

9/9

$$\text{Bag of fruit} (n, \begin{bmatrix} p_1 \\ p_2 \\ p_3 \end{bmatrix}) \sim \binom{n}{x_1, x_2} p_1^{x_1} p_2^{x_2}$$

p_1 - prob of apple
 p_2 - prob of banana
 p_3 - prob of cantalope

$$p_1 + p_2 + p_3 = 1$$

Draw n w/ replacement

Let X_1 : # of apples
 X_2 : # of bananas
 X_3 : # of cantalope

$$\vec{X} = \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix} \sim P_{\vec{X}}(\vec{x}) = \frac{n!}{x_1! x_2! x_3!} p_1^{x_1} p_2^{x_2} p_3^{x_3}$$

$$= \frac{n!}{x_1! x_2! x_3!} p_1^{x_1} p_2^{x_2} p_3^{x_3} \mathbb{1}_{x_1 + x_2 + x_3 = n} \mathbb{1}_{x_1 \in \{0, \dots, n\}} \mathbb{1}_{x_2 \in \{0, \dots, n\}} \mathbb{1}_{x_3 \in \{0, \dots, n\}}$$

$$= \binom{n}{x_1, x_2, x_3} p_1^{x_1} p_2^{x_2} p_3^{x_3} = \text{Multinomial}(n, \begin{bmatrix} p_1 \\ p_2 \\ p_3 \end{bmatrix})$$

- Generally w/ K elements

$$\text{Multinomial}(n, \begin{bmatrix} p_1 \\ \vdots \\ p_K \end{bmatrix}) = \binom{n}{p_1, \dots, p_K} p_1^{x_1} \dots p_K^{x_K}$$

$$- \text{Supp}[\vec{x}] = \{ \vec{x} \mid \vec{x} \in \mathbb{N}^k, \vec{x} \cdot \vec{1} = n \}$$

$$\vec{1} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \quad \vec{x} \in \{0, 1, \dots, n\}^k$$

$$\vec{p} \in \{ \vec{p} \mid (0, 1)^k, \vec{p} \cdot \vec{1} = 1 \}$$

$$n \in \mathbb{N}$$

Back to 2-dimensional case

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \sim \text{Multi}(n, [1-p])$$

$$p_1 = p \\ p_2 = 1-p$$

$$X_1 \sim \text{Binom}(n, p) \\ X_2 \sim \text{Binom}(n, 1-p)$$

$$\text{Is } X_1 \stackrel{d}{=} X_2? \quad \underline{\underline{\text{NO}}} \\ \text{Is } X_1, X_2 \stackrel{\text{ind}}{?} \quad \underline{\underline{\text{NO}}}$$

For two indep. r.v's, $P(X_1 = x_1 \mid X_2 = x_2) = P(X_1 = x_1)$ $\forall x_1 \in \text{Supp}[X_1]$
 $x_2 \in \text{Supp}[X_2]$

$$\textcircled{O} = P(X_1 = 1 \mid X_2 = n) \neq P(X_1 = 1) = \binom{n}{1} p(1-p)^{n-1} = np(1-p)^{n-1}$$

* When $k = \dim[\vec{x}] = 2$ & $n=1$, multinomial is a Bernoulli distribution.

* When $k=2$ & $n>1$, multinomial is a Binomial distribution.

Conditional PMF / JMF

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

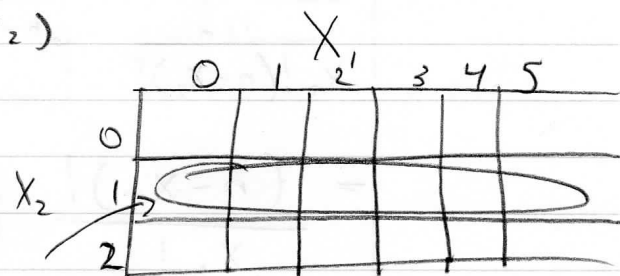
↑
Ref of Cond. prob.

Marginalization

$$P_{X_2}(x_2) = \sum_{x_1 \in \text{supp}(X_1)} P_{X_1, X_2}(x_1, x_2)$$

Marginal PMF

~~$$= \sum_{x_1 \in \{0, \dots, n\}} \frac{n!}{x_1! x_2!} p^{x_1} (1-p)^{x_2} \mathbb{1}_{x_1 + x_2 = n} \mathbb{1}_{x_2 \in \{0, \dots, n\}}$$~~



Sum over row 1

$$= \sum_{x_1 \in \{0, \dots, n\}} \frac{n!}{x_1! x_2!} p^{x_1} (1-p)^{x_2} \mathbb{1}_{x_1 + x_2 = n} \mathbb{1}_{x_2 \in \{0, \dots, n\}}$$

$$= \frac{n!}{x_2!} (1-p)^{x_2} \mathbb{1}_{x_2 \in \{0, \dots, n\}} \sum_{x_1 \in \{0, \dots, n\}} \frac{1}{x_1!} p^{x_1} \mathbb{1}_{x_1 = n - x_2}$$

$$\frac{1}{(n-x_2)!} p^{n-x_2}$$

$$= \binom{n}{x_2} (1-p)^{x_2} p^{n-x_2} = \text{Bin}(n, 1-p)$$

Back to Cond. prob.

$$P_{X_1|X_2}(x_1, x_2) := P(X_1 = x_1 | X_2 = x_2) = \frac{P_{X_1, X_2}(x_1, x_2)}{P_{X_2}(x_2)}$$

$$= \frac{\frac{n!}{x_1! x_2!} p^{x_1} (1-p)^{x_2} \mathbb{1}_{x_1 + x_2 = n}}{\frac{n!}{x_2! (n-x_2)!} p^{n-x_2} (1-p)^{x_2}}$$

$$= \frac{(n-x_2)!}{x_1!} p^{x_1 + x_2 - n} \mathbb{1}_{x_1 + x_2 = n}$$

$$= \begin{cases} \frac{x_1!}{x_1!} p^0 = 1 & \text{if } x_1 + x_2 = n \\ 0 & \text{if } x_1 + x_2 \neq n \end{cases}$$

$$= \text{Deg}(n - x_2) = \{n - x_2 \text{ w.p. } 1\}$$

degenerate

$$P_{\vec{X} | x_j}(\vec{X}, x_j) = \frac{n!}{x_1! \dots x_{j-1}! x_j! x_{j+1}! \dots x_k!} p_1^{x_1} \dots p_{j-1}^{x_{j-1}} p_j^{x_j} p_{j+1}^{x_{j+1}} \dots p_k^{x_k}$$

$$\left(\vec{X} = \begin{bmatrix} x_1 \\ x_{j+1} \\ x_{j-1} \\ \vdots \\ x_j \end{bmatrix} \right)$$

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

Let $n' := n - x_j$ (# of things left over in sample)

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

$$\left(\text{Recall: } n = x_1 + \dots + x_{j-1} + x_j + x_{j+1} + \dots + x_k \right)$$

$$\Rightarrow n' = x_1 + \dots + x_{j-1} + x_{j+1} + \dots + x_k$$

$$= \binom{n'}{x_1, \dots, x_{j-1}, x_{j+1}, \dots, x_k} \left[\frac{p_1}{(1-p_j)} \right]^{x_1} \dots \left[\frac{p_{j-1}}{(1-p_j)} \right]^{x_{j-1}} \left[\frac{p_{j+1}}{(1-p_j)} \right]^{x_{j+1}} \dots \left[\frac{p_k}{(1-p_j)} \right]^{x_k}$$

$$= \text{Multin}(n', \vec{p}')$$

$$\vec{p}' = \begin{bmatrix} \frac{p_1}{1-p_j} \\ \vdots \\ \frac{p_{j-1}}{1-p_j} \\ \frac{p_{j+1}}{1-p_j} \\ \vdots \\ \frac{p_k}{1-p_j} \end{bmatrix}$$

$$\dim[\vec{p}'] = k - 1$$

- $E[\vec{X}] = ?$
- $\text{Var}[\vec{X}] = ?$

- $\mu := E[X] \stackrel{\text{disc}}{=} \sum_{x \in \mathcal{R}} x p(x)$
 $\stackrel{\text{cont}}{=} \int x f(x) dx$

- $E[aX + b] = a\mu + b$

- $E\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n E[X_i]$ always true

- $E\left[\prod_{i=1}^n X_i\right] = \prod_{i=1}^n E[X_i]$
 \uparrow
 if X_1, \dots, X_n ind.

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

$$\sigma := E[X] := \sqrt{\sigma^2}$$

Standard error

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

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

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

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

$$\text{if } X_1, X_2 \text{ ind.} \rightarrow \boxed{\sigma_1^2 + \sigma_2^2}$$

"covariance"

$$\sigma_{12} := \text{cov}[X_1, X_2] := E[X_1 X_2] - \mu_1 \mu_2 \\ = E[(X_1 - \mu_1)(X_2 - \mu_2)]$$

$\text{cov } (+)$ means two r.v.'s are close

$\text{cov } (-)$ means two r.v.'s are far apart
(lots of apples, not a lot of bananas)