

4. If  $X \sim \mathcal{N}(0, 1)$ , then prove that  $P(|X| \geq u) \leq \sqrt{2/\pi} \frac{e^{-u^2/2}}{u}$  for all  $u > 0$ . How does this bound compare with that given by Chebyshev's inequality? [10+5 = 15 points]

5. Consider  $n$  values  $\{x_i\}_{i=1}^n$  drawn independently from a Laplacian distribution with mean 0 and parameter  $\sigma$ . The probability density for a Laplacian random variable  $X$  is given by  $f_X(x) = \frac{1}{2\sigma} e^{-|x|/\sigma}$  (note the absolute value in the exponent). Given  $\{x_i\}_{i=1}^n$ , derive the maximum likelihood estimate for  $\sigma$ , as well as its bias, variance, MSE. [15 points]

6. In this problem, we will derive higher order moments of specific random variables in a new way.

(a) Consider  $X \sim \mathcal{N}(\mu, \sigma^2)$ . Then prove that  $E[g(X)(X - \mu)] = \sigma^2 E[g'(X)]$  where  $g$  is a differentiable function such that  $E[|g'(X)|] < \infty, |g(x)| < \infty$ . Use this to derive an expression for  $E[X^3]$  in terms of  $\mu$  and  $\sigma^2$ . Do not use any other method (eg: MGFs) to derive  $E[X^3]$ . [5+5=10 points]

(b) Consider  $X \sim \text{Poisson}(\lambda)$ . Then prove that  $E[\lambda g(X)] = E[X g(X - 1)]$  where  $g$  is a function such that  $-\infty < E[g(X)] < \infty, -\infty < g(-1) < \infty$ . Use this to derive an expression for  $E[X^3]$  assuming known expressions for  $E[X], E[X^2]$ . Do not use any other method (eg: MGFs) to derive  $E[X^3]$ . [5+5=10 points]

7. (a) A student is trying to design a procedure to generate a sample from a distribution function  $F$ , where  $F$  is invertible. For this, (s)he generates a sample  $u_i$  from a  $[0, 1]$  uniform distribution using the 'rand' function of MATLAB, and computes  $v_i = F^{-1}(u_i)$ . This is repeated  $n$  times for  $i = 1 \dots n$ . Prove that the values  $\{v_i\}_{i=1}^n$  follow the distribution  $F$ . [6 points]

(b) Let  $Y_1, Y_2, \dots, Y_n$  represent data from a continuous distribution  $F$ . The empirical distribution function  $F_e$  of these data is defined as  $F_e(x) = \frac{\sum_{i=1}^n \mathbf{1}(Y_i \leq x)}{n}$  where  $\mathbf{1}(z) = 1$  if the predicate  $z$  is true and 0

otherwise. Now define  $D = \max_x |F_e(x) - F(x)|$ . Also define  $E = \max_{0 \leq y \leq 1} \left| \frac{\sum_{i=1}^n \mathbf{1}(U_i \leq y)}{n} - y \right|$  where  $U_1, U_2, \dots, U_n$  represent data from a  $[0, 1]$  uniform distribution. Now prove that  $P(E \geq d) = P(D \geq d)$ . Briefly explain what you think is the practical significance of this result in statistics. [8+6=14 points]