Lecture 5: Solving LPs – the simplex method

- Brief recap previous lecture
- The geometry of the feasible set
- Basic feasible points, “The fundamental theorem of linear programming”
- The simplex method
- Example 13.1
- Some implementation issues

Reference: N&W Ch.13.2-13.3, also 13.4-13.5

Linear programming, standard form and KKT: recap

LP: $$\min_{x \in \mathbb{R}^n} c^T x \quad \text{subject to} \quad \begin{cases} a_i x = b_i, & i \in \mathcal{E} \\ a_i x \geq b_i, & i \in \mathcal{I} \end{cases}$$

LP, standard form: $$\min_{x \in \mathbb{R}^n} c^T x \quad \text{subject to} \quad \begin{cases} Ax = b \\ x \geq 0 \end{cases}$$

Lagrangian: $$\mathcal{L}(x, \lambda, s) = c^T x - \lambda^T (Ax - b) - s^T x$$

KKT-conditions (LPs: necessary *and* sufficient for optimality):

$$\begin{aligned} A^T \lambda^* + s^* &= c, \\ Ax^* &= b, \\ x^* &\geq 0, \\ s^* &\geq 0, \\ x_i^* s_i^* &= 0, \quad i = 1, 2, \ldots, n \end{aligned}$$

Duality

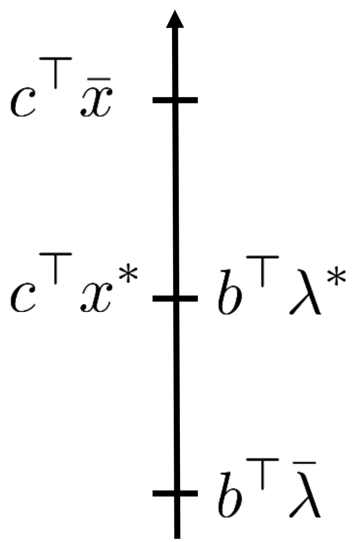
Primal problem

$$\begin{aligned} \min_{x} \quad & c^\top x \\ \text{s.t.} \quad & Ax = b \\ & x \geq 0 \end{aligned}$$

Dual problem

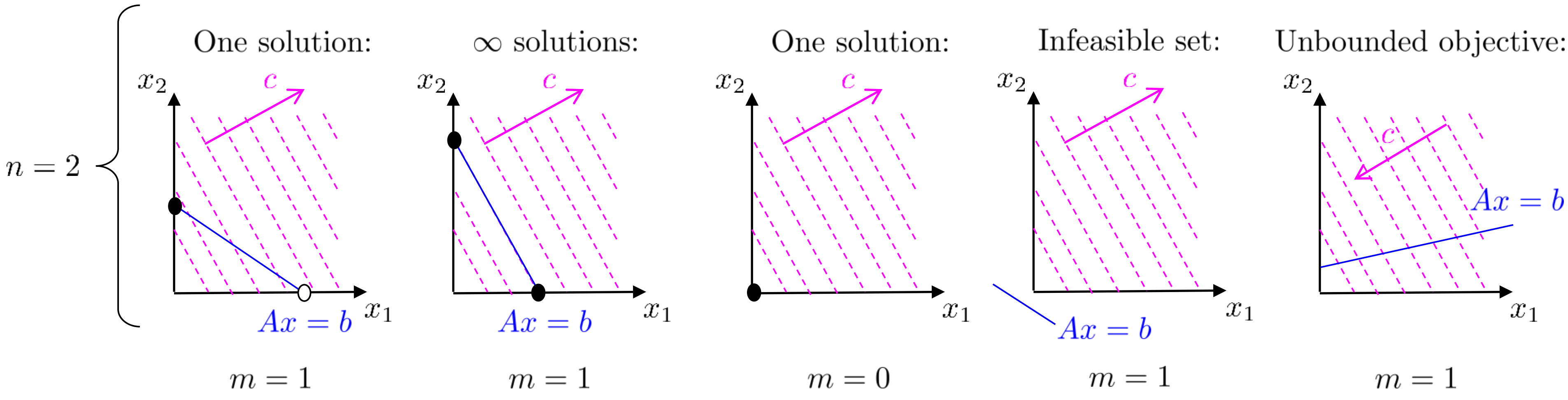
$$\begin{aligned} \max_{\lambda, s} \quad & b^\top \lambda \\ \text{s.t.} \quad & A^\top \lambda + s = c \\ & s \geq 0 \end{aligned}$$

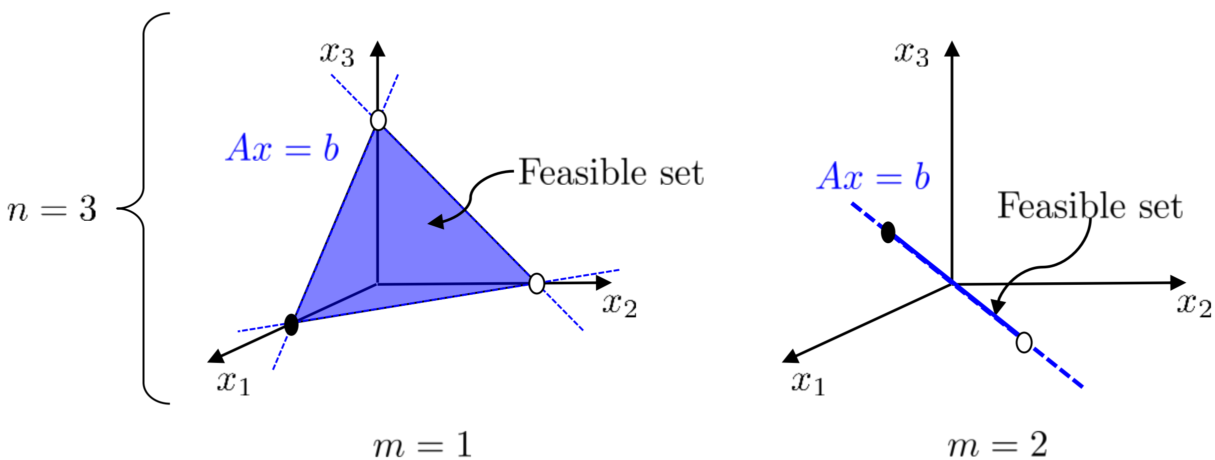
- Identical KKT conditions!
- Equal optimal value: $c^\top x^* = b^\top \lambda^*$
- Weak duality: $c^\top \bar{x} \geq c^\top x^* = b^\top \lambda^* \geq b^\top \bar{\lambda}$
- Duality gap: $c^\top \bar{x} - b^\top \bar{\lambda}$
- Strong duality (Thm 13.1):
  - i) If primal or dual has finite solution, both are equal
  - ii) If primal or dual is unbounded, the other is infeasible



LP: Geometry of the feasible set

$$\begin{aligned} \min_x \quad & c^\top x \\ \text{s.t.} \quad & Ax = b \\ & x \geq 0 \end{aligned}$$





- ● Basic optimal point (BOP)
- ○ Basic feasible point (BFP) (if they exist)

In general, the BFP has at most *m* non-zero components

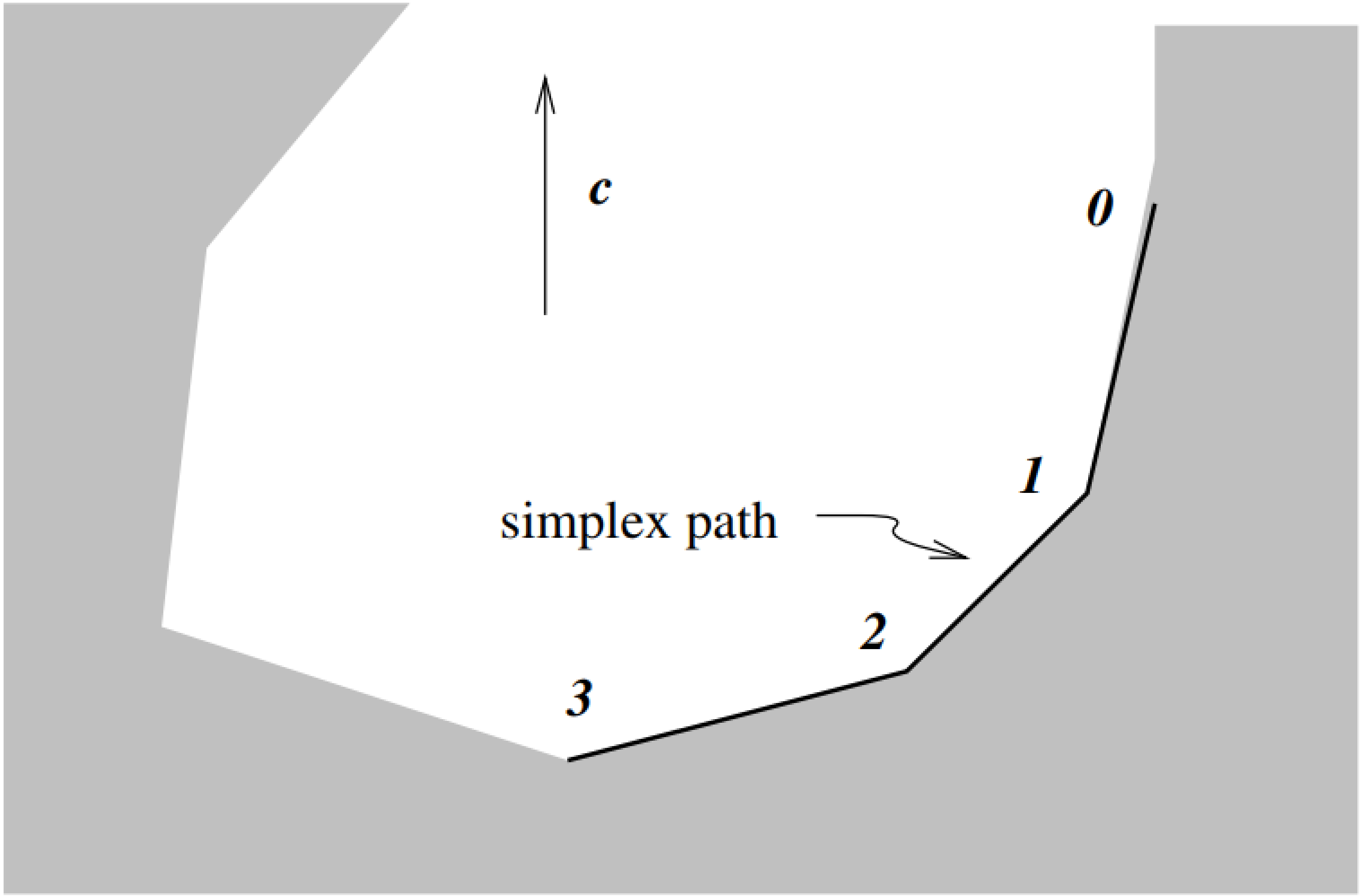
Inspired by drawings by Miguel A. Carreira-Perpinan

LP KKT conditions (necessary&sufficient)

- Simplex method iterates BFPs until one that fulfills KKT is found.

$$
\begin{aligned}
A^T\lambda + s &= c, && \text{(KKT-1)}\\
Ax &= b, && \text{(KKT-2)}\\
x &\geq 0, && \text{(KKT-3)}\\
s &\geq 0, && \text{(KKT-4)}\\
x_i s_i &= 0, \quad i = 1, 2, \ldots, n && \text{(KKT-5)}
\end{aligned}
$$

- Each step is a move from a vertex to a neighboring vertex *(one change in the basis),* that decreases the objective


c
0
1
simplex path
2
3

Check KKT-conditions for BFP

- Given BFP x, and corresponding basis $\mathcal{B}(x)$. Define

$$\mathcal{N}(x) = \{1, 2, \ldots, n\} \backslash \mathcal{B}(x)$$

- Partition x, s and c:

$$x_B = [x_i]_{i \in \mathcal{B}(x)} \quad x_N = [x_i]_{i \in \mathcal{N}(x)}$$

- KKT conditions

KKT-2: $Ax = Bx_B + Nx_N = Bx_B = b$ (since *x* is BFP)

KKT-3: $x_B = B^{-1}b \geq 0, \quad x_N = 0$ (since *x* is BFP)

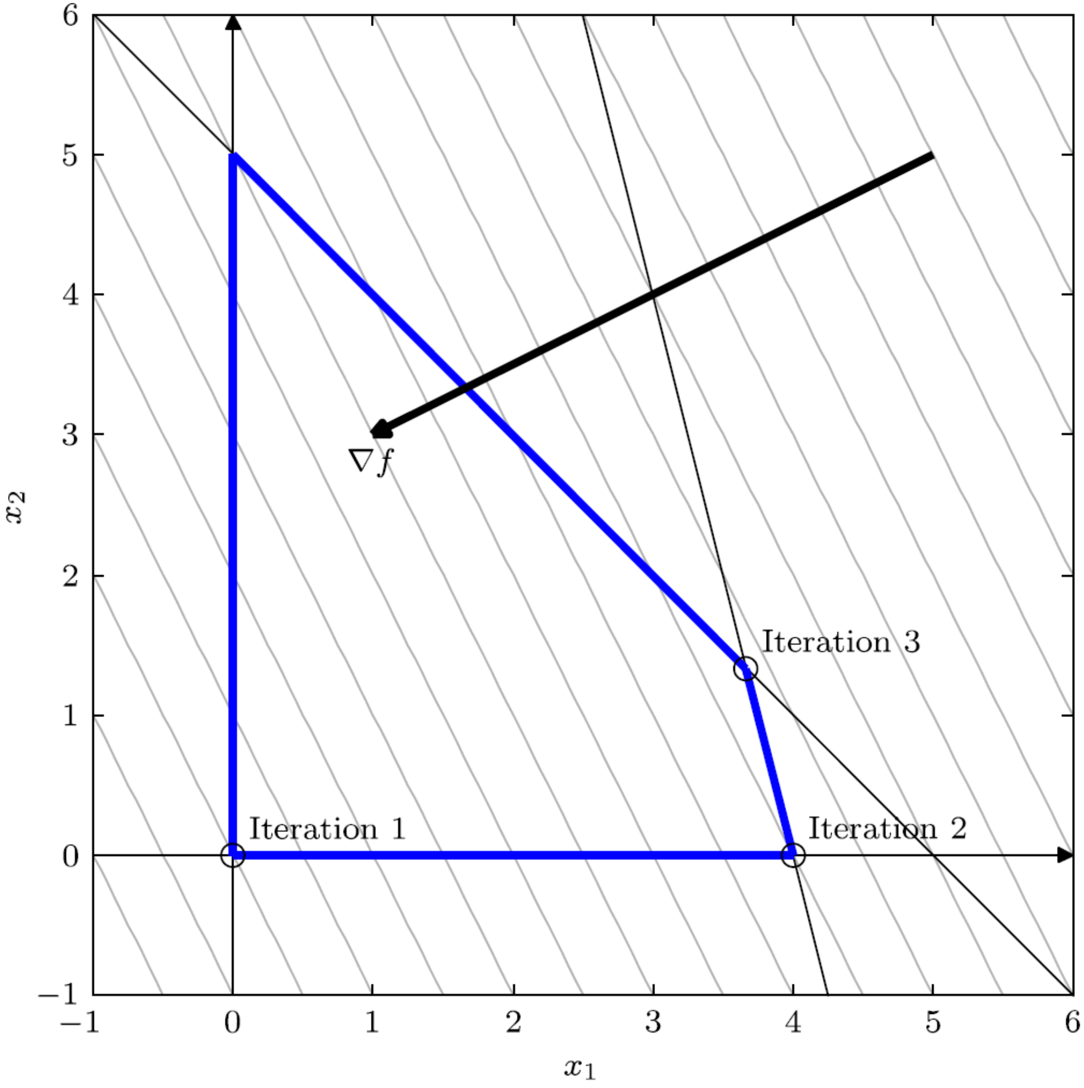
KKT-5: $x^\top s = x_B^\top s_B + x_N^\top s_N = 0$ if we choose $s_B = 0$

KKT-1: $\begin{bmatrix} B^T \\ N^T \end{bmatrix} \lambda + \begin{bmatrix} s_B \\ s_N \end{bmatrix} = \begin{bmatrix} c_B \\ c_N \end{bmatrix} \Rightarrow \begin{cases} \lambda = B^{-T} c_B \\ s_N = c_N - N^T \lambda \end{cases}$

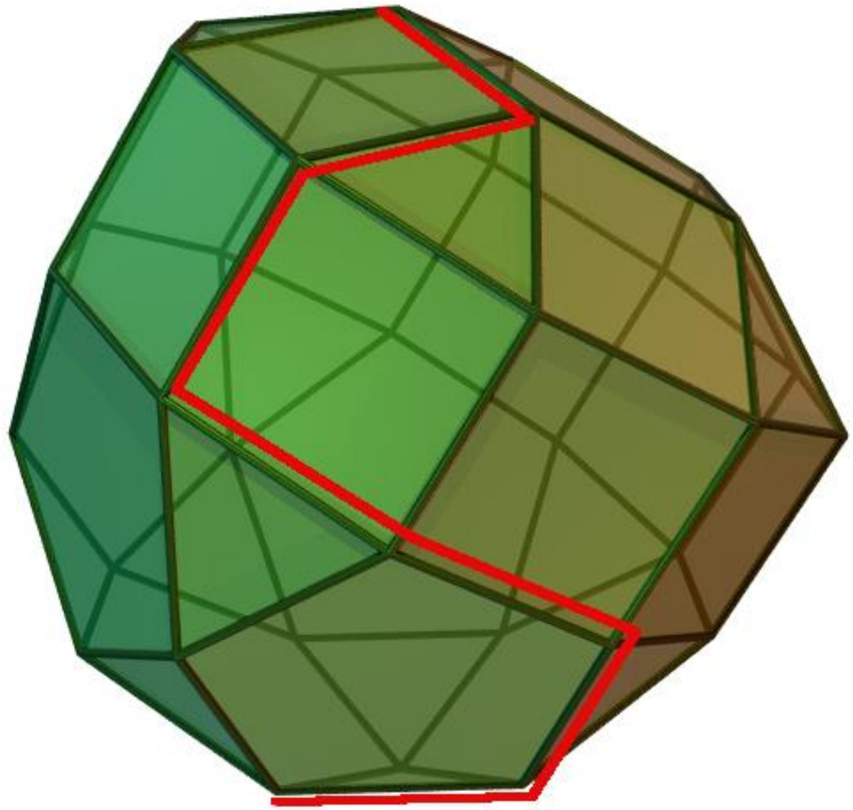
KKT-4: Is $s_N \geq 0$?

- If $s_N \geq 0$, then the BFP x fulfills KKT and is a solution
- If not, change basis, and try again
  - E.g. pick smallest element of s_N (index *q*), increase x_q along *Ax*=*b* until x_p becomes zero. Move *q* from $\mathcal{N}$ to $\mathcal{B}$, and *p* from $\mathcal{B}$ to $\mathcal{N}$. This guarantees decrease of objective, and no "cycling" (if non-degenerate).

Example 13.1 – figure



Simplex in 3D



wikipedia.org

Linear algebra – LU factorization

- Two linear systems must be solved in each iteration:
  - $B^\top \lambda = c_B$
  - $Bd = A_q$ (to find the direction to check when inreasing x_q)
  - We also had $Bx_B = b$. Since x_B is not needed in the iterations, we don't need to solve this (apart from in the final iteration)
  - This is the major work per iteration of simplex, efficiency is important!

- *B* is a general, non-singular matrix
  - Guaranteed a solution to the linear systems
  - LU factorization is the appropriate method to use (same for both systems)
  - Don't use matrix inversion!

- In each step of Simplex method, one column of *B* is replaced:
  - Can update ("maintain") the LU factorization of *B* in a smart and efficient fashion
  - No need to do a new LU factorization in each step, save time!

Other practical implementation issues (Ch. 13.5)

- Selection of "entering index" q
  - Dantzig's rule: Select the index of the most negative element in s_N
  - Other rules have proved to be more efficient in practice
- Handling of degenerate bases/degenerate steps (when a positive x_q is not possible)
  - If no degeneracy, each step leads to decrease in objective $c^\top x$ and convergence in finite number of iterations is guaranteed (Theorem 13.4)
  - Degenerate steps lead to no decrease in objective. Not necessarily a problem, but can lead to cycling (we end up in the same basis as before)
  - Practical algorithms uses perturbation strategies to avoid this
- Starting the simplex method
  - We assumed an initial BFP available – but finding this is as difficult as solving the LP
  - Normally, simplex algorithms have two phases:
    - Phase I: Find BFP
    - Phase II: Solve LP
  - Phase I: Design other LP with trivial initial BFP, and whose solution is BFP for original problem

$$\min e^\top z \text{ subject to } Ax + Ez = b, \quad (x,z) \geq 0$$

$$e = (1,1,\ldots,1)^\top, \quad E \text{ diagonal matrix with } \begin{cases} E_{jj} = 1 \text{ if } b_j \geq 0 \\ E_{jj} = -1 \text{ if } b_j < 0 \end{cases}$$

- Presolving (Ch. 13.7)
  - Reducing the size of the problem before solving, by various tricks to eliminate variables and constraints. Size reduction can be huge. Can also detect infeasibility.

Simplex – an active set method

- Complexity:
  - Typically, at most *2m* to *3m* iterations
  - Worst case: All vertices must be visited (exponential complexity in *n*)
  - Compare interior point method: Guaranteed polynomial complexity, but in practice hard to beat simplex on many problems

- Active set methods (such as simplex method):
  - Maintains explicitly an estimate of the set of inequality constraints that are active at the solution (the set $\mathcal{N}$ for the simplex method)
  - Makes small changes to the set in each iteration (a single index in simplex)

- Next week: Active set method for QP