Homework #4 Due on February 7, 2012 at noon

NOTE: The following problems are from Chapter 1 of the textbook.

- 1) Prove that in Example 6.25 (i) of the textbook, $T(X) = (X_{(1)}, X_{(n)})$ is not a complete statistic.
- 2) Let $f(x, y) = x^2 + y^2$, which maps from \mathbb{R}^2 to $(0, \infty)$. Show that f is convex function and describe the supporting hyper-plane L(x) at the point (1, 0).
- 3) The logistic regression model is

$$p(y = \pm 1 | x, w) = \frac{1}{1 + \exp(-y \cdot w^T x)}$$

where y is binary, x is a vector of covariates, and w is called the regression parameter. This model can be used for binary classification or for predicting the certainty of a binary outcome. To estimate w, the maximum likelihood estimation method is often used. The log-likelihood function l(w) can be written as

$$l(w) = -\sum_{i=1}^{n} \log(1 + \exp(-y_i \cdot w^T x_i)).$$

The MLE is the maximize of l(w) with respect to w. Assume xx^T is non-degenerated. Show that the MLE is unique if exists.

4) Let *F* and *G* be probability measures on \mathbb{R}^k . Let $h: \mathbb{R}^k \to [0, \infty)$ be convex with $h(x) \ge h(0) = 0$ for all $x \in \mathbb{R}^k$. Suppose that $E_F[h(X)] < E_G[h(X)]$. Show that there is a convex set $A \subset \mathbb{R}^k$ with $0 \in A$ such that F(A) > G(A). **Hint:** First try to prove that

$$E_F[h(X)] = -\int_{-\infty}^{\infty} h(x)dF(X > x)dx = \int_{0}^{\infty} F(h(X) > t)dt$$

5) Let $0 < \alpha < 1$.

(a) Show that the function f(x, y) = -x^αy^{1-α} is convex on {(x, y) ∈ ℝ²: x > 0 and y > 0}
(b) for positive render variable X and X with finite means up and y with finite means u

(b) for positive random variable *X* and *Y* with finite means, use the above result to prove the Hölder's inequality:

 $E[X^{\alpha}Y^{1-\alpha}] \leq [E(X)]^{\alpha}[E(Y)]^{1-\alpha}$

(c) Use parts (a) and (b) to prove that the normalizing term $A(\eta)$ is a canonical exponential family is a convex function on the natural parameter space.