## SDS 383C: Statistical Modeling I, Fall 2022 Homework 1, Due Sept 19, 12:00 Noon

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All homework must be submitted typed-in as a single pdf file. Name the file "firstname-lastname-SDS383C-HW-1.pdf" Submit this file without compression such as zip or rar. Figures accompanying the solutions must be presented close to the actual solution. Computer codes will be rarely evaluated but must still be submitted separately from the main file. Codes must be commented properly and should run easily on other machines. Precise, concise, clear, innovative solutions may be rewarded with bonus points. Explain your answer with logic reasoning and/or mathematical proofs. Organize your solutions in the same order as they were presented. If you can solve a problem using multiple techniques, present only your best solution.

- 1. (15 points) Prove Slutsky's theorem (the version taught in class).
- 2. (10 points) For  $y \sim \operatorname{Poisson}(\lambda)$ , show that  $\mathbb{E}(y) = \operatorname{var}(y) = \lambda$ . Method of moments suggests  $\overline{y}_n$ , the sample mean, as well as  $s_n^2$ , the sample variance, could both be reasonable estimators of  $\lambda$ . Which one would you prefer? Why?
- 3. (10 points) For  $(x_1, y_1), \ldots, (x_n, y_n) \stackrel{iid}{\sim} f_{x,y}$  with finite second order moments. Show that the sample correlation coefficient  $r_n$  converges in probability to the population correlation coefficient  $\rho$ .
- 4. (10 points) Notations having their usual significance, for  $y_1, \ldots, y_n \stackrel{iid}{\sim} \operatorname{Ga}(\alpha, \beta)$ , a method of moment estimator of  $\alpha$  is  $\widehat{\alpha}_n = \overline{y}_n^2/s_n^2$ . Using the multivariate delta method, show that  $SE(\widehat{\alpha}_n) \approx \sqrt{2\alpha(\alpha+1)/n}$  for large values of n.
- 5. (10 points) Now fix the values of  $\alpha$  and  $\beta$ . For your chosen values of  $\alpha$  and  $\beta$ , draw a random sample of size n=50 from a  $\operatorname{Ga}(\alpha,\beta)$  distribution. Using method of moments and assuming  $\alpha$  and  $\beta$  to now be unknown, estimate  $\alpha$  and  $\beta$ . Plot the histogram of the samples, superimposed with the true density and the estimated density.

Repeat the above procedure B=50,500 and 1000 times. Plot a histogram of  $\sqrt{n}\frac{(\widehat{\alpha}_n-\alpha)}{\sqrt{2\widehat{\alpha}_n(\widehat{\alpha}_n+1)}}$  for each of the above values of B. In each case, superimpose a Normal(0,1) distribution over the histogram.

For your final output, provide a very brief description of what you did, the plots, the codes, and your general comments, if any.

6. (5 points) For a Normal( $\mu$ ,  $\sigma^2$ ) distribution, show that the MGF is  $M(t) = \exp(\mu t + \sigma^2 t^2/2)$ .

7. (10 points) Show that a binomial random variable R with denominator m and probability  $\pi$  has cumulant generating function  $K(t) = m\log(1 - \pi + \pi e^t)$ . Find  $\lim K(t)$  as  $m \to \infty$ ,  $\pi \to 0$  in a way so that  $m\pi \to \lambda > 0$ . Show that

$$\Pr(R=r) \to \frac{\lambda^r}{r!} e^{-\lambda},$$

and hence establish that  $R \stackrel{d}{\to} \operatorname{Poisson}(\lambda)$ . Using your favorite programming language, provide a numerical illustration of the result.

[Hints: 
$$\lim_{n\to\infty} \left(1+\frac{x}{n}\right)^n = e^x$$
.]

- 8. (5 points) If  $Z \sim \text{Normal}(0,1)$ , derive the density of  $Y = Z^2$ . Although Y is determined by Z, show that they are uncorrelated.
- 9. (5 points) Let  $Y = X_1 + bX_2$  where the  $X_j$  are independent normals with means  $\mu_j$  and variances  $\sigma_j^2$ . Show that conditional on  $X_2 = x$ , the distribution of Y is normal with mean  $\mu_1 + bx$  and variance  $\sigma_1^2$ . Hence establish that

$$\int \frac{1}{\sigma_1} \phi\left(\frac{y-\mu_1-bx}{\sigma_1}\right) \frac{1}{\sigma_2} \phi\left(\frac{x-\mu_2}{\sigma_2}\right) dx = \frac{1}{\sqrt{\sigma_1^2+b^2\sigma_2^2}} . \phi\left(\frac{y-\mu_1-b\mu_2}{\sqrt{\sigma_1^2+b^2\sigma_2^2}}\right).$$

10. Read pages 62-75 (Section 3.2: Normal Model) from AC Davison's Statistical Models.