



$f^*(y) = \sup_x (y^T x - f(x))$ is convex in y
 $y^T x - f(x)$ is affine in y $y^T x - f(x)$ is concave in x if f is convex

Conjugate of Common Convex function

1. Strictly convex quadratic function

$$f(x) = \frac{1}{2} x^T a x$$

$$f^*(y) = \sup_x y^T x - \frac{1}{2} x^T a x$$

$$\nabla_x y^T x - \frac{1}{2} x^T a x = y - a x = 0$$

$$x = a^{-1} y$$

$$f^*(y) = y^T a^{-1} y - \frac{1}{2} y^T a^{-1} a a^{-1} y = \frac{1}{2} y^T a^{-1} y$$

2. Log determinant - inverse

$$f(x) = \log \det(x^T)$$

$$f^*(Y) = \sup_x \text{tr}(Y^T x) - \log \det(x^T)$$

$$= \sup_x \text{tr}(Y X) + \log \det(X)$$

if $Y \neq 0$, then Y has an eigenvector v and the associated eigenvalue $\lambda > 0$

take $X = I + t w w^T$

$$\text{tr}(Y X) + \log \det(X) = \text{tr}(Y) + t \text{tr}(w^T Y w) + \log \det(I + t w w^T)$$

$$= \text{tr}(Y) + t \lambda + (n-1) \log(1+t)$$

$$f^*(Y) = +\infty \text{ as } t \rightarrow +\infty$$

when $Y < 0$

$$\nabla_x \text{tr}(Y X) + \log \det X = Y + X^{-1} = 0 \quad X = -Y^{-1}$$

$$f^*(Y) = \text{tr}(-Y Y^{-1}) + \log \det(-Y^{-1})$$

$$f^*(Y) = \begin{cases} \log \det(-Y)^{-1} - n & Y < 0 \\ +\infty & \text{otherwise} \end{cases}$$

3. log-sum-exp

$$f(w) = \log(\sum_i e^{x_i})$$

$$f^*(y) = \sup_x (y^T x - \log(\sum_i e^{x_i}))$$

$$\text{if } y_i < 0 \quad f^*(y) \rightarrow +\infty \text{ as } x_i \rightarrow +\infty$$

$$\text{if } y > 0 \quad \sum_i y_i \neq 1 \quad \text{choose } x = t \mathbf{1}$$

$$t y^T \mathbf{1} - \log(n e^t) = t \sum_i y_i - \log n - t$$

$$f^*(y) = \begin{cases} +\infty & \sum_i y_i > 0 \\ -\infty & \sum_i y_i < 0 \end{cases}$$

when $y > 0 \quad \sum_i y_i = 1$

$$\nabla_x y^T x - \log(\sum_i e^{x_i}) = y - \frac{e^x}{\sum_i e^{x_i}} = 0 \quad y = \frac{e^x}{\sum_i e^{x_i}}$$

$$\begin{aligned}
 f^*(y) &= y^T x - \log(L^* e^x) \\
 &= \sum_i y_i \cdot \log e^{x_i} - \log \sum_j e^{x_j} \\
 &= \sum_i y_i \cdot \log e^{x_i} - \sum_i y_i \cdot \log \sum_j e^{x_j} \\
 &= \sum_i y_i \cdot \log \frac{e^{x_i}}{\sum_j e^{x_j}} \\
 &= \sum_i y_i \cdot \log y_i
 \end{aligned}$$

$$f^*(y) = \begin{cases} \sum_i y_i \cdot \log y_i & y \geq 0, \sum y_i = 1 \\ \infty & \text{otherwise} \end{cases}$$

4. Norm.

$$f(x) = \|x\| \quad \|x\|_* = \sup_{\|z\| \leq 1} x^T z$$

$$f^*(y) = \sup_{\|x\|_*} x^T y - \|x\|$$

$$\text{if } \|y\|_* > 1 \quad \|y\|_* = \sup_{\|z\| \leq 1} y^T z > 1$$

$$\text{take } x = t z^*$$

$$x^T y - \|x\| = t(z^{*T} y - \|z^*\|) \rightarrow +\infty \text{ as } t \rightarrow \infty$$

$$\text{if } \|y\|_* \leq 1 \quad \sup_{\|z\| \leq 1} y^T z \leq 1$$

$$y^T x = y^T \cdot \frac{x}{\|x\|} \cdot \|x\| \leq \|x\| \quad y^T x - \|x\| \leq 0$$

$$\text{take } x=0 \quad y^T x = 0$$

$$f^*(y) = \begin{cases} 0 & \|y\|_* \leq 1 \\ +\infty & \|y\|_* > 1 \end{cases}$$

• Inequality

$$f^*(y) = \sup_{\|x\|_*} \{x^T y - f(x)\} \quad f^*(y) \geq x^T y - f(x)$$

$$f(x) + f^*(y) \geq x^T y \quad \text{Fenchel's inequality}$$

Young's inequality for differentiable function