Exercise 3.18 [Boyd & Vandenberghe, 2004]

Adapt the proof of concavity of the log-determinant function in §3.1.5 to show the following.

(a) $f(X) = \operatorname{tr}(X^{-1})$ is convex on **dom** $f = \mathbf{S}_{++}^n$.

(b) $f(X) = (\det X)^{1/n}$ is concave on **dom** $f = \mathbf{S}_{++}^n$.

Ans: Here only does part (a).

(a) It suffices to show $g(t) = \operatorname{tr}((X + tZ)^{-1})$ is convex w.r.t. $t \in [t_0, t_1]$ where $X \in \mathbf{S}_{++}^n$, $Z \in \mathbf{S}^n$ and $[t_0, t_1]$ is an interval such that X + tZ remains positive definite. Use this property of positive definite matrix, write

$$X = S^{-1}S^{-T}, Z = S^{-1}LS^{-T}$$

then

$$g(t) = \operatorname{tr}((X + tZ)^{-1})$$

$$= \operatorname{tr}((S^{-1}(I + tL)S^{-T})^{-1})$$

$$= \operatorname{tr}(S(I + tL)^{-1}S^{T})$$

$$= \operatorname{tr}(S^{T}S(I + tL)^{-1})$$

$$g'(t) = \operatorname{tr}\left(S^{T}S\frac{d}{dt}(I + tL)^{-1}\right)$$

$$= -\operatorname{tr}(S^{T}S(I + tL)^{-1}L(I + tL)^{-1})$$

Here I made use of the identity

$$I = A^{-1}(t)A(t)$$

$$O = \left(\frac{d}{dt}A^{-1}(t)\right)A(t) + A^{-1}(t)A'(t)$$

$$\frac{d}{dt}A^{-1}(t) = -A^{-1}(t)A'(t)A^{-1}(t)$$

Now that I + tL and L are both diagonal, they commute.

$$g'(t) = -\operatorname{tr}(S^T S (I + tL)^{-1} L (I + tL)^{-1})$$

$$= -\operatorname{tr}(S^T S L (I + tL)^{-2})$$

$$g''(t) = \operatorname{tr}(S^T S L ((I + tL)^{-2} L (I + tL)^{-1} + (I + tL)^{-1} L (I + tL)^{-2}))$$

$$= 2\operatorname{tr}(S L^2 (I + tL)^{-3} S^T)$$

Since t is such that $X + tZ = S^{-1}(I + tL)S^{-T} \succ 0$, I + tL must be positive diagonal matrix, and $(I + tL)^{-3} \succ 0$; alongside with $L^2 \succeq 0$, we see $L^2(I + tL)^{-3} \succeq 0$, therefore

$$SL^2(I+tL)^{-3}S^T \succ 0$$

and $g''(t) \ge 0$ (i.e. g is convex).

Exercise 3.19 [Boyd & Vandenberghe, 2004]

Nonnegative weighted sums and integrals.

- (a) Show that $f(x) = \sum_{i=1}^r \alpha_i x_{[i]}$ is a convex function of x, where $\alpha_1 \ge \alpha_2 \ge \cdots \ge \alpha_r \ge 0$, and $x_{[i]}$ denotes the ith largest component of x. (You can use the fact that $f(x) = \sum_{i=1}^k x_{[i]}$ is convex on \mathbb{R}^n .)
- (b) Let $T(x,\omega)$ denote the trigonometric polynomial

$$T(x,\omega) = x_1 + x_2 \cos \omega + x_3 \cos 2\omega + \dots + x_n \cos(n-1)\omega.$$

Show that the function

$$f(x) = -\int_{0}^{2x} \log T(x, \omega) d\omega$$

is convex on $\{x \in \mathbb{R}^n \mid T(x,\omega) > 0, 0 \le \omega \le 2\pi\}.$

Ans: Here only does part (a).

(a) Let $\beta_i = \alpha_i - \alpha_{i+1}$; then observe

$$f(x) = \sum_{i=1}^{r} \alpha_i x_{[i]}$$

$$= \alpha_r \sum_{i=1}^{r} x_{[i]} + (\alpha_{r-1} - \alpha_r) \sum_{i=1}^{r-1} x_{[i]} + \dots + (\alpha_1 - \alpha_2) \sum_{i=1}^{1} x_{[i]}$$

$$= \alpha_r \sum_{i=1}^{r} x_{[i]} + \beta_{r-1} \sum_{i=1}^{r-1} x_{[i]} + \dots + \beta_1 \sum_{i=1}^{1} x_{[i]}$$

is a linear combination of convex functions with nonnegative coefficients and therefore convex. $\hfill\Box$

Exercise 3.22 [Boyd & Vandenberghe, 2004]

- Composition rules. Show that the following functions are convex. (a) $f(x) = -\log(-\log(\sum_{i=1}^m e^{a_i^T x + b_i}))$ on **dom** $f = \{x \mid \sum_{i=1}^m e^{a_i^T x + b_i} < 1\}$. You can use the fact that $\log(\sum_{i=1}^n e^{y_i})$ is convex. (b) $f(x, u, v) = -\sqrt{uv - x^T x}$ on $\operatorname{dom} f = \{(x, u, v) \mid uv > x^T x, u, v > 0\}$. Use the fact
- that $x^T x/u$ is convex in (x, u) for u > 0, and that $-\sqrt{x_1 x_2}$ is convex on \mathbb{R}^2_{++} .
- (c) $f(x, u, v) = -\log(uv x^T x)$ on **dom** $f = \{(x, u, v) \mid uv > x^T x, u, v > 0\}.$
- (d) $f(x,t) = -(t^p ||x||_p^p)^{1/p}$ where p > 1 and $\operatorname{dom} f = \{(x,t) \mid t \ge ||x||_p\}$. You can use the fact that $||x||_p^p/u^{p-1}$ is convex in (x,u) for u>0 (see exercise 3.23), and that $-x^{1/p}y^{1-1/p}$ is convex on \mathbb{R}^2_+ (see exercise 3.16).
- (e) $f(x,t) = -\log(t^p ||x||_p^p)$ where p > 1 and **dom** $f = \{(x,t) \mid t > ||x||_p\}$. You can use the fact that $||x||_p^p/u^{p-1}$ is convex in (x,u) for u>0 (see exercise 3.23).

Ans: Here only does part (c).

(c) Let $g(x, u, v) = uv - x^T x$, then $\nabla g(x, u, v) = [-2x^T, v, u]$ and

$$H_g(x, u, v) = \begin{bmatrix} -2I & & \\ & & 1 \\ & & 1 \end{bmatrix}$$

and for any $(x, u, v) \in \operatorname{dom} f$,

$$\begin{bmatrix} x^T, u, v \end{bmatrix} \begin{bmatrix} -2I & & \\ & & 1 \\ & & 1 \end{bmatrix} \begin{bmatrix} x \\ u \\ v \end{bmatrix} = -2x^Tx + 2uv > 0$$

That is, g is convex on **dom** f. Now that $h = -\log(\cdot)$ is convex and nonincreasing, we conclude $f = -\log(g(\cdot))$ is convex on **dom** f as well.

Additional Exercise 2.5 [Boyd & Vandenberghe, 2017]

A perspective composition rule [Marèchal]. Let $f: \mathbb{R}^n \to \mathbb{R}$ be a convex function with $f(0) \leq 0$.

- (a) Show that the perspective tf(x/t), with domain $\{(x,t) \mid t > 0, x/t \in \text{dom } f\}$, is nonincreasing as a function of t.
- (b) Let g be concave and positive on its domain. Show that the function

$$h(x) = g(x)f(x/g(x)), \quad \mathbf{dom} \ h = \{x \in \mathbf{dom} \ g \mid x/g(x) \in \mathbf{dom} \ f\}$$

is convex.

(c) As an example, show that

$$h(x) = \frac{x^T x}{(\prod_{k=1}^n x_k)^{1/n}}, \quad \text{dom } h = \mathbb{R}^n_{++}$$

is convex. Ans: Here only does part (a) and (b).

Additional Exercise 2.30 [Boyd & Vandenberghe, 2017]

Huber penalty. The infinal convolution of two functions f and g on \mathbb{R}^n is defined as

$$h(x) = \inf_{y} (f(y) + g(x - y))$$

(see exercise 2.17). Show that the infimal convolution of $f(x) = ||x||_1$ and $g(x) = (1/2)||x||_2^2$, i.e., the function

$$h(x) = \inf_{y} (f(y) + g(x - y)) = \inf_{y} \left(||y||_{1} + \frac{1}{2} ||x - y||_{2}^{2} \right)$$

is the Huber penalty

$$h(x) = \sum_{i=1}^{n} \phi(x_i), \quad \phi(u) = \begin{cases} u^2/2, |u| \le 1\\ |u| - 1/2, |u| > 1 \end{cases}$$

Ans:

Additional Exercise 2.31 [Boyd & Vandenberghe, 2017]

Suppose the function $h: \mathbb{R} \to \mathbb{R}$ is convex, nondecreasing, with $\operatorname{dom} h = \mathbb{R}$, and h(t) = h(0) for $t \leq 0$.

- (a) Show that the function $f(x) = h(||x||_2)$ is convex on \mathbb{R}^n .
- (b) Show that the conjugate of f is $f^*(y) = h^*(||y||_2)$.
- (c) As an example, derive the conjugate of $f(x) = (1/p)||x||_2^p$ for p > 1, by applying the result of part (b) with the function

$$h(t) = \frac{1}{p} \max\{0, t\}^p = \begin{cases} \frac{1}{p} t^p, t \ge 0\\ 0, t < 0 \end{cases}$$

Ans:

(a) Let $g(x) = ||x||_2$, then

$$\nabla g(x) = \frac{x^T}{\|x\|_2}$$

$$H_g(x) = \frac{1}{\|x\|_2^2} \left(I \|x\|_2 - \frac{x}{\|x\|_2} x^T \right)$$

$$= \frac{1}{\|x\|_2} \left(I - \frac{1}{\|x\|_2^2} x x^T \right)$$

$$v^T H_g(x) v = \frac{1}{\|x\|_2} \left(\|v\|_2 - \frac{(x^T v)^2}{\|x\|_2^2} \right) \ge 0 \text{ (by Cauchy inequality)}$$

Since h is convex and nondecreasing and $g = \|\cdot\|_2$ is convex, the composition $f = h \circ g$ must be convex, too.

(b) By definition,

$$f^{*}(y) = \sup_{x \in \mathbb{R}^{n}} x^{T}y - f(x)$$

$$= \sup_{x \in \mathbb{R}^{n}} x^{T}y - h(\|x\|_{2})$$

$$= \max \left\{ \sup_{x \neq 0} \|x\|_{2} \left(\frac{x}{\|x\|_{2}} \right)^{T} y - h(\|x\|_{2}), -h(0) \right\}$$

$$= \sup_{x \neq 0} \|x\|_{2} \left(\frac{x}{\|x\|_{2}} \right)^{T} y - h(\|x\|_{2}) \quad \text{(because } -h \text{ is nonincreasing)}$$

$$= \sup_{x \neq 0} \|x\|_{2} \|y\|_{2} - h(\|x\|_{2})$$

$$= \sup_{t > 0} t \|y\|_{2} - h(t)$$

The last equality follows from that the first term is maximized when x is parallel to y. Now observe the definition of h^*

$$h^*(\|y\|_2) = \sup_{t \in \mathbb{R}} t\|y\|_2 - h(t)$$

This differs from $f^*(y)$ only by the range of the minimizing variable

Additional Exercise 3.17 [Boyd & Vandenberghe, 2017]

Minimum fuel optimal control. Solve the minimum fuel optimal control problem described in exercise 4.16 of Convex Optimization, for the instance with problem data

$$A = \begin{bmatrix} -1 & 0.4 & 0.8 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}, b = \begin{bmatrix} 1 \\ 0 \\ 0.3 \end{bmatrix}, x_{des} = \begin{bmatrix} 7 \\ 2 \\ -6 \end{bmatrix}, N = 30.$$

You can do this by forming the LP you found in your solution of exercise 4.16, or more directly using CVX. Plot the actuator signal u(t) as a function of time t.

Ans: