(TODO: )

#### 3.4.1 Performing the matrix inversion in parallel

The revised simplex method as described in (TODO: reference) must occasionally spend some time reinverting the basis matrix. A simple yet attractive idea is to offload the matrix inversion onto a separate processor, which may then spend all of its time performing inversions. Then, the main processor can spend all of its time on the remaining steps of the method (while occasionally being provided with a reinverted basis matrix from the inversion processor), and one gets the added benefit of the matrix being reinverted more often (which should be good for numerical stability). (TODO: can the inversion itself be parallelised?) Unfortunately, as reported by Ho and Sundarraj[20, Table 2], the inversion consumes less than 20% of the total time of the revised simplex method, and as such, speedups are limited as per Amdahl's law (see Section 2.3.3). Furthermore, this approach does not scale to more than two processors. Therefore, we have chosen not to pursue this direction. Note, however, that ASYNPLEX incorporates the same idea of having a separate inversion processor.

#### 3.4.2 Our adaptation of ASYNPLEX

As discussed in (TODO: reference), we realised that we had too little experience with numerical computation in general and the simplex method in particular, and therefore we decided to find an existing sequential implementation of the simplex method and rewrite it as per the ASYNPLEX algorithm. Finding a suitable implementation was not easy, because one apparently needs to make a trade-off between small code size and ease of understanding on one hand and numerical stability on the other hand. As noted in (TODO: reference), all the major, well-known implementations have exceedingly large code bases. (TODO: Have we discussed rationales for our choice anywhere?) After unsuccessful attempts at understanding GLPK and (TODO: ), we chose Vanderbei's implementation.

Basing ourselves on an existing sequential implementation also has the advantage of allowing a direct comparison between the sequential and parallel versions of the same code, allowing us to better (TODO: spell "gauge") the

speedup that is offered by ASYNPLEX itself (Hall et al. measured their performance against an entirely different sequential implementation), and the further speedup that is obtained on Cell. (TODO: actually perform such comparisons)

The disadvantage, of course, is that retrofitting an sequential implementation may require a vast effort in case parts of the code does not lend itself well to parallelisation (this easily happens when the code relies on global variables or internal, static variables, because such variables will need to be duplicated so that each thread has its own instance of it.) For this reason, we chose to switch to C++(TODO: ).

### 3.4.2.1 Sparse vector and matrix representations

(TODO: This sentence goes either here or in unimplemented features) Vanderbei's implementation uses the Compressed Column Storage format, also known as the Harwell-Boeing Sparse Matrix Storage Format[35] for sparse matrices and a similar scheme for sparse vectors. A sparse  $m \times n$ -matrix containing  $k$  nonzero values is represented as two numbers telling the number of rows and columns, and three arrays:

**values** contains all  $k$  nonzero values, column by column (first all nonzero values from the first column, from top to bottom, then from the second column, and so on).

**rowIndices** contains  $k$  integers, one for each element of the *values* array, telling which row that element is located in.

**columnPositions** always contains  $n + 1$  elements — one for each column, and one additional element. Each entry contains an index into the two other arrays, which tells where the values of the corresponding column start. The last element contains  $k$ , which in effect tells us the last valid index into the two other arrays (namely  $k - 1$ ). Thus, the indices of the elements of column  $i$  are *rowIndices*[ $i$ ] through *rowIndices*[ $i + 1$ ] - 1.

For instance, the matrix

$$\begin{bmatrix} 9 & 0 & 0 \\ 0 & 2 & 7 \\ 4 & 3 & 0 \end{bmatrix}$$

would be represented as follows:

Value	9	4	2	3	7	—
Row index	0	2	1	2	1	—
Column positions	0		2		4	5

Note that we use zero-based indices. A sparse (column) vector is represented as two arrays containing the nonzeros and the row indices, and two single variables telling the number of rows and the number of nonzeros.

Unfortunately, Vanderbei did not have a structure or class that contained the arrays and variables for each sparse matrix or vector. For instance, the matrix **A** would be represented with the arrays *a* (values), *ia* (row indices), *ka* (column positions) and the variable **(TODO: )** (number of nonzeros) — a naming scheme that we found to be very impractical (all variables must be passed as parameters to functions that are to manipulate sparse vectors and matrices), and which **(TODO: oppos. facilitate)** our process of understanding his code. Therefore, we introduced structures that combined these related arrays and variables, and we refactored the code to use these structures throughout. Our structure for sparse matrices looks like this:**(TODO: remove typedefs)**

```
struct SparseMatrix {
    int rows;
    int cols;
    int numNonzeroes;
    int * rowIndices;
    int * colPos;
    TYPE * values;
};
```

Note that `TYPE` is a preprocessor symbol which facilitates experimentation with different precisions **(TODO: describe TYPE somewhere)** — it should be defined as either `float` or `double`.

Due to the vast amounts of vector manipulation (and also in order to track down some bugs we believed were related to reading/writing outside of the array bounds, but turned out to be caused by wrong memory management), we made a more elaborate sparse vector structure, which uses the `vector` class from the C++ Standard Template Library. The `at()` function performs boundary access checking on each access. **(TODO: a define to enable/disable usage of at(), and update this code)** The compiler will most likely inline the simple accessor functions and operators, so that the usage of classes with and `vector` will not incur any performance penalty (if the boundary checking is turned off). The structure looks like this:

```
class SafeSparseVector {
private:
    int rows;
    std::vector<int> rowIndices;
    std::vector<TYPE> values;
public:
    int numNonzeroes() const { return values.size(); }
    int numRows() const { return rows; }
```

```

void setRows(int rows) { this->rows = rows; }
void resize(int size) {
    rowIndices.resize(size);
    values.resize(size);
}
void clear() {
    rowIndices.clear();
    values.clear();
}
void append(TYPE value, int rowIndex) {
    values.push_back(value);
    rowIndices.push_back(rowIndex);
}
TYPE & value(int i) { return values.at(i); }
TYPE value(int i) const { return values.at(i); }
int & rowIndex(int i) { return rowIndices.at(i); }
int rowIndex(int i) const { return rowIndices.at(i); }
TYPE maxValue() const;
};

```

Beware that in order to save time, Vanderbei preallocates the arrays for any sparse vector with  $r$  rows to have size  $r$ , but only the first  $k$  entries are used at any time (where  $k$  is the number of nonzeros). Whenever the contents (and the number of nonzeros) of the vector changes, one can simply fill the arrays with as many entries as necessary, since each individual vector has a constant size throughout the program and the number of nonzeros obviously will never exceed the full vector size. Also, Vanderbei did not explicitly store the sizes of the vectors and matrices, as they could always be deduced from context (normally as having  $m$  or  $n$  rows). We feel that this practice obscures the relationship between a loop header and its body — if  $v$  is a sparse matrix with  $n$  columns and we want to write a loop that manipulates  $v$ , we prefer e.g. `for (int j = 0; j < v.cols; ++j)` to `for (int j = 0; j < n; ++j)`. Therefore, we have included the size information into our structures and have tried to use them instead of  $m$  and  $n$  (this also makes the linear algebra functions slightly more general, and it would facilitate unit testing). Note that such preallocation is not done for matrices, since this would require too much space and the main part of the algorithm rarely (TODO: or never?) changes the matrices.





# Implementation and testing

(TODO: Chapter introduction)

## 4.1 Implementation problems

### 4.1.1 Straightforward simplex implementation

Our initial plan was to begin with something we thought to be fairly straightforward and then gradually proceed towards harder problems, along the lines described in Section 3.1. Steps 1 and 2 initially seemed to have been as simple as we had assumed them to be (step 1 was based on the descriptions and pseudocode from [7] and [37]), and the Cell parallelisation went well. These implementations are listed in Appendix A.1. Unfortunately, (TODO: )

Our beliefs were reinforced by the fact that well-known works such as [7] and [37] make no mention of the standard simplex method being particularly *unstable* (they only say that other methods are being used in practice because they are more *efficient*). Agreeing with the words of Donald Knuth, “premature optimisation is the root of all evil”[26], we decided that (TODO: ) Also, [32] provided an implementation of the standard simplex method — but when we actually tried it, it turned out to run into the same kinds of stability problems as our code (TODO: Make a section detailing experiments on this). In the third edition[33], it has been replaced by an implementation of the revised simplex method.

We succeeded in finding an implementation of the standard simplex method that seemed to work well, called retroLP[41]. However, the code base was quite large, and (TODO: )

We eventually resigned and contacted a group of mathematicians with which Lasse is acquainted, describing our problems and asking them for help on how to make the standard simplex method work stably[18]. Their response (TODO: )

)

Most of the books we have consulted on the subject of linear programming simply give the standard theoretical presentation and completely neglects to mention the practical implementation difficulties — the author of this report would very much have liked a book that is detailing what one needs to do in order to make the simplex method stable. The closest we have come to this is the splendid book by Maros[29]. (TODO: )

**MPS parser** The `netlib` data sets are stored in a file format called *MPS* (Mathematical Programming System). The format hails from the punch card age; as such, it is fairly arcane (it employs fixed format), but all the simpler to parse. This was fortunate, since we could not find any available parsers, so we had to write our own (. (TODO: Put the source in the appendix) Our parser does not handle all aspects of the format, but(TODO: ) Maros[29, Chapter 6] gives a fairly compact presentation of the format.

#### 4.1.2 Numerical stability

(TODO: something on float vs. double?) Already at the beginning of the project, concerns were raised about the suitability of the Cell/B.E. for this kind of computations, since its double precision arithmetic is very slow compared to its single precision arithmetic.

In order to demonstrate that the stability problems are not caused by errors in our implementation, we have made our code support usage of the *GNU multiple precision arithmetic library* (GMP — see <http://gmplib.org/>), which among other features has a data type for representing arbitrary-size rational numbers exactly. Since the simplex methods only apply the four basic arithmetic operations throughout their operation, all numbers in the tableau will remain rational<sup>1</sup>. Compile the code by running the `buildgmp.sh` script; this will link to GMP (which must first have been downloaded, compiled and installed on the system) and tell our code to use the `mpq_class` data type for all arithmetic operations and to output results in fraction form. When using GMP, the code obviously slows down by a significant factor and the memory consumption increases (which is why this approach is useless in practice unless it is absolutely essential to obtain exact results). Table 4.1.2 on the next page shows the results for some of the small-to-medium `netlib` sets. Note that our solver performs maximisation, while the `netlib` sets are supposed to be minimised (but for some reason, the MPS format does not specify whether to maximise or minimise) — therefore, our MPS parser negates the objective function, so that the answers will have correct absolute value but wrong sign. According to the

---

<sup>1</sup>Assuming, of course, that they were initially rational — but all data formats for representing of LP problems are based on floating point numbers, which are inherently rational.

README file, The “official” `netlib` results have been obtained using the MINOS solver, version 5.3. All digits of the `netlib` results agree with our exact results. (TODO: used rev 66:abf2df...)

Data set	Netlib result	Our result	Iterations	Time
AFIRO	$-4.6475314286 \cdot 10^2$	$\frac{406659}{875}$	16	0.044 s
BRANDY	$1.5185098965 \cdot 10^3$	$\begin{array}{r} -16065877392598163704545292298 \\ 35255763845946280057831648209 \\ 5777480900411096633986368891 \\ \hline 1058002811160721713504750150 \\ 8720411569323127506371426417 \\ 345909327662918125000000000 \end{array}$	605	18.334 s
LOTFI	$-2.5264706062 \cdot 10^1$	$\frac{631617651547}{25000000000}$	537	40.362 s
SCFXM2	$3.6660261565 \cdot 10^4$	$\begin{array}{r} -487467141911986101107830583924465 \\ 3390630042031652016001773580110200 \\ 0732423011933261045459132101058706 \\ 9407177301915047835480055104995559 \\ \hline 132968811760304712675433640078488 \\ 877195894209916975474747392970467 \\ 484815850625849844147283072046261 \\ 3814446552258600000000000000000 \end{array}$	1299	2363.2 s
STOCFOR1	$-4.1131976219 \cdot 10^4$	$\begin{array}{r} 7368963026860358678147 \\ 0598121420626868798940 \\ 69612494322055836783 \\ \hline 17915412056905368048 \\ 97461796875000000000 \\ 0000000000000000000 \end{array}$	135	3.381 s

Table 4.1: Some results of our exact standard simplex implementation

### 4.1.3 (TODO: Missing citations)

(Natvig/Elster/Mujahed: This section is quite randomly placed; it is simply a list of articles I think I am going to cite, but where I haven’t yet written the context in which they are to be cited.) [16] [12] [15] [27]

## 4.2 Simplex algorithm

### 4.3 Test plan

#### 4.3.1 Unit testing

While one might argue that testing an LP solver by running it against a collection of large data sets provides sufficient evidence that the implementation is correct, one will gain even more confidence in the implementation by creating unit tests. Any decent programmer knows how to structure a program by breaking it down into functions, each performing a limited, well-defined part of the

overall task. Unit testing, on the other hand, is often neglected, even though it is highly beneficial during development. There is a lot of literature on the subject (TODO: citation), but the basic idea is simple: write code that tests other code. This is fairly straightforward to do as long as the code is partitioned into functions in a reasonable manner. Code should be written to test each nontrivial function for a number of different parameter combinations.

Another important aspect is that unit testing gives *regression testing* for free. If one discovers a bug, one should immediately add a test that demonstrates the bug *before* one fixes the code. That way, one can easily demonstrate that the bug has been fixed, and since this test is now a part of the test suite (*all* of which should be run after each change to *any* code) it will immediately discover the bug if it resurfaces — after all, in large applications bugs in one part of the code can often be triggered .

While some of these considerations are most relevant for software companies, (TODO: )

(TODO: Actually *write* some unit tests...)

### 4.3.2 Large data sets

(TODO: Something on the `netlib` LP problem set) (TODO: Set selection by H. Y. Benson and D. F. Shanno?)

### 4.3.3 Memory leaks

`valgrind` with `MemCheck` (<http://valgrind.org>) is an invaluable tool for detecting memory leaks (forgetting to release memory segments that are no longer in use, such that the program will continuously consume more and more memory) and illegal use of the memory allocation system (such as calling `free()` on the same pointer twice, which may easily cause corruption of the memory allocator's internal data structures). We have used this tool on several occasions during this project, and we believe that we have removed all memory leaks caused by our own code. The only leaks that remain are caused by Vanderbei's own code, but each leak occurs only once (not inside loops) and the data that is being allocated is needed throughout the entire program (and is automatically freed when the program terminates), so that we chose not to spend time on removing them. A `valgrind` report on one run of our (TODO: x86) solver can be found in Appendix (TODO: ).

### 4.3.4 Comparison to other implementations

Miriam currently uses the ILOG CPLEX solver, and it would therefore be reasonable to compare the time consumption of our algorithm to those of CPLEX. (TODO: Convert some `netlib` test sets to cplex format and get Chris to run them)

GLPK seems to be the most well-known open source solver, so we might also want to compare our results against it. Of course, since our implementation is based on Vanderbei's code, we will want to measure speedups relative to his implementation. Hall[17] provides relative speedups of ASYNPLEX runs on a few `netlib` sets, with which we can compare our speedups.



# Evaluation

(TODO: Chapter introduction)

## 5.1 Performance measurements

### 5.1.1 Testing environments

The x86 experiments were run on a machine containing an Intel Core2 Quad Q9550 with four cores at 2.83 GHz, with 4 GB of system memory. The compilers are gcc version 4.2.4 and (TODO: ) The system is running Ubuntu (TODO: version) with Linux kernel version (TODO: ). (TODO: The program was always run with `nice -n -20` to force the operating system to give maximal priority to the program's threads.)

The Cell experiments (TODO: )

(TODO: Describe system specifications and how timing was performed)

### 5.1.2 (TODO: What to measure)

### 5.1.3 (TODO: How to measure)

## 5.2 Results

### 5.2.1 Standard simplex method

As discussed in (TODO: reference), the standard simplex method is highly susceptible to numerical instability, and our implementation is no exception to this. It is essentially useless in practice because for most sets of realistic size, it produces answers that are off by orders of magnitude. Still, we might be able to learn something about the computation to communication ratio of the algorithm, and how much time vector operations are capable of saving. Also, Miriam stated that they are interested in such measurements.

## 5.2.2 Revised simplex method

(Natvig/Elster/Mujahed: I think I will perform timing measurements both on my C/threads implementation and on my Cell implementation.)

## 5.3 Other aspects

### 5.3.1 Code size

(TODO: Not entirely sure about this) Vanderbei's Phase I/II scheme causes the code size to be larger than necessary, because much code must be duplicated in order to work with both  $\mathbf{A}$  and  $\mathbf{A}^\top$ .

It is necessary to The debug flags, in particular `-g3`, dramatically increase code size. Optimisation flags, in particular `-O3`, reduce code size greatly (strangely, `-Os` does not seem to have any effect). As often happens in optimisation, there are tradeoffs that must be considered — for instance, while loop unrolling gives a good speedup of tight loops, it increases code size, which one cannot always afford on Cell. Thus, neither manual unrolling nor `-funroll-loops` should be done if (like us) one has a large program.

When optimising for size, one would normally want to consider using `-fno-inline` in order to disable function inlining (replacing calls to short functions by the actual function code). However, this flag actually increased the size of the object files. We suspect that this is due to heavy use of `std::vector` and its `[]` operator — the operator code itself can probably be translated into one instruction (load using memory address and offset), while a function call would require several instructions for parameter passing, stack management, etc.

The option that by far had the greatest impact on the final code size was `-s`, which tells the linker not to include symbol information (a debug (TODO: and linking) aid) in the object files. (TODO: This reduced the spu program to one-third of its original size.)

## 5.4 Thoughts on unimplemented features / ideas for future work

(TODO: Stuff we didn't get the time to do...)

### 5.4.1 Dense interior point

(TODO: Already done, according to Mujahed (or was it only the Cholesky factorisation step? - acquire reference)



### 5.4.2 Sparse interior point

The most time consuming step of many interior point algorithms is a Cholesky factorisation. (TODO: citation) Monien and Schulze[30] discuss approaches to parallelising this operation for sparse matrices, and one of those methods, called the *multifrontal method*, is elaborated by Schulze[34].

Andersen and Andersen[3] present a parallel shared memory version of the interior point algorithm that is (or was at the time) underlying the Xpress solver (see Section 2.1.7). Yet another parallel interior point algorithm is presented by Karypis et al.[23].

(TODO: Opportunities for implementing this on cell?)

### 5.4.3 Mixed precision

It may be possible to overcome the limited precision that is offered by the Cell/BE without rewriting the computation to use double precision (which will incur a massive slowdown). Some linear algebra problems can be solved by using a technique called *iterative refinement*

By performing the We have not ventured to investigate such an approach ourselves, but one may Kurzak and Dongarra[28] describe a successful implementation of a Cell/BE program for solving equations of the form  $\mathbf{Ax} = \mathbf{b}$ , which meets the LINPACK benchmark's requirements for the precision of the solution.

Similar techniques may be investigated for

(TODO: Kurzak: "Great effort has been invested throughout the years in optimizing code performance for cache-based systems, in most cases leading to the programmers reverse engineering the memory hierarchy. By requiring explicit data motion, the memory design of the Cell takes the guesswork out of the equation and delivers predictable performance.")

### 5.4.4 Representation of sparse matrices

Sparse matrices and vectors can be represented in numerous ways; Shahnaz et al.[35] give a good review of different storage schemes. Several operations in a linear solver will depend on the choice of such a representation. If one takes care to place the code for each such operation in a separate function, only a modest amount of work will be required to create implementations of several storage schemes (with the added benefit that these implementations can be tested separately, and as long as they work, the entire solver will still work). Then, one can measure how performance is impacted by the choice of storage scheme. The first alternative representation to try might be the *jagged diagonal storage*, which, according to [35], is "specially tailored for sparse matrix-vector multiplications",

and its variation *transposed jagged diagonal storage*, which is “suitable for parallel and distributed processing”.

It should be noted that some formats are intended for general matrices, while others make assumptions about the distribution of nonzeros — the latter category may be risky to use internally in the solver, since one cannot tell in advance what kind of patterns might emerge in the intermediate matrices produced in the course of the algorithm. (TODO: are we sure about this?) Vanderbei’s implementation uses the Compressed Column Storage format, also known as the Harwell-Boeing Sparse Matrix Storage Format[35].

### 5.4.5 Vectorisation

As mentioned in Section 2.2.2, utilising vector operations is essential in order to obtain the high computational throughput that is promised by the Cell/BE. While vectorisation of dense matrix-vector operations is fairly trivial ((TODO: viz.) our parallel standard simplex solver), putting vectors to good use in sparse operations is much harder. For instance, vectorisation of a simple addition of (mathematical) vectors will require the opportunity to add four adjacent numbers to four other adjacent numbers simultaneously, but with sparse representations, adjacent numbers in one vector may not correspond to adjacent numbers (or any numbers at all) in the other vector.

One approach may be to, for each nonzero number, store all four numbers that are located in the same `vector` (even if the other three are zeroes) — if the element at index  $i$  is nonzero, we would store all elements from  $\lfloor \frac{n}{4} \rfloor \cdot 4$  through  $\lfloor \frac{n}{4} \rfloor \cdot 4 + 3$ . This would permit operations on four adjacent numbers — but only if there is a matching `vector` in the other vector. Thus, the gains from this approach may be rather limited. Furthermore, it would come at the cost of an increase in the storage requirements, which may be detrimental since it would increase the traffic on the Cell/BE bus. When using the compressed column storage format as described in Section 3.4.2.1, the required space would increase from  $2k + 1$  elements to  $5k + 1$  elements (it is sufficient to store the row index of each `vector`, so only the value array would quadruple its size) in the worst case of a vector having  $k$  nonzeros with none of them spaced closer than four elements apart. For an  $m \times n$ -matrix containing  $k$  nonzeros it would increase from  $2k + n + 3$  elements to  $5k + n + 3$  elements.

### 5.4.6 Autotuning

## 5.5 Discussion

## Conclusion

The purpose of this project was to explore how linear programming algorithms, primarily variations of the simplex method, might be parallelised and implemented on the Cell Broadband Engine, a multicore processor with an innovative architecture. To the surprise of both the author and his advisor, the various simplex method turned out to be exceedingly difficult to implement sequentially, even on a regular computer and without parallelisation — a fact which we later learned is well-known within the mathematical optimisation community. (TODO: )

Thus, the project was turned into an exercise in reading and refactoring other people's code (a useful skill to have, but it does not exactly qualify as research)

### 6.1 Experiences

Building an industrial-strength LP solver is a vast amount of work and must only be undertaken with someone who has extensive knowledge of both programming and numerics.

### 6.2 Future work



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# Appendices



# Appendix A

## Code

### A.1 Sequential standard simplex method for x86

(TODO: Defines) (TODO: Input format)

**matrix.h**

```
#ifndef MATRIX_H
#define MATRIX_H

#include <iostream>
#include <vector>
#include <cmath>

#ifdef USE_GMP
#include <gmpxx.h>
#endif

class Matrix;

class Matrix {
    friend class RowIndexDescriptor;
    friend std::ostream & operator << (std::ostream &, const
        Matrix &);
public:
    Matrix(int, int);
    Matrix(int rows, int cols, TYPE * data);
    Matrix(int, int, bool);
    Matrix(const Matrix &);
    const Matrix & operator = (const Matrix &);
    ~Matrix();
    int getRows() const { return rows; }
```

```

int getCols() const { return cols; }
TYPE operator () (int r, int c) const;
TYPE & operator () (int r, int c);
Matrix operator + (const Matrix &) const;
Matrix operator - (const Matrix &) const;
Matrix operator * (const Matrix &) const;
Matrix operator * (TYPE) const;
Matrix transpose() const;
Matrix invert() const;
void multiplyRow(int row, TYPE factor);
void addRows(int sourceRow, int destinationRow, TYPE factor);
void swapRows(int firstRow, int secondRow);
void print(const std::vector<int> & basic, const std::vector<
    int> & nonbasic);
private:
    int rows;
    int cols;
    TYPE * data;
};

std::ostream & operator << (std::ostream &, const Matrix &);

inline void incr(TYPE & a, const TYPE & b) {
#ifdef ZEROING_RULE_EPSILON
    a += b;
    if (abs(a) <= EPSILON) {
        a = 0;
    }
#else
#ifdef ZEROING_RULE_RATIO
    TYPE result = a + b;
    if (result == 0 || (abs(a / result) >= RATIO && abs(b /
        result) >= RATIO)) {
        a = 0;
    }
    else {
        a = result;
    }
#else
    a += b;
#endif
#endif
}

#endif

```

**matrix.cpp**

```
#include "matrix.h"
#include <cmath>

using namespace std;

Matrix::Matrix(int rows, int cols) {
// if (rows <= 0 || cols <= 0)
//   throw std::exception();
  this->rows = rows;
  this->cols = cols;
  this->data = new TYPE[rows * cols];
  for (int i = 0; i < rows * cols; ++i)
    this->data[i] = 0;
}

Matrix::Matrix(int rows, int cols, TYPE * data) {
// if (rows <= 0 || cols <= 0)
//   throw std::exception();
  this->rows = rows;
  this->cols = cols;
  this->data = new TYPE[rows * cols];
  for (int i = 0; i < rows * cols; ++i)
    this->data[i] = data[i];
}

Matrix::Matrix(int rows, int cols, bool identity) {
// if (rows <= 0 || cols <= 0)
//   throw std::exception();
  this->rows = rows;
  this->cols = cols;
  this->data = new TYPE[rows * cols];
  for (int i = 0; i < rows * cols; ++i)
    this->data[i] = 0;
  if (identity && rows == cols) {
    for (int i = 0; i < rows; ++i) {
      (*this)(i, i) = 1;
    }
  }
}

Matrix::Matrix(const Matrix & source) {
  this->rows = source.rows;
  this->cols = source.cols;
  this->data = new TYPE[source.rows * source.cols];
  for (int i = 0; i < source.rows * source.cols; ++i)
```

```

    this->data[i] = source.data[i];
}

const Matrix & Matrix::operator = (const Matrix & source) {
    this->rows = source.rows;
    this->cols = source.cols;
    delete this->data;
    this->data = new TYPE[source.rows * source.cols];
    for (int i = 0; i < source.rows * source.cols; ++i)
        this->data[i] = source.data[i];
    return *this;
}

Matrix::~Matrix() {
    delete [] data;
}

TYPE Matrix::operator () (int r, int c) const {
    if (r < 0 || c < 0 || r >= rows || c >= cols)
        throw "Index out of range";
    return data[r * cols + c];
}

TYPE & Matrix::operator () (int r, int c) {
    if (r < 0 || c < 0 || r >= rows || c >= cols)
        throw "Index out of range";
    return data[r * cols + c];
}

ostream & operator << (ostream & out, const Matrix & matrix) {
    out << "=== " << matrix.rows << " x " << matrix.cols << " ==="
        << endl;
    for (int r = 0; r < matrix.rows; ++r) {
        out << matrix.data[r * matrix.cols];
        for (int c = 1; c < matrix.cols; ++c)
            out << ' ' << matrix.data[r * matrix.cols + c];
        out << endl;
    }
    out << "=====" << endl;
    return out;
}

void Matrix::print(const vector<int> & basic, const vector<int>
    & nonbasic) {
    cout << "=== " << rows << " x " << cols << " ===" << endl;
    for (int r = 0; r < rows; ++r) {

```

```

    if (r == 0)
        cout << "z = ";
    else
        cout << "x" << basic[r - 1] << " = ";
    cout << data[r * cols];
    for (int c = 1; c < cols; ++c)
        if (data[r * cols + c] != 0)
            cout << " " << data[r * cols + c] << "x" << nonbasic[c
                - 1];
    cout << endl;
}
cout << "=====" << endl;
}

Matrix Matrix::operator + (const Matrix & other) const {
    if (rows != other.rows && cols != other.cols)
        throw "Matrix sizes are not equal";
    Matrix result(rows, cols);
    for (int r = 0; r < rows; ++r) {
        for (int c = 0; c < cols; ++c) {
            result(r, c) = (*this)(r, c) + other(r, c);
        }
    }
    return result;
}

Matrix Matrix::operator - (const Matrix & other) const {
    if (rows != other.rows && cols != other.cols)
        throw "Matrix sizes are not equal";
    Matrix result(rows, cols);
    for (int r = 0; r < rows; ++r) {
        for (int c = 0; c < cols; ++c) {
            result(r, c) = (*this)(r, c) - other(r, c);
        }
    }
    return result;
}

Matrix Matrix::operator * (const Matrix & other) const {
    if (cols != other.rows)
        throw "Matrices are not compatible";
    Matrix result(rows, other.cols);
    for (int i = 0; i < rows; ++i) {
        for (int j = 0; j < other.cols; ++j) {
            TYPE sum = 0;
            for (int k = 0; k < cols; ++k) {
                sum += (*this)(i, k) * other(k, j);
            }
        }
    }
}

```

```

    }
    if (abs(sum) < 0.00001f)
        sum = 0.0f;
    result(i, j) = sum;
}
}
return result;
}

Matrix Matrix::operator * (TYPE factor) const {
    Matrix result(rows, cols);
    for (int r = 0; r < rows; ++r) {
        for (int c = 0; c < cols; ++c) {
            result(r, c) = (*this)(r, c) * factor;
        }
    }
    return result;
}

Matrix Matrix::transpose() const {
    Matrix result(cols, rows);
    for (int r = 0; r < rows; ++r) {
        for (int c = 0; c < cols; ++c) {
            result(c, r) = (*this)(r, c);
        }
    }
    return result;
}

void Matrix::multiplyRow(int row, TYPE factor) {
    if (factor == 1) return;
    for (int j = 0; j < cols; ++j) {
        (*this)(row, j) *= factor;
    }
}

void Matrix::addRows(int sourceRow, int destinationRow, TYPE
    factor) {
    if (factor == 0) return;
    for (int j = 0; j < cols; ++j) {
        incr((*this)(destinationRow, j), (*this)(sourceRow, j) *
            factor);
    }
}

void Matrix::swapRows(int firstRow, int secondRow) {
    if (firstRow == secondRow) return;
}

```



```

    for (int j = 0; j < cols; ++j) {
        TYPE tmp = (*this)(firstRow, j);
        (*this)(firstRow, j) = (*this)(secondRow, j);
        (*this)(secondRow, j) = tmp;
    }
}

Matrix Matrix::invert() const {
    if (rows != cols) throw "Non-square matrices cannot be
        inverted";
    Matrix self(*this);
    Matrix inverse(rows, cols, true);
    for (int rc = 0; rc < cols; ++rc) {
        // Locate row with nonzero in this column
        int searchRow = rc;
        while (searchRow < rows && self(searchRow, rc) == 0)
            ++searchRow;
        if (searchRow == rows)
            throw "Matrix is singular";
        // Swap with current row; now the current row has nonzero
        // in this column
        self.swapRows(rc, searchRow);
        inverse.swapRows(rc, searchRow);
        TYPE factor = 1 / self(rc, rc);
        self.multiplyRow(rc, factor);
        inverse.multiplyRow(rc, factor);
        for (int r = 0; r < rows; ++r) {
            if (r == rc) continue;
            TYPE factor = -self(r, rc);
            self.addRow(rc, r, factor);
            inverse.addRow(rc, r, factor);
        }
    }
    return inverse;
}

```

### TableauSimplex.h

```

#ifndef TALBEAUSIMPLEX_H
#define TALBEAUSIMPLEX_H

#include "matrix.h"
#include <string>
#include <vector>

enum SimplexResult {

```

```

    SUBOPTIMAL,
    OPTIMAL,
    UNBOUNDED,
    CYCLING
};

class TableauSimplex {
public:
    static SimplexResult solve(Matrix & tableau, std::vector<int>
        & basic, std::vector<int> & nonbasic);
    static void pivot(Matrix & tableau, std::vector<int> & basic,
        std::vector<int> & nonbasic, int leaving, int entering);
    static std::string resultToString(SimplexResult result);
};

#endif

```

### TableauSimplex.cpp

```

#include "TableauSimplex.h"
#include <cmath>
#include <vector>
#include <climits>
using namespace std;

#define INFINITY 1.0e32f

void TableauSimplex::pivot(Matrix & tableau, std::vector<int> &
    basic, std::vector<int> & nonbasic, int leaving, int
    entering) {
    cout << "Pivoting: " << leaving << " leaves, " << entering <<
        " enters" << endl;
    float xFactor = tableau(leaving, entering);
    int leavingLabel = basic[leaving - 1];
    basic[leaving - 1] = nonbasic[entering - 1];
    nonbasic[entering - 1] = leavingLabel;

    /* cout << "Basic:  ";
    for (unsigned int i = 0; i < basic.size(); ++i)
        cout << " " << basic[i];
    cout << endl << "Nonbasic:";
    for (unsigned int i = 0; i < nonbasic.size(); ++i)
        cout << " " << nonbasic[i];
    cout << endl;*/

    // Cancel out occurrences of the entering variable

```

```

for (int i = 0; i < tableau.getRows(); ++i) {
    if (i == leaving) continue;
    float factor = -tableau(i, entering) / xFactor;
    float savedColVal = tableau(i, entering);
    tableau.addRow(leaving, i, factor);
    tableau(i, entering) = savedColVal / xFactor;
}

tableau.multiplyRow(leaving, -1 / xFactor);
tableau(leaving, entering) = 1 / xFactor;
}

SimplexResult TableauSimplex::solve(Matrix & tableau, vector<
    int> & basic, vector<int> & nonbasic) {
    int n = tableau.getCols() - 1, m = tableau.getRows() - 1;
    Matrix x(n, 1);

    for (int i = 1; i < n; ++i)
        cout << tableau(0, i) << ' ';
    cout << endl;
    // Find entering variable by searching the objective function
        (row 0) for a positive coefficient (disregard the
        constant in column 0)
    int entering = -1;
    for (int j = 1; j <= n; ++j) {
        //if (tableau(0, j) > 0 && (entering == -1 || tableau(0,
            entering) < tableau(0, j)))// || (tableau(0, entering)
            == tableau(0, j) &&*/ nonbasic[j - 1] < nonbasic[
            entering - 1]))
        if (tableau(0, j) > 0 && (entering == -1 || tableau(0, j) >
            tableau(0, entering) || tableau(0, j) == tableau(0,
            entering) && nonbasic[j - 1] < nonbasic[entering - 1]))
            {
                cout << "Choosing " << j << " over " << entering << " to
                    enter; reduced cost is " << tableau(0, j) << endl;
                entering = j;
            }
    }
    if (entering == -1)
        return OPTIMAL;
    cout << "Entering variable: " << nonbasic[entering - 1] << "
        (column " << entering << ")" << endl;

    // Find leaving variable by searching the column of the
        entering variable and determine the strictest bound

```

```

int leaving = -1;
float largestRatio;
for (int i = 1; i <= m; ++i) {
    float ratio;
    if (tableau(i, 0) == 0) {
        if (tableau(i, entering) == 0)
            ratio = 0;
        else if (tableau(i, entering) < 0)
            ratio = INFINITY;
        else
            ratio = -INFINITY;
    }
    else
        ratio = -tableau(i, entering) / tableau(i, 0);
    if (ratio <= 0) continue;
    if (leaving == -1 || ratio > largestRatio || (ratio ==
        largestRatio && basic[i - 1] < basic[leaving - 1])) {
        cout << "Choosing " << i << " over " << leaving << " to
            leave; ratio is " << ratio << endl;
        largestRatio = ratio;
        leaving = i;
    }
}
if (leaving == -1)
    return UNBOUNDED;

cout << "Leaving variable: " << basic[leaving - 1] << " (row
    " << leaving << "); ratio is " << largestRatio << endl;

pivot(tableau, basic, nonbasic, leaving, entering);

return SUBOPTIMAL;
}

```

### main.cpp

```

#include "matrix.h"
#include "TableauSimplex.h"
#include <cmath>
#include <iostream>
#include <vector>
#include <cstdlib>
#include <fstream>
#include <cstring>

```

```

#include "gmpInterop.h"

using namespace std;

int main(int argc, char * argv[]) {
    int rows, cols;
    bool initiallyFeasible = true;
    bool print = argc >= 3 && strcmp(argv[2], "print") == 0;
    ifstream infile(argv[1]);
    infile >> rows >> cols;
    Matrix A(rows, cols + 1);

    for (int r = 0; r < rows; ++r) {
        for (int c = 1; c < cols; ++c) {
            readNumber(infile, A(r, c));
            if (r > 0) A(r, c) = -A(r, c); // Put the if back when
                doing maximisation
        }
        readNumber(infile, A(r, 0));
        cout << A(r, 0) << endl;
        if (r > 0 && A(r, 0) < 0)
            initiallyFeasible = false;
        A(r, cols) = 1;
    }

    vector<int> basic, nonbasic;
    // Nonbasic variables are labeled 1 .. n
    for (int i = 1; i < cols; ++i)
        nonbasic.push_back(i);
    nonbasic.push_back(0); // Phase I variable
    // Basic variables are labeled n+1 .. n+m
    for (int i = cols; i < cols + rows - 1; ++i)
        basic.push_back(i);

    char cc;
    int itcount = 0;

    // Remember that our A is -A in the article!
    Matrix obj(1, cols); // Saves the original objective function
    if (!initiallyFeasible) {
        cout << "Entering Phase I" << endl;
        for (int c = 0; c < cols; ++c) {
            obj(0, c) = A(0, c);
            A(0, c) = 0;
        }
        A(0, cols) = -1; // The goal is to maximize -x0
    }
}

```

```

int leaving = 1;
for (int i = 2; i < rows; ++i) {
    if (A(i, 0) < A(leaving, 0))
        leaving = i;
}
TableauSimplex::pivot(A, basic, nonbasic, leaving, cols);
if (print) A.print(basic, nonbasic);
while (TableauSimplex::solve(A, basic, nonbasic) ==
    SUBOPTIMAL) {
    ++itcount;
    if (print) A.print(basic, nonbasic);
    cout << itcount << ": " << A(0, 0) << endl;
    // cin >> cc;

/*
    for (int r = 0; r < A.getRows(); ++r)
        for (int c = 0; c < A.getCols(); ++c)
            if (abs(A(r, c)) < 0.00001)
                A(r, c) = 0;*/
}
cout << TableauSimplex::solve(A, basic, nonbasic) << ' ' <<
    itcount << endl;
cout << "Phase I completed" << endl;
if (print) A.print(basic, nonbasic);
/*
    for (int r = 0; r < A.getRows(); ++r)
        for (int c = 0; c < A.getCols(); ++c)
            if (abs(A(r, c)) < 0.00001)
                A(r, c) = 0;*/
if (A(0, 0) != 0) {
    cout << "Status: infeasible" << endl;
    return 0;
}
if (print) A.print(basic, nonbasic);
}

// Locate x0 and
int x0 = -1;
for (int i = 0; i < cols; ++i) {
    if (nonbasic[i] == 0) {
        x0 = i + 1;
        nonbasic.erase(nonbasic.begin() + i);
        break;
    }
}
Matrix * newTableau;
if (x0 == -1) {
    for (int j = 0; j < rows - 1; ++j) {
        if (basic[j] == 0) {

```

```

        x0 = j + 1;
        basic.erase(basic.begin() + j);
        break;
    }
}
cout << "x0 is not nonbasic, and has value " << A(x0, 0) <<
    endl;
if (A(x0, 0) != 0)
    return 0;
newTableau = new Matrix(rows - 1, cols + 1);
for (int i = /*1*/0; i < rows - 1; ++i) {
    for (int j = 0; j < cols + 1; ++j) {
        (*newTableau)(i, j) = A(i < x0 ? i : i + 1, j);
    }
}
}
else {
    newTableau = new Matrix(rows, cols);
    for (int i = /*1*/0; i < rows; ++i) {
        for (int j = 0; j < cols; ++j) {
            (*newTableau)(i, j) = A(i, j < x0 ? j : j + 1);
        }
    }
}

if (!initiallyFeasible) {
    if (print) newTableau->print(basic, nonbasic);
    (*newTableau)(0, 0) = obj(0, 0); //TODO:?
    for (int j = 1; j < cols; ++j)
        if (nonbasic[j - 1] < cols)
            (*newTableau)(0, j) = obj(0, nonbasic[j - 1]);
    for (int i = 1; i < rows; ++i) {
        if (basic[i - 1] < cols) {
            //cout << i << ' ' << obj(0, basic[i - 1]) << endl;
            (*newTableau).addRows(i, 0, obj(0, basic[i - 1]));
        }
    }
//    for (int j = 0; j < newTableau.getCols(); ++j)
//        newTableau(0, j) = -newTableau(0, j); //TODO:??
//    //TODO: retain vars from obj
}

if (print) newTableau->print(basic, nonbasic);
cout << "Entering phase II" << endl;
itcount = 0;
SimplexResult result;

```

```

while ((result = TableauSimplex::solve(*newTableau, basic,
    nonbasic)) == SUBOPTIMAL) {
    ++itcount;
    if (print) newTableau->print(basic, nonbasic);
    cout << "iteration " << itcount << ": obj. value is " << (*
        newTableau)(0, 0) << endl;
    //    cin >> cc;
}
cout << "Status: " << TableauSimplex::resultToString(result)
    << endl;
if (result == OPTIMAL) {
    for (int i = 1; i < newTableau->getRows(); ++i) {
        if (basic[i - 1] <= newTableau->getCols() && (*newTableau
            )(i, 0) != 0) {
            cout << "x" << basic[i - 1] << ": ";
            printNumber((*newTableau)(i, 0));
            cout << endl;
        }
    }
    cout << "Objective function value: ";
    printNumberFull((*newTableau)(0, 0));
    cout << endl;
}
return 0;
}

```

## A.2 Parallel standard simplex method for Cell

## A.3 ASYNPLEX, C# prototype

## A.4 ASYNPLEX for x86, based on Vanderbei

(TODO: Describe each file: purpose, and if we have changed it)

## A.5 ASYNPLEX for Cell, based on Vanderbei

(TODO: Describe each file: purpose, and if we have changed it)

## A.6 Utilities

We could not find any available parsers for the MPS or CPLEX file formats, so we had to write our own. Other people may find them useful, so we include them here. Common languages of choice for writing small text manipulation



programs are Python and Perl; we selected the former since we are more familiar with it.

*Important note:* These parsers are *not* fully compliant with the MPS and CPLEX file format specifications. They seem to work with the data sets we have used, but have not been thoroughly tested beyond that.

### **mps.py** — MPS file format parser

This parser was written Vanderbei's

```

from sys import stdin

class Row:
    label = None
    type = None
    values = None
    index = None
    def __init__(self, label, type, index):
        self.label = label
        self.type = type
        self.index = index
        self.values = {}
    def __str__(self):
        return self.label + " (" + self.type + "): " + str(self.
            values)

lines = []
for line in stdin:
    lines.append(line)

rows = {}
columnLabels = []
columnIndices = {}
i = 0
while i < len(lines):
    line = lines[i]
    i += 1
    if line[0] == ' ':
        pass
    else:
        header = line.strip()
        if header == "ROWS":
            rowIndex = 0
            while lines[i][0] == ' ':
                items = lines[i].split()
                row = Row(items[1].strip(), items[0].strip(), rowIndex)
                if row.type == "N":

```

```

        objectiveIndex = rowIndex
        rows[row.label] = row
        rowIndex += 1
        i += 1
        #print row.index, ":", row.label
    tableau = [None] * len(rows)
elif header == "COLUMNS":
        columnIndex = -1
        while lines[i][0] == ' ':
            items = lines[i].split()
            lim = 2 if len(items) == 5 else 1
            columnLabel = items[0].strip()
            if not columnIndices.has_key(columnLabel):
                columnIndex += 1
                columnLabels.append(columnLabel)
                columnIndices[columnLabel] = columnIndex
            for j in xrange(lim):
                rowLabel = items[1 + j * 2].strip()
                value = float(items[2 + j * 2].strip())
                rows[rowLabel].values[columnLabel] = value
                #print rows[rowLabel].index, ",", columnIndices[
                    columnLabel], "=", value
            i += 1
        for j in xrange(len(tableau)):
            tableau[j] = [0] * (len(columnLabels) + 1)
        for row in rows.values():
            #print "row", row.index, ":", len(row.values)
            for colLabel in row.values:
                tableau[row.index][columnIndices[colLabel]] = row.
                    values[colLabel]
elif header == "RHS":
        while lines[i][0] == ' ':
            items = lines[i].split()
            lim = 2 if len(items) == 5 else 1
            for j in xrange(lim):
                rowLabel = items[1 + j * 2].strip()
                value = float(items[2 + j * 2].strip())
                rowIndex = rows[rowLabel].index
                tableau[rowIndex][-1] = value
                #print "RHS of", rowIndex, "=", value
            i += 1

#print sum([len(r.values) for r in rows.values()])
#for row in tableau:
# tmp = row[-1]
# row[-1] = row[0]
# row[0] = tmp

```

```

# print [x for x in row if x != 0]
for row in rows.values():
    tab = tableau[row.index]
    if row.type == "G":
        #print row.index, "is G; multiplying with -1"
        for i in xrange(len(tab)):
            tab[i] = -tab[i]
    elif row.type == "E":
        #print row.index, "is E; creating new row at index ", len(
            tableau)
        tableau.append([-x for x in tab])
#print "objective function is at row", objectiveIndex, ";
    swapping"
tmp = tableau[objectiveIndex]
tableau[objectiveIndex] = tableau[0]
tableau[0] = tmp

ti = 0
while ti < len(tableau):
    nonzero = 0
    for x in tableau[ti]:
        if x != 0:
            nonzero = 1
            break
    if not nonzero:
        tableau.pop(ti)
        ti -= 1
    ti += 1
#print tableau
#for ti in xrange(len(tableau)):
# tab = tableau[ti]
# newTab = []
# for t in tab[:-1]:
#     newTab.append(t)
#     newTab.append(-t)
# newTab.append(tab[-1])
# tableau[ti] = newTab

#tableau[0] = [-x for x in tableau[0]] #for minimisation?

print len(tableau), len(tableau[0])
for tab in tableau:
    for cell in tab:
        print cell,
    print
sys.exit(0)
print "max: ",

```

```

printedAny = 0
for ci in xrange(len(tableau[0]) - 1):
    if tableau[0][ci] != 0:
        if printedAny:
            print " + ",
        printedAny = 1
        print str(tableau[0][ci]) + " x" + str(ci + 1),
print ";"
for tab in tableau[1:]:
    printedAny = 0
    for ai in xrange(len(tab) - 1):
        if tab[ai] != 0:
            if printedAny:
                print " + ",
            printedAny = 1
            print str(tab[ai]) + " x" + str(ai + 1),
    print " <= " + str(tab[-1]) + ";"
for xi in xrange(len(tableau[0]) - 1):
    print "x" + str(xi + 1) + " >= 0;"

```

### **cplex.py** — ILOG CPLEX file format parser

This parser was written in order to convert some sample data sets can output either Note that while the CPLEX format allows constraints to be split over multiple lines, this parser not handle that, so files containing split constraints must be modified by joining such constraints into one line.

```

#!/usr/bin/python
#TODO: "Free" variables may be < 0!
from sys import stdin, stderr, argv

class Equation:
    comparator = ""
    constant = 0
    values = {}
    name = ""

    def __init__(self, comparator, constant, name):
        self.comparator = comparator
        self.constant = constant
        self.values = {}
        self.name = name

class Bound:
    variable = ""

```

```
lower = 0
upper = None
free = False
fixed = False

def __init__(self, variable):#, lower, upper):
    self.variable = variable
# self.lower = lower
# self.upper = upper

def truncate(name):
    if len(name) <= 8:
        return name
    else:
        return "v" + str(hash(name) % 10000000)

def expand(string, length):
    if len(string) > length:
        raise ValueError("string too long")
    return string + " " * (length - len(string))

class LP:
    pos = 0
    lines = []
    variables = {}
    equations = []
    variableList = []
    bounds = []
    direction = "max"

    def __init__(self):
        lines = []
        variables = {}
        equations = []
        variableList = []

    def printMatrix(self):
        eqnCount = 0
        for eq in self.equations:
            if eq.comparator == "=":
                eqnCount += 2
```

```

    else:
        eqnCount += 1
    print eqnCount, len(self.variables) + 1
    for eq in self.equations:
        line = [0] * (len(self.variables) + 1)
        line[-1] = eq.constant
        for value in eq.values:
            line[self.variables[value]] = eq.values[value]
        negated = [-x for x in line]
        if eq.comparator == "<=" or eq.comparator == "=" or eq.
            comparator == "obj":
            for x in line:
                print x,
            print
        if eq.comparator == ">=" or eq.comparator == "=":
            for x in negated:
                print x,
            print
    for i in xrange(len(self.variableList)):
        stderr.write(str(i + 1) + ": " + self.variableList[i] + "
            \n")

#WARNING: Truncates names to 10 characters!
def printMPS(self):
    print "NAME                UNKNOWN"
    #print "OBJSENSE"
    #print " " + self.direction.upper()
    print "ROWS"
    for eq in self.equations:
        if eq.comparator == "=":
            print " E ",
        elif eq.comparator[0] == "<":
            print " L ",
        elif eq.comparator[0] == ">":
            print " G ",
        elif eq.comparator == "obj":
            print " N ",
        else:
            raise NameError("Illegal comparator: " + eq.comparator)
    print expand(truncate(eq.name), 8)
    print "COLUMNS"
    for var in self.variableList:
        for eq in self.equations:
            if eq.values.has_key(var):
                line = expand(" " + truncate(var), 14) + truncate(
                    eq.name)
                print expand(line, 24) + str(eq.values[var])

```

```

print "RHS"
for eq in self.equations:
    if eq.constant != 0:
        print expand("      B          " + truncate(eq.name), 24)
            + str(eq.constant)
print "BOUNDS"
for bound in self.bounds:
    if bound.free:
        print " FR BOUND      " + truncate(bound.variable)
    elif bound.fixed:
        print expand(" FX BOUND      " + truncate(bound.variable
            ), 24) + str(bound.upper)
    else:
        if bound.lower != 0:
            print expand(" LO BOUND      " + truncate(bound.
                variable), 24) + str(bound.lower)
        if bound.upper != None:
            print expand(" UP BOUND      " + truncate(bound.
                variable), 24) + str(bound.upper)
print "ENDATA"

def printForWebSolver(self):
    print "max: ",
    for eq in self.equations:
        printedAny = 0
        for varName in eq.values:
            if printedAny:
                print "+",
                printedAny = 1
            print eq.values[varName], varName,
            if eq.comparator != "obj":
                print eq.comparator, eq.constant,
            print ";"
    for v in self.variableList:
        print v, " >= 0;"

def parseObjective(self):
    tokens = self.lines[self.pos]
    self.pos += 1
    self.parseEquation(tokens, 1)

def parseEquation(self, tokens, isObjective):
    if tokens[1] != '+' and tokens[1] != '-':
        tokens.insert(1, '+')
    if isObjective:
        eq = Equation("obj", 0, "OBJ")
    else:

```

```

    eq = Equation(tokens[-2], float(tokens[-1]), tokens
                  [0][:-1])
self.equations.append(eq)
i = 1
limit = len(tokens) - 1 if isObjective else len(tokens) - 3
while i < limit:
    if tokens[i] == '-':
        sign = -1
    elif tokens[i] == '+':
        sign = 1
    else:
        print "Illegal sign on line", self.pos, ":", tokens
    if isObjective and self.direction == "max":
        sign *= -1
    try:
        value = float(tokens[i + 1])
        i += 2
    except ValueError:
        value = 1
        i += 1
    name = tokens[i]
    self.addVariable(name)
    eq.values[name] = sign * value
    i += 1

def parseEquations(self):
    while 1:
        tokens = self.lines[self.pos]
        if tokens[0][-1] != ':': break
        self.pos += 1
        self.parseEquation(tokens, 0)

def addVariable(self, name):
    if not self.variables.has_key(name):
        self.variables[name] = len(self.variables)
        self.variableList.append(name)

def parseBounds(self):
    while 1:
        tokens = self.lines[self.pos]
        if len(tokens) == 1: break
        self.pos += 1
        if len(tokens) == 2 and tokens[1] == "Free":
            bound = Bound(tokens[0])
            bound.free = True
            self.bounds.append(bound)
        elif len(tokens) == 3:

```



```

        #TODO: can the eq be turned around?
        #eq = Equation(tokens[1], float(tokens[2]))
        #eq.values[tokens[0]] = 1
        #self.equations.append(eq)
        #self.addVariable(tokens[0])
        bound = Bound(tokens[0])
        if tokens[1][0] == "<":
            bound.upper = float(tokens[2])
        elif tokens[1][0] == ">":
            bound.lower = float(tokens[2])
        elif tokens[1][0] == "=":
            bound.fixed = True
            bound.upper = float(tokens[2])
        else:
            raise NameError("Illegal bound type")
        self.bounds.append(bound)
    elif len(tokens) == 5:
        #eq = Equation(">=", float(tokens[0]))
        #eq.values[tokens[2]] = 1
        #self.equations.append(eq)
        #eq = Equation("<=", float(tokens[4]))
        #eq.values[tokens[2]] = 1
        #self.equations.append(eq)
        #self.addVariable(tokens[2])
        bound = Bound(tokens[2])
        bound.lower = float(tokens[0])
        bound.upper = float(tokens[4])
        self.bounds.append(bound)
    else:
        print "Unrecognised bounds line:", self.pos, ":",
            tokens

def parse(self):
    for line in stdin:
        tokens = line.split()
        if len(tokens) == 0 or tokens[0] == '\\\\': continue
        self.lines.append(tokens)
    self.pos = 0
    while self.pos < len(self.lines):
        if self.lines[self.pos][0] == "Maximize":
            self.direction = "max"
            self.pos += 1
            self.parseObjective()
        elif self.lines[self.pos][0] == "Minimize":
            self.direction = "min"
            self.pos += 1

```

```
        self.parseObjective()
    elif self.lines[self.pos][0] == "Subject":
        self.pos += 1
        self.parseEquations()
    elif self.lines[self.pos][0] == "Bounds":
        self.pos += 1
        self.parseBounds()
    else:
        self.pos += 1

lp = LP()
lp.parse()
if len(argv) >= 2 and argv[1] == "web":
    lp.printForWebSolver()
else:
    #lp.printMatrix()
    lp.printMPS()
```

# Appendix B

## Test sets

### B.1 Sample netlib test set

This is the `afiro` set, in MPS format (TODO: citation). It contains (TODO: rows, columns and nonzeros).

NAME	AFIRO
ROWS	
E R09	
E R10	
L X05	
L X21	
E R12	
E R13	
L X17	
L X18	
L X19	
L X20	
E R19	
E R20	
L X27	
L X44	
E R22	
E R23	
L X40	
L X41	
L X42	
L X43	
L X45	
L X46	
L X47	
L X48	
L X49	

L	X50				
L	X51				
N	COST				
COLUMNS					
X01	X48	.301	R09		-1.
X01	R10	-1.06	X05		1.
X02	X21	-1.	R09		1.
X02	COST	-.4			
X03	X46	-1.	R09		1.
X04	X50	1.	R10		1.
X06	X49	.301	R12		-1.
X06	R13	-1.06	X17		1.
X07	X49	.313	R12		-1.
X07	R13	-1.06	X18		1.
X08	X49	.313	R12		-1.
X08	R13	-.96	X19		1.
X09	X49	.326	R12		-1.
X09	R13	-.86	X20		1.
X10	X45	2.364	X17		-1.
X11	X45	2.386	X18		-1.
X12	X45	2.408	X19		-1.
X13	X45	2.429	X20		-1.
X14	X21	1.4	R12		1.
X14	COST	-.32			
X15	X47	-1.	R12		1.
X16	X51	1.	R13		1.
X22	X46	.109	R19		-1.
X22	R20	-.43	X27		1.
X23	X44	-1.	R19		1.
X23	COST	-.6			
X24	X48	-1.	R19		1.
X25	X45	-1.	R19		1.
X26	X50	1.	R20		1.
X28	X47	.109	R22		-.43
X28	R23	1.	X40		1.
X29	X47	.108	R22		-.43
X29	R23	1.	X41		1.
X30	X47	.108	R22		-.39
X30	R23	1.	X42		1.
X31	X47	.107	R22		-.37
X31	R23	1.	X43		1.
X32	X45	2.191	X40		-1.
X33	X45	2.219	X41		-1.
X34	X45	2.249	X42		-1.
X35	X45	2.279	X43		-1.
X36	X44	1.4	R23		-1.
X36	COST	-.48			

	X37	X49	-1.	R23	1.
	X38	X51	1.	R22	1.
	X39	R23	1.	COST	10.
RHS					
	B	X50	310.	X51	300.
	B	X05	80.	X17	80.
	B	X27	500.	R23	44.
	B	X40	500.		
ENDATA					

## B.2 Test sets provided by Miriam AS

These sets are in the ILOG CPLEX format.

### dp-0.lp

```

\Problem name: CPLEX solver

Maximize
  obj: v89_49 + zMax557 + zMax558 + id105
Subject To
  CapE50:      v50_49 - RgCapE50 = 0
  OutBal50_49: v50_49 - x536_49 = 0
  CapE51:      v51_49 - RgCapE51 = 0
  OutBal51_49: v51_49 - x538_49 = 0
  CapE52:      v52_49 - RgCapE52 = 0
  OutBal52_49: v52_49 - x540_49 - x542_49 = 0
  CapS59:      v59_49 - RgCapS59 = 0
  InBal59_49:  x536_49 - v59_49 = 0
  OutBal59_49: v59_49 - x548_49 - x550_49 = 0
  CapS60:      v60_49 - RgCapS60 = 0
  InBal60_49:  x550_49 - v60_49 + x544_49 = 0
  OutBal60_49: v60_49 - x552_49 = 0
  CapS61:      v61_49 - RgCapS61 = 0
  InBal61_49:  x538_49 + x540_49 - v61_49 = 0
  OutBal61_49: v61_49 - x554_49 = 0
  CapS62:      v62_49 - RgCapS62 = 0
  InBal62_49:  x542_49 - v62_49 = 0
  OutBal62_49: v62_49 - x556_49 = 0
  CapI89:      v89_49 - RgCapI89 = 0
  InBal89_49:  x548_49 - x544_49 + x554_49 + x556_49 - v89_49 -
    x546_49 = 0
  NetFlowP89:  - v89_49 + vAbs89 >= 0
  NetFlowN89:  v89_49 + vAbs89 >= 0
  CapD53:      v53_49 - RgCapD53 = 0

```

```

Dem53_49:    d53_49 <= 150
Dem53:       d53_49 <= 150
InBal53_49:  x552_49 - v53_49 = 0
OutBal53_49: - v53_49 + d53_49 = 0
CapD54:      v54_49 - RgCapD54 = 0
Dem54_49:    d54_49 <= 150
Dem54:       d54_49 <= 150
InBal54_49:  x546_49 - v54_49 = 0
OutBal54_49: - v54_49 + d54_49 = 0
Max557:      - d53_49 - d54_49 + zMax557 = 0
Comp557:     Comp557 = 0
SMax558:     - v89_49 + zMax558 = 0
Bounds
0 <= v50_49 <= 200
0 <= v51_49 <= 200
0 <= v52_49 <= 200
0 <= v53_49 <= 200
0 <= v54_49 <= 200
    zMax557 >= 299.999
    Comp557 Free
    zMax558 >= -0.001
    id105 = 0
0 <= RgCapE50 <= 200
0 <= RgCapE51 <= 200
0 <= RgCapE52 <= 200
0 <= RgCapS59 <= 120
0 <= RgCapS60 <= 200
0 <= RgCapS61 <= 120
0 <= RgCapS62 <= 120
0 <= RgCapI89 <= 900000000
0 <= RgCapD53 <= 200
0 <= RgCapD54 <= 200
End

```

**dp\_150.lp**

```

\Problem name: CPLEX solver

Maximize
  obj: v89_49 + zMax557 + zMax558 + id105
Subject To
  CapE50:    v50_49 - RgCapE50 = 0
  OutBal50_49: v50_49 - x536_49 = 0
  CapE51:    v51_49 - RgCapE51 = 0
  OutBal51_49: v51_49 - x538_49 = 0
  CapE52:    v52_49 - RgCapE52 = 0

```

```

OutBal52_49: v52_49 - x540_49 - x542_49 = 0
CapS59:      v59_49 - RgCapS59 = 0
InBal59_49:  x536_49 - v59_49 = 0
OutBal59_49: v59_49 - x548_49 - x550_49 = 0
CapS60:      v60_49 = 0
InBal60_49:  x550_49 - v60_49 + x544_49 = 0
OutBal60_49: v60_49 - x552_49 = 0
CapS61:      v61_49 = 0
InBal61_49:  x538_49 + x540_49 - v61_49 = 0
OutBal61_49: v61_49 - x554_49 = 0
CapS62:      v62_49 = 0
InBal62_49:  x542_49 - v62_49 = 0
OutBal62_49: v62_49 - x556_49 = 0
CapI89:      v89_49 - RgCapI89 = 0
InBal89_49:  x548_49 - x544_49 + x554_49 + x556_49 - v89_49 -
    x546_49 = 0
NetFlowP89:  - v89_49 + vAbs89 >= 0
NetFlowN89:  v89_49 + vAbs89 >= 0
CapD53:      v53_49 - RgCapD53 = 0
Dem53_49:    d53_49 <= 150
Dem53:       d53_49 <= 150
InBal53_49:  x552_49 - v53_49 = 0
OutBal53_49: - v53_49 + d53_49 = 0
CapD54:      v54_49 - RgCapD54 = 0
Dem54_49:    d54_49 <= 150
Dem54:       d54_49 <= 150
InBal54_49:  x546_49 - v54_49 = 0
OutBal54_49: - v54_49 + d54_49 = 0
Max557:      - d53_49 - d54_49 + zMax557 = 0
Comp557:     Comp557 = 0
SMax558:     - v89_49 + zMax558 = 0
Bounds
0 <= v50_49 <= 100
0 <= v51_49 <= 100
0 <= v52_49 <= 100
0 <= v53_49 <= 200
0 <= v54_49 <= 200
    zMax557 >= 0.999
    Comp557 Free
    zMax558 >= -0.001
    id105 = 0
0 <= RgCapE50 <= 200
0 <= RgCapE51 <= 200
0 <= RgCapE52 <= 200
0 <= RgCapS59 <= 1
0 <= RgCapI89 <= 900000000
0 <= RgCapD53 <= 200

```

```
0 <= RgCapD54 <= 200  
End
```



## Schedule

This appendix will obviously be deleted before submission.

**Week 20** Study Vanderbei code and obtain a good understanding of how what tricks are required to make revised simplex work in practice; write rough outline of background chapter on revised simplex

**Either:** If the C++ code is too cumbersome to work with:

**Week 21** Implement revised simplex (sequentially) in C#, based on Vanderbei

**Week 22** Implement ASYNPLEX in C#, based on the above code

**Or:** If the C++ code is okay to work with:

**Week 21** Rewrite Vanderbei's code to become more readable and structured in a way that is more suitable for ASYNPLEX

**Week 22** Implement ASYNPLEX in C++, based on the above code

**Week 23** Rewrite ASYNPLEX implementation from thread-based C++ or C# code to Cell

**Week 24** Run experiments on timing, precision and communication/computation ratio

**Week 25** Frenetic report writing

**Week 26** — “ —

**Week 27** — “ —; Natvig goes on vacation; I'll try to submit by Friday, July 3

**Week 28** Scouting camp (can be dropped if absolutely necessary)

**Week 29** Final deadline: Sunday, July 19