

5

9/14

$$\vec{X} \sim \text{multin}_K(n, \vec{p})$$

dimension $k=2$ $\vec{p} = \begin{bmatrix} p_1 \\ p_2 \end{bmatrix}$

$$p_{X_1|X_2}(X_1, X_2) = P(X_1 = X_1 | X_2 = X_2) = \frac{P(X_1, X_2)}{P(X_2)}$$

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

$$= \frac{\binom{n}{X_1, X_2} p_1^{X_1} p_2^{X_2}}{\binom{n}{X_2} p_2^{X_2} (1 - p_2)^{n - X_2}}$$

$J_n = \{0, \dots, n\}$
Define a ratio of indicators:

$$= \frac{n!}{X_1! X_2!} \frac{1_{X_1 = n - X_2}}{1_{X_1 + X_2 = n}} \frac{1_{X_1 \in J_n} 1_{X_2 \in J_n}}{1_{X_2 \in J_n}} \frac{p_1^{X_1} p_2^{X_2}}{p_2^{X_2} p_1^{n - X_2}} \bigg| \frac{1^u}{1^A} = \frac{1^A}{1^A} = \begin{cases} 1 & \text{if } A \\ \text{undefined} & \text{if } A^c \end{cases}$$

$$= \frac{(n - X_2)!}{X_1!} 1_{X_1 = n - X_2} \underbrace{1_{X_1 \in J_n}}_{=1 \text{ when } X_1 = n - X_2} \underbrace{1_{X_2 \in J_n}}_{=1 \text{ when } X_2 \in J_n} = \text{Deg}(n - X_2) 1_{X_2 \in J_n}$$

Hint: $P(A|B) = \frac{P(A \cap B)}{P(B)}$ which is undefined if $P(B) = 0$

Let's generalize this result a little bit.

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

$$P_{\vec{x}-j | x_j}(\vec{x}-j, x_j) = \frac{P_{\vec{x}}(\vec{x})}{P_{x_j}(x_j)} \sim \text{Multin}_{k-1}(n-x_j, ?)$$

All elements of vector \vec{p} except the j th component

$$= \text{Multin}_k(n, \vec{p}) = \frac{\binom{n}{x_1, \dots, x_k} p_1^{x_1} \dots p_{j-1}^{x_{j-1}} p_j^{x_j} p_{j+1}^{x_{j+1}} \dots p_k^{x_k}}{\binom{n}{x_j} p_j^{x_j} (1-p_j)^{n-x_j}}$$

$$= \frac{n!}{x_1! \dots x_j! \dots x_k!} \frac{1}{1_{x_1 + \dots + x_j + \dots + x_k = n}} \frac{1}{1_{x_1 \in \mathcal{J}_n}} \dots \frac{1}{1_{x_j \in \mathcal{J}_n}} \frac{p_1^{x_1} \dots p_{j-1}^{x_{j-1}} p_{j+1}^{x_{j+1}} \dots p_k^{x_k}}{(1-p_j)^{n-x_j}}$$

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

Note: $p_1 + \dots + p_k = 1$

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

divide both sides by $1 - p_j$ $\Rightarrow \frac{p_1}{1-p_j} + \dots + \frac{p_{j-1}}{1-p_j} + \frac{p_{j+1}}{1-p_j} + \dots + \frac{p_k}{1-p_j} = 1$

$$\frac{n!}{x_1! \dots x_{j-1}! x_{j+1}! \dots x_k!} \frac{1}{1_{x_1 + \dots + x_{j-1} + x_{j+1} + \dots + x_k = n'}} \frac{1}{1_{x_1 \in \mathcal{J}_n}} \dots \frac{1}{1_{x_{j-1} \in \mathcal{J}_n}} \frac{1}{1_{x_{j+1} \in \mathcal{J}_n}} \dots \frac{1}{1_{x_k \in \mathcal{J}_n}} \frac{p_1^{x_1} \dots p_{j-1}^{x_{j-1}} p_{j+1}^{x_{j+1}} \dots p_k^{x_k}}{(1-p_j)^{n-x_j}}$$

$$= \text{Multin} \left((n, \vec{p}) \right) \mathbb{1}_{\sum_{j \in J_n} x_j = n}$$

$$\begin{bmatrix} p_1 \\ \vdots \\ p_k \end{bmatrix}$$

$X \sim \text{Multin}(n, \vec{p})$ where is $E[\vec{X}]$? $\text{Var}[\vec{X}]$?

we need definitions for expectation and variance for vector RV's.

X is a scalar $p \in \mathbb{R}$

$$* E[ax + c] = a E[X] + c$$

$$* E\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n E[X_i] = n\mu \quad \text{if identically distributed}$$

$$* E\left[\prod_{i=1}^n X_i\right] = \prod_{i=1}^n E[X_i] \quad \text{if they're independent}$$

$$\sigma^2 = \text{Var}[X] = E[(X - \mu)^2] \stackrel{\text{distribution}}{=} \sum_{x \in \mathbb{R}} (x - \mu)^2 p(x)$$

$$\stackrel{\text{continues}}{=} \int_{\mathbb{R}} (x - \mu)^2 f(x) dx$$

standard deviation

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

$$\text{Var}[X] = [X^2] - \mu^2$$

$$\text{Var}[X_1 + X_2] = E[(X_1 + X_2 - (\mu_1 + \mu_2))^2]$$

$$= E[X_1^2 + X_2^2 + \mu_1^2 + \mu_2^2 - 2\mu_1 X_1 - 2\mu_1 X_2 - 2\mu_2 X_1 - 2\mu_2 X_2 + 2\mu_1 \mu_2]$$

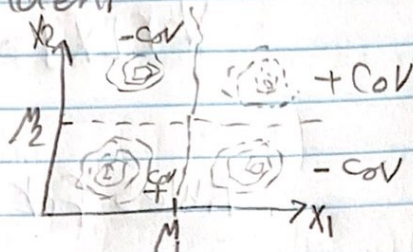
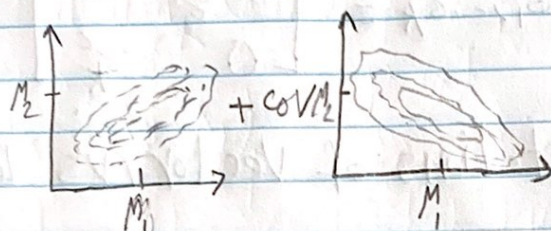
$$= E[X_1^2] + E[X_2^2] + \mu_1^2 + \mu_2^2 - 2\mu_1^2 - 2\mu_1 \mu_2 - 2\mu_2 \mu_1 - 2\mu_2^2 + 2E[X_1 X_2] + 2\mu_1 \mu_2$$

$$= \sigma_1^2 + \sigma_2^2 + 2(E[X_1 X_2] - \mu_1 \mu_2) \quad \left[\begin{aligned} E[\text{Cov}[X_1, X_2]] &= E[X_1 X_2] \\ &- \mu_1 \mu_2 = E[(X_1 - \mu_1)(X_2 - \mu_2)] \end{aligned} \right]$$

$$= \sigma_1^2 + \sigma_2^2 + 2\sigma_{12}$$

If X_1, X_2 independent $\Rightarrow \text{cov}[X_1, X_2] = 0$
 $\mu_1 \mu_2 - \mu_1 \mu_2 = 0$

$= \sigma_1^2 + \sigma_2^2$ If X_1, X_2 are independent



Rules for covariances

$a_1, a_2 \in \mathbb{R}$

① $\text{cov}[X, X] = \sigma^2$

② $\text{cov}[X_1, X_2] = \text{cov}[X_2, X_1]$

③ $\text{cov}[X_1 + X_2, X_3] = \sigma_{13} + \sigma_{23}$

④ $\text{cov}[a_1 X_1, a_2 X_2] = a_1 a_2 \sigma_{12}$

⑤ $\text{Var}[X_1 + \dots + X_n] = \sum_{i=1}^n \sum_{j=1}^n \text{cov}[X_i, X_j]$

$\vec{\mu} := E[\vec{X}] = \begin{bmatrix} E[X_1] \\ E[X_2] \\ \vdots \\ E[X_k] \end{bmatrix}$

let $m = \begin{bmatrix} x_{11} & \dots & x_{1m} \\ x_{21} & \dots & x_{2m} \\ \vdots & & \vdots \\ x_{k1} & \dots & x_{km} \end{bmatrix}$, $E(m) = \begin{bmatrix} E[x_{11}] & \dots & E[x_{1m}] \\ \vdots & & \vdots \\ E[x_{k1}] & \dots & E[x_{km}] \end{bmatrix}$

capital sigma

$\Sigma := \text{Var}[\vec{X}] = E[\vec{X} \vec{X}^T] - \underbrace{\vec{\mu} \vec{\mu}^T}_{\text{other products}} =$

$\begin{bmatrix} \text{Var}[X_1] & \text{cov}[X_1, X_2] & \dots & \text{cov}[X_1, X_k] \\ \text{cov}[X_2, X_1] & \text{Var}[X_2] & & \text{cov}[X_2, X_k] \\ \vdots & & \ddots & \vdots \\ \text{cov}[X_k, X_1] & \text{cov}[X_k, X_2] & \dots & \text{Var}[X_k] \end{bmatrix}$

The "variance - covariance matrix" It's square $k \times k$ and symmetric.

If X_1, \dots, X_K are independent then the Var-cov matrix is:

$$\text{Var}[\vec{X}] = \text{diag}\{\sigma_1^2, \dots, \sigma_K^2\} = \begin{bmatrix} \sigma_1^2 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & \sigma_K^2 \end{bmatrix}$$

Rules for expectations of vector RV's let $\vec{a} \in \mathbb{R}^K$

$$\textcircled{1} E[\vec{X} + \vec{a}] = \vec{\mu} + \vec{a}$$

$$\textcircled{2} E[\vec{a}^T \vec{X}] = E[a_1 X_1 + a_2 X_2 + \dots + a_K X_K] = a_1 \mu_1 + \dots + a_K \mu_K = \vec{a}^T \vec{\mu}$$