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Master Thesis

# **Linear programming on Cell/BE**

by

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**Abstract**

(TODO:)



# Acknowledgements

(TODO:)



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# List of Symbols and Abbreviations

Abbreviation	Description	Definition
Cell BE	Cell Broadband Engine	page 16
ILP	Integer linear programming	page 4
ILP	Instruction-level parallelism	page 16
LP	Linear programming	page 3
LS	Local Store	page 17
MFC	Memory Flow Controller	page 17
PPE	PowerPC Processor Element	page 16
PPU	PowerPC Processor Unit	page 16
SPE	Synergistic Processor Element	page 16
SPU	Synergistic Processor Unit	page 16

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# Chapter 1

## Introduction

(TODO: )

**Task description** (Natvig: 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)



# Background

(TODO: Chapter introduction)

## 2.1 Linear programming

(ITP: Section introductions)

This section is primarily based on [12], [2](TODO: and [7] if we write about artificial variables).

### 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 [2]). 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. (Natvig: This example just uses some random numbers; I will construct an example, probably using only integers, that can be solved neatly in a few iterations.) 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)
- $2x_1 + x_2 \leq 50$  (same 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

<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 [4].



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 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 an 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. (TODO: Why are not less-than allowed?) 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:  $a_{i1}x_1 + \dots + a_{in}x_n \leq b_i$  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

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

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 (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 of the constraints

**Infeasible** if it violates any constraint

**Basic** if it consists of setting all variables except the slack variables to zero

**Optimal** if it is feasible and no other feasible solutions yield a higher value for the objective function

(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>3</sup>, developed by George Dantzig[3], 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, but are implicitly maintained by the method. Because the equations will undergo extensive rewriting, it will be convenient to not 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  $\bar{c}_j$ ; the first actual tableau column (to the right of the double line) contains the  $\bar{b}_i$  constants, and 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  $\bar{a}_{ij} = a_{ij}$ . With  $n = 3$  and  $m = 3$ , the initial tableau will look like this:

		$x_1$	$x_2$	$x_3$
$\zeta$	$\bar{\zeta}$	$\bar{c}_1$	$\bar{c}_2$	$\bar{c}_3$
$x_4$	$\bar{b}_1$	$-\bar{a}_{11}$	$-\bar{a}_{12}$	$-\bar{a}_{13}$
$x_5$	$\bar{b}_2$	$-\bar{a}_{21}$	$-\bar{a}_{22}$	$-\bar{a}_{23}$
$x_6$	$\bar{b}_3$	$-\bar{a}_{31}$	$-\bar{a}_{32}$	$-\bar{a}_{33}$

Note that this is essentially just a tabular version of the standard form — for instance, the last row is interpreted as the equation  $x_6 = \bar{b}_3 - \bar{a}_{31}x_1 - \bar{a}_{32}x_2 - \bar{a}_{33}x_3$ .

<sup>3</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.

— 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  $|\mathcal{B}| = m$  and  $|\mathcal{N}| = n$ .

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 nonnegative); 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). 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.

**(TODO: relabel  $w_i$ )** It seems reasonable to select the variable with the greatest coefficient, say,  $x_e$ . 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  $x_e$  until one of the basic variables becomes zero. Let us look at row  $i$ , which is now reduced to  $w_i = b_i - a_{ie}x_e$  since all nonbasic variables except  $x_e$  are zero. If  $a_{ie}$  is positive, the value of  $w_i$  will decrease as  $x_e$  increases, so the largest allowable increase is limited by  $b_i$ . Thus, by setting  $x_e = \frac{b_i}{a_{ie}}$ ,  $w_i$  becomes zero. However, other equations may impose stricter conditions. By looking at all rows where  $a_{ie}$  is positive, we can determine an  $l$  such that  $\frac{b_l}{a_{le}}$  is minimal and set  $x_e = \frac{b_l}{a_{le}}$ . This will cause  $x_l$  to become zero. If all  $a_{ie}$  are nonnegative, we can increase  $x_e$  indefinitely without any  $w_i$  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  $x_1 = \frac{b_1}{a_{11}} = \frac{40}{1}$ , and  $x_4$  becomes zero if  $x_1 = \frac{b_2}{a_{12}} = \frac{50}{2}$ . 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 no  $b_i$  is negative, so that we can repeat the previous steps all over again. The nonbasic variable that was selected to be increased,  $x_e$ , is called the *entering variable*, since it is about to enter the collection of basic variables.  $x_l$ , which becomes zero when  $x_e$  is increased appropriately, is called the *leaving variable*, since it is to be removed from said collection. Keep in mind that since  $x_l$  is a basic variable, it only occurs in one equation, namely

$$x_l = b_l - \sum_{j \in \mathcal{N}} a_{lj} x_j. \quad (2.7)$$

We can eliminate the entering variable from (and introduce the leaving variable into) the set of *nonbasic* variables (the “main” part of the tableau) by rewriting Equation 2.7:

$$x_e = \frac{1}{a_{le}} \left( b_l - x_l - \sum_{j \in \mathcal{N} - \{e\}} a_{lj} x_j \right). \quad (2.8)$$

Now that we have an expression for  $x_e$ , we can substitute it into all of the other equations — this will eliminate  $x_e$  and introduce  $x_l$  into the rest of the tableau.

For all  $i \in \mathcal{B} - \{l\}$ , we have:

$$x_i = b_i - \sum_{j \in \mathcal{N}} a_{ij} x_j \quad (2.9)$$

$$= b_i - a_{ie} x_e - \sum_{j \in \mathcal{N} - \{e\}} a_{ij} x_j \quad (2.10)$$

$$= b_i - \frac{a_{ie}}{a_{le}} \left( b_l - x_l - \sum_{j \in \mathcal{N} - \{e\}} a_{lj} x_j \right) - \sum_{j \in \mathcal{N} - \{e\}} a_{ij} x_j \quad (2.11)$$

$$= \left( b_i - \frac{a_{ie} b_l}{a_{le}} \right) - \frac{a_{ie}}{a_{le}} x_l - \sum_{j \in \mathcal{N} - \{e\}} \left( a_{ij} - \frac{a_{ie} a_{lj}}{a_{le}} \right) x_j. \quad (2.12)$$

Although this might look complicated, it amounts to subtracting  $\frac{a_{ie}}{a_{le}}$  times the tableau row for  $x_l$  from all other tableau rows (including the objective function row), and then (TODO: )

Equation 2.8 is the new form of the tableau row that originally corresponded to the basic variable  $x_l$ . The new row, which corresponds to  $x_e$ , can be easily obtained from the old one by dividing the row by  $a_{le}$  and setting the coefficient of what is now  $x_l$  to  $\frac{1}{a_{le}}$ .

Finally, we remove  $l$  from  $\mathcal{B}$  and add it to  $\mathcal{N}$ , and remove  $e$  from  $\mathcal{N}$  and add it to  $\mathcal{B}$ .

and adding appropriate multiples of it to each of the other equations: (TODO: Complete this) This step is called a *pivot*. After pivoting, we again have a tableau in which 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: )

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

— 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  $\zeta = 30x_1 + 20x_2 = 30 \cdot 10 + 20 \cdot 30 = 900$ .

**Degeneracy and cycling** (TODO: Briefly discuss degenerate pivots.) A tableau is *degenerate* if (TODO: ). Degeneracy may cause trouble because a pivot on a degenerate row will not cause the objective function value to change. With severely bad luck, the algorithm may end up cycling through a number of degenerate states. This, however, rarely happens — according to [12], (TODO: )

### Initialisation

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. (TODO: Phase I and Phase II) This may not always be the case. We get around this by introducing an *auxiliary problem* which is based on the initial problem and is guaranteed to have a basic feasible solution, and whose solution will provide us with a starting point for solving the original problem. (TODO: Complete this)

**Formal algorithm statement**

(TODO: Use the `algorithm` package to give a compact description of the simplex method) (TODO: Should ideally be recognisable in the real code; maybe reference the real code here (or the other way around?))

**Complexity and numerical instability**

(TODO: )

(ITP: Other stuff that should perhaps be added: geometric interpretation; duality)

(TODO: Warm start)

**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 [12] and [5]. 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).

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 2.1.6).

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

$$\zeta = \sum_{j=1}^n c_j x_j \quad (2.13)$$

with respect to

$$x_{n+i} = b_i - \sum_{j=1}^n a_{ij} x_j, \quad \text{for } i = 1, \dots, m. \quad (2.14)$$

$$x_1, \dots, x_{n+m} \geq 0 \quad (2.15)$$

If we let



$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} & 1 & & \\ a_{11} & a_{12} & \cdots & a_{1n} & & 1 & \\ \vdots & \vdots & \ddots & \vdots & & & \ddots \\ a_{m1} & a_{m2} & \cdots & a_{mn} & & & 1 \end{bmatrix} \quad (2.16)$$

$$\mathbf{b} = [ b_1 \quad \cdots \quad b_m ]^T \quad (2.17)$$

$$\mathbf{c} = [ c_1 \quad \cdots \quad c_n \quad 0 \quad \cdots \quad 0 ]^T \quad (m \text{ zeroes at the end}) \quad (2.18)$$

$$\mathbf{x} = [ x_1 \quad \cdots \quad x_n \quad x_{n+1} \quad \cdots \quad x_{n+m} ]^T \quad (2.19)$$

we can express the problem quite succinctly as:

Maximise

$$\zeta = \mathbf{c}\mathbf{x} \quad (2.20)$$

with respect to

$$\mathbf{A}\mathbf{x} = \mathbf{b} \quad (2.21)$$

$$\mathbf{x} \geq 0 \quad (2.22)$$

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,  $\mathbf{c}_{\mathcal{N}} = [ c_1 \quad \cdots \quad c_n ]^T$ ) 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

$$\zeta = \mathbf{c}_{\mathcal{N}}^T \mathbf{x}_{\mathcal{N}} + \mathbf{c}_{\mathcal{B}}^T \mathbf{x}_{\mathcal{B}} \quad (2.23)$$

with respect to

$$\mathbf{N}\mathbf{x}_{\mathcal{N}} + \mathbf{B}\mathbf{x}_{\mathcal{B}} = \mathbf{b} \quad (2.24)$$

$$\mathbf{x} \geq 0 \quad (2.25)$$

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 (2.24) by  $\mathbf{B}^{-1}$  and rearrange it to get

$$\mathbf{x}_{\mathcal{B}} = \mathbf{B}^{-1}\mathbf{b} - \mathbf{B}^{-1}\mathbf{N}\mathbf{x}_{\mathcal{N}}. \quad (2.26)$$

Combining this with (2.23), we get

$$\zeta = \mathbf{c}_{\mathcal{N}}^T \mathbf{x}_{\mathcal{N}} + \mathbf{c}_{\mathcal{B}}^T \mathbf{x}_{\mathcal{B}} \quad (2.27)$$

$$= \mathbf{c}_{\mathcal{N}}^T \mathbf{x}_{\mathcal{N}} + \mathbf{c}_{\mathcal{B}}^T (\mathbf{B}^{-1}\mathbf{b} - \mathbf{B}^{-1}\mathbf{N}\mathbf{x}_{\mathcal{N}}) \quad (2.28)$$

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

This is very interesting, because it provides explicit formulas for the simplex tableau at any time given the current basic/nonbasic variable configuration. From (2.26) (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 (2.29) that  $\mathbf{c}_{\mathcal{B}}^T \mathbf{B}^{-1}\mathbf{b}$  corresponds to the current value of the objective function (obtained by setting  $\mathbf{x}_{\mathcal{N}} = 0$ ), and the current objective function coefficients from the tableau (known as  $[\bar{c}_j]$ ) are  $\mathbf{c}_{\mathcal{N}}^T - \mathbf{c}_{\mathcal{B}}^T \mathbf{B}^{-1}\mathbf{N}$ . Armed with this knowledge, we can formulate the revised simplex method:

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 [12].

## 2.1.4 Interior point algorithms

## 2.1.5 Use of LP to solve advanced flow problems

A *flow network* is a graph where a *flow* of some substance (expressed in e.g. (TODO: spell “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* node to a designated *sink* (destination) 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 flow problem, such as the Edmonds-Karp algorithm[2]. In more complex situations, no specialised algorithms exist, but LP comes to the rescue. Cormen et al.[2] give a good overview of how to express a flow problem as an LP problem, which we (TODO: spell “summarise”) here:

- There is one variable for each edge, expressing the amount of flow through that edge. (TODO: Cormen has two?)
- (TODO: Finish)

(TODO: Consult Miriam on this)

### 2.1.6 Existing LP solvers

#### ILOG CPLEX

CPLEX, developed by the company ILOG, is the industry standard LP solver (Natvig: 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 — sites such as (TODO: citation) provide CPLEX’ answers to the `netlib` problem sets, and Miriam has a licence 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.

## OOPS

### retroLP

As opposed to virtually all other LP solvers, retroLP[13] 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.”[14] 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.

## 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 goal 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[8]. Several obstacles to such goals exist; in particular the infamous *brick walls*[1]:

**Memory wall** (TODO: )

**Power wall** (TODO: )

**ILP wall** *Instruction-level parallelism* (ILP) techniques such as pipelines and (TODO: )

### 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

## 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.

## 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

[15]

**CellSS**

[9]

# Chapter 3

## Design

(TODO: Chapter introduction)

### 3.1 Overall approach

(TODO: Gradual, step by step approach)

### 3.2 Initial experiments

#### 3.2.1 Arithmetic performance

(Natvig: 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: 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 Dense simplex

In order to become familiar with programming the Cell BE, we initially implemented a few versions of the simplex method for dense problems. (Natvig’s comment: This can be justified when we have a task description and “angrepsmåte”)

#### 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++?)

(Natvig’s comment: Avoid the “not invented here” syndrome. Look into reusing existing code/libraries) We wrote a class called `Matrix`, which represents a dense matrix and supports standard matrix operations. The initial version was nonvectorised (SISD) and used just standard C++. Rewriting this to utilise the vector operations involved only a few fairly trivial steps:

- Use `malloc_align` instead of `new` to get memory blocks that are aligned on proper boundaries (TODO: Not sure if this was even necessary)
- Pad the rows with zeroes such that the number of elements in each row is a multiple of four, so that the vector operations will not “fall of the end” of each row
- Rewrite the loops in the matrix operation functions (such as `addRows` and `multiplyRow` to use vector operations. (Natvig’s comment: Preferably pseudocode here) `data` is a pointer to the array that contains the entire matrix. `physicalCols` is the number of columns rounded up to the nearest multiple of `VECTOR_WIDTH`, which is set to 4.

```
void Matrix::addRows(int sourceRow, int destinationRow,
    float factor) {
```



```

vector float factor_v = (vector float){factor, factor,
    factor, factor};
vector float * source_v = (vector float *) (data +
    sourceRow * physicalCols);
vector float * destination_v = (vector float *) (data +
    destinationRow * physicalCols);
for (int j = 0; j < physicalCols / VECTOR_WIDTH; ++j) {
    destination_v[j] = vec_madd(source_v[j], factor_v,
        destination_v[j]);
}
}

```

(TODO: Do loop unrolling as well?)

### 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 requested 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.

<sup>1</sup>After having written the application, we found that [13] essentially uses the same approach, albeit for cluster computers with MPI. (Natvig: 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?)

**3.4 Sparse simplex**

**3.5 Dense interior point**

**3.6 Sparse interior point**

# 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 these lines:

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

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 [2] and [12]), 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 [2] and [12] 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*). Also, [10] 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[11], 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`[14]. However, the code base was quite large, and

We eventually resigned and contacted a group of mathematicians with which Lasse is acquainted, asking them for help on how to make the standard simplex method work stably[6].

**Numerical stability**

## 4.2 Simplex algorithm

### 4.3 Test plan

#### 4.3.1 Unit testing

(**TODO:** )

#### 4.3.2 Large data sets

(**TODO:** Something on the `netlib` LP problem set)

#### 4.3.3 (**TODO: Other implementations**)

# Chapter 5

## Evaluation

(TODO: Chapter introduction)

### 5.1 Performance measurements

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

5.1.1 (TODO: What to measure)

5.1.2 (TODO: How to measure)

### 5.2 Results

5.2.1 Dense simplex

5.2.2 Sparse simplex

5.2.3 Dense interior point

5.2.4 Sparse interior point

### 5.3 Discussion



# Chapter 6

## Conclusion

(TODO:)

### 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 Simplex algorithm, first version

**matrix.h**

```
#ifndef MATRIX_H
#define MATRIX_H

#include <iostream>
#include <vector>

class Matrix;

class Matrix {
    friend class RowIndexDescriptor;
    friend std::ostream & operator << (std::ostream &, const
        Matrix &);
public:
    Matrix(int, int);
    Matrix(int rows, int cols, float * data);
    Matrix(int, int, bool);
    Matrix(const Matrix &);
    const Matrix & operator = (const Matrix &);
    ~Matrix();
    int getRows() const { return rows; }
    int getCols() const { return cols; }
    float operator () (int r, int c) const;
    float & operator () (int r, int c);
    Matrix operator + (const Matrix &) const;
    Matrix operator - (const Matrix &) const;
    Matrix operator * (const Matrix &) const;
    Matrix operator * (float) const;
    Matrix transpose() const;
```

```

Matrix invert() const;
void multiplyRow(int row, float factor);
void addRows(int sourceRow, int destinationRow, float factor)
;
void swapRows(int firstRow, int secondRow);
void print(const std::vector<int> & basic, const std::vector<
    int> & nonbasic);
private:
    int rows;
    int cols;
    float * data;
};

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

#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 float[rows * cols];
    for (int i = 0; i < rows * cols; ++i)
        this->data[i] = 0;
}

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

float 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];
}

float & 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) {
            float sum = 0;
            for (int k = 0; k < cols; ++k) {
                sum += (*this)(i, k) * other(k, j);
            }
            if (fabs(sum) < 0.00001f)
                sum = 0.0f;
            result(i, j) = sum;
        }
    }
    return result;
}

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

void Matrix::addRows(int sourceRow, int destinationRow, float
    factor) {
    if (factor == 0) return;
    for (int j = 0; j < cols; ++j) {
        (*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) {
        float 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);
        float factor = 1 / self(rc, rc);
        self.multiplyRow(rc, factor);
        inverse.multiplyRow(rc, factor);
        for (int r = 0; r < rows; ++r) {
            if (r == rc) continue;
            float 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 <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);
};

#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>

using namespace std;

// ASSUMES THAT INITIAL DICT IS NOT FEASIBLE
int main(int argc, char * argv[]) {
    // float aData[] = //{0, 5, 4, 3, 5, -2, -3, -1, 11, -4, -1,
    //                 -2, 8, -3, -4, -2};
    //                 {0, 4, 3, 1, -1, 1, 3, -2, 1, 5, 0, -1};
    // Matrix A(4, 3, aData);

    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) {
            infile >> A(r, c);
            if (r > 0) A(r, c) = -A(r, c); // Put the if back when
                doing maximisation
        }
        infile >> A(r, 0);
        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 (fabs(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 (fabs(A(r, c)) < 0.00001)
                A(r, c) = 0;*/
    if (A(0, 0) != 0) {
        cout << "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;
    }
}
if (x0 == -1) {
    cout << "x0 is not nonbasic!" << endl;
    return 0;
}

Matrix newTableau(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.addRow(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;
cin >> cc;
itcount = 0;

```



```

while (TableauSimplex::solve(newTableau, basic, nonbasic) ==
        SUBOPTIMAL) {
    ++itcount;
    if (print) newTableau.print(basic, nonbasic);
    cout << itcount << ": " << newTableau(0, 0) << endl;
    //    cin >> cc;
}
cout << TableauSimplex::solve(newTableau, basic, nonbasic) <<
    ' ' << itcount << endl;
cout << "Optimal value: " << newTableau(0, 0) << endl;

system("pause");
return 0;
}

```

## A.2 Utilities

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

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

```

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**

```

#!/usr/bin/python
from sys import stdin, stderr

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

    def __init__(self, comparator, constant):

```

```
        self.comparator = comparator
        self.constant = constant
        self.values = {}

class LP:
    pos = 0
    lines = []
    variables = {}
    equations = []
    variableList = []

    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")

    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 len(tokens) % 2 != 1:
        print "Illegal line length on line", self.pos, ":",
            tokens
    if isObjective:
        eq = Equation("obj", 0)
    else:
        eq = Equation(tokens[-2], float(tokens[-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
            name = tokens[i + 1]
            self.addVariable(name)
            eq.values[name] = sign
            i += 2

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":
            pass
        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])
    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])
    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.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()
lp.printMatrix()

```





# 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