

DISTRIBUTIONS FACTSHEET

DISCRETE DISTRIBUTIONS

Models based on an independent sequence of identical binary trials with success probability θ .

- **BERNOULLI** X is the total number of successes in one trial.
- **BINOMIAL** X is the total number of successes in n trials.
- **GEOMETRIC** X is the total number of trials required to obtain **one** success.
- **NEGATIVE BINOMIAL** X is the total number of trials required to obtain **n** successes. Alternative form given by considering $Y = X - n$, to give a distribution on $\{0, 1, 2, \dots\}$.
- **POISSON** X is the count of the number of events in a given (continuous) time interval. The Poisson distribution is obtained as the limiting form of the *Binomial*(n, θ) distribution, with $\lambda = n\theta$ held fixed.

Connections:

- Bernoulli/Binomial

$$X_1, \dots, X_n \sim \text{Bernoulli}(\theta) \quad \Rightarrow \quad Y = \sum_{i=1}^n X_i \sim \text{Binomial}(n, \theta)$$

- Geometric/Negative Binomial

$$X_1, \dots, X_n \sim \text{Geometric}(\theta) \quad \Rightarrow \quad Y = \sum_{i=1}^n X_i \sim \text{NegBinomial}(n, \theta)$$

- Binomial/Poisson

$$X_n \sim \text{Binomial}(n, \theta) \longrightarrow X \sim \text{Poisson}(\lambda)$$

where $\lambda = n\theta$ is held fixed and $n \longrightarrow \infty$.

- Negative Binomial/Poisson

$$X_n \sim \text{NegBinomial}(n, \theta) \quad Y_n = X_n - n \longrightarrow Y \sim \text{Poisson}(\lambda)$$

where $\lambda = n(1 - \theta)$ is held fixed and $n \longrightarrow \infty$.

Summations of Independent RVs:

- Binomial

$$\left. \begin{array}{l} X \sim \text{Binomial}(m, \theta) \\ Y \sim \text{Binomial}(n, \theta) \end{array} \right\} \Rightarrow T = X + Y \sim \text{Binomial}(m + n, \theta)$$

- Negative Binomial

$$\left. \begin{array}{l} X \sim \text{NegBinomial}(m, \theta) \\ Y \sim \text{NegBinomial}(n, \theta) \end{array} \right\} \Rightarrow T = X + Y \sim \text{NegBinomial}(m + n, \theta)$$

- Poisson

$$\left. \begin{array}{l} X \sim \text{Poisson}(\lambda_X) \\ Y \sim \text{Poisson}(\lambda_Y) \end{array} \right\} \Rightarrow T = X + Y \sim \text{Poisson}(\lambda_X + \lambda_Y)$$

CONTINUOUS DISTRIBUTIONS

- Distributions on \mathbb{R}^+

Begin with $U \sim \text{Uniform}(0, 1)$:

▶ $X = -\frac{1}{\lambda} \log U \sim \text{Exponential}(\lambda)$, for $\lambda > 0$.

▶ $Y = X^{1/\alpha} \sim \text{Weibull}(\alpha, \lambda)$, for $\alpha > 0$.

▶ If $X_1, \dots, X_n \sim \text{Exponential}(\lambda)$, independent, then $Y = \sum_{i=1}^n X_i \sim \text{Gamma}(n, \lambda)$.

▶ If $X \sim \text{Gamma}(\alpha_X, \lambda)$ and $Y \sim \text{Gamma}(\alpha_Y, \lambda)$ are independent, then

$$T = X + Y \sim \text{Gamma}(\alpha_X + \alpha_Y, \lambda)$$

- Poisson Process links

Consider events occurring independently at a constant rate λ in continuous time. Let

$$X(t, s) \equiv \text{number of events occurring in interval } [t, s]$$

$$X_i \equiv \text{time between event } i - 1 \text{ and event } i$$

$$Y_n \equiv \text{time of event } n$$

▶ $X(t, s) \sim \text{Poisson}(\lambda(s - t))$

▶ $X(0, t)$ and $X(t, s)$ are independent for $s > t$.

▶ $X_i \sim \text{Exponential}(\lambda)$, with X_1, X_2, \dots independent.

▶ $Y_n = \sum_{i=1}^n X_i \sim \text{Gamma}(n, \lambda)$.

- Distributions on \mathbb{R} : The Normal distribution and connections

▶ Suppose $X \sim N(0, 1)$. Then $Y = \mu + \sigma X \sim N(\mu, \sigma^2)$.

▶ Suppose $X \sim N(0, 1)$. Then $Y = X^2 \sim \text{Gamma}(1/2, 1/2) \equiv \text{Chisquared}(1)$.

▶ If $X_1, X_2 \sim N(0, 1)$, and $V \sim \text{Chisquared}(\nu)$ are all independent, then

$$T_1 = \frac{X_1}{X_2} \sim \text{Cauchy} \quad T_2 = \frac{X_1}{\sqrt{V/\nu}} \sim \text{Student}(\nu)$$

▶ If $V_1 \sim \text{Chisquared}(\nu_1)$ and $V_2 \sim \text{Chisquared}(\nu_2)$ are independent, then

$$T_3 = \frac{V_1/\nu_1}{V_2/\nu_2} \sim \text{Fisher}(\nu_1, \nu_2)$$

▶ If $X_1 \sim N(\mu_1, \sigma_1^2)$ and $X_2 \sim N(\mu_2, \sigma_2^2)$ are independent, then

$$Y = X_1 + X_2 \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$

- Distribution on $(0, 1)$: The Beta distribution

▶ If $X_1 \sim \text{Gamma}(\alpha_1, \beta)$ and $X_2 \sim \text{Gamma}(\alpha_2, \beta)$ are independent, then

$$V = \frac{X_1}{X_1 + X_2} \sim \text{Beta}(\alpha_1, \alpha_2)$$