

2.17(c)

The halfspace $C = \{(v, t) | f^T v + gt \leq h\}$ under perspective function $P(C) = \{v/t | (v, t) \in C, t > 0\}$

Let $x = v/t$. Then, $P(C) = \{x | f^T x \leq -g + h/t, t > 0\}$

The shape of $P(C)$ depends on the sign of h and the value of t . There are 3 situations to be considered:

(1) If $h > 0$, then $P(C) = \lim_{t \rightarrow 0} \{x | f^T x \leq -g + h/t, t > 0\} = \{x | f^T x \leq \infty\} = \mathbb{R}^n$

(2) If $h = 0$, then $P(C) = \{x | f^T x \leq -g + h/t, t > 0\}|_{h=0} = \{x | f^T x \leq -g\}$, which is a closed halfspace.

(3) If $h < 0$, then $P(C) = \lim_{t \rightarrow \infty} \{x | f^T x \leq -g + h/t, t > 0\} = \{x | f^T x < -g\}$, which is an open halfspace.

2.24(a)

Let $f(x_1, x_2) = x_1 x_2$. The closed convex set $C = \{x \in \mathbb{R}_+^2 | x_1 x_2 \geq 1\}$ can be thought of as the intersection of an infinite number of supporting hyperplanes in \mathbb{R}^2 passing through $(t, \frac{1}{t})$ for all $t > 0$.

Also, $\nabla f = \frac{\partial f}{\partial x} = (x_2, x_1) = (\frac{1}{t}, t)$.

Therefore, the tangent line passing through $(t, \frac{1}{t})$ is $L : \frac{1}{t}(x_1 - t) + t(x_2 - \frac{1}{t}) = 0$.

The convex set C is the intersection of $\frac{1}{t}(x_1 - t) + t(x_2 - \frac{1}{t}) \geq 0$ for all $t > 0$.

$$\frac{1}{t}(x_1 - t) + t(x_2 - \frac{1}{t}) \geq 0$$

$$\frac{1}{t}x_1 + tx_2 \geq 2$$

$$C = \{x \in \mathbb{R}_+^2 | \frac{1}{t}x_1 + tx_2 \geq 2, \forall t > 0\}$$

2.24(b)

The convex set $C = \{x \in \mathbb{R}^n | \|x\|_\infty \leq 1\}$ is a cube in \mathbb{R}^n . The boundary points of this convex set form the surface of the cube.

The supporting hyperplane at $\hat{x} = (\hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)$ can be expressed as $a^T x = a^T \hat{x}$, such that $a^T x \geq a^T \hat{x}$ for all $x \in C$, where $a = (a_1, a_2, \dots, a_n)$ is the normal vector of the supporting hyperplane in \mathbb{R}^n .

The value of a_i depends on the value of x_i . There are 3 situations to be considered:

(1) If $\hat{x}_i = 1$, then $a_i x_i \geq a_i \hat{x}_i = a_i \Rightarrow a_i(x_i - 1) \geq 0$. Because $x_i \leq 1$, $a_i < 0$.

(2) If $-1 < \hat{x}_i < 1$, then $a_i x_i \geq a_i \hat{x}_i$. In order for this inequality to hold for all x_i , a_i has to be 0.

(3) If $\hat{x}_i = -1$, then $a_i x_i \geq a_i \hat{x}_i = -a_i \Rightarrow a_i(x_i + 1) \geq 0$. Because $x_i \geq -1$, $a_i > 0$.

3.3

$f: \mathbb{R} \rightarrow \mathbb{R}$ is increasing and convex on its domain (a, b) , meaning $\theta f(a) + (1 - \theta)f(b) \geq f(\theta a + (1 - \theta)b)$, $0 \leq \theta \leq 1$, according to the first-order condition.

Now the the function $g(f(x)) = x$ with domain $(f(a), f(b))$ is of our interest.

$$\theta f(a) + (1 - \theta)f(b) \geq f(\theta a + (1 - \theta)b), 0 \leq \theta \leq 1$$

$$g(\theta f(a) + (1 - \theta)f(b)) \geq g(f(\theta a + (1 - \theta)b)) = \theta a + (1 - \theta)b = \theta g(f(a)) + (1 - \theta)g(f(b))$$

Let $(a', b') = (f(a), f(b))$, the inequality above can be simplified as $g(\theta a' + (1 - \theta)b') \geq \theta g(a') + (1 - \theta)g(b')$, which is exactly the first-order condition of a concave function. Therefore, g is a concave function.