Univariate distribution Multivariate distributions

Normal and related distributions

Useful measures

- Expectation: $E(x) = \int_x f(x) dx$
- Variance: $Var(x) = E((x Ex)^2) = \int_{C} (x Ex)^2 f(x) dx$
- Skewness: $E((x Ex)^3)$
- Kurtosis: $E((x Ex)^4)$

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Normal distribution

For a 1-dimensional random variable y with a mean μ and a variance σ^2 we will say that y has a univariate normal distribution

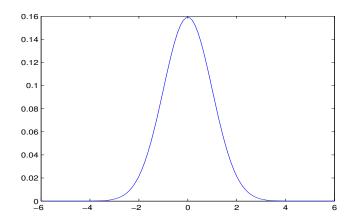
$$y \sim N(\mu, \sigma^2)$$

if its density is

$$f(y) = \frac{1}{(2\pi)^{0.5}\sigma} \exp\left[-0.5 \frac{(y-\mu)^2}{\sigma^2}\right]$$



Normal distribution N(0, 1)



Linear transformation

Normal distribution preserves under linear transformation.

$$a + bx \sim N(a + b\mu, b^2\sigma^2)$$

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- For independent $z_1 \sim \chi^2(n_1)$ and $z_2 \sim \chi^2(n_2)$ the sum $z_1 + z_2 \sim \chi^2(n_1 + n_2)$.
- For independent $z_i \sim \chi^2(1)$, what is the distribution of $\sum_{i=1}^n z_i$?
- For independent $x_i \sim N(0, 1)$, what is the distribution of $\sum_{i=1}^{n} z_i$?
- Suppose, $x_i \sim N(\mu, \sigma^2)$ are independent. Transform it into $z\chi^2(n)$.

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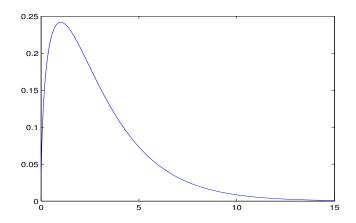


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Moments - expected value

Let $x \in \mathbb{R}^n$ be a multivariate random variable. The expected value is a $(n \times 1)$ vector

$$E(x) = \begin{bmatrix} E(x_1) \\ E(x_2) \\ \vdots \\ E(x_n) \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{bmatrix} = \mu$$

Moments - covariance matrix

The covariance matrix of the rando vector x is a $(n \times n)$ matrix

$$Var(x) = E((x - \mu)(x - \mu)') = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \cdots & \sigma_{nn} \end{bmatrix} = \Sigma$$

- $E(z) = A\mu + b$
- $Var(z) = A\Sigma A'$
- Find A and b for which $z \sim (0, I)$.

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Multidimensional Normal distribution

A K-dimensional vector of random variables $y = (y_1, y_2, \dots, y_K)'$ has a multivariate normal distribution with a mean vector μ and a covariance matrix Σ

$$y \sim N(\mu, \Sigma)$$

if its density is

$$f(y) = \frac{1}{(2\pi)^{K/2}} \det(\Sigma)^{-0.5} \exp[-0.5(y-\mu)'\Sigma^{-1}(y-\mu)]$$

Example: Multidimensional Normal

Normal distribution can be defined by marginal distributions and a covariance structure.

$$y \sim N\left(\left[\begin{array}{c}1\\2\end{array}\right], \left[\begin{array}{cc}1&0.5\\0.5&3\end{array}\right]\right)$$

What is the marginal distribution of y_1 , y_2 and what is their covariance?

Linear transformation of a Normal random vector

Suppose $y \sim N(\mu, \Sigma)$, A is a $(M \times K)$ matrix and b is a $(M \times 1)$ vector. What is the distribution of x = Ay + b?

$$X = Ay + b \sim N(A\mu + b, A\Sigma A')$$

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•
$$x = 1 + [1, 0.5]y$$

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$$E(x) = 3$$

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Knowing that $x = \sim N(\mu, \Sigma)$, find a distribution of

- C'x, when $x \sim N(0, I_K)$ and C be a square matrix, such that $C'C = I_K$.
- $\Sigma^{-1/2}(x-\mu)$.

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- $x'x \sim \chi^2(K)$
- if all characteristic roots of A are either 1 or 0 (with J non-zero roots) then $x'Ax \sim \chi^2(J)$
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Problem 1

Suppose $y \sim N(0_{K \times 1}, \Sigma)$, with a quadratic, non-singular variance-covariance matrix Σ . Show that

$$y'\Sigma^{-1}y \sim \chi^2(K)$$

Problem 2

Let $y = [y_n]$ be a $(N \times 1)$ vector of i.i.d $y_n \sim N(\mu, \sigma^2)$. What is the distribution of

$$\bullet \hat{\mu} = \frac{1}{N} \sum_{n=1}^{N} y_n$$

Hint: find matrices A and M (idempotent) such that: $\hat{\mu} = Ay$ and $\hat{\sigma}^2 = y'My$

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Normal vector and a quadratic form

Suppose

$$y \sim N(\mu, \sigma^2 I_K)$$

and

- M is $(K \times K)$, symmetric and idempotent matrix.
- A is a $(N \times K)$ matrix.
- \bullet AM = 0

Show that Ay and y'My are independent.

Example

Let $y = [y_n]$ be a $(N \times 1)$ vector of $y_n \sim N(\mu, \sigma^2)$. Show that the estimators of a mean and a variance are independent.

$$\bullet \hat{\mu} = \frac{1}{N} \sum_{n=1}^{N} y_n$$

•
$$\hat{\sigma}^2 = \frac{1}{N} \sum_{n=1}^{N} (y_n - \bar{y}_N)^2$$

Hint: use matrices *A* and *M* from previous example.

t-distribution

Suppose $z \sim N(0,1)$ and $u \sim \chi^2(m)$ are independent. Then

$$T = \frac{z}{\sqrt{u/m}}$$

has a *t*-distribution with *m* degrees of freedom.

$$T \sim t(m)$$

Example

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$$\hat{\sigma}^2 = \frac{1}{N} \sum_{n=1}^{N} (y_n - \bar{y}_N)^2$$

Show that

$$\sqrt{N-1}\frac{\hat{\mu}-\mu}{\sqrt{\hat{\sigma}^2}}\sim t(N-1)$$

F-distribution

Suppose $u \sim \chi^2(m)$ and $v \sim \chi^2(n)$ are independent. Then

$$F=\frac{u/m}{v/n}$$

has a *F*-distribution with *m* and *n* degrees of freedom.

$$F \sim F(m, n)$$