ORF522 – Linear and Nonlinear Optimization

4. The simplex method
• Problem sizes in different formulations. What is m?

• Vector x is a basic solution if and only if there exists m columns of A being linearly independent. I'm just wondering what if there aren't m independent columns, what does it mean? Also, what does it mean if there're multiple sets of independent columns. Does it have any geometric meaning, like any relationship with the extreme points in polyhedron?
Recap
Equivalence

Theorem

Given a nonempty polyhedron $P = \{x \mid Ax \leq b\}$

Let $x \in P$

$x$ is a vertex $\iff$ $x$ is an extreme point $\iff$ $x$ is a basic feasible solution
Basic feasible solution

\[ P = \{ x \mid a_i^T x \leq b_i, \quad i = 1, \ldots, m \} \]
Basic feasible solution

\[ P = \{ x \mid a_i^T x \leq b_i, \quad i = 1, \ldots, m \} \]

Active constraints at \( \bar{x} \)

\[ \mathcal{I}(\bar{x}) = \{ i \in \{1, \ldots, m\} \mid a_i^T \bar{x} = b_i \} \]

Index of all the constraints satisfied as equality
Basic feasible solution

\[ P = \{ x \mid a_i^T x \leq b_i, \quad i = 1, \ldots, m \} \]

**Active constraints at** \( \bar{x} \)

\[ \mathcal{I}(\bar{x}) = \{ i \in \{1, \ldots, m\} \mid a_i^T \bar{x} = b_i \} \]

Index of all the constraints satisfied as **equality**

**Basic solution** \( \bar{x} \)

- \( \{ a_i \mid i \in \mathcal{I}(\bar{x}) \} \) has \( n \) linearly independent vectors
Basic feasible solution

\[ P = \{ x \mid a_i^T x \leq b_i, \quad i = 1, \ldots, m \} \]

**Active constraints at \( \bar{x} \)**

\[ \mathcal{I}(\bar{x}) = \{ i \in \{1, \ldots, m\} \mid a_i^T \bar{x} = b_i \} \]

**Index of all the constraints satisfied as equality**

**Basic solution \( \bar{x} \)**

- \( \{ a_i \mid i \in \mathcal{I}(\bar{x}) \} \) has \( n \) linearly independent vectors

**Basic feasible solution \( \bar{x} \)**

- \( \bar{x} \in P \)
- \( \{ a_i \mid i \in \mathcal{I}(\bar{x}) \} \) has \( n \) linearly independent vectors
Standard form polyhedra

Definition

Standard form LP

\[
\begin{align*}
\text{minimize} & \quad c^T x \\
\text{subject to} & \quad Ax = b \\
& \quad x \geq 0
\end{align*}
\]

Assumption

\[ A \in \mathbb{R}^{m \times n} \text{ has full row rank } m \leq n \]

Interpretation

\[ P \text{ lives in } (n - m)\text{-dimensional subspace} \]
Basic solutions
Standard form polyhedra

\[ P = \{ x \mid Ax = b, \ x \geq 0 \} \]

with \( A \in \mathbb{R}^{m \times n} \) has full row rank \( m \leq n \)

\( x \) is a **basic solution** if and only if

- \( Ax = b \)
- There exist indices \( B(1), \ldots, B(m) \) such that
  - columns \( A_{B(1)}, \ldots, A_{B(m)} \) are linearly independent
  - \( x_i = 0 \) for \( i \neq B(1), \ldots, B(m) \)

\( x \) is a **basic feasible solution** if \( x \) is a **basic solution** and \( x \geq 0 \)
From geometry to standard form

minimize $c^T x$
subject to $Ax \leq b$
From geometry to standard form

minimize \[ c^T (x^+ - x^-) \]

subject to \[ Ax \leq b \]

subject to

\[
\begin{bmatrix}
A & -A & I
\end{bmatrix}
\begin{bmatrix}
x^+ \\
x^-
\end{bmatrix} = b
\]

\[(x^+, x^-, s) \geq 0\]
From geometry to standard form

minimize \( c^T(x^+ - x^-) \)
subject to \( Ax \leq b \)

Variables: \( \tilde{n} = 2n + m \)
(Equality) constraints: \( \tilde{m} = m \implies \text{active} \)
From geometry to standard form

minimize \( c^T(x^+ - x^-) \)

subject to \( Ax \leq b \)

\[
\begin{bmatrix}
A & -A & I
\end{bmatrix}
\begin{bmatrix}
x^+
\newline
x^-
s
\end{bmatrix} = b
\]

\((x^+, x^-, s) \geq 0\)

Variables: \( \tilde{n} = 2n + m \)

(Equality) constraints: \( \tilde{m} = m \implies \text{active} \)

For a basic solution \( \implies \) We need \( \tilde{n} - \tilde{m} = 2n \)

active inequalities \( \Rightarrow \tilde{x}_i = 0 \) (non basic)
From geometry to standard form

minimize \( c^T(x^+ - x^-) \)
subject to \( Ax \leq b \)

minimize \( c^T x \)
subject to \( Ax \leq b \)

\[ \begin{bmatrix} A & -A & I \end{bmatrix} \begin{bmatrix} x^+ \\ x^- \\ s \end{bmatrix} = b \]

\( (x^+, x^-, s) \geq 0 \)

Variables: \( \tilde{n} = 2n + m \)
(Equality) constraints: \( \tilde{m} = m \implies \text{active} \)

For a basic solution \( \implies \) We need \( \tilde{n} - \tilde{m} = 2n \)
active inequalities \( \Rightarrow \tilde{x}_i = 0 \) (non basic)

Which corresponds to \( m \) inequalities inactive \( \Rightarrow \tilde{x}_i > 0 \) (basic)
From geometry to standard form

minimize \( c^T (x^+ - x^-) \)
subject to \(Ax \leq b\)

\[
\begin{bmatrix}
A & -A & I
\end{bmatrix}
\begin{bmatrix}
x^+
-x^-
s
\end{bmatrix} = b
\]

\( (x^+, x^-, s) \geq 0 \)

Variables: \( \tilde{n} = 2n + m \)
(Equality) constraints: \( \tilde{m} = m \implies \text{active} \)

For a basic solution \( \implies \) We need \( \tilde{n} - \tilde{m} = 2n \)
active inequalities \( \Rightarrow \) \( \tilde{x}_i = 0 \) (non basic)

Which corresponds to \( m \) inequalities inactive \( \Rightarrow \) \( \tilde{x}_i > 0 \) (basic)

Formal proof at Theorem 2.4 LO book
Constructing basic solution

1. Choose any $m$ independent columns of $A$: $A_{B(1)}, \ldots, A_{B(m)}$
2. Let $x_i = 0$ for all $i \neq B(1), \ldots, B(m)$
3. Solve $Ax = b$ for the remaining $x_{B(1)}, \ldots, x_{B(m)}$
Constructing basic solution

1. Choose any \( m \) independent columns of \( A \): \( A_{B(1)}, \ldots, A_{B(m)} \)
2. Let \( x_i = 0 \) for all \( i \neq B(1), \ldots, B(m) \)
3. Solve \( Ax = b \) for the remaining \( x_{B(1)}, \ldots, x_{B(m)} \)

\[
\text{Basis matrix } A_B = \begin{bmatrix}
A_{B(1)} & A_{B(2)} & \cdots & A_{B(m)}
\end{bmatrix},
\text{Basis columns } x_B = \begin{bmatrix} x_{B(1)} \\ \vdots \\ x_{B(m)} \end{bmatrix},
\text{Basic variables}
\]

\[
\text{Solve } A_B x_B = b
\]
Constructing basic solution

1. Choose any \( m \) independent columns of \( A: A_{B(1)}, \ldots, A_{B(m)} \)
2. Let \( x_i = 0 \) for all \( i \neq B(1), \ldots, B(m) \)
3. Solve \( A x = b \) for the remaining \( x_{B(1)}, \ldots, x_{B(m)} \)

\[
\begin{align*}
\text{Basis matrix} & \quad \text{Basis columns} & \quad \text{Basic variables} \\
A_B & = \begin{bmatrix} A_{B(1)} & A_{B(2)} & \cdots & A_{B(m)} \end{bmatrix}, & x_B & = \begin{bmatrix} x_{B(1)} \\ \vdots \\ x_{B(m)} \end{bmatrix} & \longrightarrow & \text{Solve } A_B x_B = b
\end{align*}
\]

If \( x_B \geq 0 \), then \( x \) is a basic feasible solution
Optimality of extreme points

minimize \( c^T x \)
subject to \( Ax \leq b \)

If
- \( P \) has at least one extreme point
- There exists an optimal solution \( x^* \)

Then, there exists an optimal solution which is an extreme point of \( P \)

We only need to search between extreme points
Conceptual algorithm

- Start at corner
- Visit neighboring corner that improves the objective
Today’s agenda
Readings: [Chapter 3, LO]

Simplex method
- Iterate between neighboring basic solutions
- Optimality conditions
- Simplex iterations
The simplex method
Top 10 algorithms of the 20th century

1946: Metropolis algorithm
1947: Simplex method
1950: Krylov subspace method
1951: The decompositional approach to matrix computations
1957: The Fortran optimizing compiler
1959: QR algorithm
1962: Quicksort
1965: Fast Fourier transform
1977: Integer relation detection
1987: Fast multipole method
The simplex method
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1962: Quicksort
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1977: Integer relation detection
1987: Fast multipole method

[SIAM News (2000)]
Neighboring basic solutions
Neighboring solutions

Two basic solutions are **neighboring** if their basic indices differ by exactly one variable.
Neighboring solutions

Two basic solutions are neighboring if their basic indices differ by exactly one variable.

Example

\[
\begin{bmatrix}
1 & -1 & 0 & 3 & -2 \\
2 & 0 & -1 & -1 & 0 \\
0 & 2 & 4 & -1 & 4 \\
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4 \\
x_5 \\
\end{bmatrix}
= 
\begin{bmatrix}
b_1 \\
b_2 \\
b_3 \\
\end{bmatrix}
\]

\begin{bmatrix}
-5 \\
-1 \\
14 \\
\end{bmatrix}
Neighboring solutions

Two basic solutions are neighboring if their basic indices differ by exactly one variable.

Example

\[
A = \begin{bmatrix}
1 & -1 & 0 & 3 & -2 \\
2 & 0 & -1 & -1 & 0 \\
0 & 2 & 4 & -1 & 4 \\
\end{bmatrix}
\]

\[
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4 \\
x_5 \\
\end{bmatrix} = \begin{bmatrix}
b \\
-5 \\
-1 \\
14 \\
\end{bmatrix}
\]

\[
B = \{1, 3, 5\} \quad x_2 = x_4 = 0
\]

\[
A_B x_B = b \quad \rightarrow \quad x_B = \begin{bmatrix}
x_1 \\
x_3 \\
x_5 \\
\end{bmatrix} = \begin{bmatrix}
0 \\
1 \\
2.5 \\
\end{bmatrix}
\]
Neighboring solutions

Two basic solutions are **neighboring** if their basic indices differ by exactly one variable.

### Example

\[
A = \begin{bmatrix}
1 & -1 & 0 & 3 & -2 \\
2 & 0 & -1 & -1 & 0 \\
0 & 2 & 4 & -1 & 4 \\
\end{bmatrix},
\quad x = \begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4 \\
x_5 \\
\end{bmatrix},
\quad b = \begin{bmatrix}
-5 \\
-1 \\
14 \\
\end{bmatrix}
\]

\[
B = \{1, 3, 5\} \quad x_2 = x_4 = 0
\]

\[
A_B x_B = b \quad x_B = \begin{bmatrix}
x_1 \\
x_3 \\
x_5 \\
\end{bmatrix} = \begin{bmatrix}
0 \\
1 \\
2.5 \\
\end{bmatrix}
\]

\[
\overline{B} = \{1, 3, 4\} \quad y_2 = y_5 = 0
\]

\[
A_{\overline{B}} y_{\overline{B}} = b \quad y_{\overline{B}} = \begin{bmatrix}
y_1 \\
y_3 \\
y_4 \\
\end{bmatrix} = \begin{bmatrix}
0.1 \\
3.0 \\
-1.7 \\
\end{bmatrix}
\]
Feasible directions

Conditions

\[ P = \{ x \mid Ax = b, \ x \geq 0 \} \]

Given a basis matrix \( A_B = \begin{bmatrix} A_B(1) & \ldots & A_B(m) \end{bmatrix} \)

we have basic feasible solution \( x \):

- \( x_B \) solves \( A_B x_B = b \)
- \( x_i = 0, \ \forall i \neq B(1), \ldots, B(m) \) 

& \( x > 0 \)
Feasible directions

Conditions

\[ P = \{ x \mid Ax = b, \ x \geq 0 \} \]

Given a basis matrix \( A_B = \begin{bmatrix} A_B(1) & \cdots & A_B(m) \end{bmatrix} \)
we have basic feasible solution \( x \):

- \( x_B \) solves \( A_B x_B = b \)
- \( x_i = 0, \ \forall i \neq B(1), \ldots, B(m) \)

Let \( x \in P \), a vector \( d \) is a feasible direction at \( x \) if \( \exists \theta > 0 \) for which \( x + \theta d \in P \)

Feasible direction \( d \)

- \( A(x + \theta d) = b \implies Ad = 0 \)
- \( x + \theta d \geq 0 \)
Feasible directions
Computation

Nonbasic indices \((x_i \approx 0)\)
- \(d_j = 1\)  \(\rightarrow\) Basic direction
- \(d_k = 0, \forall k \notin \{j, B(1), \ldots, B(m)\}\)

Feasible direction \(d\)
- \(A(x + \theta d) = b \implies Ad = 0\)
- \(x + \theta d \geq 0\)
Feasible directions

Computation

Nonbasic indices
• \( d_j = 1 \)
• \( d_k = 0, \forall k \notin \{j, B(1), \ldots, B(m)\} \)

Basic indices
\[
Ad = 0 = \sum_{i=1}^{n} A_i d_i = A_B d_B + A_j = 0 \implies d_B = -A_B^{-1} A_j
\]

Feasible direction \( d \)
• \( A(x + \theta d) = b \implies Ad = 0 \)
• \( x + \theta d \geq 0 \)

\( d_N = (0, \ldots, 0, 1, \ldots, 0) \)
Feasible directions

Computation

Nonbasic indices

- $d_j = 1$  \quad \rightarrow \quad \text{Basic direction}
- $d_k = 0$, $\forall k \notin \{j, B(1), \ldots, B(m)\}$

Basic indices

$$Ad = 0 = \sum_{i=1}^{n} A_i d_i = A_B d_B + A_j = 0 \implies d_B = -A_B^{-1} A_j$$

Non-negativity (non-degenerate assumption)

- Non-basic variables: $x_i = 0$. Nonnegative direction $d_i \geq 0$
- Basic variables: $x_B > 0$. Therefore $\exists \theta > 0$ such that $x_B + \theta d_B \geq 0$
Feasible directions

Example

\[ P = \{ x \mid x_1 + x_2 + x_3 = 2, \ x \geq 0 \} \]

\[ x = (2, 0, 0) \quad B = \{1\} \]
Feasible directions

Example

\[ P = \{ x \mid x_1 + x_2 + x_3 = 2, \quad x \geq 0 \} \]

\[ x = (2, 0, 0) \quad B = \{1\} \]

Nonbasic index \( j = 3 \) \( \rightarrow \) \( d = (-1, 0, 1) \)

\[ A_B d_B = -A_j \quad \Rightarrow \quad d_j = 1 \quad d_B = -1 \]
How does the cost change?

Cost improvement

\[ c^T (x + \theta d) - c^T x = \theta c^T d \]
How does the cost change?

Cost improvement

\[ c^T (x + \theta d) - c^T x = \theta c^T d \]

New cost
How does the cost change?

Cost improvement

\[ c^T (x + \theta d) - c^T x = \theta c^T d \]

New cost \quad Old cost
How does the cost change?

Cost improvement

\[ c^T(x + \theta d) - c^T x = \theta c^T d \]

New cost  \quad Old cost

We call \( \bar{c}_j \) the **reduced cost** of (introducing) variable \( x_j \) in the basis

\[ \bar{c}_j = c^T d = \sum_{i=1}^{n} c_i d_i = c_j + c_B^T d_B = c_j - c_B^T A_B^{-1} A_j \]
Reduced costs

Interpretation
Change in objective/marginal cost of adding $x_j$ to the basis

$$\bar{c}_j = c_j - c_B^T A_B^{-1} A_j$$

- $\bar{c}_j > 0$: adding $x_j$ will increase the objective (bad)
- $\bar{c}_j < 0$: adding $x_j$ will decrease the objective (good)
Reduced costs

Interpretation
Change in objective/marginal cost of adding $x_j$ to the basis

$$\bar{c}_j = c_j - c_B^T A_B^{-1} A_j$$

Cost per-unit increase of variable $x_j$

- $\bar{c}_j > 0$: adding $x_j$ will increase the objective (bad)
- $\bar{c}_j < 0$: adding $x_j$ will decrease the objective (good)
Reduced costs

Interpretation
Change in objective/marginal cost of adding $x_j$ to the basis

\[ \bar{c}_j = c_j - c_B^T A_B^{-1} A_j \]

Cost per-unit increase of variable $x_j$

- $\bar{c}_j > 0$: adding $x_j$ will increase the objective (bad)
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Cost to change other variables compensating for $x_j$ to enforce $Ax = b$
Reduced costs

Interpretation
Change in objective/marginal cost of adding $x_j$ to the basis

$$
\bar{c}_j = c_j - c_B^T A_B^{-1} A_j
$$

Cost per-unit increase of variable $x_j$

Cost to change other variables compensating for $x_j$ to enforce $Ax = b$

- $\bar{c}_j > 0$: adding $x_j$ will increase the objective (bad)
- $\bar{c}_j < 0$: adding $x_j$ will decrease the objective (good)

Reduced costs for basic variables is 0

$$
\bar{c}_B(i) = c_B(i) - c_B^T A_B^{-1} A_B(i) = c_B(i) - c_B^T (A_B^{-1} A_B)e_i = c_B(i) - c_B(i) = 0
$$
Vector of reduced costs

Reduced costs

\[ \bar{c}_j = c_j - c_B^T A_B^{-1} A_j \]

Full vector in one shot?

\[ \bar{c} = (\bar{c}_1, \ldots, \bar{c}_n) \]
Vector of reduced costs

\[ \bar{c}_j = c_j - c_B^T A_B^{-1} A_j \]

Isolate basis \( B \)-related components \( p \)

(they are the same across \( j \))

\[ \bar{c}_j = c_j - A_j^T (A_B^{-1})^T c_B = c_j - A_j^T p \]

Full vector in one shot?

\[ \bar{c} = (\bar{c}_1, \ldots, \bar{c}_n) \]
Vector of reduced costs

Reduced costs
\[ \tilde{c}_j = c_j - c_B^T A_B^{-1} A_j \]

Isolate basis \( B \)-related components \( p \)
(they are the same across \( j \))
\[ \tilde{c}_j = c_j - A_j^T (A_B^{-1})^T c_B = c_j - A_j^T p \]

Full vector in one shot?
\[ \tilde{c} = (\tilde{c}_1, \ldots, \tilde{c}_n) \]

Obtain \( p \) by solving linear system
\[ p = (A_B^{-1})^T c_B \quad \Rightarrow \quad A_B^T p = c_B \]

Note: \((M^{-1})^T = (M^T)^{-1}\)
for any square invertible \( M \)
Vector of reduced costs

Reduced costs
\[ \vec{c}_j = c_j - c_B A_B^{-1} A_j \]

Isolate basis \( B \)-related components \( p \)
(they are the same across \( j \))
\[ \vec{c}_j = c_j - A_j^T (A_B^{-1})^T c_B = c_j - A_j^T p \]

Full vector in one shot?
\[ \vec{c} = (\vec{c}_1, \ldots, \vec{c}_n) \]

Obtain \( p \) by solving linear system
\[ p = (A_B^{-1})^T c_B \quad \Rightarrow \quad A_B^T p = c_B \]

Note: \((M^{-1})^T = (M^T)^{-1}\)
for any square invertible \( M \)

Computing reduced cost vector

1. Solve \( A_B^T p = c_B \)
2. \( \vec{c} = c - A^T p \)
Optimality conditions
Optimality conditions

Theorem

Let $x$ be a basic feasible solution associated with basis matrix $A_B$
Let $\bar{c}$ be the vector of reduced costs.

If $\bar{c} \geq 0$, then $x$ is optimal
Optimality conditions

Theorem

Let $x$ be a basic feasible solution associated with basis matrix $A_B$
Let $\bar{c}$ be the vector of reduced costs.

If $\bar{c} \geq 0$, then $x$ is optimal

Remark

This is a **stopping criterion** for the simplex algorithm.
If the **neighboring solutions** do not improve the cost, we are done (because of convexity).
Optimality conditions

Proof

For a basic feasible solution $x$ with basis $B$ the reduced costs are $\bar{c} \geq 0$. 
Optimality conditions

Proof

For a basic feasible solution $x$ with basis $B$ the reduced costs are $\bar{c} \geq 0$. Consider any feasible solution $y$ and define $d = y - x$. 
Optimality conditions

Proof

For a basic feasible solution $x$ with basis $B$ the reduced costs are $\bar{c} \geq 0$. Consider any feasible solution $y$ and define $d = y - x$

Since $x$ and $y$ are feasible, then $Ax = Ay = b$ and $Ad = 0$

$$Ad = A_B d_B + \sum_{i \in N} A_i d_i = 0 \quad \Rightarrow \quad d_B = -\sum_{i \in N} A_B^{-1} A_i d_i$$

$N$ are the nonbasic indices
Optimality conditions

Proof

For a basic feasible solution $x$ with basis $B$ the reduced costs are $\bar{c} \geq 0$. Consider any feasible solution $y$ and define $d = y - x$

Since $x$ and $y$ are feasible, then $Ax = Ay = b$ and $Ad = 0$

$$Ad = A_B d_B + \sum_{i \in N} A_i d_i = 0 \quad \Rightarrow \quad d_B = - \sum_{i \in N} A_B^{-1} A_i d_i$$

The change in objective is

$$c^T d = c_B^T d_B + \sum_{i \in N} c_i d_i = \sum_{i \in N} (c_i - c_B^T A_B^{-1} A_i) d_i = \sum_{i \in N} \bar{c}_i d_i$$

$N$ are the nonbasic indices
Optimality conditions

Proof

For a basic feasible solution $x$ with basis $B$ the reduced costs are $\bar{c} \geq 0$. Consider any feasible solution $y$ and define $d = y - x$

Since $x$ and $y$ are feasible, then $Ax = Ay = b$ and $Ad = 0$

$$Ad = A_Bd_B + \sum_{i \in N} A_i d_i = 0 \quad \Rightarrow \quad d_B = -\sum_{i \in N} A_B^{-1} A_i d_i$$

The change in objective is

$$c^T d = c_B^T d_B + \sum_{i \in N} c_i d_i = \sum_{i \in N} (c_i - c_B^T A_B^{-1} A_i) d_i = \sum_{i \in N} \bar{c}_i d_i$$

Since $y \geq 0$ and $x_i = 0$, $i \in N$, then $d_i = y_i - x_i \geq 0$, $i \in N$

$$c^T d = c^T (y - x) \geq 0 \quad \Rightarrow \quad c^T y \geq c^T x.$$
Simplex iterations
Stepsize

What happens if some $\bar{c}_j < 0$?
We can decrease the cost by bringing $x_j$ into the basis.
Stepsize

What happens if some $\bar{c}_j < 0$?
We can decrease the cost by bringing $x_j$ into the basis

How far can we go?

$$\theta^* = \max\{\theta \mid \theta \geq 0 \text{ and } x + \theta d \geq 0\}$$

$d$ is the $j$-th basic direction
**Stepsize**

What happens if some $c_j < 0$?
We can decrease the cost by bringing $x_j$ into the basis

**How far can we go?**

$$\theta^* = \max\{\theta \mid \theta \geq 0 \text{ and } x + \theta d \geq 0\}$$

$d$ is the $j$-th basic direction

**Unbounded**

If $d \geq 0$, then $\theta^* = \infty$. The LP is unbounded.
Stepsize

What happens if some $c_j < 0$?
We can decrease the cost by bringing $x_j$ into the basis

How far can we go?

$$\theta^* = \max\{\theta \mid \theta \geq 0 \text{ and } x + \theta d \geq 0\}$$

$d$ is the $j$-th basic direction

Unbounded
If $d \geq 0$, then $\theta^* = \infty$. The LP is unbounded.

Bounded
If $d_i < 0$ for some $i$, then

$$\theta^* = \min_{\{i \mid d_i < 0\}} \left( -\frac{x_i}{d_i} \right) = \min_{i \in B \mid d_i < 0} \left( -\frac{x_i}{d_i} \right)$$

(Since $d_i \geq 0$, $i \notin B$)
Moving to a new basis

Next feasible solution

\[ x + \theta^* d \]
Moving to a new basis

Next feasible solution

\[ x + \theta^* d \]

Let \( B(\ell) \in \{ B(1), \ldots, B(m) \} \) be the index such that \( \theta^* = -\frac{x_{B(\ell)}}{d_{B(\ell)}} \). Then,

\[ x_{B(\ell)} + \theta^* d_{B(\ell)} = 0 \]
Moving to a new basis

Next feasible solution

\[ x + \theta^* d \]

Let \( B(\ell) \in \{B(1), \ldots, B(m)\} \) be the index such that \( \theta^* = -\frac{x_{B(\ell)}}{d_{B(\ell)}} \). Then,

\[ x_{B(\ell)} + \theta^* d_{B(\ell)} = 0 \]

New solution

- \( x_{B(\ell)} \) becomes 0 (exits)
- \( x_j \) becomes \( \theta^* \) (enters)
Moving to a new basis

Next feasible solution

\[ x + \theta^* d \]

Let \( B(\ell) \in \{B(1), \ldots, B(m)\} \) be the index such that \( \theta^* = -\frac{x_{B(\ell)}}{d_{B(\ell)}} \). Then,

\[ x_{B(\ell)} + \theta^* d_{B(\ell)} = 0 \]

New solution

- \( x_{B(\ell)} \) becomes 0 (exits)
- \( x_j \) becomes \( \theta^* \) (enters)

New basis

\[ A_{\tilde{B}} = \begin{bmatrix} A_{B(1)} & \cdots & A_{B(\ell-1)} & A_j & A_{B(\ell+1)} & \cdots & A_{B(m)} \end{bmatrix} \]
An iteration of the simplex method

First part

We start with

- a basic feasible solution \( x \)
- a basis matrix \( A_B = \begin{bmatrix} A_B(1) & \ldots & A_B(m) \end{bmatrix} \)

1. Compute the reduced costs \( \bar{c} \)
   - Solve \( A_B^T p = c_B \)
   - \( \bar{c} = c - A_B^T p \)

2. If \( \bar{c} \geq 0 \), \( x \) optimal. break

3. Choose \( j \) such that \( \bar{c}_j < 0 \)
An iteration of the simplex method
Second part

4. Compute search direction $d$ with $d_j = 1$ and $A_Bd_B = -A_j$

5. If $d_B \geq 0$, the problem is **unbounded** and the optimal value is $-\infty$. **break**

6. Compute step length $\theta^* = \min_{\{i \in B | d_i < 0\}} \left(-\frac{x_i}{d_i}\right)$

7. Define $y$ such that $y = x + \theta^*d$

8. Get new basis $\bar{B}$ ($i$ exits and $j$ enters)
Example

\[ P = \{x \mid x_1 + x_2 + x_3 = 2, \quad x \geq 0\} \]

\[ x = (2, 0, 0) \quad B = \{1\} \]

Basic index \( j = 3 \quad \rightarrow \quad d = (-1, 0, 1) \]
\[ d_j = 1 \]
\[ A_Bd_B = -A_j \quad \Rightarrow \quad d_B = -1 \]
Example

\[ P = \{ x \mid x_1 + x_2 + x_3 = 2, \quad x \geq 0 \} \]

\[ x = (2, 0, 0) \quad B = \{1\} \]

**Basic index**  \( j = 3 \quad \longrightarrow \quad d = (-1, 0, 1) \]
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**Stepsiz**e  \( \theta^* = -\frac{x_1}{d_1} = 2 \)
Example

\[ P = \{ x \mid x_1 + x_2 + x_3 = 2, \ x \geq 0 \} \]

\[ x = (2, 0, 0) \quad B = \{1\} \]

**Basic index** \( j = 3 \)

\[ d = (-1, 0, 1) \quad \]

\[ d_j = 1 \]

\[ A_B d_B = -A_j \quad \Rightarrow \quad d_B = -1 \]

**Stepsize** \( \theta^* = -\frac{x_1}{d_1} = 2 \)

**New solution** \( y = x + \theta^* d = (0, 0, 2) \quad \bar{B} = \{3\} \)
Finite convergence

Assume that

- \( P = \{ x \mid Ax = b, x \geq 0 \} \) not empty
- Every basic feasible solution non degenerate
Finite convergence

Assume that

\[ P = \{ x \mid Ax = b, x \geq 0 \} \text{ not empty} \]
\[ \text{Every basic feasible solution non degenerate} \]

Then

\[ \text{The simplex method terminates after a finite number of iterations} \]
\[ \text{At termination we either have one of the following} \]

\[ \text{an optimal basis } B \]
\[ \text{a direction } d \text{ such that } Ad = 0, \quad d \geq 0, \quad c^T d < 0 \text{ and the optimal cost is } -\infty \]
Finite convergence
Proof sketch

At each iteration the algorithm improves
• by a **positive** amount $\theta^*$
• along the **direction** $d$ such that $c^T d < 0$
Finite convergence

Proof sketch

At each iteration the algorithm improves
- by a \textbf{positive} amount $\theta^*$
- along the \textbf{direction} $d$ such that $c^T d < 0$

Therefore
- The cost strictly decreases
- No basic feasible solution can be visited twice
Finite convergence
Proof sketch

At each iteration the algorithm improves
• by a positive amount $\theta^*$
• along the direction $d$ such that $c^T d < 0$

Therefore
• The cost strictly decreases
• No basic feasible solution can be visited twice

Since there is a finite number of basic feasible solutions
The algorithm must eventually terminate
The simplex method

Today, we learned to:

• **Iterate** between basic feasible solutions
• **Verify** optimality and unboundedness conditions
• **Apply** a single iteration of the simplex method
• **Prove** finite convergence of the simplex method in the non-degenerate case
Next lecture

- Finding initial basic feasible solution
- Degeneracy
- Complexity