

Introduction to Mathematical Programming

IE496

Lecture 6

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Reading for This Lecture

- Bertsimas 3.1-3.2.

What We've Learned So Far

- We are interested in the **extreme points** of polyhedra.
- There is a one-to-one correspondence between the extreme points of a polyhedron and the **basic feasible solutions**.
- We can construct **basic solutions** by
 - Choosing a **basis** B of m linearly independent columns of A .
 - Solve the system $Bx_B = b$ to obtain the values of the basic variables.
 - Set $x_N = 0$.
- We can move between adjacent (nondegenerate) basic solutions by removing one column of the basis and replacing it with another.
- In the presence of **degeneracy**, we might stay at the same extreme point.
- These are the building blocks we need to construct algorithms for solving LPs.

Iterative Search Algorithms

- Many optimization algorithms are *iterative* in nature.
- Geometrically, this means that they move from a given starting point to a new point in a specified *search direction*.
- This search direction is calculated to be both *feasible* and *improving*.
- The process stops when we can no longer find a feasible, improving direction.
- For linear programs, *it is always possible to find a feasible improving direction* if we are not at an optimal point.
- This is essentially what makes linear programs “easy” to solve.

Feasible and Improving Directions

Definition 1. Let \hat{x} be an element of a polyhedron \mathcal{P} . A vector $d \in \mathbb{R}^n$ is said to be a **feasible direction** if there exists $\theta \in \mathbb{R}_+$ such that $\hat{x} + \theta d \in \mathcal{P}$.

Definition 2. Consider a polyhedron \mathcal{P} and the associated linear program $\min_{x \in \mathcal{P}} c^\top x$ for $c \in \mathbb{R}^n$. A vector $d \in \mathbb{R}^n$ is said to be an **improving direction** if $c^\top d < 0$.

Notes:

Constructing Feasible Search Directions

- Consider a BFS \hat{x} , so that $\hat{x}_N = 0$.
- Any feasible direction must increase the value of at least one of the nonbasic variables (why?).
- We will consider moving in *basic directions* that increase the value of exactly one of the nonbasic variables, say variable j . This means

- In order to remain feasible, we must also have $Ad = 0$ (why?), which means

Constructing Improving Search Directions

- Now we know how to construct feasible search directions—how do we ensure they are improving?
- Recall that we must have $c^\top d < 0$.

Definition 3. Let \hat{x} be a basic solution, let B be an associated basis matrix, and let c_B be the vector of costs of the basic variables. For each j , we define the **reduced cost** \bar{c}_j of variable j by

$$\bar{c}_j = c_j - c_B^\top B^{-1} A_j.$$

- The basic direction associated with variable j is **improving** if and only if $\bar{c}_j < 0$.
- Note that all basic variables have a reduced cost of 0 (why?).

Optimality Conditions

Theorem 1. Consider a basic feasible solution \hat{x} associated with a basis matrix B and let \bar{c} be the corresponding vector of reduced costs.

- If $\bar{c} \geq 0$, then \hat{x} is *optimal*.
- If \hat{x} is optimal and nondegenerate, then $\bar{c} \geq 0$.

Notes:

Optimal Bases

Definition 4. A basis matrix B is said to **optimal** is

- $B^{-1}b \geq 0$, and
- $\bar{c} \geq 0$.

Notes:

An Algorithm for Linear Programming

We will develop the following basic algorithm for linear programming:

1. Find an **initial BFS**.
2. Compute the **reduced costs**.
3. Determine an **improving feasible direction d** .
4. Move as far as possible in direction d to a new BFS.
5. If the new BFS is not **optimal**, then repeat.

The Step Length

- For now, we will assume that we can find an initial BFS (Step 1).
 - We will also assume nondegeneracy.
 - We have already seen how to compute the reduced costs and find an improving feasible direction (Steps 2 and 3).
 - The distance we move in the computed direction is the *step length*.
 - We want to move as far as possible, so the step length is
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- What determines the step length?

Determining the Step Length

- If $d \geq 0$, then the step length is ∞ and the linear program is unbounded.
 - if $d_i < 0$, then $\hat{x}_i + \theta d_i \geq 0 \Rightarrow \theta \leq -\frac{\hat{x}_i}{d_i}$.
 - Therefore, we can compute the step length explicitly as
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- Note that we need only consider the **basic variables** in this computation.

Determining the Next Solution

- Once we have θ^* , the new feasible solution is $\hat{x} + \theta^*d$. Is this a BFS?
 - One variable that was nonbasic now has positive value (the *entering variable*).
 - One (at least) variable that was basic now has value 0 (the *leaving variable*).
 - If j is the entering variable and i is the leaving variable, define the new set of basic variables by
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- Is the corresponding matrix \bar{B} a basis matrix?

Determining the Next Basis

Theorem 2.

- The columns $A_{\bar{B}(i)}$ for $i \in [1..m]$ are linearly independent and hence \bar{B} does form a basis matrix.
- The vector $\hat{x} + \theta^*d$ is the BFS corresponding to \bar{B} .

Notes:

The Simplex Method

A typical iteration of the simplex method:

1. Start with a specified basis matrix B and a corresponding BFS x^0 .
2. Compute the reduced cost vector \bar{c} . If $\bar{c} \geq 0$, then x^0 is optimal.
3. Otherwise, choose j for which $\bar{c}_j < 0$.
4. Compute $u = B^{-1}A_j$. If $u \leq 0$, then $\theta^* = \infty$ and the LP is unbounded.
5. Otherwise, $\theta^* = \min_{\{i=1, \dots, m: u_i > 0\}} \frac{x_{B(i)}^0}{u_i}$.
6. Choose l such that $\theta^* = \frac{x_{B(l)}^0}{u_l}$ and form a new basis, replacing $A_{B(l)}$ with A_j . The values of the new basic variables are $x_j^1 = \theta^*$ and $x_{B(i)}^1 = x_{B(i)}^0 - \theta^* u_i$ if $i \neq l$.