

DISTRIBUTIONS FACTSHEET

DISCRETE DISTRIBUTIONS

Models based on an independent sequence of identical ‘Bernoulli’ 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 as $n \rightarrow \infty$ of the *Binomial*(n, θ) distribution, with $\lambda = n\theta$ held fixed.

Connections:

- Bernoulli/Binomial

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

- Geometric/Negative Binomial

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

- Binomial/Poisson

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

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

- Negative Binomial/Poisson

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

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

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

$$\begin{aligned} X(t, s) &\equiv \text{number of events occurring in interval } [t, s) \\ X_i &\equiv \text{time between event } i - 1 \text{ and event } i \\ Y_n &\equiv \text{time of event } n \end{aligned}$$

- ▶ $X(t, s) \sim \text{Poisson}(\lambda(s - t))$
- ▶ $X(0, t)$ 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 $Y = X^2 \sim \text{Gamma}(1/2, 1/2) \equiv \chi_1^2$, the chisquared distribution on 1 degree of freedom.
- ▶ If $X_1, X_2 \sim N(0, 1)$, and $V \sim \chi_\nu^2$ are all independent, then

$$T_1 = \frac{X_1}{X_2} \sim \text{Cauchy}, \quad T_2 = \frac{X_1}{\sqrt{V/\nu}} \sim t_n,$$

with t_n denoting Student's t -distribution on n degrees of freedom.

- ▶ If $V_1 \sim \chi_{\nu_1}^2$ and $V_2 \sim \chi_{\nu_2}^2$ are independent, then

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

the F -distribution on ν_1, ν_2 degrees of freedom.

- ▶ 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

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