Due: 11:59pm Saturday, July 23 Instructor: Ethan P. Marzban

Instructions:

- Please submit your work to Gradescope by no later than the due date posted above.
- Be sure to show your work; correct answers with no supporting work will not be awarded full points.
- 2 randomly selected questions/parts will be graded, but you must still turn in your work for all problems in order to be eligible to earn full credit.

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1. **The Multinomial Distribution.** Recall that the Binomial distribution arises in the context of tracking the number of successes across n independent Bernoulli(p) trials. Definitionally, then, we require a binary division; namely a well-defined notion of "success" and "failure." Oftentimes, in Statistical Modeling, this is too stringent of a restriction.

Suppose our n independent trials each result in one of r outcomes; as a simple case, when r=3, we might say that our outcomes are "success," "failure," and "neutral." Additionally, suppose that each trial results in outcome i with probability p_i , for $i=1,\cdots,r$. Let X_i denote the number of outcomes of type i we see (again, for $i=1,\cdots,r$); then the random vector (X_1,\cdots,X_r) is said to follow the **Multinomial Distribution** with parameters n (total number of trials), r (number of possible outcomes on each trial), and p_1,\cdots,p_r (the probability of each outcome). We denote this:

$$(X_1, \dots, X_r) \sim \text{Multi}(n, r, p_1, \dots, p_n)$$

Over the next few parts, we will investigate the Multinomial distribution in greater detail.

PART I: Deriving the Joint P.M.F.

- (a) Suppose that PSTAT 120A has 100 students and 4 Discussion Sections (we can call them Sections 1 through 4). Further suppose that section 1 must contain 15 students, section 2 must contain 35, Section 3 must contain 20, and Section 4 must contain 30. In how many ways can we divide the students among these 4 sections?
- (b) If n and r are positive integers, and k_1, \dots, k_r are nonnegative integers that sum to n (i.e. $k_1 + \dots, k_r = n$), then the number of ways of assigning lables $1, 2, \dots, r$ to n items so that, for each $i = 1, 2, \dots, r$ exactly k_i items receive label i, is the **multinomial coefficient**

$$\binom{n}{k_1, k_2, \cdots, k_r} = \frac{n!}{(k_1!) \times (k_2!) \times \cdots \times (k_r)!}$$

Rewrite your answer to part (a) using a multinomial coefficient.

- (c) Now, let's return to the Multinomial distribution. Find $p_{X_1,\dots,X_r}(k_1,\dots,k_r)$, the joint p.m.f. of (X_1,\dots,X_r) . You may find it useful to revisit the methodology we used when deriving the p.m.f. of the Binomial distribution.
- (d) Speaking of the Binomial Distribution, show that the $Multi(n, 2, p_1, p_2)$ distribution is equivalent to the Binomial distribution.

PART II: Using the Joint P.M.F. In all parts that follow, continue to take $(X_1, \dots, X_r) \sim \text{Multi}(n, r, p_1, \dots, p_r)$

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- (e) What is the marginal distribution of X_1 ? (No summations needed; just make an argument about exactly *what* X_1 measures.)
- (f) Give an expression for $Cov(X_i, X_j)$, for $i, j = 1, \dots, r$. **Hint:** There are two possible ways to solve this part.
 - (1) Consider the indicator defined by

$$\mathbb{1}_{k,i} = \begin{cases} 1 & \text{if trial } k \text{ gives outcome } i \\ 0 & \text{if trial } I \text{ gives an outcome other than } i \end{cases}$$

and express X_i as a suitable sum of these indicators.

- (2) Alternatively, you can recognize the distribution of $(X_1 + X_2)$, compute its variance, and then use previously-derived results about variances of sums of random variables to obtain an equation involving $Cov(X_i, X_j)$ that you can solve for.
- 2. The Multivariate Normal Distribution Suppose we have a random vector $\vec{X} = (X_1, \dots, X_n)$ with variance-covariance matrix Σ . Additionally, consider a vector $\vec{\mu} := (\mu_1, \dots, \mu_n)$; we say that \vec{X} follows the multivariate normal distribution with parameters $\vec{\mu}$ and Σ if the joint p.d.f. of \vec{X} is given by

$$f_{\vec{X}}(\vec{x}) = (2\pi)^{-n/2} \cdot \left[\det(\mathbf{\Sigma}) \right]^{-1/2} \cdot \exp\left\{ -\frac{1}{2} (\vec{x} - \vec{\mu})^{\mathsf{T}} \mathbf{\Sigma}^{-1} (\vec{x} - \vec{\mu}) \right\}$$

and we abbreviate this $\vec{X} \sim \mathcal{N}_n(\vec{\mu}, \Sigma)$ (where the subscript n denotes the dimension of \vec{X}).

(a) Suppose n=2; the resulting distribution is called the **Bivariate Normal**. If we denote the elements of $\vec{\mu}$ by μ_X and μ_Y , and the the variances of X and Y as σ_X , σ_Y , respectively, and if we use ρ to denote Corr(X,Y), then the p.d.f. of (X,Y) becomes

$$f_{X,Y}(x,y) = \frac{1}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho^2}}\exp\left\{-\frac{1}{2(1-\rho^2)}\left[\left(\frac{x-\mu_X}{\sigma_X}\right)^2 + \left(\frac{y-\mu_Y}{\sigma_Y}\right)^2 - 2\rho\left(\frac{x-\mu_X}{\sigma_X}\right)\left(\frac{y-\mu_Y}{\sigma_Y}\right)\right\}\right]$$

Sketch the level curves of $f_{X,Y}(x,y)$ (i.e. the curves in the xy-plane over which the graph of $f_{X,Y}(x,y)$ remain constant). Your sketch does not need to be fully to scale, but be sure to label as much as you can.

- (b) Let $\vec{X} \sim \mathcal{N}_n(\vec{\mu}, \Sigma)$. Further suppose that the X_i 's are uncorrelated. Show that the X_i 's are independent; in other words, show that **uncorrelated does imply independent in the setting of a multivariate normal distribution**. (Hint: Consider what happens to the structure of Σ when the X_i 's are uncorrelated. Additionally, your "proof" doesn't need to be super rigorous.)
- 3. Let *X* and *Y* be two continuous random variables with: $\mathbb{E}[X] = 6$, Var(X) = 4, $\mathbb{E}[Y] = 6$, Var(Y) = 3, and Cov(X,Y) = -1. Use Chebyshev's Inequality to provide a bound for $\mathbb{P}(9 \le X + Y \le 15)$; be sure to specify whether this bound is an *upper* or *lower* bound.