

Multivariate distributions (again)

Recap

Section 4.6 of Casella & Berger discusses multivariate distributions (more than 2 random variables at a time). While often focusing on the bivariate case (X, Y) , we've already seen the main distributional ideas for (X_1, \dots, X_k) :

1. Joint cdfs: for $x_1, \dots, x_k \in \mathbb{R}$

$$\longrightarrow F(x_1, \dots, x_k) = P(X_1 \leq x_1, X_2 \leq x_2, \dots, X_k \leq x_k)$$

2. Jointly Discrete: joint pmf $f(x_1, \dots, x_k) = P(X_1 = x_1, X_2 = x_2, \dots, X_k = x_k)$,

$$\longrightarrow P((X_1, \dots, X_k) \in A) = \sum_{(x_1, \dots, x_k) \in A} f(x_1, \dots, x_k), \quad A \subset \mathbb{R}^k$$

3. Jointly Continuous: joint pdf $f(x_1, \dots, x_k)$ where

$$P((X_1, \dots, X_k) \in A) = \int \cdots \int_A f(x_1, \dots, x_k) dx_1 dx_2 \cdots dx_k, \quad A \subset \mathbb{R}^k$$

4. Expectations: let $g: \mathbb{R}^k \rightarrow \mathbb{R}$, define

$$Eg(X_1, \dots, X_k) = \begin{cases} \sum_{(x_1, \dots, x_k)} g(x_1, \dots, x_k) f(x_1, \dots, x_k) & \text{Discrete} \\ \int \cdots \int g(x_1, \dots, x_k) f(x_1, \dots, x_k) dx_1 \cdots dx_k & \text{Continuous} \end{cases}$$

(Handwritten notes: "fix" above X_1, \dots, X_p ; X_{p+1}, \dots, X_k circled in red)

5. Marginal distribution of (X_1, \dots, X_p) obtained by summing or integrating out over values x_{p+1}, \dots, x_k of other variables: fix $x_1, \dots, x_p \in \mathbb{R}$,

$$f_{X_1, \dots, X_p}(x_1, \dots, x_p) = \begin{cases} \sum_{(x_{p+1}, \dots, x_k)} f(x_1, \dots, x_p, x_{p+1}, \dots, x_k) & \text{discrete} \\ \int \cdots \int f(x_1, \dots, x_p, x_{p+1}, \dots, x_k) dx_{p+1} \cdots dx_k & \text{continuous} \end{cases}$$

(Handwritten notes: (x_{p+1}, \dots, x_k) circled in red; $dx_{p+1} \cdots dx_k$ underlined in red)

6. Conditionals of X_1, \dots, X_p given $X_{p+1} = x_{p+1}, \dots, X_k = x_k$

$$f_{X_1, \dots, X_p | X_{p+1}, \dots, X_k}(x_1, \dots, x_p) = \frac{f(x_1, \dots, x_k)}{f_{X_{p+1}, \dots, X_k}(x_{p+1}, \dots, x_k)}$$

(Handwritten note: X_1, \dots, X_p underlined in red)

Multivariate Distributions

Common Multivariate Models

Multivariate distributions so far

- textbook examples of $f(x, y)$
- hierarchical models: $f(x, y) = f_X(x)f_{Y|X=x}(y|x)$
- X_1, \dots, X_n independent with common $f_X(x)$

There are really not so many standard families of multivariate distributions.

Most often, the commonly referenced distributions are

- ✓ 1. Multiple Hypergeometric (generalizing the hypergeometric)
 - ✓ 2. Multinomial (generalizing the Binomial)
 - ✓ 3. Dirichlet (generalizing the Beta)
 - ⊗ 4. Multivariate Normal Distribution (generalizing the normal)
- } not so important for US.

Out of these, the multivariate normal distribution is by far the most important in statistics.

Multivariate Distributions

Multiple Hypergeometric Distribution without replacement

- Sample K at random from a population containing N_i items of type i , $i =$

$1, \dots, \ell$

$N_1 = \#$ of items in Population of type 1

$N_2 = \#$ of " " " " type 2

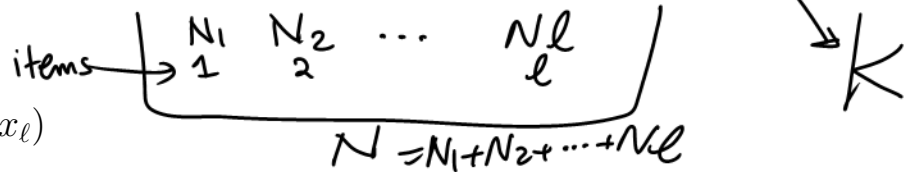
\vdots
 $N_\ell = \#$ of " " " " type ℓ

$$N = N_1 + N_2 + \dots + N_\ell$$

- Let $X_i = \#$ of items in the sample of type i .

- Then $X = (X_1, \dots, X_\ell)$ has a multiple hypergeometric distribution with joint pmf

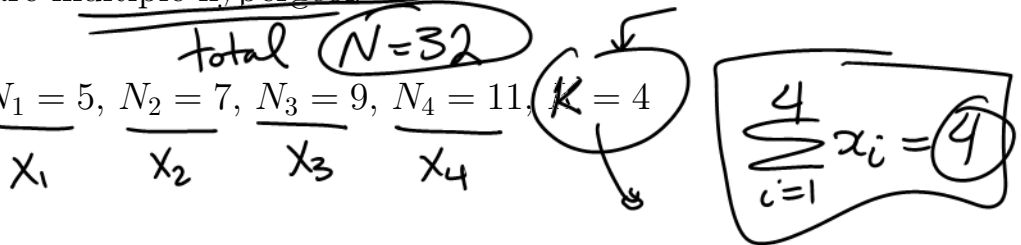
$$\rightarrow P(X_1 = x_1, \dots, X_\ell = x_\ell) = f(x_1, \dots, x_\ell)$$



$$\binom{N}{K} = \begin{cases} \frac{\binom{N_1}{x_1} \binom{N_2}{x_2} \dots \binom{N_\ell}{x_\ell}}{\binom{N_1 + N_2 + \dots + N_\ell}{K}} & \text{integer } x_1, \dots, x_\ell \geq 0, \sum_{i=1}^{\ell} x_i = K \\ 0 & \text{otherwise} \end{cases}$$

- Here individual marginal distributions are hypergeometric; conditionals of some given others are multiple hypergeometric

- Example ($\ell = 4$): $N_1 = 5, N_2 = 7, N_3 = 9, N_4 = 11, K = 4$



$$X_1 \sim \text{Hypergeometric}(K=4, M=5=N_1, N=32)$$

$$\rightarrow P(X_1 = x_1) = \sum_{(x_2, x_3, x_4)} P(X_2 = x_2, X_3 = x_3, X_4 = x_4, X_1 = x_1)$$

$$\frac{P(X_1 = x_1, X_2 = x_2, X_3 = x_3, X_4 = 2)}{P(X_4 = 2)} \sim \text{Multiple Hypergeometric dist.}$$

$N_1 = 5, N_2 = 7, N_3 = 9$

$K = X_4 = 4 - x_4 = 2$

Multivariate Distributions

Multinomial Distribution

- Suppose $0 \leq p_1, p_2, \dots, p_k$ are probabilities such that $\sum_{i=1}^k p_i = 1$.
- Consider a series of n identical trials where, on each trial, one can get exactly one of k possible outcomes o_1, \dots, o_k .
- Let $X_i = \#$ of trials resulting in outcome o_i .
- Then $X = (X_1, \dots, X_k)$ has a multinomial(n, p_1, \dots, p_k) distribution with joint pmf

$$P(X_1 = x_1, \dots, X_k = x_k) = f(x_1, \dots, x_k) = \begin{cases} \frac{n!}{x_1! x_2! \dots x_k!} p_1^{x_1} p_2^{x_2} \dots p_k^{x_k} & \text{integer } x_1, \dots, x_k \geq 0, \sum_{i=1}^k x_i = n \\ 0 & \text{otherwise} \end{cases}$$

Handwritten notes: $\binom{n}{x_1, x_2, \dots, x_k} \Rightarrow$ (circled in purple). $x_1 + x_2 + x_3 + x_4 = 4$ (circled in purple). $x_1, x_2, x_3 \mid x_4 = 2$ (circled in purple).

- $\frac{n!}{x_1! x_2! \dots x_k!}$ is the multinomial coefficient, counting number of ways/arrangements that n trials could result in x_1 outcomes o_1 , x_2 outcomes o_2 , ..., x_k outcomes o_k .

- Here individual marginal distributions are Binomial(n, p_i); conditionals of some given others are multinomial.

- Example ($k = 4, n = 4$):

$$(X_1, X_2, X_3, X_4)$$

$$X_1 \sim \text{Bin}(4, p_1)$$

$$P(X_1 = x_1) = \sum_{x_2, x_3, x_4} P(X_1 = x_1, X_2 = x_2, X_3 = x_3, X_4 = x_4) = \dots$$

$$X_3 \sim \text{Bin}(n, p_3)$$

$$X_1, X_2, X_3 \mid X_4 = 2 \sim \text{multinomial} \left(\binom{n}{*} p_1^*, p_2^*, p_3^* \right) \text{ with } p_1^* + p_2^* + p_3^* = 1$$

Handwritten notes: $p_1^* = \frac{p_1}{p_1 + p_2 + p_3}, p_2^* = \frac{p_2}{p_1 + p_2 + p_3}, p_3^* = \frac{p_3}{p_1 + p_2 + p_3}$ (circled in purple).

$$\mathbb{P}(X_1=x_1, X_2=x_2, X_3=x_3 | X_4=2) = \frac{\mathbb{P}(X_1=x_1, \dots, X_4=x_4)}{\mathbb{P}(X_4=2)}$$

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Multivariate Distributions

Dirichlet Distribution

- Suppose Y_1, \dots, Y_k are independent and $Y_i \sim \text{Gamma}(\alpha_i, 1)$, $i = 1, \dots, k$

$$0 < X_i < 1, \sum_{i=1}^k X_i = 1$$

- Let $X_i = Y_i / \sum_{j=1}^k Y_j$

- Then $X = (X_1, \dots, X_k)$ has a Dirichlet($\alpha_1, \dots, \alpha_k$) distribution

- Note that X_1, \dots, X_k are random variables which sum to 1

- Here individual marginal distributions are Beta($\alpha_i, \sum_{j=1, j \neq i}^k \alpha_j$) conditionals of some given others are scalar multiples of Dirichlets

- Example ($k = 4$): $\alpha_1 = 3, \alpha_2 = 2, \alpha_3 = 4, \alpha_4 = 1$