

$\vec{X} \sim \text{multin}_K(n, \vec{P})$  of dim  $K$

$K=2 \quad \vec{P} = \begin{bmatrix} p_1 \\ p_2 \end{bmatrix}$

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

$P(x_2) = \text{Bin}(n, p_2) = \text{Bin}(n, 1-p_1)$

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

$$\frac{n!}{x_2! (n-x_2)!} \mathbb{1}_{x_2 \in J_n} p_2^{x_2} p_1^{n-x_2}$$

$\mathbb{1}_{x_2 \in J_n}^u$  Define a ratio of indicators:

$$\mathbb{1}_A^u := \frac{\mathbb{1}_A}{\mathbb{1}_A} = \begin{cases} 1 & \text{if } A \\ \text{undef} & \text{if } A^c \end{cases}$$

$\text{Deg}(n-x_2) \mathbb{1}_{x_2 \in J_n}^u$

hint  $P(A|B) = \frac{P(A, B)}{P(B)}$  which is  
undef if prob b is zero  
call it undef if  $x_2$  is ilig

$$= \frac{(n-x_2)!}{x_1!} \mathbb{1}_{x_1=n-x_2} \underbrace{\mathbb{1}_{x \in J_n}}_{=1 \text{ when } x_1=n-x_2} \mathbb{1}_{x_2 \in J_n}^u$$

$$= \begin{bmatrix} p_1 \\ \vdots \\ p_K \end{bmatrix}$$

let's generalize this result a bit  $\vec{X} \sim \text{multin}_K(n, \vec{P})$   $K$  dimension vector

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

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

$$= \frac{\text{Multin}_K(n, \vec{P})}{\text{Bin}(n, p_j)} = \frac{\binom{n}{x_1, x_2, \dots, x_K} p_1^{x_1} \dots p_{j-1}^{x_{j-1}} p_j^{x_j} p_{j+1}^{x_{j+1}} \dots p_K^{x_K}}{\binom{n}{x_j} p_j^{x_j} (1-p_j)^{n-x_j}}$$



$$= \frac{n!}{x_1! \dots x_j! \dots x_k!} \mathbb{1}_{x_1 + \dots + x_j + \dots + x_k = n} \mathbb{1}_{x_1 \in J_n} \dots \mathbb{1}_{x_j \in J_n} \dots \mathbb{1}_{x_k \in J_n} \dots \quad (P_1^{x_1} \dots P_{j+1}^{x_{j+1}} \dots P_k^{x_k})$$

$\underbrace{\quad}_{= n - x_j}$

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

$\mathbb{1}_{x_j \in J_n}^n$

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  $p_1 + \dots + p_k = 1$

$\Rightarrow p_1 + \dots + p_{j+1} + \dots + p_k = 1 - p_j$  it's a trick

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

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

$$= \frac{n'!}{x_1! \dots x_{j-1}! x_{j+1}! \dots x_k!} \mathbb{1}_{x_1 + \dots + x_{j-1} + x_{j+1} + \dots + x_k = n'} \mathbb{1}_{x_1 \in J_n} \mathbb{1}_{x_{j-1} \in J_n} \dots \mathbb{1}_{x_k \in J_n} \dots$$

$\left( P_1^{x_1} \dots P_{j-1}^{x_{j-1}} P_{j+1}^{x_{j+1}} \dots P_k^{x_k} \right) \mathbb{1}_{x_j \in J_n}^n$

$$\frac{(1-p_j)^{x_1 + \dots + x_{j-1} + x_{j+1} + \dots + x_k}}{P_1^{x_1} \dots P_{j-1}^{x_{j-1}} P_{j+1}^{x_{j+1}} \dots P_k^{x_k}}$$

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

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

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

$x$  is a scalar r.v  $a, c \in \mathbb{R}$

rule \*  $E[aX + c] = aE[X] + c$  If identically distributed iid

\*  $E\left[\sum_{i=1}^n x_i\right] = \sum_{i=1}^n E[x_i] = n \cdot \mu$

\*  $E\left[\prod_{i=1}^n x_i\right] = \prod_{i=1}^n E[x_i]$  If they are independent

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

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

$\sum_{x \in \mathbb{R}} (x - \mu)^2 P(x)$  discrete

$\int_{\mathbb{R}} (x - \mu)^2 f(x) dx$  continuous



$$\text{Var}[X_1 + X_2] = E[(X_1 + X_2) - (M_1 + M_2)]^2$$

now we foil

$$= E[X_1^2 + X_2^2 + M_1^2 + M_2^2 - 2M_1X_1 - 2M_1X_2 - 2M_2X_1 - 2M_2X_2 + 2X_1X_2 + 2M_1M_2]$$

$$= E[X_1^2] + E[X_2^2] + M_1^2 + M_2^2 - 2M_1^2 - 2M_1M_2 - 2M_2M_1 - 2M_2^2 + 2E[X_1X_2] + 2M_1M_2$$

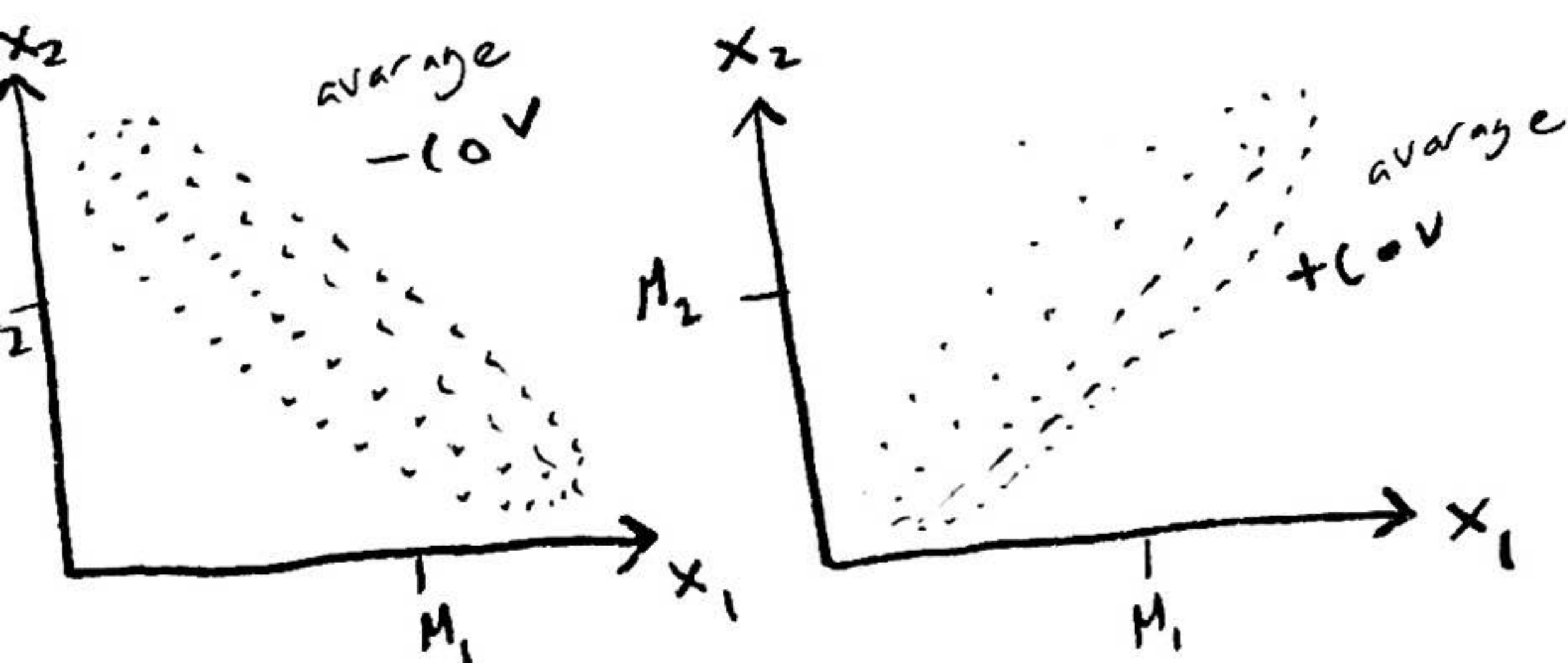
$G_{12} = G_{21}$  it's the same

remember  $\text{Var}[X] = E[X^2] - M^2$

$$= \sigma_1^2 + \sigma_2^2 + 2(E[X_1X_2] - M_1M_2)$$

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

$$= \sigma_1^2 + \sigma_2^2 \rightarrow \text{if } X_1, X_2 \text{ are independent}$$

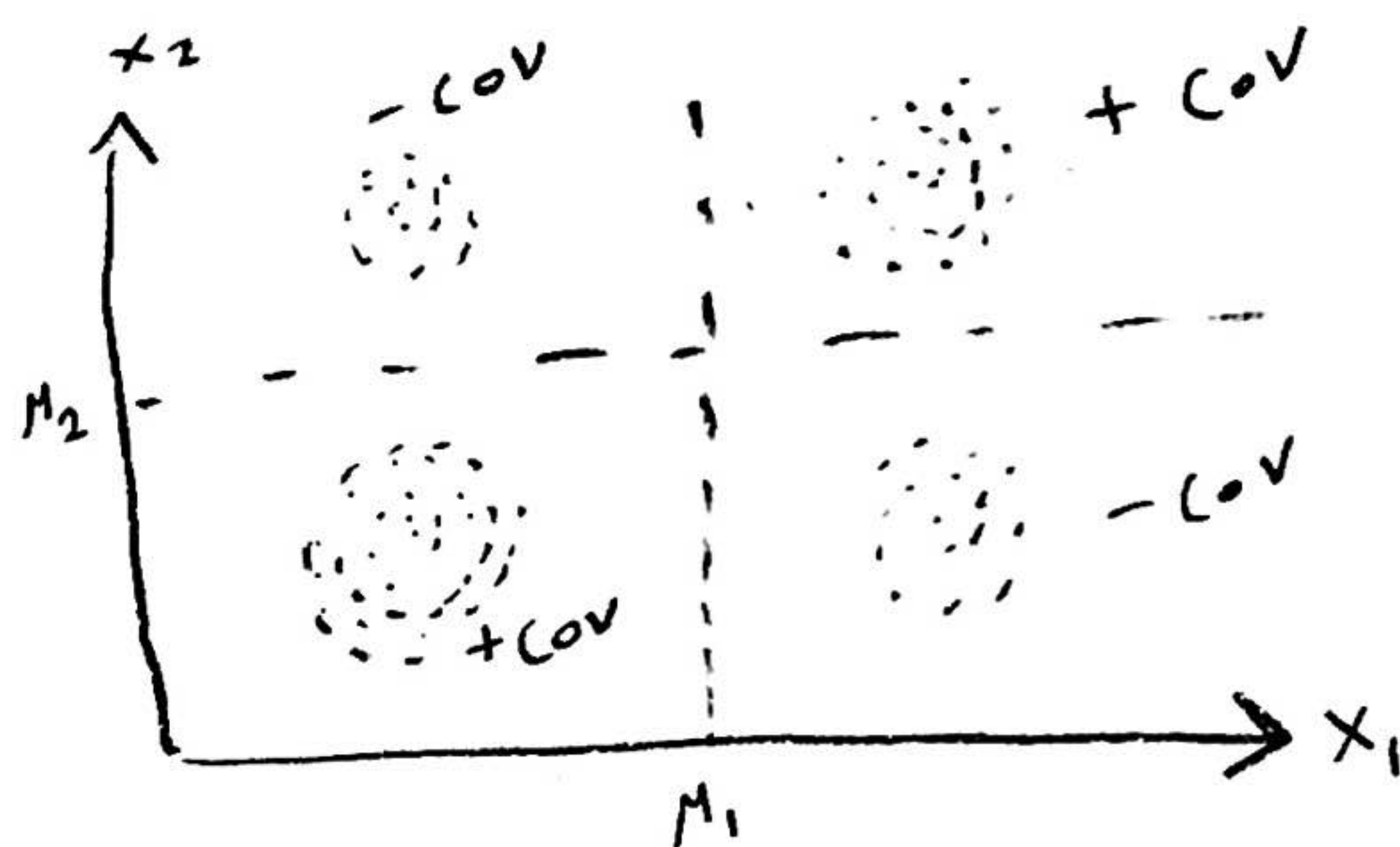


$$\rightarrow G_{12}$$

$$\text{Cov}[X_1, X_2] := E[X_1X_2] - M_1M_2$$

If  $X_1, X_2$  independent

$$\Rightarrow \text{Cov}[X_1, X_2] = M_1M_2 - M_1M_2 = 0$$



rules for covariances  $a_1, a_2 \in \mathbb{R}$

$$① \text{Cov}[X, X] = \sigma^2$$

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

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

$$④ \text{Cov}[a_1X_1, a_2X_3] = a_1a_2G_{13}$$

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

$$\vec{M} := E[\vec{X}]$$

expectation of the vector

$$= \begin{bmatrix} E[X_1] \\ E[X_2] \\ \vdots \\ E[X_n] \end{bmatrix}$$

let  $M :=$  this is a matrix of rv's

$$= \begin{bmatrix} X_{11}, \dots, X_{1n} \\ X_{21}, \dots, X_{2n} \\ \vdots \\ X_{n1}, \dots, X_{nn} \end{bmatrix}$$

$$E[M] = \begin{bmatrix} E[X_{11}] \dots E[X_{1n}] \\ \vdots \\ E[X_{n1}] \dots E[X_{nn}] \end{bmatrix}$$



$$\text{Var}[\vec{X}] := E[\underbrace{\vec{X} \vec{X}^T}_{\text{outer product}}] - \underbrace{\vec{\mu} \vec{\mu}^T}_{\text{H.W.}} = \begin{bmatrix} \text{Var}[X_1] & \dots & \text{Cov}[X_1, X_2] & \dots & \text{Cov}[X_1, X_K] \\ \text{Cov}[X_2, X_1] & \text{Var}[X_2] & & & \text{Cov}[X_2, X_K] \\ & & \ddots & & \vdots \\ \text{Cov}[X_K, X_1] & \text{Cov}[X_K, X_2] & \dots & \text{Cov}[X_K, X_{K-1}] & \text{Var}[X_K] \end{bmatrix}$$

Capital sigma  $\sim \alpha$

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:

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

Rules for expectation of vector r.v's

let  $\vec{a} \in \mathbb{R}^K$

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

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