

First, recall the definition of the convex conjugate (also known as the Fenchel dual) of an arbitrary function  $f$ .

**Definition 1.** Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be an arbitrary function. Define the convex conjugate  $f^* : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{+\infty\}$

$$f^*(z) \triangleq \sup_{\mathbf{x} \in \mathbb{R}^n} \langle z, \mathbf{x} \rangle - f(\mathbf{x}). \quad (1)$$

Note that  $f^*$  can take the value  $+\infty$  if the difference in (1) can always be made larger. (E.g. consider  $f(x) = |x|$ .) Also,  $f^*$  is always convex regardless of  $f$ , since it is the pointwise supremum of affine functions. However, for convex  $f$  there is also a close connection between the convex conjugate and the subdifferential, which could be useful for the homework.

**Proposition 1.** Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be convex, and  $f^*$  its conjugate. Then for any  $\mathbf{x}, z$  we have

$$\langle \mathbf{x}, z \rangle \leq f(\mathbf{x}) + f^*(z), \quad (2)$$

with equality if and only if  $z \in \partial f(\mathbf{x})$ .

Intuitively, looking at Figure 1, you can see that the conjugate represents the maximum amount you can shift an affine function  $\mathbf{x} \mapsto \langle z, \mathbf{x} \rangle$  down, while still remaining above or equal to  $f$  somewhere. Moreover, Proposition 1 tells us that for those  $\mathbf{x}$  achieving the supremum in (1) for  $f^*(z)$ , we must have  $z \in \partial f(\mathbf{x})$ . I.e.,  $z$  is a subgradient for points  $\mathbf{x}$  that are the last to lose contact as you shift  $\mathbf{x} \mapsto \langle z, \mathbf{x} \rangle$ .

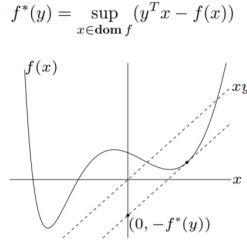


Figure 1: Illustration of the convex conjugate.

An unrelated but possibly also useful property from linear algebra is the Von-Neumann trace inequality.

**Proposition 2** (Von-Neumann trace inequality). Let  $\mathbf{X}, \mathbf{Y} \in \mathbb{R}^{D \times N}$ . Assume without loss of generality that  $r = \text{rank}(\mathbf{X}) \geq \text{rank}(\mathbf{Y}) = r'$ . Let  $\mathbf{X} = \mathbf{U}_X \Sigma_X \mathbf{V}_X^\top$  and  $\mathbf{Y} = \mathbf{U}_Y \Sigma_Y \mathbf{V}_Y^\top$  be their respective compact rank- $r$  SVDs. Also let  $\mathbf{U}'_X \Sigma'_X \mathbf{V}'_X{}^\top$  and  $\mathbf{U}'_Y \Sigma'_Y \mathbf{V}'_Y{}^\top$  contain just the top  $r'$  singular vectors. Then

$$\langle \mathbf{X}, \mathbf{Y} \rangle \leq \langle \Sigma_X, \Sigma_Y \rangle, \quad (3)$$

with equality if and only if  $\mathbf{U}'_Y{}^\top \mathbf{U}'_X = \mathbf{V}'_Y{}^\top \mathbf{V}'_X = \Pi \in \mathbb{R}^{r' \times r'}$ , for a permutation matrix  $\Pi$  satisfying  $\langle \Pi^\top \Sigma'_X \Pi, \Sigma'_Y \rangle = \langle \Sigma_X, \Sigma_Y \rangle$ . If all singular values are unique,  $\Pi = \mathbf{I}$ .

*Proof.* Let  $\mathbf{P} = \mathbf{U}_Y^\top \mathbf{U}_X$ ,  $\mathbf{Q} = \mathbf{V}_Y^\top \mathbf{V}_X$ , and  $\widehat{\mathbf{X}} = \mathbf{P} \Sigma_X \mathbf{Q}^\top$ . Note that both  $\mathbf{P}$  and  $\mathbf{Q}$  are  $r \times r$  orthogonal matrices. By the cyclic property of trace, we have  $\langle \mathbf{X}, \mathbf{Y} \rangle = \langle \widehat{\mathbf{X}}, \Sigma_Y \rangle$ . Furthermore, note that

$$\langle \widehat{\mathbf{X}}, \Sigma_Y \rangle = \sum_{i=1}^{r'} \sigma_{Y_i} \mathbf{p}_i^\top \Sigma_X \mathbf{q}_i, \quad (4)$$

where the  $\mathbf{p}_i, \mathbf{q}_i$  are rows of  $\mathbf{P}, \mathbf{Q}$  respectively. Now consider the optimization problem

$$\max_{\mathbf{P}, \mathbf{Q}} \sum_{i=1}^{r'} \sigma_{Y_i} \mathbf{p}_i^\top \Sigma_X \mathbf{q}_i \quad \text{s.t.} \quad \mathbf{P}^\top \mathbf{P} = \mathbf{Q}^\top \mathbf{Q} = \mathbf{I}, \quad (5)$$

whose optimal value is an (achievable) upper bound for (4). By induction on  $r'$ , one can show that the maximizers  $(\mathbf{P}^*, \mathbf{Q}^*)$  of (5) satisfy  $\mathbf{p}_i^* = \mathbf{q}_i^* = \mathbf{e}_{\pi(i)} \in \mathbb{R}^r$  for  $i = 1, \dots, r'$  and some permutation  $\pi : [r'] \rightarrow [r']$  such that  $\sigma_{Y_i} \mathbf{p}_i^{*\top} \Sigma_X \mathbf{q}_i^* = \sigma_{Y_i} \sigma_{X_{\pi(i)}} = \sigma_{Y_i} \sigma_{X_i}$ . Taking  $\Pi = [\mathbf{e}_{\pi(1)} \cdots \mathbf{e}_{\pi(r')}] \in \mathbb{R}^{r' \times r'}$ , this also means  $\langle \Pi^\top \Sigma'_X \Pi, \Sigma'_Y \rangle = \langle \Sigma_X, \Sigma_Y \rangle$ . Moreover, note that if all singular values are unique,  $\pi$  must be the identity.  $\square$