Homework 1

Convex Optimization

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1 Exercises

Convex Sets

- Let $\mathcal{C} = \left\{x \in \mathbb{R}^2_+ \mid x_1 x_2 \geq 1\right\}$. We can see that $\mathcal{C} = \left\{(x_1, x_2) \in \mathbb{R}^2_{+*} \mid x_1 \geq \frac{1}{x_2}\right\}$. Thus, $\mathcal{C}$ is the epigraph of $x \mapsto \frac{1}{x}$ which is convex since its derivative is $x \mapsto \frac{1}{x^4}$. Thus, $\boxed{\mathcal{C} \text{ is convex.}}$
- In general, $\boxed{\text{this set is not convex.}}$ Indeed, for sets in $\mathbb{R}$, take $S = \{-1, 1\}, T = \{0\}$. Then the set of points closer to S than to T is $\{x \in \mathbb{R} \mid x \leq -0.5 \vee x \geq 0.5\}$ which is not an interval and thus not convex.
- Let us take $x_1, x_2 \in \{x \mid x + S_2 \subseteq S_1\}$. For $x = \lambda x_1 + (1 - \lambda)\, x_2$ consider $x + y$ for $y \in S_2$:

$$x + y = \lambda x_1 + (1 - \lambda)\, x_2 + y = \lambda(x_1 + y) + (1 - \lambda x_2 + y)$$

  Since $x_i + S_2 \subseteq S_1$ for $i = 1, 2$, and since S_1 is convex, for all $y \in S_2$ the above sum is in S_1 and thus $x + S_2 \subseteq S_2$. Finally, $\boxed{\text{our set is convex.}}$
- Let $x_1, x_2 \in \{x \mid \exists y \in S_2, x + y \in S_1\}$. Then let y_1, y_2 be associated points to x_1, x_2. For $x = \lambda x_1 + (1 - \lambda)\, x_2$ and $y = \lambda y_1 + (1 - \lambda) y_2$. Then, since S_2 is convex, $y \in S_2$. Moreover :

$$x + y = \underbrace{\lambda \underbrace{(x_1 + y_1)}_{\in S_1} + (1 - \lambda) \underbrace{(x_2 + y_2)}_{\in S_1}}_{\in S_1 \text{ since } S_1 \text{ is convex}}$$

  Then, $\boxed{\text{our set is convex.}}$

Convex Functions

- The hessian of f at (x, y) is the matrix $\begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$. On $\mathbb{R}^2$ this matrix is not positive nor negative and thus the function is neither convex, or concave. However, the upper level sets are convex (from our first example) and thus $\boxed{\text{the function is quasi-concave.}}$
- On $\mathbb{R}^2_{+*}$, the hessian of the function is positive semidefinite and thus $\boxed{\text{the function is convex.}}$
- The hessian matrix of f is the matrix $\begin{pmatrix} 0 & -\frac{1}{x_2^2} \\ -\frac{1}{x_2^2} & \frac{2x_1}{x_2^3} \end{pmatrix}$ Since its determinant is < 0 the Hessian is not positive semi-definite and the function is not convex. However, its sublevel sets are defined by the equations $x_1 \leq \alpha x_2$ and are thus convex (since half-planes). Thus, $\boxed{f \text{ is quasi-convex}}$.

- Let us define the Löwner order $\preceq$ as the partial order defined by the convex cone of positive semi-definite matrices. We know that :

$$A \preceq B \Rightarrow B^{-1} \preceq A^{-1} \forall A, B \in S^n_{++}$$

From this, we know that for all $t \leq 1$:

$$((1-t)X + tY)^{-1} \preceq (1-t)X^{-1} + tY^{-1}$$

By linearity of the trace, we can now see that $\boxed{X \mapsto \mathrm{Tr}(X^{-1}) \text{ is convex}}$.

Fenchel Conjugate

- We have :

$$\boxed{f^*(y) = \sup_x \left({}^{\mathsf{t}}xy - \|x\|\right) = \begin{cases} 0 & \text{if } \|y\|_* \leq 1 \\ \infty & \text{otherwise} \end{cases}}$$

To show this, let y such that $\|y\|_* = \sup_{\|x\| \leq 1} \|{}^{\mathsf{t}}xy\| \leq 1$. Then by Cauchy-Schwarz inequality, we know that ${}^{\mathsf{t}}xy \leq \|x\| \|y\|_* \leq \|x\|$ and the term in the supremum is always ≤ 0. If $\|y\|_* > 1$ however, then there exists z such that $\|z\| \leq 1$ such that ${}^{\mathsf{t}}zy > 1$. Taking $x = tz$ in the supremum, we know that $f^*(y) \geq t\left({}^{\mathsf{t}}zy - \|z\|\right)$ which goes to infinity with $t \to \infty$. Thus, the fenchel conjugate of a norm is the convex indicator of the unit ball of the dual norm.

- Let us denote the infimal convolution of g, h by $g \Box h$. Then we will show that :

$$\boxed{(g \Box h)^* = (g^* + h^*)}$$

Note that :

$$\begin{aligned} (g \Box h)^*(\alpha) =& \sup_{x,y} \left\{ {}^{\mathsf{t}}x\alpha - g(y) - h(x-y) \right\} \\ =& \sup_{x_1, x_2} \left\{ {}^{\mathsf{t}}(x_1 + x_2)\alpha - g(x_1) - h(x_2) \right\} \\ =& \sup_{x_1, x_2} \left\{ {}^{\mathsf{t}}x_1\alpha - g(x_1) \right\} + \sup_{x_2} \left\{ {}^{\mathsf{t}}x_2\alpha - h(x_2) \right\} \\ =& g^* + h^* \end{aligned}$$

Given $g = \|\cdot\|_1$ and $h = \frac{1}{2\alpha}\|\cdot\|_2^2$. Let $x = u + v$. Then :

$$f(x) = \inf_v \{g(x-v) + h(v)\}$$

Substituting the expressions, we get :

$$\begin{aligned} f(x) =& \inf_v \left\{ \|x - v\|_1 + \frac{1}{2\alpha}\|v\|_2^2 \right\} \\ =& \sum_{i=1}^n \inf_{v_i} \left\{ |x_i - v_i| + \frac{1}{2\alpha} v_i^2 \right\} \end{aligned}$$

We will now compute the infima independently. We have two cases :

1. $v_i \leq x_i$: Let $\varphi(v_i) = x_i - v_i + \frac{1}{2\alpha}v_i^2$. We want to find a minimum for φ, which is found at $v_i = \alpha$. This solution is valid if $\alpha \leq x_i$.
2. $v_i > x_i$: Let $\varphi(v_i = \frac{1}{2\alpha} + v_i - x_i$. We want to find a minimum for φ, which is at $v_i = -\alpha$. This solution is valid if $\alpha > x_i$.

Then, we have three possible cases for the optimal v_i :

1. If $x_i \geq \alpha$, $v_i = \alpha$
2. If $x_i \leq -\alpha$, $v_i = -\alpha$
3. If $-\alpha < x_i < \alpha$, $v_i = x_i$.

Plugging this into f :

$$\boxed{f(x) = \sum_{i=1}^{n} \left(\begin{cases} \frac{1}{2\alpha} x_i^2 & |x_i| \leq \alpha \\ |x_i - \alpha| - \frac{\alpha}{2} & |x_i| > \alpha \end{cases} \right)}$$

- We want to compute :

$$\ell^*(y) = \sup_{z \in \mathbb{R}} \{yz - \ell(z)\} \text{ where } \ell : z \mapsto \log\left(1 + e^{-z}\right)$$

We differentiate $\varphi(z)$ the function in the supremum :

$$\varphi'(z) = y - \frac{1}{1 + e^z}$$

Then, we find $z = \log\left(\frac{1-y}{y}\right)$, which only makes sense for $y \in]0, 1[$. Finally, we compute :

$$\begin{aligned} \ell^*(y) =& y \log\left(\frac{1-y}{y}\right) + \log(1-y) \\ =& y\log(1-y) - y\log(y) + \log(1-y) \\ =& \log(1-y) - y\log(y) \end{aligned}$$

In the end,

$$\boxed{l^*(y) = \log(1-y) - y\log(y)}$$

Duality

- The Lagrangian of the problem associated with $Ax = b$ is :

$$\mathcal{L}(x, \lambda) = \frac{1}{2}\|Ax - b\|_2^2 + \alpha\|x\|_1 - {}^{\mathsf{t}}\lambda(Ax - b) = \frac{1}{2}\|Ax - b\|_2^2 + \alpha\|x\|_1 - {}^{\mathsf{t}}\lambda Ax + {}^{\mathsf{t}}\lambda b$$

Then, by separating terms involving x :

$$\mathcal{L}(x, \lambda) = \frac{1}{2}\|b\|_2^2 - \frac{1}{2}\|\lambda - b\|_2^2 + {}^{\mathsf{t}}\lambda b + \alpha\|x\|_1 - \left({}^{\mathsf{t}}\lambda A\right)x$$

In solving $\max_\lambda \min_x \mathcal{L}(x, \lambda)$, the inner minimization on x only depends on $\|x\|_1$ and $({}^{\mathsf{t}}\lambda A)\,x$. Minimizing it results in $\|{}^{\mathsf{t}}A\lambda\|_\infty \leq \alpha$. Finally, we get that :

$$\boxed{\max_{\lambda \in \mathbb{R}^m} -\frac{1}{2}\|\lambda - b\|_2^2 + \frac{1}{2}\|b\|_2^2 - \inf_{\{\|\cdot\|_\infty \leq 1\}}\left(\frac{{}^{\mathsf{t}}A\lambda}{\alpha}\right) \text{ is a dual problem for the LASSO}}$$

- We start with :

$$\min_{w, w_1, \ldots, w_m \in \mathbb{R}^n} \left\{ \frac{1}{n}\sum_{i=1}^{m} h_i(w_i) + \frac{\lambda}{2}\|w\|_2^2 \;\middle|\; w_i = w, \forall i \in [\![1, m]\!] \right\}$$

Its Lagrangian is :

$$\mathcal{L}(w, w_1, \ldots, w_m, v_1, \ldots, v_m) = \frac{1}{n}\sum_{i=1}^{m} h_i(w_i) + \frac{\lambda}{2}\|w\|_2^2 + \sum_{i=1}^{m} {}^{\mathsf{t}}v_i(w - w_i) = \frac{\lambda}{2}\|w\|_2^2 + \sum_{i=1}^{m} {}^{\mathsf{t}}v_i w + \sum_{i=1}^{m} \frac{1}{n}h_i(w_i) - {}^{\mathsf{t}}v_i w_i$$

For the minimization step, we minimize for each of the w_i and for w. Let $g_i(v_i)$ be the minimized value of $\frac{1}{n}h_i(w_i) - {}^{\mathsf{t}}v_i w_i$. For w, we want to minimize $\frac{\lambda}{2}\|w\|_2^2 + \sum_{i=1}^{m} {}^{\mathsf{t}}v_i w$, which is quadratic in w. Computing its minimum we find $\frac{-1}{2\lambda}\|\sum_{i=1}^{m} v_i\|_2^2$. Finally, the dual problem is :

$$\boxed{\max_{v_1,\ldots,v_m} \sum_{i=1}^{m} g_i(v_i) - \frac{1}{2\lambda}\left\|\sum_{i=1}^{m} v_i\right\|_2^2}$$

For logistic regression, we have :

$$h_i : w \mapsto \log\left(1 + \exp\left(-y_i {}^{\mathsf{t}}x_i w\right)\right)$$

Then we can derive :

$$g_i(v_i) = \min_{w_i}\left\{\frac{1}{n}\log\left(1 + \exp\left(-y_i {}^{\mathsf{t}}x_i w_i\right)\right) - {}^{\mathsf{t}}v_i w_i\right\}$$

Since h_i is differentiable, we can compute its gradient :

$$\nabla h_i(w_i) = \frac{1}{n} \cdot \frac{-y_i x_i}{1 + \exp(y_i {}^{\mathsf{t}}x_i w_i)}$$

which gives us a minimality condition :

$$\frac{-y_i x_i}{1 + \exp(y_i {}^{\mathsf{t}}x_i w_i)} = n v_i$$

which rearranges to :

$$w_i = \frac{\log\left(\frac{-{}^{\mathsf{t}}v_i y_i x_i - n\|v_i\|_2^2}{n\|v_i\|_2^2}\right)}{\|x_i\|_2^2} x_i = \frac{t}{\|x_i\|_2^2} x_i$$

Inputing this into $y_i {}^{\mathsf{t}}x_i w_i$:

$$y_i {}^{\mathsf{t}}x_i w_i = y_i t\, {}^{\mathsf{t}}x_i \frac{x_i}{\|x_i\|_2^2} = y_i t$$

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