

Recall: $X_i \sim \text{Multi}_2(n, \vec{p})$

$$\begin{aligned} \text{we know } P(X_1, X_2) &:= P(X_1 = x_1 | X_2 = x_2) \\ &= \frac{P(X_1, X_2)}{P(X_2)} = \text{Deg}(n - x_2) \end{aligned}$$

Last time $P(X_2) = \text{Bin}(n, p_2) = \text{Bin}(n, 1 - p_1)$

Let $J_n := \{0, 1, \dots, n\}$

$$P(X_1, X_2) = \frac{\binom{n}{x_1, x_2} p_1^{x_1} p_2^{x_2}}{\binom{n}{x_2} p_2^{x_2} (1 - p_2)^{n - x_2}} = \frac{\frac{n!}{x_1! x_2!} \prod_{x_1 + x_2 = n} \prod_{x_1 \in J_n} \prod_{x_2 \in J_n} p_1^{x_1} p_2^{x_2}}{\frac{n!}{x_2! (n - x_2)!} \prod_{x_2 \in J_n} p_2^{x_2} p_1^{n - x_2}}$$

$$\text{Let } \mathbb{I}_A^u = \frac{\mathbb{I}_A}{\mathbb{I}_A} = \begin{cases} 1 & \text{if } A \\ 0 & \text{if } A^c \end{cases} = \frac{(n - x_2)!}{x_1!} \prod_{x_1 = n - x_2} \prod_{x_1 \in J_n} \mathbb{I}_{x_2 \in J_n}^u = \text{Deg}(n - x_2) \prod_{x_2 \in J_n} \mathbb{I}_A^u$$

Let's generalize this conditional probab:

$\vec{X} \sim \text{Multi}_k(n, \vec{p})$

$$P_{\vec{x}-j}(\vec{x}-j, x_j) = \frac{P_{\vec{x}}(\vec{x})}{P_{x_j}(x_j)} = \text{Multi}_{k-1}(n - x_j, \vec{p}) = \frac{\text{Multi}_k(n, \vec{p})}{\text{Bin}(n, p_j)}$$

$$= \frac{\binom{n}{x_1, \dots, x_j, \dots, x_k} p_1^{x_1} \dots p_j^{x_j} \dots p_k^{x_k}}{\binom{n}{x_j} p_j^{x_j} (1 - p_j)^{n - x_j}} = \frac{\frac{n!}{x_1! \dots x_j! \dots x_k!} \prod_{x_1 + \dots + x_k = n} \prod_{x_1 \in J_n} \dots \prod_{x_k \in J_n} p_1^{x_1} \dots p_{j-1}^{x_{j-1}} p_{j+1}^{x_{j+1}} \dots p_k^{x_k}}{\frac{n!}{x_j! (n - x_j)!} \prod_{x_j \in J_n} (1 - p_j)^{n - x_j}}$$

Note: $p_1 + \dots + p_k = 1 \Rightarrow p_1 + \dots + p_{j-1} + p_{j+1} + \dots + p_k = 1 - p_j$

$$= \frac{p_1}{1 - p_j} + \dots + \frac{p_{j-1} + p_{j+1} + \dots + p_k}{1 - p_j} = 1$$

Note: $n - x_j = x_1 + \dots + x_{j-1} + x_{j+1} + \dots + x_k$

Let $n' = n - x_j$

$$= \frac{n!}{x_1! \dots x_{j-1}! x_{j+1}! \dots x_k!} \prod_{x_1 + \dots + x_{j-1} + x_{j+1} + \dots + x_k = n'} \prod_{x_1 \in J_n} \dots \prod_{x_{j-1} \in J_n} \prod_{x_{j+1} \in J_n} \dots \prod_{x_k \in J_n} p_1^{x_1} \dots p_{j-1}^{x_{j-1}} p_{j+1}^{x_{j+1}} \dots p_k^{x_k} \prod_{x_j \in J_n} \mathbb{I}_A^u$$

$$(1 - p_j)$$

$$= \text{Mult}_{k-1}(n, \vec{\mu}, \vec{\Sigma}) \prod_{j \in [k]} \mathbb{1}_{x_j \in \mathcal{X}_j}$$

if $\vec{X} \sim \text{Mult}_k(n, \vec{\mu})$ what is $E[\vec{X}]$, $\text{Var}[\vec{X}]$?

$$E[aX + c] = aE[X] + c$$

$$E[\prod x_i] = \prod E[x_i]$$

$$E[\sum x_i] = \sum E[x_i] \stackrel{\text{i.i.d.}}{=} n\mu$$

$$\sigma^2 := \text{Var}[X] := E[(X - \mu)^2]$$

$$\sigma := \text{SD}[X] := \sqrt{\text{Var}[X]}$$

$$\text{Var}[X_1 + X_2] = \sigma_1^2 + \sigma_2^2 + 2 \underbrace{(E[X_1 X_2] - \mu_1 \mu_2)}_{\text{Cov}(X_1, X_2)} \stackrel{\text{if indep.}}{=} \sigma_1^2 + \sigma_2^2$$

Covariance Rules

$$\text{Cov}[X, X] = \sigma^2$$

$$\text{Cov}[aX_1, aX_2] = a_1 a_2 \sigma_{12}$$

$$\text{Cov}[X_1, X_2] = \text{Cov}[X_2, X_1]$$

$$\text{Var}[X_1 + \dots + X_n] = \sum \sum \text{Cov}[X_i, X_j]$$

$$\text{Cov}[X_1 + X_2, X_3] = \text{Cov}[X_1, X_3] + \text{Cov}[X_2, X_3]$$

Additionally:

$$E[\vec{X}] = \begin{bmatrix} E[X_1] \\ \vdots \\ E[X_k] \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_k \end{bmatrix} \quad \text{let } m := \begin{bmatrix} x_{11} & \dots & x_{1m} \\ \vdots & & \vdots \\ x_{n1} & \dots & x_{nm} \end{bmatrix}$$

$$E[m] = \begin{bmatrix} \mu_{11} & \dots & \mu_{1m} \\ \vdots & & \vdots \\ \mu_{n1} & \dots & \mu_{nm} \end{bmatrix}$$

$$\text{Var}[\vec{X}] := E[\vec{X} \vec{X}^T] - \vec{\mu} \vec{\mu}^T = \begin{bmatrix} \text{Var}[X_1] & \text{Cov}[X_1, X_2] & \dots & \text{Cov}[X_1, X_k] \\ \vdots & \text{Var}[X_2] & & \vdots \\ \vdots & & \ddots & \vdots \\ \text{Cov}[X_k, X_1] & \dots & \dots & \text{Var}[X_k] \end{bmatrix}$$

$$= \sum$$

if X_1, \dots, X_k are indep. what is the varcov matrix?

$$\Sigma = \text{diag}\{\sigma_1^2, \dots, \sigma_k^2\} = \begin{bmatrix} \sigma_1^2 & & 0 \\ & \ddots & \\ 0 & & \sigma_k^2 \end{bmatrix}$$

$$E[aX + \tilde{c}] = \begin{bmatrix} a\mu_1 + c_1 \\ a\mu_k + c_k \end{bmatrix} = a\bar{\mu} + \tilde{c}$$

$$E[\tilde{a}^T X] = E[a_1 x_1 + \dots + a_k x_k] = a_1 \mu_1 + \dots + a_k \mu_k = \tilde{a}^T \bar{\mu}$$