

Some Solutions to Homework due 2/16

1.3, #30. Suppose that S_1, \dots, S_m are all convex subsets of \mathbf{R}^n (for the same n). To prove: $S_1 \cap \dots \cap S_m$ is convex.

Proof: Suppose that $\mathbf{x}, \mathbf{y} \in S_1 \cap \dots \cap S_m$. We must show that any point \mathbf{v} on the line segment joining \mathbf{x} and \mathbf{y} belongs to $S_1 \cap \dots \cap S_m$.

Since $\mathbf{x}, \mathbf{y} \in S_1 \cap \dots \cap S_m$, certainly it's true that $\mathbf{x} \in S_1$ and $\mathbf{y} \in S_1$. Then since S_1 is a convex set by assumption, $\mathbf{v} \in S_1$.

Similarly, for each $i = 1, \dots, m$, $\mathbf{v} \in S_i$. Therefore $\mathbf{v} \in S_1 \cap \dots \cap S_m$. Q.E.D.

1.3, #34. Proof: Suppose that \mathbf{x}_1 and \mathbf{x}_2 both satisfy $A\mathbf{x} > b$. We must show that any point \mathbf{v} on the line segment joining \mathbf{x}_1 and \mathbf{x}_2 also satisfies $A\mathbf{x} > b$.

If $\mathbf{v} = \mathbf{x}_1$ or \mathbf{x}_2 , the inequality is satisfied by assumption. Any other \mathbf{v} on the line segment in question has the form $\mathbf{v} = \lambda\mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2$ for some real number λ such that $0 < \lambda < 1$. In particular, $\lambda > 0$ and $1 - \lambda > 0$.

We know that $A\mathbf{x}_1 > b$ and $A\mathbf{x}_2 > b$. Multiply these by λ and $1 - \lambda$ respectively, and add. This gives the inequality below. The rest basic matrix algebra:

$$A\mathbf{v} = A(\lambda\mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2) = \lambda(A\mathbf{x}_1) + (1 - \lambda)(A\mathbf{x}_2) > \lambda b + (1 - \lambda)b = b.$$

So $A\mathbf{v} > b$. Q.E.D.

1.4, #16. By definition (it's in Section 1.4), \mathbf{x} is a convex combination of points $\mathbf{x}_1, \dots, \mathbf{x}_m \in \mathbf{R}^n$ if and only if

$$\mathbf{x} = a_1\mathbf{x}_1 + \dots + a_m\mathbf{x}_m \quad \text{for some scalars } a_1, \dots, a_m \text{ such that } a_i \geq 0 \text{ for all } i = 1, \dots, m, \text{ and } a_1 + \dots + a_m = 1.$$

354, s04

HOMEWORK 2/16

2

Now suppose that objective function of a LPP is z , and the optimal value z_{opt} is attained at $\mathbf{x}_1, \dots, \mathbf{x}_m$. Then, $z(\mathbf{x}_1) = z(\mathbf{x}_2) = \dots = z(\mathbf{x}_m) = z_{opt}$. Let $\mathbf{x} = a_1\mathbf{x}_1 + \dots + a_m\mathbf{x}_m$ be any convex combination as above. We must show that $z(\mathbf{x}) = z_{opt}$.

Let \mathbf{c} be the cost vector for the LPP. Thus, $z = \mathbf{c}^T \mathbf{x}$. Using basic properties of matrix operations,

$$\begin{aligned} z(\mathbf{x}) &= \mathbf{c}^T \mathbf{x} = \mathbf{c}^T (a_1\mathbf{x}_1 + \dots + a_m\mathbf{x}_m) = \mathbf{c}^T (a_1\mathbf{x}_1) + \dots + \mathbf{c}^T (a_m\mathbf{x}_m) \\ &= a_1(\mathbf{c}^T \mathbf{x}_1) + \dots + a_m(\mathbf{c}^T \mathbf{x}_m) = a_1z(\mathbf{x}_1) + \dots + a_mz(\mathbf{x}_m) \\ &= a_1z_{opt} + \dots + a_mz_{opt} = (a_1 + \dots + a_m)z_{opt} = 1 \cdot z_{opt} \\ &= z_{opt}. \quad \text{Q.E.D.} \end{aligned}$$

(Two related side points: a) It is also true that if $\mathbf{x}_1, \dots, \mathbf{x}_m$ are all feasible, then \mathbf{x} is feasible, but the problem is not asking for a proof of this. b) The property $a_1 \geq 0, \dots, a_m \geq 0$ never needs to be used in the given problem. But it is necessary for showing that \mathbf{x} is feasible.)

A. First let's prove it for vectors in \mathbf{R}^1 by showing that $y = -\log x$ is a convex function, that is, for all positive real numbers x_1, x_2 and all λ such that $0 \leq \lambda \leq 1$, it is true that

$$(1) \quad -\log(\lambda x_1 + (1 - \lambda)x_2) \leq \lambda(-\log x_1) + (1 - \lambda)(-\log x_2).$$

One way to show this is to use the geometric interpretation of (1), that the graph of $y = -\log x$, for $x_1 \leq x \leq x_2$, lies below the line segment joining the points $(x_1, \log x_1)$ and $(x_2, \log x_2)$ on the graph. This is true because the graph is concave up, which in turn is true because $y'' = (-1/x)' = 1/x^2 > 0$ for all x . **Note:** This explanation would have been adequate.

Another way, which is more analytical and is rigorous, is essentially to prove that any real-valued function defined on any interval in \mathbf{R} , and with a positive second derivative everywhere on that interval, is convex. Write

$f(x) = -\log x$ and use Taylor's formula with remainder, with $n = 1$, "centered" at $x = x_0$:

$$f(x) = f(x_0) + f'(x_0)(x - x_0) + \frac{1}{2}f''(c)(x - x_0)^2 \text{ for some } c \text{ between } x \text{ \& } x_0.$$

This is true for all positive x and x_0 . Since $f''(c) > 0$ for all c between x_1 and x_2 ,

$$f(x) > f(x_0) + f'(x_0)(x - x_0).$$

Now, a) substitute $x = x_1$ and multiply through by λ (which is ≥ 0 by assumption); b) then do the same with $x = x_2$ and $1 - \lambda$; and c) add the results:

$$\lambda f(x_1) \geq \lambda f(x_0) + \lambda f'(x_0)(x_1 - x_0)$$

$$(1 - \lambda)f(x_2) \geq (1 - \lambda)f(x_0) + (1 - \lambda)f'(x_0)(x_2 - x_0)$$

$$\lambda f(x_1) + (1 - \lambda)f(x_2) \geq \lambda f(x_0) + \lambda f'(x_0)(x_1 - x_0)$$

$$+ (1 - \lambda)f(x_0) + (1 - \lambda)f'(x_0)(x_2 - x_0)$$

$$= f(x_0) + f'(x_0)[\lambda(x_1 - x_0) + (1 - \lambda)(x_2 - x_0)].$$

$$= f(x_0) + f'(x_0)[\lambda x_1 + (1 - \lambda)x_2 - x_0].$$

Substitute $x_0 = \lambda x_1 + (1 - \lambda)x_2$ and the second term on the right becomes 0, and the inequality is what we wanted to prove.

Now what about \mathbf{R}^n ? Let $\mathbf{x}_1 = [x_{11} \dots, x_{1n}]^T$ and $\mathbf{x}_2 = [x_{21} \dots, x_{2n}]^T$ be vectors in \mathbf{R}^n , with all coordinates positive (so that the logs will be

defined). Then

$$f(\lambda \mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2) = f\left(\lambda \begin{bmatrix} x_{11} \\ \vdots \\ x_{1n} \end{bmatrix} + (1 - \lambda) \begin{bmatrix} x_{21} \\ \vdots \\ x_{2n} \end{bmatrix}\right)$$

$$= f\left(\begin{bmatrix} \lambda x_{11} + (1 - \lambda)x_{21} \\ \vdots \\ \lambda x_{1n} + (1 - \lambda)x_{2n} \end{bmatrix}\right)$$

$$= -\sum_{i=1}^n \log(\lambda x_{1i} + (1 - \lambda)x_{2i})$$

$$\leq -\sum_{i=1}^n [\lambda \log x_{1i} + (1 - \lambda) \log x_{2i}] \text{ (we've proved it for } \mathbf{R}^1)$$

$$= -\lambda \sum_{i=1}^n \log x_{1i} - (1 - \lambda) \sum_{i=1}^n \log x_{2i}$$

$$= \lambda f(\mathbf{x}_1) + (1 - \lambda)f(\mathbf{x}_2). \quad \text{Q.E.D.}$$

B. (Compare #34 above) **Proof.** Suppose that $f(\mathbf{x}) \leq b$ is satisfied by $\mathbf{x} = \mathbf{x}_1$ and $\mathbf{x} = \mathbf{x}_2$. We must show that it is satisfied by any \mathbf{x} on the line segment joining \mathbf{x}_1 and \mathbf{x}_2 . Any such \mathbf{x} has the form $\mathbf{x} = \lambda \mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2$ for some λ such that $0 \leq \lambda \leq 1$.

We know that

$$f(\mathbf{x}_1) \leq b \quad \text{and} \quad f(\mathbf{x}_2) \leq b.$$

Multiply these by λ and $1 - \lambda$ respectively. Since $\lambda \geq 0$ and $1 - \lambda \geq 0$, the inequalities remain true:

$$\lambda f(\mathbf{x}_1) \leq \lambda b \quad \text{and} \quad (1 - \lambda)f(\mathbf{x}_2) \leq (1 - \lambda)b.$$

Add these (the second inequality below) and use the fact that f is convex (the first inequality below):

$$f(\lambda \mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2) \leq \lambda f(\mathbf{x}_1) + (1 - \lambda)f(\mathbf{x}_2) \leq \lambda b + (1 - \lambda)b = b. \quad \text{Q.E.D.}$$