

Probability Distributions Cheat Sheet

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Continuous Distributions

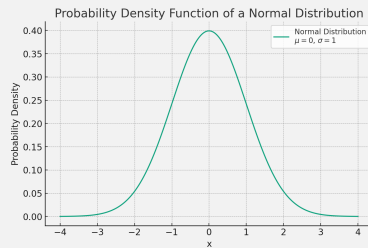
Normal (Gaussian) Distribution

Description: Described by its mean (μ) and standard deviation (σ), and has the classic "bell curve" shape.

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

$$Mean: \mu$$

$$Variance: \sigma^2$$



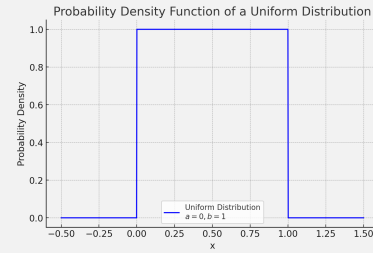
Uniform Distribution

Description: Models equally likely outcomes between two boundaries, a and b . It is characterized by constant probability density over its support.

$$PDF: f(x) = \begin{cases} \frac{1}{b-a} & \text{for } a \leq x \leq b \\ 0 & \text{otherwise} \end{cases}$$

$$Mean: \mu = \frac{a+b}{2}$$

$$Variance: \sigma^2 = \frac{(b-a)^2}{12}$$



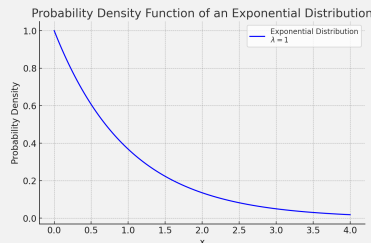
Exponential Distribution

Description: Models the time between events in a Poisson point process, i.e., events occur continuously and independently at a constant average rate.

$$PDF: f(x; \lambda) = \lambda e^{-\lambda x} \text{ for } x \geq 0$$

$$Mean: \frac{1}{\lambda}$$

$$Variance: \frac{1}{\lambda^2}$$



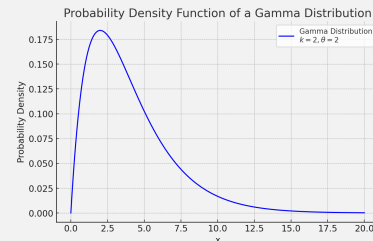
Gamma Distribution

Description: Models the time until an event occurs a specific number of times, given a continuous and constant arrival rate. It generalizes the exponential distribution.

$$PDF: f(x; k, \theta) = \frac{x^{k-1} e^{-\frac{x}{\theta}}}{\theta^k \Gamma(k)} \text{ for } x > 0$$

$$Mean: \mu = k\theta$$

$$Variance: \sigma^2 = k\theta^2$$



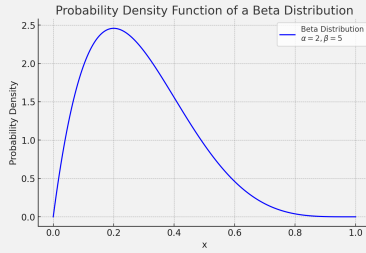
Beta Distribution

Description: Models the distribution of probabilities, representing all the possible values of probability when outcomes are distributed according to a binomial distribution. It is especially useful in Bayesian inference and is defined on the interval $[0, 1]$.

PDF: $f(x; \alpha, \beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha, \beta)}$ for $0 \leq x \leq 1$

Mean: $\mu = \frac{\alpha}{\alpha+\beta}$

Variance: $\sigma^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$



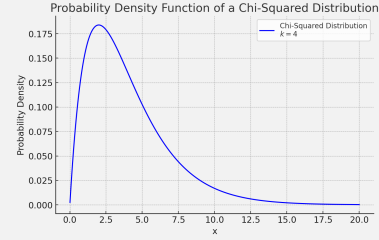
Chi-Squared Distribution

Description: A special case of the Gamma distribution, used primarily in hypothesis testing and in the construction of confidence intervals. It describes the distribution of the sum of the squares of k independent standard normal random variables.

PDF: $f(x; k) = \frac{1}{2^{\frac{k}{2}} \Gamma(\frac{k}{2})} x^{\frac{k}{2}-1} e^{-\frac{x}{2}}$ for $x > 0$

Mean: $\mu = k$

Variance: $\sigma^2 = 2k$



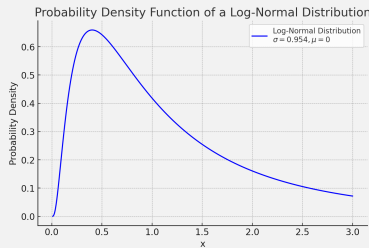
Log-Normal Distribution

Description: Models variables that are the product of many independent, identically distributed random variables. It is suitable for representing variables that cannot be negative and have a long right tail, such as income, length of time, and biological measurements.

PDF: $f(x; \mu, \sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}}$ for $x > 0$

Mean: $\mu = e^{\mu + \frac{\sigma^2}{2}}$

Variance: $\sigma^2 = (e^{\sigma^2} - 1)e^{2\mu + \sigma^2}$



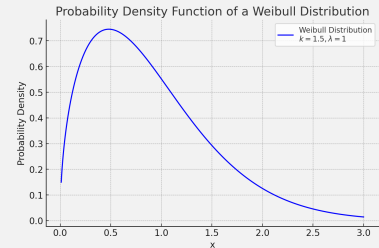
Weibull Distribution

Description: Commonly used in reliability engineering and failure analysis, the Weibull distribution is flexible, able to model various types of data. It is characterized by a scale parameter λ and a shape parameter k , which dictate the distribution's spread and form, respectively.

PDF: $f(x; k, \lambda) = \frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k}$ for $x > 0$

Mean: $\mu = \lambda \Gamma\left(1 + \frac{1}{k}\right)$

Variance: $\sigma^2 = \lambda^2 \left[\Gamma\left(1 + \frac{2}{k}\right) - \left(\Gamma\left(1 + \frac{1}{k}\right)\right)^2 \right]$



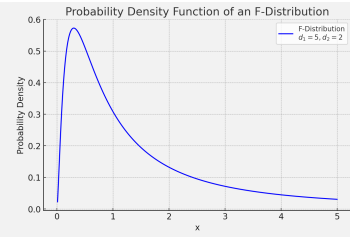
F-Distribution

Description: Used primarily in the analysis of variance (ANOVA), comparing two variances, and in regression analysis. The F-distribution arises from the division of two chi-squared distributions divided by their respective degrees of freedom.

$$PDF: f(x; d_1, d_2) = \frac{\sqrt{\frac{(d_1 x)^{d_1} \cdot d_2^{d_2}}{(d_1 x + d_2)^{d_1 + d_2}}}}{x \cdot B\left(\frac{d_1}{2}, \frac{d_2}{2}\right)} \text{ for } x > 0$$

$$Mean: \mu = \frac{d_2}{d_2 - 2} \text{ for } d_2 > 2$$

$$Variance: \sigma^2 = \frac{2d_2^2(d_1 + d_2 - 2)}{d_1(d_2 - 2)^2(d_2 - 4)} \text{ for } d_2 > 4$$



Discrete Distributions

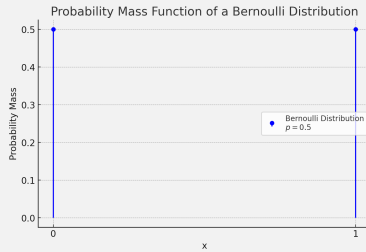
Bernoulli Distribution

Description: Models a single trial with two possible outcomes (success with probability p and failure with probability $1 - p$).

PMF: $P(X = k) = p^k(1 - p)^{1-k}$ for $k \in \{0, 1\}$

Mean: $\mu = p$

Variance: $\sigma^2 = p(1 - p)$



Binomial Distribution

Description: Models the number of successes in a fixed number of independent Bernoulli trials, each with the same probability of success.

PMF: $P(X = k) = \binom{n}{k} p^k (1 - p)^{n-k}$ for $k = 0, 1, \dots, n$

Mean: $\mu = np$

Variance: $\sigma^2 = np(1 - p)$

Figure Placeholder