Common Probability Distributions

Name	Symbol / Representation	PDF and CDF	Generation and Applications	Relationship to Normal
Normal	$X \sim \mathcal{N}(\mu, \sigma^2)$	PDF: $\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x-\mu)^2}{2\sigma^2}}$ CDF: $\Phi\left(\frac{x-\mu}{\sigma}\right)$	Generated via CLT or Box-Muller transform; used in modeling natural variation	Baseline distribution; many others converge to it under limiting conditions
Binomial	$X \sim \operatorname{Bin}(n, p)$	$\begin{array}{c} PMF: \left(\begin{smallmatrix} n \\ k \end{smallmatrix} \right) p^k (1-p)^{n-k} \\ CDF: \sum_{i=0}^k \left(\begin{smallmatrix} n \\ i \end{smallmatrix} \right) p^i (1-p)^{n-i} \end{array}$	Counts successes in n Bernoulli trials; used in discrete event modeling	Approximates normal when n is large and p not near 0 or 1
Poisson	$X \sim \operatorname{Pois}(\lambda)$	PMF: $\frac{\lambda^k e^{-\lambda}}{k!}$ CDF: $\sum_{i=0}^k \frac{\lambda^i e^{-\lambda}}{i!}$	Models rare events over time/space; used in queuing, traffic, biology	Approaches normal as $\lambda \to \infty$
Gamma	$X \sim \Gamma(\alpha, \beta)$	PDF: $\frac{\beta^{\alpha}}{\Gamma(\alpha)}x^{\alpha-1}e^{-\beta x}$ CDF: $\frac{\gamma(\alpha,\beta x)}{\Gamma(\alpha)}$	Sum of α exponential variables; used in waiting times, Bayesian priors	Sum of squared normals yields chi-square, a special case of gamma
Lognormal	$X \sim \text{Log}\mathcal{N}(\mu, \sigma^2)$	PDF: $\frac{1}{x\sigma\sqrt{2\pi}}e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}}$ CDF: $\Phi\left(\frac{\ln x - \mu}{\sigma}\right)$	Exponentiated normal; used in finance, reliability, and multiplicative processes	Log of lognormal is normal
Exponential	$X \sim \operatorname{Exp}(\lambda)$	PDF: $\lambda e^{-\lambda x}$ CDF: $1 - e^{-\lambda x}$	Time between Poisson events; memoryless; used in survival analysis	Special case of gamma with $\alpha=1$
Beta	$X \sim \mathrm{Beta}(\alpha, \beta)$	PDF: $\frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)}$ CDF: $I_x(\alpha,\beta)$	Models probabilities and proportions; used in Bayesian inference	No direct convergence, but appears in normalized transformations
Multinomial	$X \sim \operatorname{Mult}(n; p_1, \dots, p_k)$	PMF: $\frac{n!}{x_1!\cdots x_k!}p_1^{x_1}\cdots p_k^{x_k}$ CDF: Not typically defined (multivariate)	Generalization of binomial for ¿2 outcomes; used in NLP, categorical modeling	Each marginal binomial can approximate normal; joint distribution approaches multivariate normal
Chi-Square	$X \sim \chi_k^2$	PDF: $\frac{1}{2^{k/2}\Gamma(k/2)}x^{k/2-1}e^{-x/2}$ CDF: $\frac{\gamma(k/2,x/2)}{\Gamma(k/2)}$	Sum of squares of k standard normals; used in hypothesis testing	Derived from squared standard normals
Student's t	$X \sim t_{\nu}$	PDF: $\frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\Gamma\left(\frac{\nu}{2}\right)} \left(1 + \frac{x^2}{\nu}\right)^{-\frac{\nu+1}{2}}$	Used in small-sample inference; arises from normal with unknown variance	Converges to standard normal as $\nu \to \infty$
F- distribution	$X \sim F_{d_1,d_2}$	$\frac{PDF:}{\frac{(d_1/d_2)^{d_1/2}x^{d_1/2-1}}{B(d_1/2,d_2/2)(1+\frac{d_1}{d_2}x)^{(d_1+d_2)/2}}}$	Ratio of scaled chi-squares; used in ANOVA and variance testing	Related to normal via chi- square components
Bernoulli	$X \sim \mathrm{Bern}(p)$	PMF: $P(X = 1) = p$, $P(X = 0) = 1 - p$	Single trial success/failure; building block for binomial	Sum of Bernoulli trials leads to binomial, then normal
Geometric	$X \sim \text{Geom}(p)$	PMF: $P(X = k) = (1 - p)^{k-1}p$	Counts trials until first success; memoryless	No direct convergence, but approximates exponential in continuous limit
Pareto	X \sim Pareto (x_m, α)	$\begin{array}{c} \text{PDF: } \frac{\alpha x_m^{\alpha}}{x^{\alpha+1}} \text{ for } x \geq x_m \\ \text{CDF: } 1 - \left(\frac{x_m}{x}\right)^{\alpha} \end{array}$	Models wealth, file sizes, failure rates with heavy tails; used in economics and risk	Heavy-tailed; diverges from normal; tails decay more slowly

Table continued from previous page					
Name	Symbol / Representation	PDF and CDF	Generation and Applications	Relationship to Normal	
Uniform (continu- ous)	$X \sim \mathcal{U}(a,b)$	$\begin{array}{c} PDF: \ \frac{1}{b-a} \ for \ x \in [a,b] \\ CDF: \ \frac{x-a}{b-a} \end{array}$	Models equal likelihood; used in simulation and random sampling	Sum of many uniforms approximates normal (CLT)	