

HW4

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1. (a). We assume that employees work h hours per day,

So for the optimization problem:

$$\begin{aligned} & \text{maximize } \sum_{i=1}^5 ((2-15h)k_i) - s_i - c_i \\ & \text{subject to } k_i - 3 \geq 0 \quad i=1, \dots, 5 \\ & \sum_{i=1}^5 s_i \leq 2 \quad \sum_{i=1}^5 15hk_i \end{aligned}$$

(b). This is a LP optimization problem.

(c). First, we need to convert it to a convex optimization problem.

$$\begin{aligned} & \text{minimize } \sum_{i=1}^5 (s_i + c_i - (2-15h)k_i) \\ & \text{subject to } 3 - k_i \leq 0 \quad i=1, \dots, 5 \\ & \sum_{i=1}^5 (s_i - 30hk_i) \leq 0 \end{aligned}$$

$$L(k, \lambda_1, \lambda_2) = \sum_{i=1}^5 (s_i + c_i - (2-15h)k_i) + \sum_{i=1}^5 \lambda_{1,i} (3 - k_i) + \lambda_2 (\sum_{i=1}^5 (s_i - 30hk_i))$$

(d). dual problem:

$$\begin{aligned} \nabla_k L &= \sum_{i=1}^5 (15h - 2) - \sum_{i=1}^5 \lambda_{1,i} - \sum_{i=1}^5 30\lambda_2 h \\ - \sum_{i=1}^5 \lambda_{1,i} - \sum_{i=1}^5 30\lambda_2 h &= 0 \quad (\text{complementary slackness}) \end{aligned}$$

so for the $15h - 2$, if $2 > 15h$, then $\nabla_k L < 0$, it's unbounded below

$$g(\lambda_1, \lambda_2) = -\infty$$

if $2 < 15h$, then $\nabla_k L > 0$,

$$\text{when } k=0, \quad g(\lambda_1, \lambda_2) = \inf_k L = \sum_{i=1}^5 (s_i + c_i) + 3 \sum_{i=1}^5 \lambda_{1,i} + \sum_{i=1}^5 \lambda_2 s_i$$

2. (a). When $p_i = 0$, it can satisfy the constraints in the context.

(b). When $i=1$, $p_1 - M \leq u_1$

For the perturbed problem,

We assume that strong duality holds, and that the dual optimum is attained.

$$\begin{aligned} p^*(u, v) &\geq p^*(0, 0) - \lambda^{*T} u - v^{*T} v \quad v^* = 0 \\ &= p^*(0, 0) - \lambda^{*T} u \end{aligned}$$

$\lambda_1 = 100$, and it's large, and we loosen the constraint, $u_1 > 0$,

the optimal value is guaranteed to decrease greatly.

So L should increase the energy budget for store $i=1$.

(c). When $i=2$, $\lambda_2 = 0.001$, λ_2 is small, and we loosen the constraint, $u_2 > 0$,

the optimal value will not decrease too much.

so L should not increase the energy budget for store $i=2$.

3. We know that the equality constraint doesn't exist,

then $v_i = 0$,

$$f_i(x) \leq u_i, \quad p^*(0, 0) = g(\lambda^*, v^*) \leq f_0(x) + \lambda^{*T} u$$

$$f_0(x) \geq p^*(0, 0) - \lambda^{*T} u$$

we can replace $f_0(x)$ with $p^*(u, v)$

then $p^*(u, v) \geq p^*(0, 0) - \lambda^{*T} u$.

4. For the KKT conditions:

$$\textcircled{1} f_i(\tilde{x}) \leq 0$$

$$\textcircled{2} h_i(\tilde{x}) = 0 \quad \text{primal feasible}$$

$$\textcircled{3} \tilde{\lambda}_i \geq 0 \quad \text{dual feasible}$$

$$\textcircled{4} \tilde{\lambda}_i^* f_i(x^*) = 0 \rightarrow \text{complementary slackness}$$

$$\textcircled{5} \frac{\partial L}{\partial x} = 0$$

$$Ax = \begin{bmatrix} -2 & -1 & 0 \\ 4 & 3 & 1 \\ 1 & 1 & 1 \\ 4 & 2 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix} = \begin{bmatrix} -3 \\ 6 \\ 1 \\ 6 \end{bmatrix} \leq \begin{bmatrix} -3 \\ 6 \\ 1 \\ 7 \end{bmatrix}$$

for complementary slackness, $f_4(x) < 0$, then $\lambda_4 = 0$.

$$L(x, \lambda) = C^T x + \lambda^T (Ax - b)$$

$$\text{then } \frac{\partial L}{\partial x} = C^T + \lambda^T A = 0$$

$$[30, 4, -8] + [\lambda_1, \lambda_2, \lambda_3, \lambda_4] \begin{bmatrix} -2 & -1 & 0 \\ 4 & 3 & 1 \\ 1 & 1 & 1 \\ 4 & 2 & 0 \end{bmatrix}$$

$$\text{so } \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \end{bmatrix} = \begin{bmatrix} 40 \\ 14 \\ -6 \\ 0 \end{bmatrix}$$

for complementary slackness, $\lambda_i^* > 0$, $f_i(x^*) = 0$.

$f_3(x^*) = 0$, but $\lambda_3 < 0$, so x^* isn't an optimal solution.

5. For this problem, we need to prove the objective function is a convex function.

$$f(x) = \max(x) - \min(x).$$

$$\text{We need to prove } f(\theta x_1 + (1-\theta)x_2) \leq \theta f(x_1) + (1-\theta)f(x_2)$$

Because $f(x) \geq 0$, $x_1, x_2 \in \mathbb{R}^n$

$$\text{then } f(\theta x) = \theta f(x)$$

$$f(\theta x_1 + (1-\theta)x_2) = \max(\theta x_1 + (1-\theta)x_2) - \min(\theta x_1 + (1-\theta)x_2)$$

$$\theta f(x_1) + (1-\theta)f(x_2) = \theta \max(x_1) - \theta \min(x_1) + (1-\theta)\max(x_2) - (1-\theta)\min(x_2)$$

$$\begin{aligned} \text{We know that: } \max(\theta x_1 + (1-\theta)x_2) &\leq \theta \max(x_1) + (1-\theta)\max(x_2) \\ \min(\theta x_1 + (1-\theta)x_2) &\geq \theta \min(x_1) + (1-\theta)\min(x_2) \end{aligned}$$

so $f(x)$ is a convex function, this is a convex optimization problem