HOMEWORK #6 SOLUTION

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1. Exercise 6.1 Illustrate local sensitivity analysis

Problem: Make an original example to illustrate the local-analysis concepts of this chapter. **Solution:**

2. Exercise 6.2 Illustrate global sensitivity analysis

Problem: Using AMPL, make an original example, with at least three constraints, graphing the objective value of (P), as a single b[i] is varied from $-\infty$ to $+\infty$. As you work on this, bear in mind Theorem 6.3. Solution:

3. Exercise 6.3 "I feel that I know the change that is needed." - Mahatma Gandhi

Problem: We are given 2m numbers satisfying $L_i \leq 0 \leq U_i$, i = 1, 2, ..., m. Let β be an optimal basis for all of the m problems

(3.1)
$$\min_{\mathbf{c}'x} c'x \\
\text{s.t.} \quad Ax = b + \Delta_i e^i; \\
x > 0.$$

for all Δ_i satisfying $L_i \leq \Delta_i \leq U_i$. Lets be clear on what this means: For each *i* individually, the basis β is optimal when the *i*th right-hand side component is changed from b_i to $b_i + \Delta_i$, as long as Δ_i is in the interval $[L_i, U_i]$.

The point of this problem is to be able to say something about *simultaneously* changing all of the b_i . Prove that we can simultaneously change b_i to

$$\tilde{b}_i := b_i + \lambda_i \left\{ \begin{array}{c} L_i \\ U_i \end{array} \right\}$$

where $\lambda_i \geq 0$, when $\sum_{i=1}^m \lambda_i \leq 1$. [Note that in the formula above, for each i we can i = 1 pick either L_i (a decrease) or U_i (an increase)].

Proof:

Let
$$D_i = \left\{ \begin{array}{c} L_i \\ U_i \end{array} \right\}$$
, so $\max_{k:h_k^i > 0} -\frac{\overline{b}_k}{h_k^i} \le D_i \le \min_{k:h_k^i < 0} -\frac{\overline{b}_k}{h_k^i}$, where $\overline{b} = A_{\beta}^{-1}b \ge 0$, $h^i = A_{\beta}^{-1}e^i$, and $x = 1$. m

Thus, what we need to prove is that the basis β is optimal when we simultaneously change b_i to $\tilde{b}_i := b_i + \lambda_i D_i$, where $\sum_{i=1}^m \lambda_i = 1$. In the other word, we need to prove that the basis β is optimal for (3.2), where $\sum_{i=1}^m \lambda_i = 1$.

(3.2)
$$\min_{\mathbf{s.t.}} c'x \\ \mathbf{s.t.} \quad Ax = b + \sum_{i=1}^{m} \lambda_i D_i e^i; \\ x > 0$$

Consider a fixed and optimal basis β for (3.3). For β to be optimal for (3.2), we need $A_{\beta}^{-1}(b + \sum_{i=1}^{m} \lambda_i D_i e^i) = \overline{b} + \sum_{i=1}^{m} \lambda_i D_i h^i \geq 0$.

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For
$$k = 1...m$$
,
$$\overline{b}_k + \sum_{i=1}^m \lambda_i D_i h_k^i = \overline{b}_k + \sum_{i=1,h_k^i > 0}^m \lambda_i D_i h_k^i + \sum_{i=1,h_k^i < 0}^m \lambda_i D_i h_k^i + \sum_{i=1,h_k^i < 0}^m \lambda_i D_i h_k^i + \sum_{i=1,h_k^i < 0}^m \lambda_i (\max_{k':h_{k'}^i > 0} - \frac{\overline{b}_{k'}}{h_{k'}^i}) h_k^i + \sum_{i=1,h_k^i < 0}^m \lambda_i (\min_{k':h_{k'}^i < 0} - \frac{\overline{b}_{k'}}{h_{k'}^i}) h_k^i + \sum_{i=1,h_k^i < 0}^m \lambda_i (-\frac{\overline{b}_k}{h_k^i}) h_k^i = \overline{b}_k + \sum_{i=1,h_k^i > 0}^m \lambda_i (-\overline{b}_k) + \sum_{i=1,h_k^i < 0}^m \lambda_i (-\overline{b}_k)$$

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$$= \overline{b}_k + \sum_{i=1}^m \lambda_i (-\overline{b}_k)$$

$$= \overline{b}_k + (-\overline{b}_k) \sum_{i=1}^m \lambda_i$$

$$\geq \overline{b}_k + (-\overline{b}_k)$$

$$= 0$$

Thus, $\overline{b} + \sum_{i=1}^{m} \lambda_i D_i h^i \geq 0$, and β is feasible and hence still optimal for (3.2).

4. Exercise 6.4 Domain for objective variations

Problem: Prove Theorem 6.4: The domain of g is a convex set.

Proof:

Suppose that c^j is in the domain of g, for j = 1, 2. Therefore, there exist x^j that are feasible for (4.1), for j = 1, 2.

(4.1)
$$\min_{s.t.} c^{j'}x$$

$$s.t. \quad Ax = b;$$

$$x \ge 0.$$

For any $0 < \lambda < 1$, consider $\hat{c} := \lambda c^1 + (1 - \lambda)c^2$, to prove the domain of g is a convex set, we need to prove that (4.2) is feasible and not unbounded.

(4.2)
$$\min_{\mathbf{c}' x} \hat{\mathbf{c}}' x \\
\text{s.t.} \quad Ax = b; \\
x \ge 0.$$

Consider $\hat{x} := \lambda x^1 + (1 - \lambda)x^2$,

- x^j that are feasible for (4.1), for j=1,2
- $\therefore x^j \geq 0$, and $Ax^j = b$, for j = 1, 2

$$\therefore A\widehat{x} = A(\lambda x^1 + (1 - \lambda)x^2) = \lambda Ax^1 + (1 - \lambda)Ax^2 = \lambda b + (1 - \lambda)b = b$$

- $\therefore \lambda > 0$
- $\hat{x} = \lambda x^1 + (1 \lambda)x^2 \ge 0$
- \hat{x} is a feasible solution to (4.2)
- \therefore (4.2) is feasible

Consider the objective function $\hat{c}'x$ of (4.2),

- $\therefore c^j$ is in the domain of g, for j = 1, 2
- \therefore (4.1) is not unbounded for j=1,2
- $\therefore \exists k^j \in \mathbb{R}$, for any x, such that $c^{j'}x \geq k^j$, for j = 1, 2
- $\therefore \text{ for a feasible solution } \overline{x} \text{ of } (4.2), \ \widehat{c}' \overline{x} = (\lambda c^1 + (1 \lambda)c^2)' \overline{x} = \lambda c^{1'} \overline{x} + (1 \lambda)c^{2'} \overline{x} \ge (\lambda k^1 + (1 \lambda)k^2)$
- $:: k^1, k^2 \in \mathbb{R}, 0 < \lambda < 1$
- \therefore (4.2) is feasible and not unbounded
- $\therefore \hat{c}$ is in the domain g
- \therefore the domain of g is a convex set

5. Exercise 6.5 Concave piecewise-linear function

Problem: Prove Theorem 6.5: g is a concave piecewise-linear function on its domain. **Proof:**

The function g is

(5.1)
$$g(c) := \min \quad c'x$$
s.t.
$$Ax = b;$$

$$x \ge 0.$$

So a basis β is feasible or not for (5.1), independent for c_{β} . So g can be written as

$$g(c) = \min \left\{ c'_{\beta}(A_{\beta}^{-1}b) : \beta \text{ is a feasible basis for (5.1)} \right\}$$

- $\therefore c'_{\beta}(A_{\beta}^{-1}b)$ are affine functions
- $\therefore g$ is the pointwise minimum of a finite number of affine functions
- \therefore g is a concave piecewise-linear function