

ReviewContinuous random variables

$$P\{X \leq a\} = \int_{-\infty}^a f_X(x) dx$$

$f_X(x)$ = probability density

$$E(X) = \int_{-\infty}^{\infty} x f_X(x) dx$$

$$\text{var}(X) = E(X^2) - E(X)^2$$

$$f_X(x) \geq 0$$

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

Examples:

Uniform distribution

$$f_X(x) = \begin{cases} \frac{1}{b-a} \\ 0 \end{cases}$$

$$a < b$$
$$a \leq x \leq b$$

(1-variable)

Gaussian (normal) distribution: Characterised by

expected value μ and variance σ^2

$$f_X(x) = \frac{1}{(\sqrt{2\pi})\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Standard Gaussian: $\mu = 0$, $\sigma^2 = 1$

$$f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

The exponential random variable

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & x < 0 \end{cases}$$

The hazard rate function of a random variable X

$$\lambda(x) = \frac{f_X(x)}{1 - \int_{-\infty}^x f_X(t) dt}$$

(The exponential variable has constant hazard rate λ for $x > 0$.)

The χ^2 random variable with k degrees of freedom

$$f_X(x) = \begin{cases} \frac{1}{2^{k/2} \Gamma(k/2)} x^{k/2-1} e^{-x/2} & x \geq 0 \\ 0 & x < 0 \end{cases}$$

$$\Gamma(\alpha) = \int_0^{\infty} e^{-x} x^{\alpha-1} dx.$$

$$\alpha > 0 \text{ integer} \Rightarrow \Gamma(\alpha) = (\alpha-1)!$$

$$\text{Generally: } \Gamma(\alpha) = (\alpha-1) \Gamma(\alpha-1).$$

$$\Gamma\left(\frac{1}{2}\right) = \sqrt{\pi}.$$

The Student t with k degrees of freedom

$$\frac{\Gamma\left(\frac{k+1}{2}\right)}{\sqrt{k\pi} \Gamma\left(\frac{k}{2}\right)} \left(1 + \frac{t^2}{k}\right)^{-\frac{k+1}{2}} = f_X(t)$$

k=1 Cauchy

To get to the forces of the distributions,
we need to talk about joint (multivariate)
distributions: $X_1, \dots, X_n : S \rightarrow \mathbb{R}$

Discrete — only countably many values:
joint probability mass function

$$p_{X_1, \dots, X_n}(x_1, \dots, x_n) = P\{X_1 = x_1\} \cap \dots \cap \{X_n = x_n\}.$$

Example: The multinomial random variables

with probabilities $p_1, \dots, p_m$, $p_1 + \dots + p_m = 1$
 N trials

$$p_{X_1, \dots, X_m}(N_1, \dots, N_m) = \binom{N}{N_1, \dots, N_m} p_1^{N_1} \dots p_m^{N_m}.$$

jointly continuous: $\exists$ joint probability density

$$f_{X_1, \dots, X_m}(x_1, \dots, x_m)$$

$$P\{(X_1, \dots, X_n) \in B\} = \int \dots \int_B f_{X_1, \dots, X_n}(x_1, \dots, x_n) dx_1 \dots dx_n$$

$\uparrow$
 measurable
 subset of $\mathbb{R}^n$

Omit one variable:

$$f_{X_1, \dots, X_{n-1}}(x_1, \dots, x_{n-1}) = \int_{-\infty}^{\infty} f_{X_1, \dots, X_n}(x_1, \dots, x_n) dx_n$$

Substitution theorem: If $y_1, \dots, y_n$ are a bijective function of $x_1, \dots, x_n$

$$dy_1 \dots dy_n = |J| dx_1 \dots dx_n$$

$$J = \det \begin{pmatrix} \partial y_1 / \partial x_1 & \dots & \partial y_1 / \partial x_n \\ \vdots & & \vdots \\ \partial y_m / \partial x_1 & \dots & \partial y_m / \partial x_n \end{pmatrix}$$

$$f_{y_1, \dots, y_m}(y_1, \dots, y_m) = f_{x_1, \dots, x_n}(x_1(y_1, \dots, y_m), \dots, x_n(y_1, \dots, y_m)) \cdot |J|^{-1}$$

Independent variables $X_1, \dots, X_n$

$$P(\{X_1 \in B_1\} \cap \dots \cap \{X_n \in B_n\}) = P\{X_1 \in B_1\} \cdot \dots \cdot P\{X_n \in B_n\}.$$

Stories: For any two jointly distributed random variables X, Y

$$E(X + Y) = E(X) + E(Y) \quad \left(\begin{array}{l} \text{if the} \\ \text{wght and} \\ \text{wde exist} \end{array} \right)$$

If X, Y are independent then

$$\text{var}(X + Y) = \text{var}(X) + \text{var}(Y),$$

Gaussian story:

The sum of independent Gaussians is a Gaussian (E and var are additive).

Central limit theorem: X_i are independent,
have the same distribution, variance σ^2 and
expected value μ then the distribution

of

$$\frac{\sqrt{n}}{\sigma} \left(\frac{X_1 + \dots + X_n}{n} - \mu \right)$$

converges to the distribution of the
standard Gaussian.

Multivariate Gaussian
symmetric matrix

A positive - definite

$$\frac{\sqrt{\det A}}{(2\pi)^{n/2}} e^{-\vec{x}^T A \vec{x} / 2} = f_{\vec{X}}(\vec{x})$$

← covariance matrix

$$\vec{X} = \begin{pmatrix} X_1 \\ \vdots \\ X_n \end{pmatrix}$$

$$\text{cov}(X, Y) = E(XY) - E(X)E(Y)$$

($\text{cov}(X, Y) = 0$ n't X, Y are independent).

Story of χ^2

$$\chi^2 = X_1^2 + \dots + X_k^2$$

$X_1, \dots, X_k$ = independent
standard normals

Pearson test: testing an observed sampling against the multinomial distribution:

N trials n variables $X_1, \dots, X_n$ expected for $X_i \approx p_i \cdot N$, Observed $= O_i$

$$\sum_{i=1}^n \frac{(O_i - p_i \cdot N)^2}{p_i \cdot N} = \chi^2_{\underbrace{n-1}}$$

$\nwarrow$ $n-1$ degrees of freedom.

Bayesian analysis: can reject the hypothesis with certainty $C\%$ if $\chi^2 > C$ percentile
(95%)

Student t story : $T = \frac{Z \sqrt{k}}{\chi_k^2}$

Z = standard normal

$\chi_k^2 = \chi^2$ with k degrees of freedom

Z, χ_k^2 are independent.

$X_1, \dots, X_n$ independent random variables
same distribution (assume normal)

Testing the expected value against a number μ_0

$$T = \frac{\frac{1}{n} (X_1 + \dots + X_n) - \mu_0}{\sqrt{\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n(n-1)}}$$

$$\bar{X} = \frac{1}{n} (X_1 + \dots + X_n)$$

degrees of freedom: $k = n - 1$.

(One-tailed test $\begin{matrix} > \text{mean} \\ \text{alb.} < \text{mean} \end{matrix} \left. \vphantom{\begin{matrix} > \text{mean} \\ \text{alb.} < \text{mean} \end{matrix}} \right\} \leftarrow 95\%$

two-tailed test $\neq \text{mean.} \leftarrow 90\%$