THE LP PROBLEM IN STANDARD FORM

 $\min_{x \in \mathbb{R}^n} c'x,$ $Ax = b, \ x \ge \mathbf{0}.$

- $x \ge 0$ means $x_i \ge 0, i = 1, \cdots, n$.
- A of size $r \times n$ is supposed to have full rank r.
- Ω is a **polytope (polyhedron** if bounded).
- This is a *convex* optimization problem ⇒ KKT conditions sufficient for a global minimum.

GEOMETRY OF THE FEASIBLE SET

Definition: The point $x_e \in \partial \Omega$ (= the boundary of Ω) is an *extreme point* if

$$x_e = heta y + (1 - heta) z \ , \ y, z \in \Omega \ , \ 0 < heta < 1$$

implies that $y = z = x_e$.

Where are the extreme points for a *line segment*, for \mathbb{R} and \mathbb{R}^n_+ , a *cube*, and a *sphere* (all sets closed)?

The extreme points for Ω are the *vertices*.



Definition: A feasible point x ($x \ge 0$, Ax = b) is called a *basic point* if there is an index set $\mathcal{B} = \{i_1, \dots, i_r\}$, where the corresponding subset of columns of A,

$$\left\{a_{i_1},\cdots,a_{i_r}\right\},$$

are linearly independent, and $x_i = 0$ for all $i \notin \mathcal{B}$.

If x_i happens to be 0 also for some $i \in \mathcal{B}$, we say that the basic point is *degenerate*.

For a basic point, the corresponding r imes r matrix

$$B = \left[a_{i_1}, \cdots, a_{i_r}\right],$$

will be *non-singular*, and the equation $Bx_B = b$ has a unique solution.

The Fundamental Theorem for LP (N&W Theorem 13.2):

- 1. If $\Omega \neq \emptyset$, it contains basic points.
- 2. If there are optimal solutions, there are optimal basic points (basic solutions).

Theorem (N&W Theorem 13.3): The basic points are the extreme points of Ω .

The number of basic points is between 1 (because of the first statement in the Fundamental Theorem) and $\binom{n}{r}$.

THE SIMPLEX ALGORITHM

- The *Simplex Algorithm* is reported to have been discovered by G. B. Dantzig in 1947.
- The idea of the Simplex Algorithm is to search for the minimum by going from vertex to vertex (from basic point to basic point) in Ω.
- Hand calculations are *never used* anymore!

The Simplex Iteration Step

We assume that the problem has the standard form, and that we are located in a basic point which, after a rearrangement of variables, has the form

$$x = \left[\begin{array}{c} x_B \\ \mathbf{0} \end{array} \right].$$

The partition is therefore according to $A = [B \ N]$, where B is non-singular, and

$$Ax = \begin{bmatrix} B & N \end{bmatrix} \begin{bmatrix} x_B \\ \mathbf{0} \end{bmatrix} = Bx_B = b.$$

Split a general $x \in \Omega$ in the same way,

$$Ax = \begin{bmatrix} B & N \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = Bx_1 + Nx_2 = b.$$

Hence,

$$x_1 = B^{-1} (b - Nx_2) = x_B - B^{-1} Nx_2.$$

Note also that

$$f(x) = c'x = [c_1 \ c_2] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

= $c'_1 x_1 + c'_2 x_2$
= $c'_1 (x_B - B^{-1} N x_2) + c'_2 x_2$
= $c'_1 x_B + (c'_2 - c'_1 B^{-1} N) x_2$

Around $[x_B \ 0]'$, we may express both x_1 and f(x) in terms of x_2 .

We are located at $x_1 = x_B$, $x_2 = 0$, and try to change one of the components $(x_2)_j$ of x_2 so that

$$f(x) = c'_1 x_B + \left(c'_2 - c'_1 B^{-1} N\right) x_2$$

decreases.

• If
$$(c'_2 - c'_1 B^{-1} N) \ge 0 \Rightarrow$$
 FINISHED!

Assume that
$$(c'_2 - c'_1 B^{-1} N)_j < 0$$
:

• If all components of x_1 increase when $(x_2)_j$ increases, then

$$\min c'x = -\infty.$$

\Rightarrow FINISHED!

If not, we have the situation shown in Fig. 1.



Figure 1: Change in x_1 when $(x_2)_j$ increases from 0.

- The Simplex algorithm always converges if all basic points are non-degenerate.
- Degenerate basic point: Try a different component of x₂. (FINISHED if impossible!)
- It is straightforward to construct a generalized Simplex Algorithm for bounds of the form

$$l_i \leq x_i \leq u_i, \ i = 1, \cdots, n.$$

- If we *LU*-factorize *B* once, we can update the factorization with the new column without making a complete new factorization (N&W, Sec. 13.4).
- It is often preferable to take the "steepest ridge" (fastest decrease in the objective) out from where we are (N&W, Sec. 13.5).

Starting the Simplex Method

The Simplex method consists of two phases:

- Phase 1: Find a first basic point
- Phase 2: Solve the original problem

The Phase 1 algorithm:

- 1. Turn the signs in Ax = b so that $b \ge 0$.
- 2. Introduce additional variables $y \in \mathbb{R}^r$ and solve the extended problem

$$\min (y_1 + \dots + y_r),$$

 $[A \ I] \begin{bmatrix} x \\ y \end{bmatrix} = b, \ x, y \ge 0.$

(Note that $\begin{bmatrix} 0 & b \end{bmatrix}'$ already is a basic point for the extended problem!).

Assume that the solution of the extended problem is

$$\left[\begin{array}{c} x_0\\ y_0 \end{array}\right]$$

- If $y_0 \neq 0$, then the original problem is infeasible $(\Omega = \emptyset)$.
- If $y_0 = 0$, then x_0 is a basic point (= possible start for the original problem).
- This is not the only Phase 1 algorithm.

1 EPILOGUE

• Open Problem: Are there LP algorithms of polynomial complexity?

- The Simplex Method has exponential complexity in the worst case (*Kree–Minty–Cheval counterexample*)
- Interior Point Methods (Khatchiyan, 1978): $\#Op \propto \mathcal{O}\left(n^4L\right)$
- Karmankar (1984): $\#Op \propto \mathcal{O}\left(n^{3.5}L\right)$
- Current record (?): Interior Barrier Primal–Dual methods, $\#Op \propto \mathcal{O}(n^3L)$. (We return to this method after discussing penalty and barrier methods)
- Solving large LP problems is BIG business!
- Entering data into the computer for large LP problems is a lot of work. Look up a description of the industry standard "*MPS Data Format*" on the *internet*.

LINEAR PROGRAMMING IN MATLAB OPTIMIZATION TOOLBOX

(may be a little outdated!)

Basic function: **linprog**

Solves the general LP-problem

$$\min_{x} f'x,$$
$$Ax \le b$$
$$A_{eq.}x = b_{eq.}$$
$$lb \le x \le ub$$

where f, x, b, b_{eq}, lb , and ub are vectors and A, A_{eq} are matrices (may be entered as *sparse* matrices)

Syntax:

Х	=	linprog(f, A, b, Aeq, beq)
Х	=	linprog(f, A, b, Aeq, beq, lb, ub)
Х	=	linprog(f, A, b, Aeq, beq, lb, ub, x0)
Х	=	linprog(f, A, b, Aeq, beq, lb, ub, x0, options)
[x,f\	/al]	= linprog()
Г <u>с</u> .		

[x,fval,exitflag]	= linprog()
[x,fval,exitflag,output]	= linprog()
[x,fval,exitflag,output,lambda]	= linprog()

Example: The Standard form:

$$\min c'x,$$
$$Ax = b,$$
$$x \ge 0.$$

x = linprog(c,[],[],A,b,zeros(size(c)),[])

• Note the Matlab convention with *placeholders,* "[]"

INPUT:

xo: Starting point. Used only for medium problems (*Nelder-Mead amoeba*).

Options: Structure of parameters

LargeScale: 'on'/'off'

Display:	'off'/'iter'/'final' (large scale problems)
MaxIter:	Max number of iterations
Simplex:	'on'/'off' ('on' ignores x0)
TolFun:	Objective tolerance (large scale problems)

OUTPUT:

x,fval: Solution and objective

exitflag:

- 1 Iteration terminated OK
- 0 Number of iterations exceeded MaxIter
- -2 No feasible point found
- -3 Problem is unbounded
- -4 NaN value encountered
- -5 Both primal and dual are infeasible
- -7 Search direction became too small

output: Structure of iteration information

iterations: algorithm: cgiterations: message:	Number of iterations Algorithm used The number of PCG iterations (large-scale algorithm only) Output message
lambda:	Structure of Lagrange multipliers
ineqlin: eqlin	for linear inequalities $Ax \le b$, for linear equalities $A_{eq}x = b_{eq}$,

- lower for lb,
- upper for ub.

ALGORITHMS:

Small/Medium scale:	SIMPLEX-like including Phase 1	
Large scale:	Primal-dual inner method	

EXAMPLES FROM THE DOCUMENTATION

A. Small Problem

subject to

Find x that minimizes

$$f(x) = -5x_1 - 4x_2 - 6x_3$$
$$x_1 - x_2 + x_3 \le 20$$
$$3x_1 + 2x_2 + 4x_3 \le 42$$
$$3x_1 + 2x_2 \le 30$$
$$0 \le x_1, 0 \le x_2, 0 \le x_3$$

First, enter the coefficients, then call LINPROG:

```
f = [-5 -4 -6]';
A = [1-1 1
      324
      3 2 0];
b = [20 42 30]';
lb = zeros(3,1);
[x,fval,exitflag,output,lambda] = ... linprog(f,A,b,[],[],lb);
                = [0 15 3]
= -78.0
     Х
     fval
     output:
            iterations: 6
            algorithm: 'large-scale: interior point' (!)
            cgiterations: 0
            message: 'Optimization terminated.'
     lambda.ineqlin = [0 1.5 0.5]lambda.lower = [1 0 0]
```

For solution by the Simplex method:

```
      f = [-5 -4 -6]'; \\ A = [1 -1 1 \\ 3 2 4 \\ 3 2 0]; \\ b = [20 42 30]'; \\ lb = zeros(3,1); \\ options = optimset('LargeScale','off','Simplex','on'); \\ [x,fval,exitflag,output,lambda] = ... \\ linprog(f,A,b,[],[],lb,[],[],options);
```

(NB! If you forget enough placeholders, [], you get the error message "LINPROG only accepts inputs of data type double")

Now output gives:

3
'medium scale: simplex'
[]
'Optimization terminated.'

(same solution!)

B Medium Problem

This problem is stored as a Matlab MAT-file.

- 48 unknowns
- 30 inequality constraints
- 20 equality constraints
- $x \ge 0$

Entered into Matlab simply by

load sc50b

А	30x48	(sparse)
Aeq	20x48	(sparse)
b	30x1	
beq	20x1	
f	48x1	
lb	48x1	

Sparsity patterns:



```
⇒load sc50b
options = optimset('LargeScale','off','Simplex','on');
[x,fval,exitflag,output,lambda] = ...
linprog(f,A,b,Aeq,beq,lb,[],[],options);
```

x = [30 28 42 ... 102.4870]

Only lambda.ineqlin(2) and lambda.ineqlin(3) equal to 0: only inequality 2 and 3 non-active.

max(lambda.lower)= 8.2808e-015 \implies x_i > 0 for i = 1,...,48.

output =

iterations:	43
algorithm:	'medium scale: simplex'
cgiterations:	[]
message:	'Optimization terminated.'

Large scale option:

```
options = optimset('LargeScale','on');
[x,fval,exitflag,output,lambda] = ...
linprog(f,A,b,Aeq,beq,lb,[],[],options);
```

output =

iterations: 8 algorithm: 'large-scale: interior point' cgiterations: 0 message: 'Optimization terminated.'

Same solution!

With display of results for each iteration:

options = optimset('LargeScale','on','Display','iter');

Residuals: Primal Dual Duality Total Infeas Infeas A*x-b A'*y+z-f Gap Rel Infeas A'*y+z-f -x'*z Error Iter0:1.50e+032.19e+011.91e+041.00e+02Iter1:1.15e+023.18e-153.62e+039.90e-01Iter2:8.32e-131.96e-154.32e+029.48e-01Iter3:3.51e-121.87e-157.78e+016.88e-01 Iter4:1.81e-113.50e-162.38e+012.69e-01Iter5:2.63e-101.23e-155.05e+006.89e-02Iter6:5.88e-112.72e-161.64e-012.34e-03Iter7:2.61e-122.59e-161.09e-051.55e-07 8: 7.97e-14 5.67e-13 1.09e-11 3.82e-12 Iter Optimization terminated.

FOR MORE INFO: Read documentation of linprog!

OPTIMIZATION SOFTWARE – 2010

http://wiki.mcs.anl.gov/NEOS/index.php/NEOS_Wiki

(NEOS = Network-Enabled Optimization System)

- <u>AIMMS</u> modeling system
- <u>AMPL</u> modeling language.
- <u>ANALYZE</u> linear programming model analysis.
- <u>APOPT</u> nonlinear programming.
- <u>APMonitor</u> modeling language.
- <u>ASA</u> adaptive simulated annealing.
- <u>BPMPD</u> linear programming.
- BQPD quadratic programming.
- **BT** minimization.
- **<u>BTN</u>** block truncated Newton.
- <u>CBC</u> mixed-integer linear programming.
- <u>CML</u> constrained maximum likelihood.
- <u>CNM</u> linear algebra and minimization.
- <u>CO</u> constrained optimization.
- <u>COMPACT</u> design optimization.
- <u>CONOPT</u> nonlinear programming.
- <u>CONSOL-OPTCAD</u> engineering system design.
- <u>CONTIN</u> systems of nonlinear equations.
- <u>CLP</u> linear programming.
- <u>CPLEX</u> linear programming.
- <u>C-WHIZ</u> linear programming models.
- <u>DATAFORM</u> model management system.
- <u>DFNLP</u> nonlinear data fitting.
- <u>DOC</u> Design Optimization Control Program.
- <u>DONLP2</u> nonlinear constrained optimization.
- <u>DOT</u> Design Optimization Tools.
- EASY FIT parameter estimation in dynamic systems.
- <u>Excel and Quattro Pro Solvers</u> spreadsheet-based linear, integer and nonlinear programming
- <u>EZMOD</u> modeling environment for decision support systems

- <u>FortMP</u> linear and mixed integer quadratic programming.
- <u>FSQP</u> nonlinear and minmax constrained optimization, with feasible iterates.
- <u>GAMS</u> General Algebraic Modeling System.
- <u>GAUSS</u> matrix programming language.
- <u>GENESIS</u> structural optimization software.
- <u>GENOS 1.0</u> nonlinear network optimization.
- <u>GINO</u> nonlinear programming.
- <u>GRG2</u> nonlinear programming.
- <u>GOM</u> Global Optimization for Mathematica.
- <u>GUROBI</u> linear programming.
- <u>HOMPACK</u> nonlinear equations and polynomials.
- <u>HOPDM</u> linear programming (interiorpoint).
- <u>HARWELL Library</u> linear and nonlinear programming, nonlinear equations, data fitting.
- <u>HS/LP Linear Optimizer</u> linear programming.
- <u>ILOG</u> constraint-based programming and nonlinear optimization.
- <u>IMSL</u> Fortran and C Library.
- <u>IPOPT</u> nonlinear programming.
- <u>KNITRO</u> nonlinear programming.
- KORBX linear programming.
- <u>LAMPS</u> linear and mixed-integer programming.
- <u>LANCELOT</u> large-scale problems.
- <u>LBFGS</u> unconstrained minimization.
- <u>LBFGS-B</u> bound-constrained minimization.
- <u>LGO IDE</u> continuous and Lipschitz global optimization.

- <u>LINDO</u> linear, mixed-integer and quadratic programming.
- <u>LINGO</u> modeling language.
- <u>LIPSOL</u> linear programming.
- <u>LNOS</u> linear programming/network flow problems.
- <u>LOQO</u> Linear programming, unconstrained and constrained nonlinear optimization.
- <u>LP88 and BLP88</u> linear programming.
- <u>LSGRG2</u> nonlinear programming.
- <u>LSNNO</u> large scale optimization.
- <u>LSSOL</u> least squares problems.
- <u>M1QN3</u> unconstrained optimization.
- MATLAB optimization toolbox.
- <u>MAXLIK</u> maximum likelihood estimation.
- <u>MCS</u> global optimization.
- <u>MILP88</u> mixed integer programming.
- <u>MINOS</u> linear programming and nonlinear optimization.
- <u>MINTO</u> mixed integer linear programming.
- <u>MINPACK-1</u> nonlinear equations and least squares.
- <u>MIPIII</u> mixed integer programming.
- <u>MODFIT</u> parameter estimation in dynamic systems.
- <u>MODLER</u> linear programming modeling language.
- <u>MODULOPT</u> unconstrained problems and simple bounds.
- <u>MOSEK</u> linear programming and convex optimization.
- <u>MPL</u> modeling system
- <u>MPSIII</u> mathematical programming system.
- <u>NAG C Library</u> nonlinear and quadratic programming, minimization
- <u>NAG Fortran Library</u> nonlinear and quadratic programming, minimization
- <u>NETFLOW</u> network optimization.
- <u>NITSOL</u> systems of nonlinear equations.
- <u>NLopt</u> local and global nonlinear optimization, including nonlinear constraints, with and without usersupplied gradients

- <u>NLPE</u> minimization and least squares problems.
- <u>NLPJOB</u> Mulicriteria optimization.
- <u>NLPQL</u> nonlinear programming.
- <u>NLPQLB</u> nonlinear programming with constraints.
- <u>NLSSOL</u> constrained nonlinear least squares problems.
- <u>NLPSPR</u> nonlinear programming.
- <u>NOVA</u> nonlinear programming.
- <u>NPSOL</u> nonlinear programming.
- <u>ODRPACK</u> NLS and ODR problems.
- <u>OML</u> linear and mixed-integer programming, model management.
- <u>OPL Studio</u> optimization language and solver environment.
- <u>OPTDES</u> design optimization tool.
- <u>OPTECH</u> global optimization.
- <u>OptiA</u> unconstrained, constrained, quadratic, minimax, nonsmooth, and global optimization
- <u>OPTIMA Library</u> optimization and sensitivity analysis.
- <u>OPTIMAX</u> component software for optimization
- <u>OPTMUM</u> optimization.
- <u>OPTPACK</u> constrained and unconstrained optimization.
- <u>OptQuest</u> global optimization
- <u>OSL</u> linear, quadratic and mixedinteger programming.
- <u>PCOMP</u> modelling language with automatic differentiation.
- <u>PCx</u> linear programming with a primal-dual interior-point method.
- <u>PDEFIT</u> parameter estimation in partial differential equations.
- <u>PETSc</u> parallel solution of nonlinear equations and unconstrained minimization problems.
- <u>PLAM</u> algebraic modeling language for mixed integer programming, constraint logic programming, etc.
- <u>PORT 3</u> minimization, least squares, etc.
- <u>PROC LP</u> linear and integer programming.
- <u>PROC NETFLOW</u> network optimization.

- <u>PROC NLP</u> various quadratic and nonlinear optimization problems.
- <u>PROPT</u> optimal control software for MATLAB users.
- <u>Q01SUBS</u> quadratic programming for matrices.
- <u>QAPP</u> quadratic assignment problems.
- <u>QL</u> quadratic programming.
- <u>**OPOPT</u>** linear and quadratic problems.</u>
- <u>RANDMOD</u> linear programming model randomizer.
- <u>SCIP</u> mixed-integer linear programming.
- <u>SIMUSOLV</u> modeling software.
- <u>SPRNLP</u> sparse and dense nonlinear programming, sparse nonlinear least squares, including the <u>SOCS</u> package for optimal control
- <u>SPEAKEASY</u> numerical problems and operations research.
- <u>SNOPT</u> large-scale quadratic and nonlinear programming problems.
- <u>SQOPT</u> large-scale linear and convex quadratic programming problems.
- <u>SQP</u> nonlinear programming.
- <u>SYMPHONY</u> mixed-integer linear programming.

- <u>SYNAPS Pointer</u> multidisciplinary design optimization software
- <u>SYSFIT</u> parameter estimation in systems of nonlinear equations.
- <u>TENMIN</u> unconstrained optimization.
- <u>TENSOLVE</u> nonlinear equations and least squares.
- <u>TN/TNBC</u> minimization.
- <u>TNPACK</u> nonlinear unconstrained minimization.
- <u>TSA88</u> network linear programming.
- <u>TOMLAB</u> Matlab Optimization.
- <u>UNCMIN</u> unconstrained optimization.
- <u>VE08</u> nonlinear optimization.
- <u>VE10</u> nonlinear least squares.
- <u>VIG and VIMDA</u> decision support system.
- <u>What'sBest</u> linear and mixed integer programming.
- <u>WHIZARD</u> linear programming, mixed-integer programming.
- <u>XLSOL</u> Linear, integer and nonlinear programming for AMPL models
- <u>XPRESS-MP</u> from Dash Associates linear and integer programming.

TMA 4180 Optimeringsteori

Minimum Cost Network Flow Analysis Using LP

Harald E. Krogstad March 2007



Sink



Source

An arc is characterized by

- Prize pr. flow unit along arc
- Lower bound (for initiating transport)
- Upper bound (capacity)

Sources: (Production/providers)

- Capacity
- Cost pr. unit delivered to the network

Sinks (Consumers/receivers):

- Capacity
- Income to network from deliveries

Source: Production b>0. Sink: Absorption, b < 0. Variables $x = \{x_i\}, x_i \ge 0$. (flow in the arcs)

NB! 2 variables for each arc: 2 directions



Price for delivery:
$$f(x) = \sum_{arcs} c_i x_i = c'x$$

Cost for one unit along arc "*i*": $\{c_i\}$ Upper bound on capacity for arc "*i*": $\{ub_i\}$ Lower bound on capacity for arc "*i*": $\{lb_i\}$

The LP formulation:

$$\min_{x} c'x$$

$$\sum_{\text{outflow}} x_{i} - \sum_{\text{inflow}} x_{i} = b_{n}, n = 1, \dots, Nodes,$$

$$lb \leq x \leq ub.$$

$$\min_{x} c'x$$

$$A_{eq}x = b_{eq}$$

$$lb \leq x \leq ub$$

The matrix is a *sparse* matrix with only -1, 0, and -1

Simsys_sparse

B MATLAB CENTRAL

An open exchange for the MATLAB and Simulink user community

http://www.mathworks.com/matlabcentral/

Per Bergström Luleå University of Technology



RANDOM NETWORK GENERATION

Prescribe:

- Numbers of sources and sinks
- Max number of arcs around one node
- Min number of arcs around one node
- Random upper bound
- Distribution of nodes
- Interactive network modification
- Random costs

The algorithm provides:

- Number of nodes
- Upper bound of capacity
- A_{eq} matrix
- Balanced production/consumption at the sources and sinks

[Aeq,beq,lb,ub,c]=simsys_sparse(100);

Solution in Matlab: x = linprog(c,[],[],Aeq,beq,lb,ub)



RANDOMLY GENERATED NETWORK

The LP-problem:

- Number of arcs: 304
- Lower bounds: 0
- Upper bounds: -
- Equality constraints: 48











 $\dim(x) = 3782$ $\dim(A_{eq}) = 506 \times 3782$



Practical Optimization: A Gentle Introduction

John W. Chinneck Systems and Computer Engineering Carleton University Ottawa, Ontario K1S 5B6 Canada http://www.sce.carleton.ca/faculty/chinneck/po.html

(very soft introduction ☺)