Yale University
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Assignment 3

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P.1.

(a)

The gradient and Hessian are given by

$$\begin{aligned}\boldsymbol{\nabla} f(x) &= \log x \\ \boldsymbol{\nabla}^2 f(x) &= \mathrm{Diag}(1/x_1, \dots, 1/x_n).\end{aligned}$$

Here the logarithm is applied component-wise and $\mathrm{Diag} : \mathbb{R}^n \to \mathbb{R}^{n\times n}$ maps a vector to the diagonal matrix whose diagonal entries are precisely given by the input vector.

(b)

By our work in class, f is strictly convex if and only if $\boldsymbol{\nabla}^2 f \succ 0$ since f is twice differentiable. Indeed, the eigenvalues of $\boldsymbol{\nabla}^2 f$ are given by

$$1/x_1, \dots, 1/x_n$$

and are all positive over $\mathbb{R}^n_{>0}$. Thus f is indeed strictly convex.

(c)

Suppose towards a contradiction that f is α-strongly convex for some $\alpha > 0$. Let e_1 be the vector which is all zero except for a one in the first entry. We have for all $\lambda > 0$,

$$\begin{aligned}f(\lambda e_1 + \lambda e_1) &\geq f(\lambda e_1) + \langle \boldsymbol{\nabla} f(\lambda e_1), \lambda e_1 \rangle + \frac{\alpha}{2}\|\lambda e_1\|_2^2 \\ 2\lambda \log(2\lambda) - 2\lambda &\geq \lambda \log \lambda - \lambda + \lambda \log \lambda + \frac{\alpha}{2}\lambda^2 \\ 2\lambda \log\left(\frac{2\lambda}{\lambda}\right) &\geq \lambda + \frac{\alpha}{2}\lambda^2 \\ 2\log 2 &\geq 1 + \frac{\alpha}{2}\lambda.\end{aligned}$$

This is a contradiction since we can make the RHS arbitrarily large while the LHS stays constant.

(d)

$$
\begin{aligned}
D_f(x, y) &:= f(y) - f(x) - \langle \boldsymbol{\nabla} f(x), y - x \rangle \\
&= \sum_{i=1}^{n} y_i \log y_i - y_i - x_i \log x_i + x_i - (y_i - x_i) \log x_i \\
&= \sum_{i} y_i \log y_i - y_i + x_i - y_i \log x_i \\
&= \boxed{\sum_{i=1}^{n} y_i \log \frac{y_i}{x_i} + x_i - y_i}.
\end{aligned}
$$

By inspection, this is not symmetric for all $x, y > 0$.

(e)

We wish to show that

$$
D_f(x, y) \geq \frac{1}{2} \|y - x\|_1^2
$$

for all $x, y \in \Delta^n := \{x \in \mathbb{R}^n_{>0} : \sum_{i=1}^n x_i = 1\}$. First, we remark that in Δ^n,

$$
D_f(x, y) = \sum_{i=1}^{n} y_i \log \frac{y_i}{x_i} = \mathrm{KL}(y \| x).
$$

Now, Pinsker's inequality states that

$$
D_f(x, y) = \mathrm{KL}(y \| x) \geq \frac{1}{2} \|y - x\|_1^2.
$$

and so f is 1-strongly convex with respect to the 1-norm, as desired.

P.2.

(a)

First suppose that $d = n$. We have a system of linear inequalities

$$-\mathbb{1} \leq Ax \leq \mathbb{1}$$

where the i-th row of $A \in \mathbb{R}^{m \times n}$ is a_i. By assumption, A has full column rank so that A is injective. We can therefore define a linear left inverse $B : A(\mathbb{R}^n) \to \mathbb{R}^n$ such that $BAx = x$. But then

$$\|x\| = \|BAx\| \leq \|B\|_{\text{op}} \cdot \|Ax\|$$

for all $x \in \mathbb{R}^n$. In particular, $x \in P$ implies that $\|Ax\| \leq \sqrt{n}$ and consequently $\|x\| \leq \|B\|_{\text{op}} \sqrt{n}$. This shows that P is indeed bounded.

Now suppose that $d < n$. Then we can find some $0 \neq b \in \mathbb{R}^n$ orthogonal to all the a_i's. Clearly $\lambda b \in P$ for every $\lambda \in \mathbb{R}$ since $\langle a_i, \lambda b \rangle = 0 \leq 1$ for all $i \in [m]$. However, P cannot be bounded since $\|\lambda b\| = |\lambda| \cdot \|b\|$ can be made arbitrarily large.

(b)

The gradient and Hessian are given by

$$\begin{aligned} g_j(x) &= \sum_{i=1}^{m} 2 \frac{\langle a_i, x \rangle}{1 - \langle a_i, x \rangle^2} a_i \\ H(x) &= \sum_{i=1}^{m} 2 \frac{1 + \langle a_i, x \rangle^2}{(1 - \langle a_i, x \rangle^2)^2} a_i a_i^T. \end{aligned}$$

(c)

$F(x)$ is finite if and only if for all i,

$$\begin{aligned} 1 - \langle a_i, x \rangle^2 &> 0 \\ |\langle a_i, x \rangle| &< 1. \end{aligned}$$

So $\operatorname{dom} F = \operatorname{int} P$ is the interior of P.

For every $x \in \operatorname{dom} f$, we observe that $H(x)$ is a non-negative linear combination of symmetric rank 1 matrices which are positive semidefinite. It follows that H is positive semidefinite and so F is convex.

(d)

We know that the zeros of the gradient are precisely the global minimizers of F as it is convex. We have $g(0) = 0$ so that 0 is a minimizer.

Furthermore, for $x \in \operatorname{dom} F \setminus 0$, there is some a_i such that $\langle a_i, x \rangle \neq 0$. Thus g is a sum of non-negative functions and one of them takes positive value at x. So $g(x) > 0$ and x is not a minimizer.

It follows that 0 is the unique minimizer.

(e)

We remark that $G(h) := h^T H(x) h$ is convex since its second derivative is $2H(x) \succeq 0$. Thus $\mathcal{E}_x$ is a level-set of a convex function which is necesarily convex. Indeed, for all $h_1, h_2 \in \mathcal{E}_x, \lambda \in [0,1]$,

$$\begin{aligned} G[\lambda h_1 + (1-\lambda)h_2] &\leq \lambda G(h_1) + (1-\lambda)G(h_2) \\ &\leq \lambda + (1-\lambda) \\ &= 1 \end{aligned}$$

so that the line segment $[h_1, h_2] \subseteq \mathcal{E}_x$ as desired.

We claim that any $h \in \mathcal{E}_x$ satisfies $\langle a_i, h\rangle^2 \leq 1$ for all $i \in [m]$. Suppose otherwise, there is some $\bar{i}$ such that the inequality is violated. We have

$$\begin{aligned} h^T H(x) h &= \sum_{i=1}^m 2\frac{1+\langle a_i, x\rangle^2}{(1-\langle a_i, x\rangle^2)^2}\langle a_i, h\rangle^2 \\ &> 2\frac{1+\langle a_{\bar{i}}, x\rangle^2}{(1-\langle a_{\bar{i}}, x\rangle^2)^2} \cdot 1 \\ &\geq 2. \end{aligned}$$

The last inequality follows from the observation that $\frac{1+z^2}{(1-z^2)^2}$ attains its minimum at $z = 0$. But then $h \notin \mathcal{E}_x$ which is a contradiction. By contradiction, $\mathcal{E}_x \subseteq P$ for all $x \in \operatorname{dom} F$.