



Solution 1

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ECE 6108
Linear Programming and Network Flows



- Problem 1

$$B_{new} = B + (\underline{a} - \underline{b}_i) \underline{e}_i^T$$

- Problem 9

$$B = LU \Rightarrow U = L^{-1}B$$

$$B_{new} = [\underline{b}_1 \underline{b}_2, \dots, \underline{b}_{i-1}, \underline{a}, \underline{b}_{i+1} \dots \underline{b}_n]$$

In this case, it is best to move column \underline{a} to the end.

This can be done via a permutation matrix on the right.

This corresponds to exchanging the variables associated the columns.

$$\hat{B}_{new} = [\underline{b}_1 \underline{b}_2, \dots, \underline{b}_{i-1}, \underline{b}_{i+1} \dots \underline{b}_n, \underline{a}]$$

$$L^{-1} \hat{B}_{new} = [\underline{u}_1 \underline{u}_2, \dots, \underline{u}_{i-1}, \underline{u}_{i+1} \dots \underline{u}_n, L^{-1} \underline{a}] = H$$

H = upper Hessenberg matrix



$$H = L^{-1} \hat{B}_{new}$$

$$H = \begin{bmatrix} x & x & x & x \\ 0 & x & x & x \\ 0 & x & x & x \\ 0 & 0 & x & x \end{bmatrix}; i = 2$$

H can be made upper triangular by applying elementary transformations of the form (for $j = i, i+1, \dots, n-1$):

$$M_j = \begin{bmatrix} 1 & & & \\ & 1 & & \\ & -m_{j+1,j} & 1 & \\ & & & 1 \end{bmatrix}; m_{j+1,j} = \frac{h_{j+1,j}}{h_{jj}}$$

$$\Rightarrow \hat{U} = M_{n-1} \dots M_i H$$

$$\Rightarrow \hat{B}_{new} = L M_i^{-1} \dots M_{n-1}^{-1} \hat{U} = \hat{L} \hat{U}$$

computational load = $O((n-i)^2 + n^2) \Rightarrow O(n^2)$ since $1 \leq i \leq n$.



□ Problem 10

$$B = QR \Rightarrow R = Q^T B$$

$$\hat{B}_{new} = [\underline{b}_1 \underline{b}_2, \dots, \underline{b}_{i-1}, \underline{b}_{i+1} \dots \underline{b}_n, \underline{a}]$$

$$Q^T \hat{B}_{new} = [\underline{r}_1 \underline{r}_2, \dots, \underline{r}_{i-1}, \underline{r}_{i+1} \dots \underline{r}_n, Q^T \underline{a}] = H$$

H = upper Hessenberg matrix

Apply Givens transformations $J^T(j, j+1)$ for $j = i, i+1, \dots, n-1$ so that

$$J^T(n-1, n) \dots J^T(i, i+1) H = \hat{R} \Rightarrow J^T(n-1, n) \dots J^T(i, i+1) Q^T \hat{B}_{new} = \hat{R}$$

$$\Rightarrow \hat{Q} = Q J(i, i+1) \dots J(n-1, n)$$

computational load = $O(n^2)$

$$J(i, i+1) = \begin{bmatrix} 1 & & \\ & c & s \\ & -s & c \\ & & 1 \end{bmatrix}; i = 2$$



□ Problem 2

a) $f_1(x) = x \Rightarrow \text{convex}; f_2(x) = x^2 \Rightarrow \text{convex}$

$f_1(x)f_2(x) = x^3 \Rightarrow \text{not convex}$

Other: $f_1(x) = x \Rightarrow \text{convex}; f_2(x) = -x \Rightarrow \text{convex}$

$f_1(x)f_2(x) = -x^2 \Rightarrow \text{concave}$

$f_1(x) = e^{-x} \Rightarrow \text{convex}; f_2(x) = e^x - 1 \Rightarrow \text{convex}$

$g = f_1(x)f_2(x) = 1 - e^{-x} \Rightarrow \text{No}$

$\nabla^2 g = f_1 \nabla^2 f_2 + f_2 \nabla^2 f_1 + \nabla f_1 \nabla f_2$

Need: $f_1 > 0; f_2 > 0; \nabla f_1 \nabla f_2 > 0$

b) (i) $f(x_1, x_2) = x_1 x_2 \Rightarrow \nabla^2 f(x_1, x_2) = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \Rightarrow \text{indefinite} \Rightarrow \text{not convex}$

(ii) $f(x_1, x_2) = e^{x_1+x_2} \Rightarrow \nabla^2 f(x_1, x_2) = e^{x_1+x_2} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \Rightarrow \text{convex but not strictly convex}$

(iii) $f(x) = \tan x, 0 < x < 1 \Rightarrow \nabla^2 f(x) = 2 \tan x \sec^2 x > 0 \text{ for } 0 < x < 1 \Rightarrow \text{strictly convex}$

(iv) $f(x_1, x_2) = e^{-x_1-x_2} + x_1^2 - 2x_1 \Rightarrow \nabla^2 f(x_1, x_2) = e^{-x_1-x_2} \begin{bmatrix} 1+2e^{x_1+x_2} & 1 \\ 1 & 1 \end{bmatrix} > 0 \Rightarrow \text{strictly convex}$

(v) $f = \max(f_1, f_2)$ where $f_1 = x_1^2 + x_2^2; f_2 = x_1^2 - x_2$

f_1 is strictly convex; f_2 is convex.

If f_1 and f_2 are convex, $\max(f_1, f_2)$ is convex. why?



□ Problem 2

If f_1 and f_2 are convex, $\max(f_1, f_2)$ is convex. why?

$$f_1(\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2) \leq \alpha f_1(\underline{x}_1) + (1-\alpha) f_1(\underline{x}_2)$$

$$f_2(\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2) \leq \alpha f_2(\underline{x}_1) + (1-\alpha) f_2(\underline{x}_2)$$

$$\begin{aligned} f(\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2) &= \max(f_1(\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2), f_2(\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2)) \\ &\leq \max(\alpha f_1(\underline{x}_1) + (1-\alpha) f_1(\underline{x}_2), \alpha f_2(\underline{x}_1) + (1-\alpha) f_2(\underline{x}_2)) \\ &\leq \alpha \max(f_1(\underline{x}_1), f_2(\underline{x}_1)) + (1-\alpha) \max(f_1(\underline{x}_2), f_2(\underline{x}_2)) \\ &= \alpha f(\underline{x}_1) + (1-\alpha) f(\underline{x}_2) \end{aligned}$$

□ Problem 3

a) If $f(\underline{x})$ is convex, $f(A\underline{x} + \underline{b})$ is convex.

$$f(\alpha(A\underline{x}_1 + \underline{b}) + (1-\alpha)(A\underline{x}_2 + \underline{b})) \leq \alpha f(A\underline{x}_1 + \underline{b}) + (1-\alpha) f(A\underline{x}_2 + \underline{b})$$

Alternatively, let $\underline{y} = A\underline{x} + \underline{b} \Rightarrow f(\underline{y}) = f(A\underline{x} + \underline{b})$

$$\nabla_{\underline{y}} f(\underline{y}) = A \nabla_{\underline{x}} f(\underline{x}) \Rightarrow \nabla_{\underline{yy}}^2 f(\underline{y}) = A \nabla_{\underline{xx}}^2 f(\underline{x}) A^T \Rightarrow \text{convex}$$

b) $g(x_1) = f(x_1, x_2, \dots, x_n) \mid_{x_2, \dots, x_n = \text{fixed}}$

$$\begin{aligned} g(\alpha x_1' + (1-\alpha)x_1'') &= f(\alpha x_1' + (1-\alpha)x_1'', x_2, \dots, x_n) \\ &\leq \alpha f(x_1', x_2, \dots, x_n) + (1-\alpha) f(x_1'', x_2, \dots, x_n) \\ &= \alpha g(x_1') + (1-\alpha) g(x_1'') \end{aligned}$$



□ Problem 4

$f(\underline{x}) = \underline{x}^T Q \underline{x}$ is convex if Q is PD.

$$\begin{aligned} f(\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2) &= [\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2]^T Q [\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2] \\ &= \alpha^2 \underline{x}_1^T Q \underline{x}_1 + 2\alpha(1-\alpha) \underline{x}_1^T Q \underline{x}_2 + (1-\alpha)^2 \underline{x}_2^T Q \underline{x}_2 \\ \alpha f(\underline{x}_1) + (1-\alpha) f(\underline{x}_2) &= \alpha \underline{x}_1^T Q \underline{x}_1 + (1-\alpha) \underline{x}_2^T Q \underline{x}_2 \\ f(\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2) - \alpha f(\underline{x}_1) - (1-\alpha) f(\underline{x}_2) &= \\ &= \alpha(\alpha-1)(\underline{x}_1^T Q \underline{x}_1 - 2\underline{x}_1^T Q \underline{x}_2 + \underline{x}_2^T Q \underline{x}_2) \\ &= \alpha(\alpha-1)(\underline{x}_1 - \underline{x}_2)^T Q (\underline{x}_1 - \underline{x}_2) < 0 \text{ if } Q > 0 \text{ and } \underline{x}_1 \neq \underline{x}_2 \end{aligned}$$

□ Problem 5

$$\begin{aligned} f(\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2) &= \sum_{i=1}^n f_i(\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2) \\ &\leq \sum_{i=1}^n \alpha f_i(\underline{x}_1) + (1-\alpha) f_i(\underline{x}_2) = \alpha f(\underline{x}_1) + (1-\alpha) f(\underline{x}_2) \end{aligned}$$



□ Problem 6

$H = \{\underline{x} : \underline{c}^T \underline{x} = k\}$ is convex. Suppose $\underline{c}^T \underline{x}_1 = \underline{c}^T \underline{x}_2 = k$

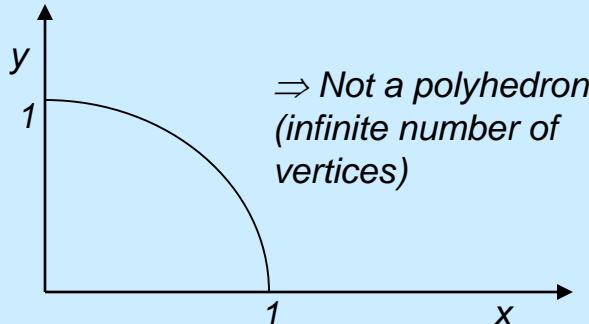
$$\underline{c}^T (\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2) = \alpha \underline{c}^T \underline{x}_1 + (1-\alpha) \underline{c}^T \underline{x}_2 = k$$

$H^+ = \{\underline{x} : \underline{c}^T \underline{x} \leq k\}$ is convex. Suppose $\underline{c}^T \underline{x}_1 = \underline{c}^T \underline{x}_2 \leq k$

$$\underline{c}^T (\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2) = \alpha \underline{c}^T \underline{x}_1 + (1-\alpha) \underline{c}^T \underline{x}_2 \leq k$$

□ Problem 7

(i) $\{(x, y) : (x, y) > 0 \text{ and } x \cos \theta + y \sin \theta \leq 1 \forall \theta \in [0, \pi/2]\}$





□ Problem 7

$$(ii) x^2 - 8x + 15 \leq 0 \Rightarrow (x-3)(x-5) \leq 0$$

$$\Rightarrow x \in [3,5] \Rightarrow \text{polyhedron}$$

$$(iii) \text{ consider } \{x \mid x \leq 0, x \geq 1\} = \text{empty set}$$

\Rightarrow intersection of convex sets \Rightarrow polyhedron

•Some authors (e.g., Luenberger) let polytopes be empty and define polyhedrons as strictly non-empty.

□ Problem 8

consider $\underline{x}_1 \in s$ and $\underline{x}_2 \in s \exists f(\underline{x}_1) \leq c$ and $f(\underline{x}_2) \leq c$

Then $f(\alpha \underline{x}_1 + (1-\alpha) \underline{x}_2) \leq \alpha f(\underline{x}_1) + (1-\alpha) f(\underline{x}_2) \leq \alpha c + (1-\alpha)c = c$

$\Rightarrow \alpha \underline{x}_1 + (1-\alpha) \underline{x}_2 \in s$