

# Lecture #5.

$$X \sim \text{Multin}_2(n, \vec{p})$$

$$\text{Deg } (n-x_2) = P_{X_1|X_2}(x_1, x_2) = P(X_1 = x_1 | X_2 = x_2) = \frac{P(X_1, X_2)}{P(X_2)}$$

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

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

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

$$\mathbb{1}_A = \frac{\mathbb{1}_A}{\mathbb{1}_A} = \begin{cases} 1 & \text{if } A \\ \text{undefined} & \text{if } A' \end{cases}$$

$$\frac{(n-x_2)!}{x_1!} \prod_{x_1=n-x_2} \prod_{x_1 \in J_n} p_1^{x_1} p_2^{x_2} = 1 \text{ if } x_1 = n-x_2$$

\* Let's generalize this ~~condition~~

conditional probability a little bit:

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

the vector w/o the jth component.

$$P_{\vec{X}-j|X_j}(\vec{x}-j, x_j) = \frac{P_{\vec{X}}(\vec{x})}{P_{X_j}(x_j)}$$

$$= \text{Multin}_{K-1}(n-x_j, ?) = \frac{\text{Multin}_K(n, \vec{p})}{\text{Bin}(n, p_j)}$$

$$= \frac{\binom{n}{x_1, \dots, x_j, \dots, x_K} p_1^{x_1} \dots p_j^{x_j} \dots p_K^{x_K}}{\binom{n}{x_j} p_j^{x_j} (1-p_j)^{n-x_j}}$$

$$\binom{n}{x_j} p_j^{x_j} (1-p_j)^{n-x_j}$$

$$\text{Deg } (n-x_2) \prod_{x_2 \in J_n} P(A|B) = \frac{P(A, B)}{P(B)} \text{ if } P(B) \neq 0$$

$$= \frac{n!}{x_1! \dots x_j! \dots x_K!} \prod_{x_1+\dots+x_j+\dots+x_K=n} \prod_{x_1 \in J_n} \dots \prod_{x_j \in J_n} \dots \prod_{x_K \in J_n}$$

$$\frac{n!}{x_j! (n-x_j)!} \prod_{x_j \in J_n} (1-p_j)^{n-x_j}$$

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

$$\text{if divide both sides by } 1-p_j = \frac{p_1}{1-p_j} + \dots + \frac{p_{j-1}}{1-p_j} + \frac{p_{j+1}}{1-p_j} + \dots + \frac{p_K}{1-p_j} = 1$$

$$\text{Note: } n-x_j = x_1 + \dots + x_{j-1} + x_{j+1} + \dots + x_K \rightarrow \text{prob zero}$$

$$\text{Let } n' := n - x_j$$

$$= \frac{n!}{x_1! \dots x_{j-1}! x_{j+1}! \dots x_K!} \prod_{x_1+\dots+x_{j-1}+x_{j+1}+\dots+x_K=n'} \prod_{x_1 \in J_n} \dots \prod_{x_{j-1} \in J_n} \prod_{x_{j+1} \in J_n} \dots \prod_{x_K \in J_n}$$

HW:  $\text{Cov}[X_1, X_2] = E[(X_1 - \mu_1)(X_2 - \mu_2)]$

$$= \binom{n}{x_1, \dots, x_{j-1}, x_{j+1}, \dots, x_k} \binom{p_1^{x_1} \dots p_{j-1}^{x_{j-1}} p_{j+1}^{x_{j+1}} \dots p_k^{x_k}}{p_j^{x_j}} \mathbb{1}_{x_j \in J_n}$$

$$= \text{Multi}_{k-1}(n', \vec{p}') \mathbb{1}_{x_j \in J_n}$$

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

\* REVIEW FROM Math 241. Let  $X_1, \dots, X_n$  be rv's and  $a, c \in \mathbb{R}$

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

$$E[\sum X_i] = \sum E[X_i] \stackrel{\text{identically dist.}}{=} n \cdot \mu$$

$$E[\prod X_i] \stackrel{\text{i.i.d. indep.}}{=} \prod E[X_i]$$

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

$$= E[X^2] - \mu^2$$

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

$$= E[X_1^2 + X_2^2 + \mu_1^2 + \mu_2^2 + 2X_1X_2 - 2X_1\mu_1 - 2X_1\mu_2 - 2X_2\mu_1 - 2X_2\mu_2 + 2\mu_1\mu_2]$$

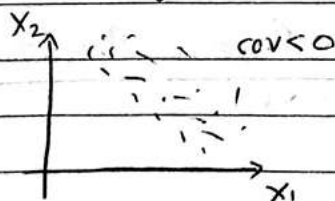
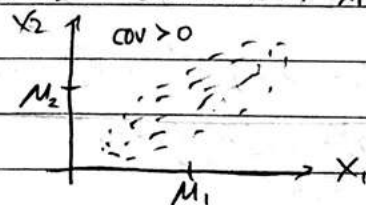
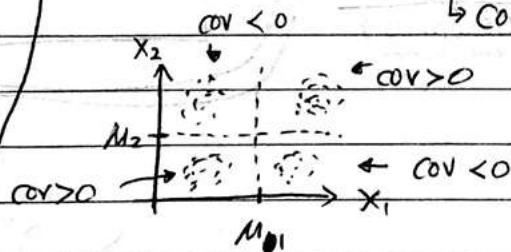
$$= E[X_1^2] + E[X_2^2] + \mu_1^2 + \mu_2^2 + 2E[X_1X_2]$$

$$- 2\mu_1^2 - 2\mu_1\mu_2 - 2\mu_1\mu_2 - 2\mu_2^2 + 2\mu_1\mu_2$$

$$= \sigma_1^2 + \mu_1^2 + \sigma_2^2 + \mu_2^2 + \mu_1^2 + \mu_2^2 + 2E[X_1X_2] - 2\mu_1^2 - 2\mu_1\mu_2 - 2\mu_2^2$$

$$= \sigma_1^2 + \sigma_2^2 + 2(E[X_1X_2] - \mu_1\mu_2) = \sigma_1^2 + \sigma_2^2 + 2\text{Cov}[X_1, X_2] \stackrel{\text{if } X_1, X_2 \text{ indep.}}{=} \sigma_1^2 + \sigma_2^2$$

$\text{Cov}(X_1, X_2)$ : COVARIANCE OF  $X_1$  WITH  $X_2$



Covariance Rules:

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

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

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

$$\text{Cov}[a_1X_1, a_2X_2] = a_1a_2\sigma_{1,2}$$

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

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

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

$$\text{Var}[\vec{x}] := E[\underbrace{\vec{x}\vec{x}^T}_{\substack{\text{outer product} \\ (k \times 1)(1 \times k) = k \times k \\ \text{matrix}}}]] - \underbrace{\vec{\mu}\vec{\mu}^T}_{\text{matrix}} = \begin{bmatrix} \text{Var}[X_1] & \text{Cov}[X_1, X_2] & \dots & \text{Cov}[X_1, X_k] \\ \text{Cov}[X_2, X_1] & \text{Var}[X_2] & & \text{Cov}[X_2, X_k] \\ \vdots & \vdots & \ddots & \vdots \\ \text{Cov}[X_k, X_1] & \text{Cov}[X_k, X_2] & \dots & \text{Var}[X_k] \end{bmatrix}$$

Variance-covariance matrix

and it is symmetric

If  $X_1, \dots, X_k$  are independent, what is the varcov matrix?

$$\hookrightarrow \Sigma = \text{diag} \{ \sigma_1^2, \dots, \sigma_k^2 \} := \begin{bmatrix} \sigma_1^2 & & & \\ & \sigma_2^2 & & \\ & & \sigma_3^2 & \\ & & & \ddots \\ & & & & \sigma_k^2 \end{bmatrix}$$

Rules about vector w expectations

$$E[aX + \vec{c}] = \begin{bmatrix} a\mu_1 + c_1 \\ a\mu_2 + c_2 \\ \vdots \\ a\mu_k + c_k \end{bmatrix} = a\vec{\mu} + \vec{c}$$

$$E[\vec{a}^T X] = E[a_1 X_1 + \dots + a_k X_k] = a_1 \mu_1 + \dots + a_k \mu_k = \vec{a}^T \vec{\mu}$$