

# **Solving Linear and Integer Programs**

Robert E. Bixby  
ILOG, Inc. and Rice University

Ed Rothberg  
ILOG, Inc.

## **DAY 2**

# Dual Simplex Algorithm

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## Some Motivation

- ❑ Dual simplex vs. primal (2002): **Dual > 2x faster**
- ❑ CPLEX 9.0 – 2003
  - ❑ Primal **1.2x** improvement
  - ❑ Dual **1.7x** improvement
- ❑ Best algorithm of MIP
- ❑ There isn't much in books about implementing the dual.

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## Dual Simplex Algorithm

(Lemke, 1954: Commercial codes ~1990)

**Input:** A dual feasible basis  $B$  and vectors

$$X_B = A_B^{-1}b \quad \text{and} \quad D_N = c_N - A_N^T B^{-T} c_B.$$

□ **Step 1:** (Pricing) If  $X_B \geq 0$ , stop,  $B$  is optimal; else let

$$i = \operatorname{argmin}\{X_{Bk} : k \in \{1, \dots, m\}\}.$$

□ **Step 2:** (BTRAN) Solve  $B^T z = e_i$ . Compute  $\alpha_N = -A_N^T z$ .

□ **Step 3:** (Ratio test) If  $\alpha_N \leq 0$ , stop, (D) is unbounded; else, let

$$j = \operatorname{argmin}\{D_k / \alpha_k : \alpha_k > 0\}.$$

□ **Step 4:** (FTRAN) Solve  $A_B y = A_j$ .

□ **Step 5:** (Update) Set  $B_i = j$ . Update  $X_B$  (using  $y$ ) and  $D_N$  (using  $\alpha_N$ )

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# Implementing the Dual Simplex Algorithm

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## Implementation Issues for Dual Simplex

1. **Finding an initial feasible basis, or the concluding that there is none**
2. **Pricing:** Dual steepest edge
3. **Solving the linear systems**
  - LU factorization and factorization update
  - BTRAN and FTRAN – exploiting sparsity
4. **Numerically stable ratio test:** Bound shifting and perturbation
5. **Bound flipping:** Exploiting “boxed” variables to combine many iterations into one.

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## Issue 0 Preparation: **Bounds on Variables**

In practice, simplex algorithms need to accept LPs in the following form:

$$\begin{aligned} & \text{Minimize} && c^T x \\ & \text{Subject to} && Ax = b \quad (\text{P}_{\text{BD}}) \\ & && l \leq x \leq u \end{aligned}$$

where  $l$  is an  $n$ -vector of **lower bounds** and  $u$  an  $n$ -vector of **upper bounds**.  $l$  is allowed to have  $-\infty$  entries and  $u$  is allowed to have  $+\infty$  entries. (Note that  $(\text{P}_{\text{BD}})$  is in standard form if  $l_j = 0$ ,  $u_j = +\infty \forall j$ .)

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### (Issue 0 – Bounds on variables) Basic Solution

A **basis** for  $(\text{P}_{\text{BD}})$  is a triple  $(B, L, U)$  where  $B$  is an ordered  $m$ -element subset of  $\{1, \dots, n\}$  (just as before),  $(B, L, U)$  is a partition of  $\{1, \dots, n\}$ ,  $l_j > -\infty \forall j \in L$ , and  $u_j < +\infty \forall j \in U$ .  $N = L \cup U$  is the set of **nonbasic** variables. The associated **(primal) basic solution**  $X$  is given by  $X_L = l_L$ ,  $X_U = u_U$  and

$$X_B = A_B^{-1}(b - A_L l_L - A_U u_U).$$

This solution is **feasible** if

$$l_B \leq X_B \leq u_B.$$

The associated **dual basic solution** is defined exactly as before:

$D_B = 0$ ,  $\Pi^T A_B = c_B^T$ ,  $D_N = c_N - A_N^T \Pi$ . It is **dual feasible** if

$$D_L \geq 0 \text{ and } D_U \leq 0.$$

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**(Issue 0 – Bounds on variables)  
The Full Story**

- ❑ **Modify simplex algorithm**
  - ❑ Only the “Pricing” and “Ratio Test” steps much be changed substantially.
  - ❑ The complicated part is the ratio test
- ❑ **Reference:** See Chvátal for the primal

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**Issue 1  
The Initial Feasible Basis – Phase I**

- ❑ **Two parts to the solution**
  1. Finding some initial basis (probably not feasible)
  2. Modified simplex algorithm to find a feasible basis

Reference for Primal: **R.E. Bixby (1992), “Implementing the simplex method: the initial basis”, *ORSA Journal on Computing* 4, 267—284.**

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**(Issue 1 – Initial feasible basis)**  
**Initial Basis**

- Primal and dual bases are the same. We begin in the context of the primal. Consider

$$\begin{array}{ll} \text{Minimize} & c^T x \\ \text{Subject to} & Ax = b \\ & l \leq x \leq u \end{array} \quad (\text{P}_{\text{BD}})$$

- **Assumption:** Every variable has some finite bound.
- **Trick:** Add **artificial variables**  $x_{n+1}, \dots, x_{n+m}$ :

$$Ax + I \begin{pmatrix} x_{n+1} \\ \vdots \\ x_{n+m} \end{pmatrix} = b$$

where  $l_j = u_j = 0$  for  $j = n+1, \dots, n+m$ .

- **Initial basis:**  $B = (n+1, \dots, n+m)$  and for each  $j \notin B$ , pick some finite bound and place  $j$  in  $L$  or  $U$ , as appropriate.

**(Issue 1 – Initial feasible basis)**  
**Solving the Phase I**

- If the initial basis is not dual feasible, we consider the problem:

$$\begin{array}{ll} \text{Maximize} & \sum (d_j : d_j < 0) \\ \text{Subject to} & A^T \pi + \underline{d} = c \end{array}$$

- This problem is “locally linear”: Define  $\kappa \in \mathbb{R}^n$  by  $\kappa_j = 1$  if  $D_j < 0$ , and 0 otherwise. Let

$$K = \{j : D_j < 0\} \text{ and } \underline{K} = \{j : D_j \geq 0\}$$

Then our problem becomes

$$\begin{array}{ll} \text{Maximize} & \kappa^T d \\ \text{Subject to} & A^T \pi + d = c \\ & d_K \leq 0, d_{\underline{K}} \geq 0 \end{array}$$

- Apply dual simplex, and whenever  $d_j$  for  $j \in K$  becomes 0, move it to  $\underline{K}$ .

## Issue 2 Pricing

- ❑ The textbook rule: Choose the largest primal violation is **TERRIBLE**: For a problem in standard form

$$j = \operatorname{argmin}\{X_{B_i} : i = 1, \dots, m\}$$

- ❑ **Geometry is wrong**: Maximizes rate of change relative to axis; better to do relative to edge.
- ❑ Goldfarb and Forrest 1992 suggested the following **steepest-edge** alternative

$$j = \operatorname{argmin}\{X_{B_i}/\eta_i : i = 1, \dots, m\}$$

where  $\eta_i = \|\mathbf{e}_i^T \mathbf{A}_B^{-1}\|_2$ , and gave an efficient update.

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## Example: Pricing

Model: dfl001

### Pricing: Greatest infeasibility

Dual simplex - Optimal: Objective = 1.1266396047e+07  
Solution time = 1339.86 sec. Iterations = 771647 (0)

### Pricing: Goldfarb-Forrest steepest-edge

Dual simplex - Optimal: Objective = 1.1266396047e+07  
Solution time = 24.48 sec. Iterations = 18898 (0)

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### Issue 3 Solving FTRAN, BTRAN

- ❑ **Computing LU factorization:** See Suhl & Suhl (1990). “Computing sparse LU factorization for large-scale linear programming basis”, ORSA Journal on Computing 2, 325-335.
- ❑ **Updating the Factorization:** Forrest-Tomlin update is the method of choice. See Chvátal Chapter 24.
- ❑ **Exploiting sparsity:** This is the main recent development.

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### (Issue 3 – Solving FTRAN & BTRAN)

We must solve two linear systems per iteration:

$$\begin{array}{cc} \text{FTRAN} & \text{BTRAN} \\ A_B y = A_j & A_B^T z = e_i \end{array}$$

where

$$\begin{array}{ll} A_B = \text{basis matrix} & (\text{very sparse}) \\ A_j = \text{entering column} & (\text{very sparse}) \\ e_i = \text{unit vector} & (\text{very sparse}) \end{array}$$

$\Rightarrow y$  and  $z$  are typically very sparse

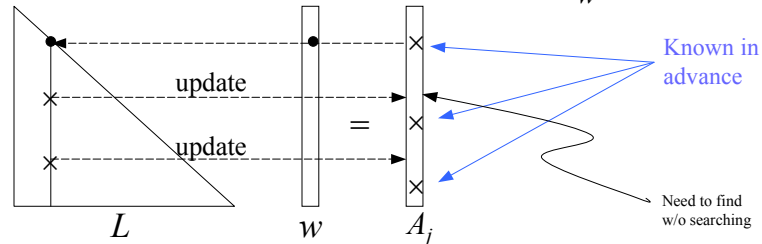
**Example:** Model pla85900 (from TSP)

Constraints	85900
Variables	144185
Average $ y $	15.5

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$$A_B = \begin{matrix} & & U \\ L & & \end{matrix}$$

Triangular solve:  $Lw = A_j$  ( $A_B y = L(Uy) = A_j$ )



**Graph structure:** Define an acyclic digraph  $D = (\{1, \dots, m\}, E)$  where  $(i, j) \in E \Leftrightarrow l_{ij} \neq 0$  and  $i \neq j$ .

**Solving using  $D$ :** Let  $X = \{i \in V: A_{ij} \neq 0\}$ . Compute  $\underline{X} = \{j \in V: \exists \text{ a directed path from } j \text{ to } X\}$ .  $\underline{X}$  can be computed in time linear in  $|E(\underline{X})| + |\underline{X}|$ .

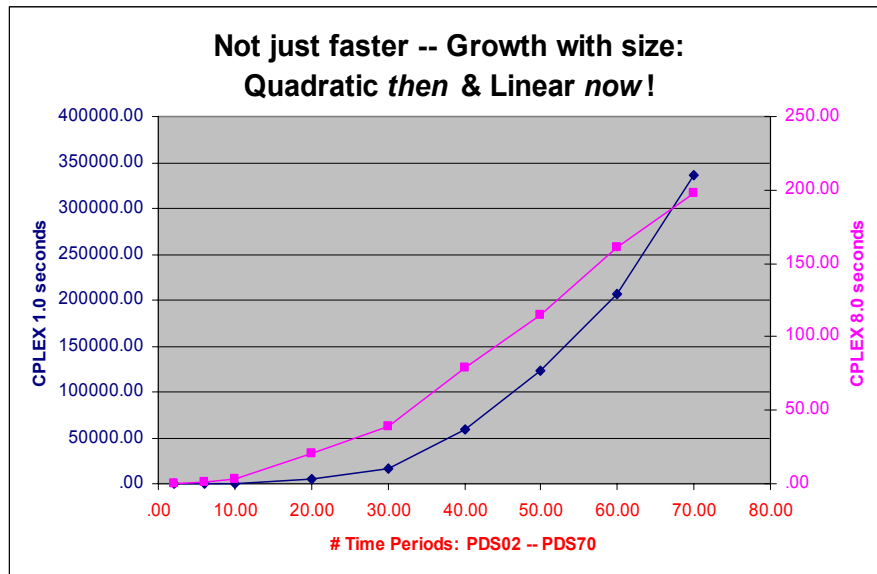
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## PDS Models

"Patient Distribution System": Carolan, Hill, Kennington, Niemi, Wichmann, *An empirical evaluation of the KORBX algorithms for military airlift applications*, Operations Research 38 (1990), pp. 240-248

MODEL	ROWS	CPLEX1.0	CPLEX5.0	CPLEX8.0	SPEEDUP
		1988	1997	2002	1.0 → 8.0
<i>pds02</i>	2953	0.4	0.1	0.1	4.0
<i>pds06</i>	9881	26.4	2.4	0.9	29.3
<i>pds10</i>	16558	208.9	13.0	2.6	80.3
<i>pds20</i>	33874	5268.8	232.6	20.9	247.3
<i>pds30</i>	49944	15891.9	1154.9	39.1	406.4
<i>pds40</i>	66844	58920.3	2816.8	79.3	743.0
<i>pds50</i>	83060	122195.9	8510.9	114.6	1066.3
<i>pds60</i>	99431	205798.3	7442.6	160.5	1282.2
<i>pds70</i>	114944	335292.1	21120.4	197.8	1695.1
		Primal Simplex	Dual Simplex	Dual Simplex	

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## Issue 4 Ratio Test and Finiteness

The “standard form” dual problem is

$$\begin{aligned} & \text{Maximize } b^T \pi \\ & \text{Subject to } A^T \pi + d = c \\ & \qquad \qquad \qquad d \geq 0 \end{aligned}$$

Feasibility means

$$d \geq 0$$

However, in practice this condition is replaced by

$$d \geq -\epsilon e$$

where  $e^T = (1, \dots, 1)$  and  $\epsilon = 10^{-6}$ . Reason: **Degeneracy**.  
In 1972 Paula Harris proposed suggested exploiting this fact to improve numerical stability.

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### (Issue 4 – Ratio test & finiteness)

$$\boxed{\text{STD. RATIO TEST}} \quad j_{\text{enter}} = \operatorname{argmin}\{D_j/\alpha_j : \alpha_j > 0\}$$

**Motivation:** Feasibility  $\Rightarrow$  step length  $\theta$  satisfies

$$D_N - \theta\alpha_N \geq 0$$

However, the bigger the step length, the bigger the change in the objective. So, we choose

$$\theta_{\max} = \min\{D_j/\alpha_j : \alpha_j > 0\}$$

Using  $\varepsilon$ , we have

$$\theta_{\max}^\varepsilon = \min\{(D_j + \varepsilon)/\alpha_j : \alpha_j > 0\} > \theta_{\max}$$

$$\boxed{\text{HARRIS RATIO TEST}} \quad j_{\text{enter}} = \operatorname{argmax}\{\alpha_j : D_j/\alpha_j \leq \theta_{\max}^\varepsilon\}$$

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### (Issue 4 – Ratio test & finiteness)

#### □ Advantages

- Numerical stability –  $\alpha_{j_{\text{enter}}} = \text{“pivot element”}$
- Degeneracy – Reduces # of 0-length steps

#### □ Disadvantage

- $D_{j_{\text{enter}}} < 0 \Rightarrow$  objective goes in wrong direction

#### □ Solution: BOUND SHIFTING

- If  $D_{j_{\text{enter}}} < 0$ , we replace the lower bound on  $d_{j_{\text{enter}}}$  by something less than its current value.
- Note that this shift changes the problem and must be removed: 5% of cases, this produces dual infeasibility  $\Rightarrow$  process is iterated.

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## Example: Bound-Shifting Removal

Problem 'pilot87.sav.gz' read.  
Reduced LP has 1809 rows, 4414 columns, and 70191 nonzeros.

```

Iteration log . . .
Iteration: 1 Scaled dual infeas = 0.697540
Iteration: 733 Scaled dual infeas = 0.000404
Iteration: 790 Dual objective = -185.892207
...
Iteration: 16326 Dual objective = 302.786794
Removing shift (3452). ← Shift 1: ε = 10-7
Iteration: 16417 Scaled dual infeas = 0.207796
Iteration: 16711 Scaled dual infeas = 0.000021
Iteration: 16726 Dual objective = 296.758656
Elapsed time = 104.36 sec. (17000 iterations).
Iteration: 17072 Dual objective = 300.965492
...
Iteration: 17805 Dual objective = 301.706409
Removing shift (76). ← Shift 2: ε = 10-8
Iteration: 17919 Scaled dual infeas = 0.000060
Iteration: 17948 Dual objective = 301.708660
Elapsed time = 114.42 sec. (18000 iterations).
Removing shift (10). ← Shift 3: ε = 10-9
Iteration: 18029 Scaled dual infeas = 0.000050
Iteration: 18039 Dual objective = 301.710058
Removing shift (1).

Dual simplex - Optimal: Objective = 3.0171034733e+002
Solution time = 116.44 sec. Iterations = 18095 (1137)

```

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### (Issue 4 – Ratio test & finiteness)

**Finiteness:** Bound shifting is closely related to the “perturbation” method employed in CPLEX if no progress is being made in the objective.

“No progress” ⇒

$$d_j \geq -\varepsilon \quad j = 1, \dots, n$$

is replaced by

$$d_j \geq -\varepsilon - \varepsilon_j \quad j = 1, \dots, n,$$

where  $\varepsilon_j$  is random uniform on  $[0, \varepsilon]$ .

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## Issue 5 Bound Flipping

- **A basis is given by a triple (B,L,U)**
  - L = non-basics at lower bound: Feasibility  $D_L \geq 0$
  - U = non-basics at upper bound: Feasibility  $D_U \leq 0$
- **Ratio test:** Suppose  $X_{B_i}$  is the leaving variable, and the step length is blocked by some variable  $d_j, j \in L$ , that is about to become negative and such that  $u_j < +\infty$ :
  - **Flipping means:** Move  $j$  from  $L$  to  $U$ .
  - **Check:** Do an update to see if  $X_{B_i}$  is still favorable
- Can combine many iterations into a single iteration.

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## Example: Bound Flipping

```

Problem 'fit2d.sav.gz' read.
Initializing dual steep norms . . .

Iteration log . . .
Iteration:    1  Dual objective    =    -80412.550000
Perturbation started.
Iteration:   203  Dual objective    =    -80412.550000
Iteration:  1313  Dual objective    =    -80412.548666
Iteration:  2372  Dual objective    =    -77028.548350
Iteration:  3413  Dual objective    =    -71980.245530
Iteration:  4316  Dual objective    =    -70657.605570
Iteration:  5151  Dual objective    =    -68994.477061
Iteration:  5820  Dual objective    =    -68472.659371
Removing perturbation.

Dual simplex - Optimal: Objective = -6.8464293294e+004
Solution time = 18.74 sec. Iterations = 5932 (0)

Problem 'fit2d.sav.gz' read.
Initializing dual steep norms . . .

Iteration log . . .
Iteration:    1  Dual objective    =    -77037.550000

Dual simplex - Optimal: Objective = -6.8464293294e+004
Solution time = 1.88 sec. Iterations = 201 (0)

```

}

w/o flipping

}

w/ flipping

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