

# Probability Distributions

## 1 Univariate discrete distributions

Distribution	Probability mass function	Mean, variances
Uniform $\mathcal{U}(N)$	$f(x N) = \frac{1}{N+1}$ , $x = 0, 1, 2, \dots, N$ .	$E(X) = \frac{N}{2}$ $Var[X] = \frac{N(N+2)}{12}$
Poisson $\mathcal{POI}(\lambda)$	$f(x \lambda) = \frac{\lambda^x e^{-\lambda}}{x!}$ , $x = 0, 1, \dots$ $\lambda > 0$ .	$E(X) = \lambda$ $Var(X) = \lambda$
Multinomial $\mathcal{MN}(n, p_1, \dots, p_k)$	$f(x n, p_1, \dots, p_k)$ $= \frac{n!}{x_1! \dots x_k!} p_1^{x_1} \dots p_k^{x_k}$ , $x_i = 0, 1, \dots, n$ . $0 \leq p_i \leq 1$ . $\sum_{i=1}^k p_i = 1$ .	$E(X_i) = np_i$ $Var(X_i) = np_i q_i$ $Cov(X_i, X_j) = -np_i p_j$ $q_i = 1 - p_i$
Binomial $\mathcal{BN}(n, p)$ (= $\mathcal{MN}(n, p, q)$ )	$f(x n, p) = \binom{n}{x} p^x q^{n-x}$ , $q = 1 - p$ , $x = 0, 1, \dots, n$ . $0 \leq p \leq 1$ .	$E(X) = np$ $Var(X) = npq$
Bernoulli $\mathcal{BR}(p)$ (= $\mathcal{BN}(1, p)$ )	$f(x p) = p^x q^{1-x}$ , $q = 1 - p$ , $x = 0, 1$ . $0 \leq p \leq 1$ .	$E(X) = p$ $Var(X) = pq$
Negative Binomial $\mathcal{NB}(r, p)$	$f(x r, p) = \binom{r+x-1}{x} p^r q^x$ , $q = 1 - p$ , $x = 0, 1, \dots$ . $0 \leq p \leq 1$ .	$E(X) = \frac{rq}{p}$ $Var(X) = \frac{rq}{p^2}$
Geometric $\mathcal{GEO}(p)$ (= $\mathcal{NB}(1, p)$ )	$f(x p) = pq^x$ , $q = 1 - p$ , $x = 0, 1, \dots$ . $0 \leq p \leq 1$ .	$E(X) = \frac{q}{p}$ $Var(X) = \frac{q}{p^2}$
Hypergeometric $\mathcal{HG}(n, m, k)$	$f(x n, m, k) = \frac{\binom{m}{x} \binom{n-m}{k-x}}{\binom{n}{k}}$ , $\max(0, m - n + k) \leq x$ $\leq \min(m, k)$ . $n, m, k \geq 0$ .	$E(X) = \frac{km}{n}$ $Var(X) = \frac{km(n-m)(n-k)}{n^2(n-1)}$

## 2 Univariate continuous distributions

Distribution	Probability density function	Mean, variances
Uniform $\mathcal{U}(a, b)$	$f(x a, b) = \frac{1}{b-a}$ , $-\infty < a < x < b < \infty$ .	$E(X) = \frac{a+b}{2}$ $Var(X) = \frac{(b-a)^2}{12}$
Normal $\mathcal{N}(\mu, \sigma^2)$	$f(x \mu, \sigma^2)$ $= (2\pi\sigma^2)^{-\frac{1}{2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$ , $-\infty < \mu, x < \infty$ . $\sigma > 0$ .	$E(X) = \mu$ $Var(X) = \sigma^2$
Gamma $\mathcal{G}(\alpha, \beta)$	$f(x \alpha, \beta)$ $= \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} \exp(-\beta x)$ , $x, \alpha, \beta > 0$ .	$E(X) = \frac{\alpha}{\beta}$ $Var(X) = \frac{\alpha}{\beta^2}$
Exponential $\mathcal{EX}(\beta)$ (= $\mathcal{G}(1, \beta)$ )	$f(x \beta) = \beta \exp(-\beta x)$ , $0 \leq x < \infty$ . $\beta > 0$ .	$E(X) = \frac{1}{\beta}$ $Var(X) = \frac{1}{\beta^2}$
Chisquare $\chi^2(\nu)$ (= $\mathcal{G}(\frac{\nu}{2}, \frac{1}{2})$ )	$f(x \nu) = 2^{-\nu/2} \Gamma(\frac{\nu}{2})^{-1}$ $\times x^{\nu/2-1} \exp(-\frac{x}{2})$ , $x, \nu > 0$ .	$E(X) = \nu$ $Var(X) = 2\nu$
Inverted Gamma $\mathcal{IG}(\alpha, \beta)$ (= $\mathcal{G}(\alpha, \beta)^{-1}$ )	$f(x \alpha, \beta)$ $= \frac{\beta^\alpha}{\Gamma(\alpha)} x^{-(\alpha+1)} \exp(-\beta x^{-1})$ , $x, \alpha, \beta > 0$ .	$E(X) = \frac{\beta}{\alpha-1}$ , ( $\alpha > 1$ ) $Var(X) = \frac{\beta^2}{(\alpha-1)^2(\alpha-2)}$ , ( $\alpha > 2$ )
Inverted chisquare Inv- $\chi^2(\nu)$ (= $\chi^2(\nu)^{-1}$ )	$f(x \nu) = 2^{-\nu/2} \Gamma(\frac{\nu}{2})^{-1}$ $\times x^{-(\frac{\nu}{2}+1)} \exp(-\frac{1}{2x})$ , $x, \nu > 0$ .	$E(X) = \frac{1}{\nu-2}$ , ( $\nu > 2$ ) $Var(X) = \frac{2}{(\nu-2)^2(\nu-4)}$ , ( $\nu > 4$ )
Scaled inverted chisquare Inv- $\chi^2(\nu, s^2)$ (= $\mathcal{IG}(\frac{\nu}{2}, \frac{\nu s^2}{2})$ )	$f(x \nu, s^2) = \left(\frac{\nu s^2}{2}\right)^{-\nu/2} \Gamma(\frac{\nu}{2})^{-1}$ $\times x^{-(\frac{\nu}{2}+1)} \exp\left(-\frac{\nu s^2}{2x}\right)$ , $x, \nu > 0$ .	$E(X) = \frac{\nu s^2}{\nu-2}$ , ( $\nu > 2$ ) $Var(X) = \frac{2\nu^2 s^4}{(\nu-2)^2(\nu-4)}$ , ( $\nu > 4$ )

Distribution	Probability density function	Mean, variances
$t$ $\mathcal{T}_\nu(\mu, \sigma^2)$	$f(x \nu, \mu, \sigma^2) = \Gamma\left(\frac{\nu+1}{2}\right)$ $\times \Gamma\left(\frac{\nu}{2}\right)^{-1} \Gamma\left(\frac{1}{2}\right)^{-1} (\nu\sigma^2)^{-\frac{1}{2}}$ $\times \left\{1 + \frac{1}{\nu} \frac{(x-\mu)^2}{\sigma^2}\right\}^{-\frac{\nu+1}{2}},$ $-\infty < \mu, x < \infty. \nu, \sigma^2 > 0.$	$E(X) = \mu$ $(\nu > 1)$ $Var(X) = \frac{\nu}{\nu-2}\sigma^2$ $(\nu > 2)$
Cauchy $\mathcal{C}(\mu, \sigma^2)$ $(= \mathcal{T}_1(\mu, \sigma^2))$	$f(x \theta, \sigma)$ $= (\pi\sigma)^{-1} \left\{1 + \frac{(x-\mu)^2}{\sigma^2}\right\}^{-1},$ $-\infty < x, \mu < \infty. \sigma^2 > 0.$	$E(X) = \text{does not exist}$ $Var(X) = \text{does not exist}$
Beta $\mathcal{BE}(\alpha, \beta)$	$f(x \alpha, \beta)$ $= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1},$ $0 < x < 1. \alpha, \beta > 0.$	$E(X) = \frac{\alpha}{\alpha+\beta}$ $Var(X)$ $= \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$
$F$ 分布 $\mathcal{F}(\nu_1, \nu_2)$	$f(x \nu_1, \nu_2)$ $= \frac{\Gamma\left(\frac{\nu_1+\nu_2}{2}\right)}{\Gamma\left(\frac{\nu_1}{2}\right)\Gamma\left(\frac{\nu_2}{2}\right)} \left(\frac{\nu_1}{\nu_2}\right)^{\nu_1/2}$ $\times x^{\frac{\nu_1-2}{2}} \left(1 + \frac{\nu_1}{\nu_2}x\right)^{-\frac{\nu_1+\nu_2}{2}},$ $x, \nu_1, \nu_2 > 0.$	$E(X) = \frac{\nu_2}{\nu_2-2}$ $(\nu_2 > 2)$ $Var(X) = \frac{2\nu_2^2}{(\nu_2-2)^2}$ $\times \frac{(\nu_1+\nu_2-2)}{\nu_1(\nu_2-4)}, (\nu_2 > 4)$
Pareto $\mathcal{PA}(\alpha, \beta)$	$f(x \alpha, \beta) = \alpha\beta^\alpha x^{-(\alpha+1)},$ $x > \beta. \alpha, \beta > 0.$	$E(X) = \frac{\alpha\beta}{\alpha-1}, \alpha > 1$ $Var(X) =$ $\frac{\alpha\beta^2}{(\alpha-1)^2(\alpha-2)}, \alpha > 2$
Lognormal $\mathcal{LN}(\mu, \sigma^2)$ $(= \ln \mathcal{N}(\mu, \sigma^2))$	$f(x (\mu, \sigma) = (2\pi\sigma^2)^{-\frac{1}{2}}$ $\times x^{-1} \exp\left(-\frac{(\log(x)-\mu)^2}{2\sigma^2}\right),$ $-\infty < \mu < \infty. x, \sigma^2 > 0.$	$E(X) = \exp\left(\mu + \frac{\sigma^2}{2}\right)$ $Var(X)$ $= \exp(2\mu + \sigma^2)$ $\times \{\exp(\sigma^2) - 1\}$

### 3 Multivariate continuous distributions

Distribution	Probability density function	Mean, variances
Multivariate normal $\mathcal{N}(\mu, \Sigma)$	$f(x \mu, \Sigma) = (2\pi)^{-k/2}  \Sigma ^{-1/2}$ $\times \exp -\frac{1}{2}(x - \mu)' \Sigma^{-1}(x - \mu),$ $x = (x_1, \dots, x_k)',$ $-\infty < x_i, \mu_i < \infty.$ $\Sigma = \{\sigma_{ij}\} : \text{positive definite}$	$E(X_i) = \mu_i$ $Var(X_i) = \sigma_{ii}$ $Cov(X_i, X_j) = \sigma_{ij}$
Multivariate $t$ $\mathcal{T}_\nu(\mu, \Sigma)$	$f(x \mu, \Sigma, \nu) = \Gamma(\frac{\nu+k}{2})\Gamma(\frac{\nu}{2})^{-1}$ $\times (\pi\nu)^{-\frac{k}{2}}  \Sigma ^{-\frac{1}{2}} \{1 +$ $\frac{1}{\nu}(x - \mu)' \Sigma^{-1}(x - \mu)\}^{-\frac{\nu+k}{2}},$ $x = (x_1, \dots, x_k)',$ $-\infty < x_i, \mu_i < \infty. \nu > 0.$ $\Sigma = \{\sigma_{ij}\} : \text{positive definite}$	$E(X_i) = \mu_i$ $(\nu > 1)$ $Var(X_i) = \frac{\nu}{\nu-2} \sigma_{ii}$ $Cov(X_i, X_j)$ $= \frac{\nu}{\nu-2} \sigma_{ij}$ $(\nu > 2)$
Dirichlet $\mathcal{D}(\alpha_1, \dots, \alpha_k)$	$f(x \alpha_1, \dots, \alpha_k) =$ $\frac{\Gamma(\alpha_0)}{\Gamma(\alpha_1) \dots \Gamma(\alpha_k)} x_1^{\alpha_1-1} \dots x_k^{\alpha_k-1},$ $0 \leq x_i \leq 1. \sum_{i=1}^k x_i = 1.$ $\alpha_i > 0. \alpha_0 = \sum_{i=1}^k \alpha_i.$	$E(X_i) = \frac{\alpha_i}{\alpha_0}$ $Var(X_i)$ $= \frac{\alpha_i(\alpha_0 - \alpha_i)}{\alpha_0^2(\alpha_0 + 1)}$ $Cov(X_i, X_j)$ $= -\frac{\alpha_i \alpha_j}{\alpha_0^2(\alpha_0 + 1)}$
Wishart $\mathcal{W}(\alpha, \Sigma)$	$f(X \alpha, \Sigma) = \Gamma_k(\alpha)^{-1}  \Sigma ^{-\frac{\alpha}{2}}$ $\times  X ^{\frac{\alpha-(k+1)}{2}} \exp -\frac{\text{tr}(\Sigma^{-1}X)}{2},$ $X, \Sigma: k \times k \text{ positive definite}$ $\Gamma_k(\alpha) = 2^{\frac{\alpha k}{2}} \pi^{\frac{k(k-1)}{4}}$ $\times \prod_{i=1}^k \Gamma(\frac{\alpha+1-i}{2}), \alpha > k - 1.$	$E(X_{ij}) = \alpha \sigma_{ij}$ $Var(X_{ij})$ $= \alpha(\sigma_{ii}\sigma_{jj} + \sigma_{ij}^2)$ $Cov(X_{ij}, X_{kl})$ $= \alpha(\sigma_{ik}\sigma_{jl} + \sigma_{il}\sigma_{jk})$
Inverse Wishart $\mathcal{IW}(\alpha, \Sigma)$ ( $= \mathcal{W}(\alpha, \Sigma)^{-1}$ )	$f(X \alpha, \Sigma) = \Gamma_k(\alpha)^{-1}  \Sigma ^{-\frac{\alpha}{2}}$ $\times  X ^{-\frac{\alpha+k+1}{2}} \exp -\frac{\text{tr}(\Sigma^{-1}X^{-1})}{2},$ $X, \Sigma: k \times k \text{ positive definite}$ $\Gamma_k(\alpha): \text{same as above}$ $\Sigma^{-1} = \{\sigma^{ij}\}.$	$E(X_{ij}) = \frac{\sigma^{ij}}{\alpha - k - 1}$ $(\alpha > k + 1)$ $Var(X_{ij}): \text{omitted}$ $Cov(X_{ij}, X_{kl}): \text{omitted}$