

Elements of Probability Theory

matrix-free

Contents

1 Random Variables and Distributions	2
1.1 Univariate Random Variables and Distributions	2
1.2 Bivariate Random Variables and Distributions	3
2 Moments	5
2.1 Expected Value or Mean	5
2.2 Variance and Standard Deviation	6
2.3 Higher order Moments	7
2.4 Covariance and Correlation	7
2.5 Conditional Expectation and Variance	8
3 Random Vectors and Random Matrices	9
4 Important Distributions	9
4.1 Univariate Normal Distribution	9
4.2 Bivariate Normal Distribution	9
4.3 Multivariate Normal Distribution	10

1 Random Variables and Distributions

A *random variable* is a variable whose values are determined by a probability distribution. This is a casual way of defining random variables which is sufficient for our level of analysis. For more advanced probability theory, a random variable will be defined as a real-valued function over some probability space.

In section 1 to 3, a random variable is denoted by capital letters, e.g. X , whereas its realizations are denoted by small letters, e.g. x .

1.1 Univariate Random Variables and Distributions

A *univariate discrete random variable* is a variable that takes a countable number K of real numbers with certain probabilities. The probability that the random variable X takes the value x_k among the K possible realizations is given by the *probability distribution*

$$P(X = x_k) = P(x_k) = p_k$$

with $k = 1, 2, \dots, K$. K may be ∞ in some cases. This can also be written as

$$P(x_k) = \begin{cases} p_1 & \text{if } X = x_1 \\ p_2 & \text{if } X = x_2 \\ \vdots & \\ p_K & \text{if } X = x_K \end{cases}$$

Note that

$$\sum_{k=1}^K p_k = 1.$$

A *univariate continuous random variable* is a variable that takes a continuum of values in the real line. The distribution of a continuous random variable X can be characterized by a *density function* or *probability*

density function (pdf) $f(x)$. The nonnegative function $f(x)$ is such that

$$P(x_1 \leq X \leq x_2) = \int_{x_1}^{x_2} f(x)dx.$$

defines the probability that X takes a value in the interval $[x_1, x_2]$. Note that there is no chance that X takes exactly the value x , $P(X = x) = 0$. The probability that X takes any value on the real line is

$$\int_{-\infty}^{\infty} f(x)dx = 1.$$

The distribution of a univariate random variable X is alternatively described by the *cumulative distribution function (cdf)*

$$F(x) = P(X < x).$$

The cdf of a discrete random variable X is

$$F(x) = \sum_{x_k \leq x} P(X = x_k) = \sum_{x_k \leq x} p_k.$$

and of a continuous random variable X

$$F(x) = \int_{-\infty}^x f(t)dt$$

$F(x)$ has the following properties:

- $F(x)$ is monotonically nondecreasing
- $F(-\infty) = 0$ and $F(\infty) = 1$.
- $F(x)$ is continuous to the left

1.2 Bivariate Random Variables and Distributions

A *bivariate continuous random variable* is a variable that takes a continuum of values in the plane. The distribution of a bivariate continuous random variable (X, Y) can be characterized by a *joint density function*

or *joint probability density function*, $f(x, y)$. The nonnegative function $f(x, y)$ is such that

$$P(x_1 \leq X \leq x_2, y_1 \leq Y \leq y_2) = \int_{x_1}^{x_2} \int_{y_1}^{y_2} f(x, y)dydx$$

defines the probability that X and Y take values in the interval $[x_1, x_2]$ and $[y_1, y_2]$, respectively. Note that

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y)dydx = 1.$$

The *marginal density function* or *marginal probability density function* is given by

$$f(x) = \int_{-\infty}^{\infty} f(x, y)dy$$

such that

$$P(x_1 \leq X \leq x_2) = P(x_1 \leq X \leq x_2, -\infty \leq Y \leq \infty) = \int_{x_1}^{x_2} f(x)dx.$$

The *conditional density function* or *conditional probability density function* with respect to the event $\{Y = y\}$ is given by

$$f(y|x) = \frac{f(x, y)}{f(x)}$$

provided that $f(x) > 0$. Note that

$$\int_{-\infty}^{\infty} f(y|x)dy = 1.$$

Two random variables X and Y are called *independent*, if and only if

$$f(x, y) = f(x) \cdot f(y)$$

If X and Y are *independent*, then:

- $f(y|x) = f(y)$
- $P(x_1 \leq X \leq x_2, y_1 \leq Y \leq y_2) = P(x_1 \leq X \leq x_2) \cdot P(y_1 \leq Y \leq y_2)$

More generally, if a finite set of n continuous random variables $X_1, X_2, X_3, \dots, X_n$ are mutually independent, then

$$f(x_1, x_2, x_3, \dots, x_n) = f(x_1) \cdot f(x_2) \cdot f(x_3) \cdot \dots \cdot f(x_n).$$

2 Moments

2.1 Expected Value or Mean

The *expected value* or *mean* of a *discrete* random variable with probability distribution $P(x_k)$ and $k = 1, 2, \dots, K$ is defined as

$$E[X] = \sum_{k=1}^K x_k P(x_k)$$

if the series converges absolutely.

The *expected value* or *mean* of a *continuous* univariate random variable with density function $f(x)$ is defined as

$$E[X] = \int_{-\infty}^{\infty} x f(x) dx$$

if the integral exists.

For a random variable Z which is a continuous function ϕ of a discrete random variable X , we have:

$$E[Z] = E[\phi(X)] = \sum_{k=1}^K \phi(x_k) P(x_k)$$

For a random variable Z which is a continuous function ϕ of the continuous random variables X and Y , we have:

$$E[Z] = E[\phi(X)] = \int_{-\infty}^{\infty} \phi(x) f(x) dx$$

$$E[Z] = E[\phi(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \phi(x, y) f(x, y) dx dy$$

The following rules hold in general, i.e. for discrete, continuous and mixed types of random variables:

- $E[\alpha] = \alpha$
- $E[\alpha X + \beta Y] = \alpha E[X] + \beta E[Y]$
- $E[\sum_{i=1}^n X_i] = \sum_{i=1}^n E[X_i]$
- $E[XY] = E[X]E[Y]$ if X and Y are independent

where $\alpha \in \mathbb{R}$ and $\beta \in \mathbb{R}$ are constants.

2.2 Variance and Standard Deviation

The variance of a univariate random variable X is defined as

$$V[X] = E[(X - E[X])^2] = E[X^2] - (E[X])^2$$

The variance has the following properties:

- $V[X] \geq 0$
- $V[X] = 0$ if and only if $X = E[X]$

The following rules hold in general, i.e. for discrete, continuous and mixed types of random variables:

- $V[\alpha X + \beta] = \alpha^2 V[X]$
- $V[X + Y] = V[X] + V[Y] + 2\text{Cov}[X, Y]$
- $V[X - Y] = V[X] + V[Y] - 2\text{Cov}[X, Y]$
- $V[\sum_{i=1}^n X_i] = \sum_{i=1}^n V[X_i]$ if X_i and X_j independent for all $i \neq j$

where $\alpha \in \mathbb{R}$ and $\beta \in \mathbb{R}$ are constants.

Instead of the variance, one often considers the *standard deviation*

$$\sigma_X = \sqrt{V[X]}.$$

2.3 Higher order Moments

The j -th moment around zero is defined as

$$E[(X - E[X])^j].$$

2.4 Covariance and Correlation

The *Covariance* between two random variables X and Y is defined as:

$$\begin{aligned} \text{Cov}[X, Y] &= E[(X - E[X])(Y - E[Y])] \\ &= E[XY] - E[X]E[Y] \\ &= E[(X - E[X])Y] = E[X(Y - E[Y])] \end{aligned}$$

The following rules hold in general, i.e. for discrete, continuous and mixed types of random variables:

- $\text{Cov}[\alpha X + \gamma, \beta Y + \mu] = \alpha\beta\text{Cov}[X, Y]$
- $\text{Cov}[X_1 + X_2, Y_1 + Y_2]$
 $= \text{Cov}[X_1, Y_1] + \text{Cov}[X_1, Y_2] + \text{Cov}[X_2, Y_1] + \text{Cov}[X_2, Y_2]$
- $\text{Cov}[X, Y] = 0$ if X and Y are independent

where $\alpha \in \mathbb{R}$, $\beta \in \mathbb{R}$, $\gamma \in \mathbb{R}$ and $\mu \in \mathbb{R}$ are constants.

The *correlation coefficient* between two random variables X and Y is defined as:

$$\rho_{X,Y} = \frac{\text{Cov}[X, Y]}{\sigma_X \sigma_Y}$$

where σ_X and σ_Y denote the corresponding standard deviations. The correlation coefficient has the following property:

- $-1 \leq \rho_{X,Y} \leq 1$

The following rule holds:

- $\rho_{\alpha X + \gamma, \beta Y + \mu} = \rho_{X,Y}$
- $\rho_{X,Y} = 0$ if X and Y are independent

where $\alpha \in \mathbb{R}$ and $\beta \in \mathbb{R}$ are constants.

We say that

- X and Y are *uncorrelated* if $\rho = 0$
- X and Y are *positively correlated* if $\rho > 0$
- X and Y are *negatively correlated* if $\rho < 0$

2.5 Conditional Expectation and Variance

Let (X, Y) be a bivariate discrete random variable and $P(y_k|X)$ the conditional probability of $Y = y_k$ given X . Then the *conditional expected value* or *conditional mean* of Y given X is

$$E[Y|X] = E_{Y|X}[Y] = \sum_{k=1}^K y_k P(y_k|X).$$

Let (X, Y) be a bivariate continuous random variable and $f(y|x)$ the conditional density of Y given X . Then the *conditional expected value* or *conditional mean* of Y given X is

$$E[Y|X] = E_{Y|X}[Y] = \int_{-\infty}^{\infty} y f(y|X) dy.$$

The *law of iterated means* or *law of iterated expectations* holds in general, i.e. for discrete, continuous or mixed random variables:

$$E_X[E[Y|X]] = E[Y].$$

The conditional variance of Y given X is given by

$$V[Y|X] = E[(Y - E[Y|X])^2 | X] = E[Y^2 | X] - (E[Y|X])^2.$$

The *law of total variance* is

$$V[Y] = E_X[V[Y|X]] + V_X[E[Y|X]].$$

3 Random Vectors and Random Matrices

In the matrix version, this section generalizes the rules about moments to random vectors and random matrices.

4 Important Distributions

4.1 Univariate Normal Distribution

The density of the *univariate normal distribution* is given by:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}.$$

The normal distribution is characterized by the two parameters μ and σ . The mean of the normal distribution is $E[X] = \mu$ and the variance $V[X] = \sigma^2$. We write $X \sim N(\mu, \sigma^2)$.

The univariate normal distribution with mean $\mu = 0$ and variance $\sigma^2 = 1$ is called the *standard normal distribution* $N(0, 1)$.

4.2 Bivariate Normal Distribution

The density of the *bivariate normal distribution* is

$$f(x, y) = \frac{1}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho^2}} \exp\left\{-\frac{1}{2(1-\rho^2)}\left[\left(\frac{x-\mu_X}{\sigma_X}\right)^2 + \left(\frac{y-\mu_Y}{\sigma_Y}\right)^2 - 2\rho\left(\frac{x-\mu_X}{\sigma_X}\right)\left(\frac{y-\mu_Y}{\sigma_Y}\right)\right]\right\}.$$

If (X, Y) follows a bivariate normal distribution, then:

- The marginal densities $f(x)$ and $f(y)$ are univariate normal.
- The conditional densities $f(x|y)$ and $f(y|x)$ are univariate normal.
- $E[X] = \mu_X$, $V[X] = \sigma_X^2$, $E[Y] = \mu_Y$, $V[Y] = \sigma_Y^2$.
- The correlation coefficient between X and Y is $\rho_{X,Y} = \rho$.
- $E[Y|X] = \mu_Y + \rho\frac{\sigma_Y}{\sigma_X}(X - \mu_X)$ and $V[Y|X] = \sigma_Y^2(1 - \rho^2)$.

The above properties characterize the normal distribution. It is the only distribution with all these properties.

Further important properties:

- If (X, Y) follows a bivariate normal distribution, then $aX + bY$ is also normally distributed:

$$aX + bY \sim N(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2 + 2\rho\sigma_X\sigma_Y).$$

The reverse implication is not true.

- If X and Y are bivariate normally distributed with $\text{Cov}[X, Y] = 0$, then X and Y are independent.

4.3 Multivariate Normal Distribution

If the n variables in (X_1, X_2, \dots, X_n) follow a multivariate normal distribution, then:

- The marginal densities $f(x_i)$ for $i = 1, 2, \dots, n$ are univariate normal.
- The conditional densities $f(x_i|\cdot)$, conditional on one or a subset of the other $n - 1$ variables, are univariate normal.
- Any linear combination $\alpha_1x_1 + \alpha_2x_2 + \dots + \alpha_nx_n$, where $\alpha_1, \dots, \alpha_n$ are constants, is univariate normal.

References

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