

# Vectors of Discrete Random Variables

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In fact, many common statistical formulas can be expressed most clearly and succinctly in the language of vectors and matrices.

The term **multivariate** is often used to describe the distributions we encounter working with random vectors.

# Vectors of Discrete Random Variables

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Multivariate discrete random variables (or random vectors) are a straightforward generalization of ordinary discrete random variables.

In place of a univariate probability mass function

$$p(x) = P(X = x)$$

we have a **joint** probability mass function, which in the 2-dimensional or bivariate case is:

$$p(x_1, x_2) = P(X_1 = x_1 \text{ and } X_2 = x_2)$$

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In some cases, we will want to consider the component random variables  $X_1$  and  $X_2$  as univariate or one-dimensional random variables in their own right. These are called the **marginal** distributions of  $X_1$  and  $X_2$ .

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Expected values are defined much the same way, except we have to sum over each dimension. In the bivariate case, the expected value of  $X_1$ , the first component, is defined by:

$$\mu_1 = E(X_1) = \sum_{R(X)} \sum_{R(Y)} x_1 \cdot p(x_1, x_2)$$

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The expected value of the second component  $X_2$  is:

$$\mu_2 = E(X_2) = \sum_{R(X)} \sum_{R(Y)} x_2 \cdot p(x_1, x_2)$$

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Variances are defined similarly. In the bivariate case, the variance of  $X_1$ , the first component, is defined by:

$$\sigma_1^2 = V(X_1) = \sum_{R(X)} \sum_{R(Y)} (x_1 - \mu_1)^2 \cdot p(x_1, x_2)$$

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The variance of the second component  $X_2$  is:

$$\sigma_2^2 = V(X_2) = \sum_{R(X)} \sum_{R(Y)} (x_2 - \mu_2)^2 \cdot p(x_1, x_2)$$



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In the multivariate case there is an additional construct called the **covariance** of  $X_1$  and  $X_2$  defined by

$$\sigma_{12} = Cov(X_1, X_2) = \sum_{R(X)} \sum_{R(Y)} (x_1 - \mu_1)(x_2 - \mu_2) \cdot p(x_1, x_2)$$

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The covariance is closely related to the **correlation coefficient**  $\rho(X_1, X_2)$ , which is defined as:

$$\rho_{12} = \frac{\sigma_{12}}{\sqrt{\sigma_1^2 \sigma_2^2}}$$

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It is usually convenient to use vector notation to describe a bivariate random variable and its expectation:

$$X = \begin{bmatrix} X_1 \\ X_2 \end{bmatrix}$$

and

$$\mu = E(X) = \begin{bmatrix} E(X_1) \\ E(X_2) \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}$$

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In the three dimensional case, the notation is:

$$X = \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix}$$

and

$$\mu = E(X) = \begin{bmatrix} E(X_1) \\ E(X_2) \\ E(X_3) \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix}$$

# Vectors of Discrete Random Variables

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Finally, the general case of  $n$  dimensions is:

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{bmatrix}$$

and

$$\mu = E(X) = \begin{bmatrix} E(X_1) \\ E(X_2) \\ \vdots \\ E(X_n) \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{bmatrix}$$

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In the bivariate case,  $X = (X_1, X_2)$  and the generalization of the variance  $V(X)$  is the **variance-covariance matrix** defined by

$$\begin{aligned}\Sigma = V(X) &= \begin{bmatrix} V(X_1) & Cov(X_1, X_2) \\ Cov(X_1, X_2) & V(X_2) \end{bmatrix} \\ &= \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix}\end{aligned}$$

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In the three dimensional case,  $X = (X_1, X_2, X_3)$  and

$$\begin{aligned}\Sigma = V(X) &= \begin{bmatrix} V(X_1) & Cov(X_1, X_2) & Cov(X_1, X_3) \\ Cov(X_1, X_2) & V(X_2) & Cov(X_2, X_3) \\ Cov(X_1, X_3) & Cov(X_2, X_3) & V(X_3) \end{bmatrix} \\ &= \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & \sigma_2^2 & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & \sigma_3^2 \end{bmatrix}\end{aligned}$$

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In the case of  $n$  dimensions,  $X = (X_1, X_2, \dots, X_n)$  and

$$\Sigma = V(X) = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} & \cdots & \sigma_{1n} \\ \sigma_{12} & \sigma_2^2 & \cdots & & \\ \sigma_{13} & \vdots & \sigma_3^2 & & \vdots \\ \vdots & & & \ddots & \\ \sigma_{1n} & & \cdots & & \sigma_n^2 \end{bmatrix}$$



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In  $n$  dimensions, there are

$$\frac{n(n+1)}{2} \text{ distinct variances and covariances}$$