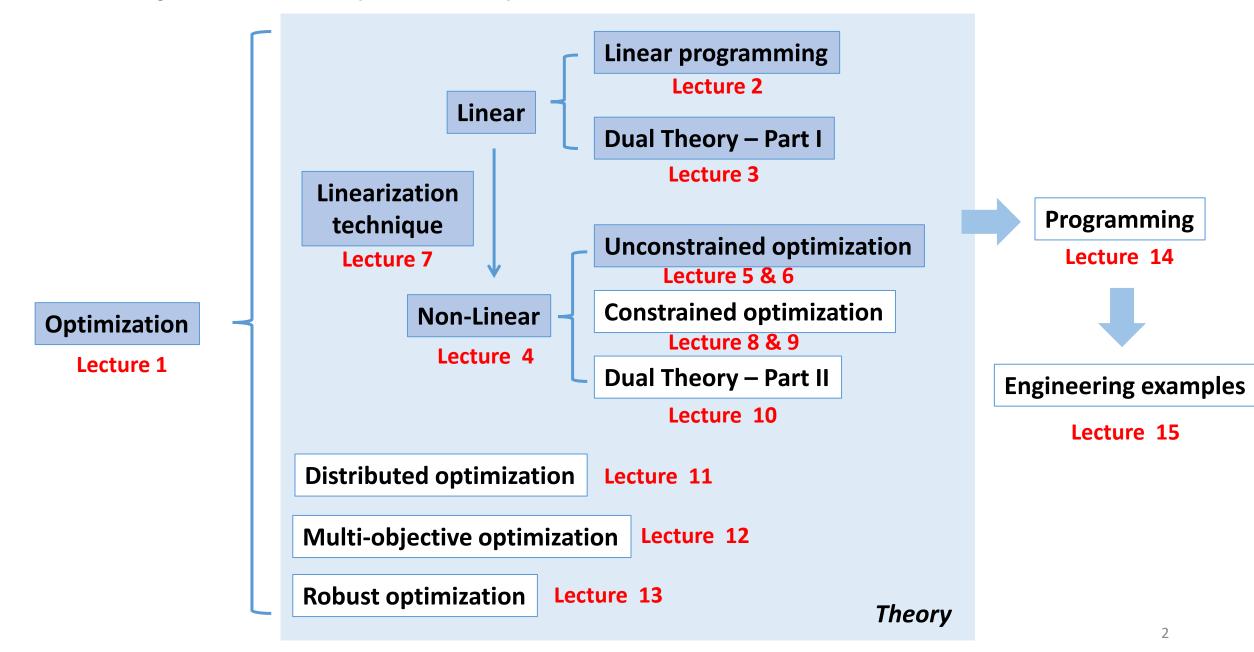
MAEG4070 Engineering Optimization

Lecture 7 Linearization Techniques

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Content of this course (tentative)



Overview

Despite the various algorithms we have learned to solve nonlinear optimization problems, they can be computationally inefficient with a growing number of variables; may only reach a local optimum.

In today's lecture, we will introduce a new kind of optimization problem – mixed integer linear programming (MILP); and try to solve the nonlinear optimization by turning it into MILPs via linearization techniques.

$$\min_{x,z} c^T x + d^T z$$
s.t. $Ax + Bz \le b$

$$x \in \mathbb{R}^n, z \in \{0, 1\}^m \text{ (or } z \in \mathbb{Z}^n)$$

Knapsack problem

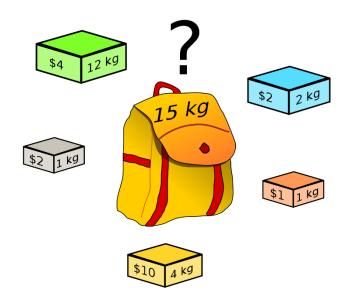
- The weight capacity of the knapsack is c
- Weight of each item is w_k , $\forall k = 1, ..., K$
- Value of each item is v_k , $\forall k = 1, ..., K$
- We aim to maximize the total value

$$\max_{x_k, \forall k=1,...,K} \sum_{k=1}^K v_k x_k$$

s.t.
$$\sum_{k=1}^K w_k x_k \le c$$

$$x_k \in \{0,1\}, \forall k=1,...,K$$

 $x_k = 1$ means item k is included $x_k = 0$ means item k is not included

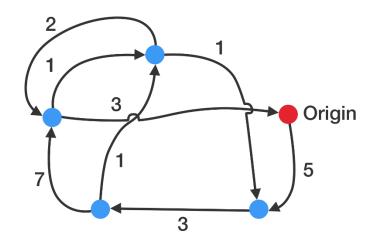


Solution:

- Try all possible situations
- Dynamic programming
- heuristic

Traveling Salesman problem

- There are *n* cities, and the salesman want to find the shortest route to visit every city once and returns to the origin.
- The distance between city i and city j is d_{ij} , and $d_{ii} = \infty$.



 $x_{ij} = 1$ if the salesman travels from city i to city j.

To ensure each city is visited only once, there is only one way in and only one way out of the city.

$$\sum_{j=1}^{n} x_{ij} = 1, \forall i = 1, ..., n$$

$$\sum_{j=1}^{n} x_{ij} = 1, \forall j = 1, ..., n$$

However..

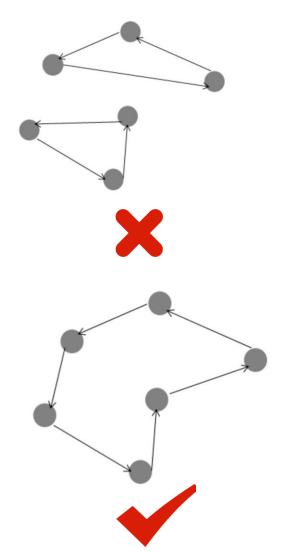
It is possible that there are loops.

To eliminate the subtours, Dantzig, Fulkerson and Johnson proposed the DFJ formulation in 1954.

$$\sum_{i,j \in S} x_{ij} \le |S| - 1, \forall S \subset \{1, ..., n\}, 1 < |S| < n$$

For example, let n = 10, $S = \{2,3,4\}$, |S| = 3The subtour elimination constraint is

$$x_{23} + x_{24} + x_{34} + x_{32} + x_{42} + x_{43} \le 2$$



The problem can be modeled as

$$\min_{x_{ij}, \forall i, j} \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} x_{ij}$$

$$\sum_{j=1}^{n} x_{ij} = 1, \forall i = 1, ..., n$$

$$\sum_{i=1}^{n} x_{ij} = 1, \forall j = 1, ..., n$$

$$\sum_{i,j \in S} x_{ij} \leq |S| - 1, \forall S \subset \{1, ..., n\}, 1 < |S| < n$$

$$x_{ij} \in \{0, 1\}, \forall i, j$$

Another formulation

$$\min_{x_{ij}, \forall i, j} \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} x_{ij}$$

$$\sum_{j=1}^{n} x_{ij} = 1, \forall i = 1, ..., n$$

$$\sum_{i=1}^{n} x_{ij} = 1, \forall j = 1, ..., n$$

$$u_i - u_j + n x_{ij} \le n - 1, 1 < i \ne j \le n$$

$$x_{ij} \in \{0, 1\}, \forall i, j, u_i \in \mathbb{R}$$

 $x_{ij} = 1$ if the salesman travels from city i to city j.

Solution Methods

To solve the MILP, we can

- Enumeration
 - ✓ The number of feasible solutions are finite
 - ✓ High computational burden under high dimension
- Relaxation and rounding
- Branch and bound
 - ✓ Relax integrality requirement
 - ✓ Enumeration on non-integer solutions
 - ✓ Cut branches without an optimal solution
 - ✓ Used by solvers: CPLEX, Gurobi

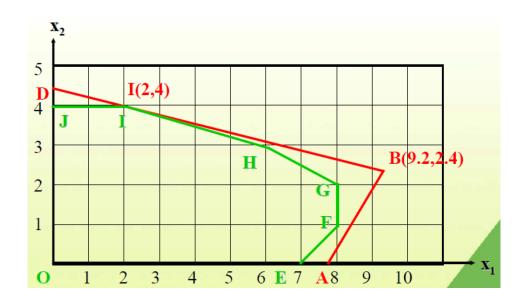
Solution Methods

We compare the performance of different methods using the following example. Let's consider the optimization:

$$\max_{x_1, x_2} 3x_1 + 13x_2$$
s.t. $2x_1 + 9x_2 \le 40$

$$11x_1 - 8x_2 \le 82$$

$$x_1, x_2 \in \mathbb{Z}_+$$



	Relaxed LP	Rounding	Nearest feasible	Exact Solution
Optimal point	(9.2, 2.4)	(9, 2)	(8, 2)	(2, 4)
Optimal value	58.8	infeasible	50	58

Minimizing a convex piecewise linear function (univariate)

$$\min_{x} f(x)$$

s.t. $x_1 \le x \le x_4$

where

$$f(x) = \begin{cases} k_1 x + b_1, & x \in [x_1, x_2] \\ k_2 x + b_2, & x \in [x_2, x_3] \\ k_3 x + b_3, & x \in [x_3, x_4] \end{cases}$$

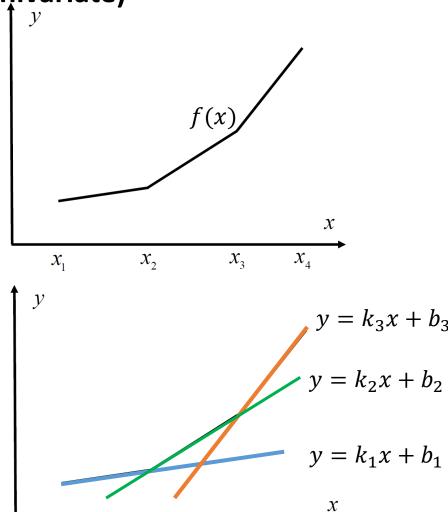


$$\min_{x,\sigma} \sigma$$
s.t. $\sigma \ge k_1 x + b_1$

$$\sigma \ge k_2 x + b_2$$

$$\sigma \ge k_3 x + b_3$$

$$x_1 < x < x_4$$



 $\mathcal{X}_{\scriptscriptstyle \Delta}$

 \mathcal{X}_3

 \mathcal{X}_2

 \mathcal{X}_{1}

Minimizing a convex piecewise linear function (univariate)

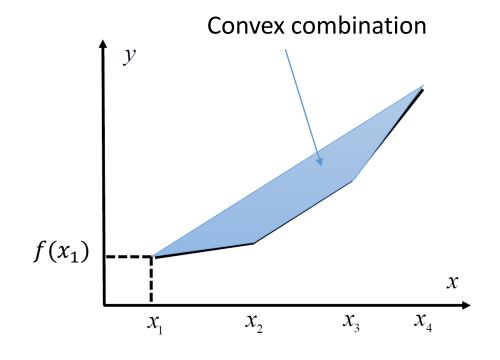
Another equivalent form

$$\min_{x,y,\lambda} y$$
s.t. $x = \sum_{n=1}^{N} \lambda_n x_n$

$$y = \sum_{n=1}^{N} \lambda_n f(x_n)$$

$$0 \le \lambda_n \le 1, \forall n = 1, ..., N$$

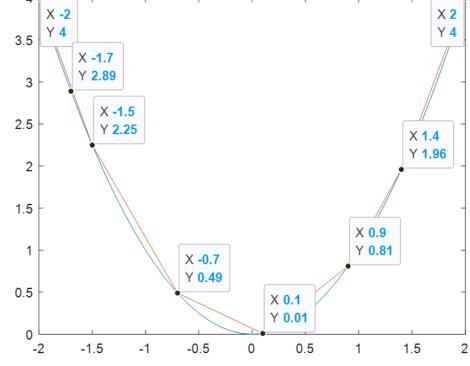
$$\sum_{n=1}^{N} \lambda_n = 1$$



Example

For the function $f(x) = x^2$ Take some sample points x = -2, -1.5, -0.7, 0.1, 0.9, 1.4, 2

We can use a piecewise linear function to approximate it, then minimizing f(x) is equivalent to



$$\min_{x,y,\sigma} y$$
s.t. $x = -2\sigma_1 - 1.5\sigma_2 - 0.7\sigma_3 + 0.1\sigma_4 + 0.9\sigma_5 + 1.4\sigma_6 + 2\sigma_7$

$$y = 4\sigma_1 + 2.25\sigma_2 + 0.49\sigma_3 + 0.01\sigma_4 + 0.81\sigma_5 + 1.96\sigma_6 + 4\sigma_7$$

$$\sigma_k \ge 0, \forall k = 1, ..., 7$$

$$\sum_{k=0}^{7} \sigma_k = 1$$

$$x^* = 0.1, y^* = 0.01$$

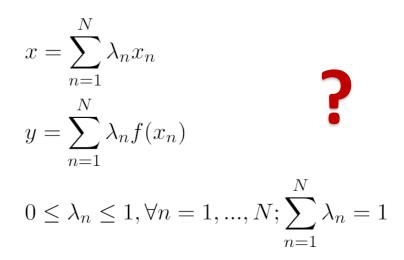
More segments, more accurate But more time-consuming

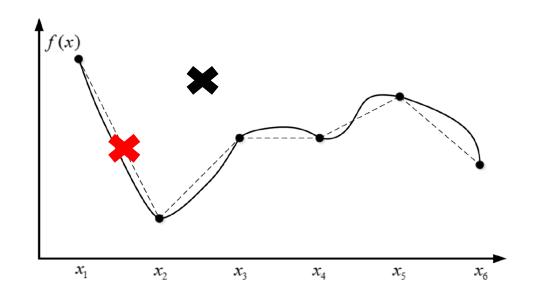
When the function appear in constraints

Representing a piecewise linear function (univariate)

We can approximate a nonlinear function by a piecewise linear function as in the Fig.

How to represent this piecewise linear function in a MILP form?





How to tackle this issue?

Representing a piecewise linear function (univariate)

Special-ordered set of Type 2 (SOS2)

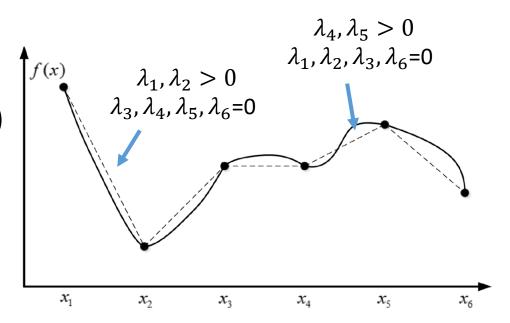
 An ordered set of non-negative variables, of which at most two consecutive elements can take strictly positive values, and the remaining ones equals to zero.

$$x = \sum_{n=1}^{N} \lambda_n x_n$$

$$y = \sum_{n=1}^{N} \lambda_n f(x_n)$$

$$0 \le \lambda_n \le 1, \forall n = 1, ..., N; \sum_{n=1}^{N} \lambda_n = 1$$

$$\lambda \text{ is S0S2}$$



$$\lambda_{1} \leq \theta_{1}
\lambda_{2} \leq \theta_{1} + \theta_{2}
\lambda_{3} \leq \theta_{2} + \theta_{3}
...
\lambda_{N-1} \leq \theta_{N-2} + \theta_{N-1}
\lambda_{N} \leq \theta_{N-1}
\lambda_{i} \geq 0, n = 1, ..., N; \sum_{n=1}^{N} \lambda_{n} = 1
\theta_{s} \in \{0, 1\}, s = 1, ..., (N-1); \sum_{n=1}^{N-1} \theta_{s} = 1$$

Example

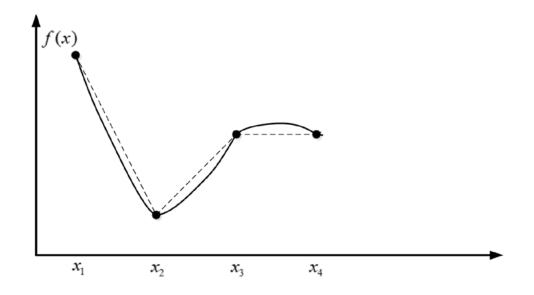
$$\lambda_{1} \leq \theta_{1}$$

$$\lambda_{2} \leq \theta_{1} + \theta_{2}$$

$$\lambda_{3} \leq \theta_{2} + \theta_{3}$$

$$\lambda_{4} \leq \theta_{3}$$

$$\theta \in \{0,1\}, \sum_{i=1}^{4} \theta_{i} = 1$$



If $\theta_1=1$, then we have $\lambda_1\leq 1, \lambda_2\leq 1, \lambda_3\leq 0, \lambda_4\leq 0$ Since $0\leq \lambda_i\leq 1$, we have $\lambda_3=0, \lambda_4=0$

$$x = x_1 \lambda_1 + x_2 \lambda_2$$
$$y = y_1 \lambda_1 + y_2 \lambda_2$$

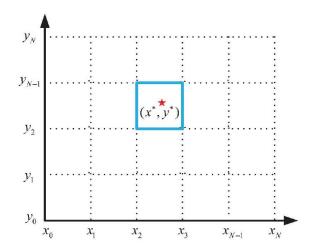
Line segment between (x_1, y_1) and (x_2, y_2)

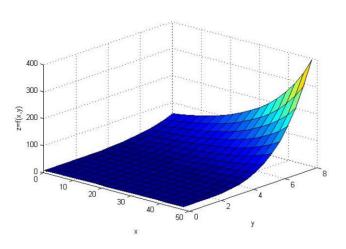
Representing a piecewise linear function (bivariate)

$$x = \sum_{m=1}^{M} \sum_{n=1}^{N} \lambda_{mn} x_n; \lambda^n = \sum_{m=1}^{M} \lambda_{mn} \text{ is S0S2}$$

$$y = \sum_{m=1}^{M} \sum_{n=1}^{N} \lambda_{mn} y_m; \lambda^m = \sum_{n=1}^{N} \lambda_{mn} \text{ is S0S2}$$

$$f(x,y) = \sum_{m=1}^{M} \sum_{n=1}^{N} \lambda_{mn} f_{mn}, \lambda_{mn} \ge 0, \forall m, \forall n; \sum_{m=1}^{M} \sum_{n=1}^{N} \lambda_{mn} = 1$$





Linearize the product of two binary variables

Consider $z = xy, x, y \in \{0,1\}$ It can be linearized by

How about
$$z = 3xy$$
?

Proof of equivalence:

1. If y = 0, then the first inequality becomes z = 0 and the second $0 \le x \le 1$. Meanwhile, we have z = xy = 0.

 $0 \le z \le y$

 $0 \le x - z \le 1 - y$

- 2. If x = 0, then we have $0 \le z \le y$ and $0 \le -z \le 1 y$, therefore, z = 0 and $0 \le y \le 1$.
- 3. If x = 1 and y = 1, then we have $0 \le z \le 1$ and $0 \le 1 z \le 0$, thus, z = 1.

Linearize the product of a binary and a continuous variable

Consider $z = xy, x \in [x_l, x_u], y \in \{0,1\}$ How about z = 3xy? It can be linearized by

$$x_l y \le z \le x_u y$$

$$x_l (1 - y) \le x - z \le x_u (1 - y)$$

Proof of equivalence:

- 1. If y = 0, then the first inequality becomes z = 0 and the second $x_l \le x \le x_u$. Meanwhile, we have z = xy = 0.
- 2. If y=1, then the second inequality becomes x=z and the first $x_l \le x=z \le x_u$. Meanwhile, we have z=xy=x.

Linearize monomial of binary variables

Consider
$$z = x_1 x_2 ... x_N, x_n \in \{0,1\}, \forall n = 1, ..., N$$

It is equivalent to

$$z \in \{0,1\}$$

$$z \le \frac{x_1 + \dots + x_N}{N}$$

$$z \ge \frac{x_1 + \dots + x_N - n + 1}{N}$$

- If one of the $x_n = 0$, then the first inequality removes z = 1 from the feasible region, and the second inequality is redundant.
- If all $x_n = 1$, then the second inequality removes z = 0 from the feasible region, and the first inequality is redundant.

Complementary and slackness condition in KKT condition (will learn in lecture 8)

Consider condition $0 \le x \perp y \ge 0$ It is equivalent to $x, y \ge 0, xy = 0$ And can be linearized by

$$0 \le x \le Mz$$
$$0 \le y \le M(1-z)$$
$$z \in \{0,1\}^n$$

Proof of equivalence:

- 1. If x = 0, y > 0, then let z = 0
- 2. If x > 0, y = 0, then let z = 1
- 3. If x = 0, y = 0, then let z = 0 or z = 1

Remark: M can be chosen as the upper bound of the values of x, y; called big-M method in literature.

Still remember the complementary and slackness condition?

Primal problem

Dual problem

$$\min_{x} c^{T} x$$
s.t. $Ax \ge b$

$$x \ge 0$$

$$\max_{\lambda} b^{T} \lambda$$

$$A^{T} \lambda \le c$$

$$\lambda \ge 0$$

Complementary and slackness: Suppose x^* , λ^* are the primal and dual optimal solutions, respectively. Then, we have

$$a_n^T x^* > b \Rightarrow \lambda_n^* = 0$$

 $\lambda_n^* > 0 \Rightarrow a_n^T x^* = b$

$$0 \le \lambda \perp (Ax - b) \ge 0$$

 $0 \le \lambda \perp (Ax - b) \ge 0$ How to linearize this constraint?

Minimum values

Consider
$$y = \min\{x_1, \dots, x_n\}$$
, $x_i \in \left[x_i^l, x_i^u\right]$
Let $L = \min\{x_1^l, \dots, x_n^l\}$. It can be represented as
$$x_i^l \leq x_i \leq x_i^u, \forall i$$

$$y \leq x_i, \forall i$$

$$x_i - \left(x_i^u - L\right)(1 - z_i) \leq y, \forall i$$

$$z_i \in \{0,1\}, \sum_{i=1}^n z_i = 1$$

Proof of equivalence:

- Only one $z_i = 1$ and others =0.
- If $z_i = 1$, we have $x_i^l \le x_i \le x_i^u$, $y \le x_i$, $x_i \le y$
- If $z_i = 0$, we have $x_i^l \le x_i \le x_i^u$, $y \le x_i$, $x_i y \le x_i^u L$

For example, if $z_1 = 1$ $y = x_1$ $y \le x_2, ..., y \le x_n$

Maximum values

Consider
$$y = \max\{x_1, ..., x_n\}$$
, $x_i \in \left[x_i^l, x_i^u\right]$
Let $U = \max\{x_1^u, ..., x_n^u\}$. It can be represented as
$$x_i^l \leq x_i \leq x_i^u, \forall i$$

$$y \geq x_i, \forall i$$

$$x_i + \left(U - x_i^l\right)(1 - z_i) \geq y, \forall i$$

$$z_i \in \{0,1\}, \sum_{i=1}^n z_i = 1$$

Proof of equivalence:

- Only one $z_i = 1$ and others =0.
- If $z_i = 1$, we have $x_i^l \le x_i \le x_i^u$, $y \ge x_i$, $x_i \ge y$
- If $z_i = 0$, we have $x_i^l \le x_i \le x_i^u$, $y \ge x_i$, $y x_i \le U x_i^l$

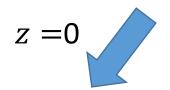
Absolute values

$$y = |x|, x \in \mathbb{R}, |x| \le x^u$$

It can be represented as

$$0 \le y - x \le 2x^{u}z, \quad x^{u}(1-z) \ge x$$

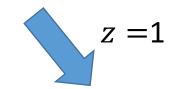
 $0 \le y + x \le 2x^{u}(1-z), \quad -x^{u}z \le x$
 $-x^{u} \le x \le x^{u}, \quad z \in \{0,1\}$



$$0 \le y - x \le 0, \qquad x^u \ge x$$

$$0 \le y + x \le 2x^u, \qquad 0 \le x$$

$$-x^u \le x \le x^u$$



$$0 \le y - x \le 2x^{u}, \quad 0 \ge x$$

$$0 \le y + x \le 0, \quad -x^{u} \le x$$

$$-x^{u} \le x \le x^{u}$$

Thanks!