

# Non Linear Programming: Homework 4

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## 1 3.32 Products and quotients of convex functions on $\mathbb{R}$

*Remark.* Consider functions on  $\mathbb{R}$ . Assume differentiability too. Let  $D$  be the differential operator with respect to  $x$ .

### 1.1 a

**Theorem 1.1.1.** *If  $f, g$  are convex, both nondecreasing (or nonincreasing) +ve functions, then  $fg$  is convex.*

*Proof.*  $D^2 f(x)g(x) = D^2 f(x)g(x) + 2Df(x)Dg(x) + f(x)D^2 g(x) \geq 0$ . All terms in this sum are non-negative from the assumptions.  $\square$

### 1.2 b

**Theorem 1.2.1.** *If  $f, g$  are concave, +ve, with  $f$  nondecreasing and  $g$  nonincreasing,  $fg$  is concave.*

*Proof.*  $D^2 f(x)g(x) = D^2 f(x)g(x) + 2Df(x)Dg(x) + f(x)D^2 g(x) \geq 0$ . All terms in this sum are non-positive from the assumptions.  $\square$

### 1.3 c

**Theorem 1.3.1.** *If  $f$  is convex, nondecreasing, +ve.  $g$  is concave, nonincreasing, +ve. Then,  $f/g$  is convex.*

*Proof.*  $D^2 f(x)/g(x) = D^2 f(x)/g(x) - 2Df(x)Dg(x)/g(x)^2 - f(x)D^2 g(x)/g(x)^2 - f(x)D^2 g(x)/g(x)^2 + 2f(x)(Dg(x))^2/g(x)^3 \geq 0$ . All terms in this sum are non-negative from the assumptions.  $\square$

## 2 3.36 (a)-(d) Conjugate functions

### 2.1 Hint

Problem 3.36 concerns conjugate functions, and is likely to be quite difficult for some of you. Conjugates often defy intuition. I recommend a two-step approach:

\* First, determine the \*domain\* of the conjugate, by trying to find general conditions under which the supremum is unbounded. Many conjugate functions have bounded domains even when the original function does not.

\* Then, choose a point inside the domain and determine the supremum.

Do not be surprised by strange results! (Though verify them!)

*Notation.* Given  $f(x)$ , conjugate function is  $f'(y) = \sup_{x \in \text{dom}(x)} (y^T x - f(x))$ . Assume that  $y$  is not 0.

### 2.2 a max

$f'(y) = \sup_{x \in \text{dom}(x)} (y^T x - f(x)) = \infty$ . This is a special case of part b below.

### 2.3 b Sum of top k values

Let  $y_{(i)}$  denote entry of  $y$  corresponding to  $i$ th largest entry of  $x$ ,  $x_{[i]}$ .  $f'(y) = \sup_{x \in \text{dom}(x)} \sum_{i=1}^k (y_{(i)} - 1)x_{[i]} + \sum_{i=k+1}^n y_{(i)}x_{[i]} = \infty$ , when  $n > k$ .

### 2.4 c Piecewise linear fn

$f'(y) = \sup_{x \in \text{dom}(x)} \min_i (y - a_i)x - b_i$ . This will correspond to  $x$  which is either be unbounded if  $y > a_n$ , or a point where two linear pieces whose slopes are such that  $a_i \leq y \leq a_{i+1}$  intersect.

### 2.5 d Powers

$f'(y) = \sup_{x \in \text{dom}(x)} yx - x^p$ . To find the supremum, set the gradient to 0 to get:  $y - px^{p-1} = 0$ . This is indeed the maximum because the hessian happens to be  $-px^{p-2} \leq 0$  for  $p > 1$ . So, the maximizing  $x$  is  $g(y) = (\frac{y}{p})^{\frac{1}{p-1}}$ . So,  $f'(y) = yg(y) - g(y)^p$ .

For  $p < 0$ ,  $f'(y) = \infty$ .

## 3 3.49 Log concavity

### 3.1 a Logistic fn

$\log f(x) = x - \log(1 + e^x)$ . We see that  $D^2(\log f(x)) = -e^{3x}/(1 + e^x) \leq 0$ , so  $f(x)$  is log concave.

### 3.2 b Harmonic mean

From the slides, we know that  $g(x) = x^{-1}$  is log concave. It is also decreasing. So,  $\log g(x)$  is concave and decreasing. Consider  $h : R_{++}^n \rightarrow R$ :  $h(x) = \sum x_i^{-1}$ . This, being a sum of concave functions, is concave. Applying the rules of function composition, we have that  $\log g(h(x))$  is concave. So,  $f(x)$  is log concave.

### 3.3 c Product over sum

From the slides, we know that  $g(x) = x^{-1}$  is log concave. It is also decreasing. So,  $\log g(x)$  is concave and decreasing. Consider  $h : R_{++}^n \rightarrow R$ :  $h(x) = \sum x_i$  is also concave. So,  $\log g(h(x)) = (\sum x_i)^{-1}$  is log concave. Also, functions  $f_i(x) = x_i$  are all log concave. Product of log concave functions is log concave. So,  $f(x) = \frac{\prod_i x_i}{\sum_i x_i}$  is also log concave.

### 3.4 d Determinant over trace

We use part c and claim that  $g(\lambda) = \frac{\prod_i \lambda_i}{\sum_i \lambda_i}$  is log concave in  $\lambda$ . So,  $\log g(\lambda)$  is concave and increasing (seen by taking the derivative and seeing its non-negativity). The eigenvalue function,  $\lambda(X)$  is convex.

So, by composition rules,  $f(X) = \frac{\det(X)}{\text{tr}(X)} = g(\lambda(X))$  is log concave.

## 4 3.51

Let  $p$  be a degree  $k$  polynomial on  $R$ , with all roots  $\{r_i\}$  being real. So,  $p(x) = \prod_{i=1}^k (x - r_i)$  and  $\log p(x) = \sum_{i=1}^k \log(x - r_i)$ .  $\log(x - r_i)$  is a concave function (composition of concave fn with affine transformation). So,  $\log p(x)$  is concave where it is +ve and  $x$  exceeds all  $r_i$ .