

GENERAL PROBABILITY

Basic Probability Relationships

$$\begin{aligned} \Pr(A \cup B) &= \Pr(A) + \Pr(B) - \Pr(A \cap B) \\ \Pr(A \cup B \cup C) &= \Pr(A) + \Pr(B) + \Pr(C) \\ &\quad - \Pr(A \cap B) - \Pr(B \cap C) - \Pr(A \cap C) \\ &\quad + \Pr(A \cap B \cap C) \\ \Pr(A') &= 1 - \Pr(A) \end{aligned}$$

Law of Total Probability

$$\Pr(B) = \sum_{i=1}^n \Pr(B \cap A_i)$$

De Morgan's Law

$$\begin{aligned} \Pr[(A \cup B)'] &= \Pr(A' \cap B') \\ \Pr[(A \cap B)'] &= \Pr(A' \cup B') \end{aligned}$$

Conditional Probability

$$\Pr(A|B) = \frac{\Pr(A \cap B)}{\Pr(B)}$$

Independence

$$\begin{aligned} \Pr(A \cap B) &= \Pr(A) \cdot \Pr(B) \\ \Pr(A|B) &= \Pr(A) \end{aligned}$$

Bayes' Theorem

$$\Pr(A_k|B) = \frac{\Pr(B|A_k) \cdot \Pr(A_k)}{\sum_{i=1}^n \Pr(B|A_i) \cdot \Pr(A_i)}$$

Combinatorics

$$\begin{aligned} n! &= n \cdot (n-1) \cdot \dots \cdot 2 \cdot 1 \\ {}^n P_k &= \frac{n!}{(n-k)!} \\ {}^n C_k &= \binom{n}{k} = \frac{n!}{(n-k)! \cdot k!} \end{aligned}$$

UNIVARIATE PROBABILITY DISTRIBUTIONS

*Learn both discrete and continuous cases

*Probability Mass Function (PMF)

$$\begin{aligned} \sum_{\text{all } x} p_X(x) &= 1 \\ \Pr(X = a) &= 0 \text{ (continuous)} \end{aligned}$$

*Cumulative Distribution Function (CDF)

$$\begin{aligned} F_X(x) &= \Pr(X \leq x) = \sum_{i \leq x} p_X(i) \\ \Pr(a < X \leq b) &= F_X(b) - F_X(a) \\ f_X(x) &= \frac{d}{dx} F_X(x) \text{ (continuous)} \end{aligned}$$

*Expected Value

$$\begin{aligned} E[c] &= c \\ E[g(X)] &= \int_{-\infty}^{\infty} g(x) \cdot f_X(x) dx \\ E[g(X)] &= \int_0^{\infty} g'(x) \cdot S_X(x) dx, \text{ for } x \geq 0 \\ E[g(X)|j \leq X \leq k] &= \frac{\int_j^k g(x) \cdot f_X(x) dx}{\Pr(j \leq X \leq k)} \\ E[c \cdot g(X)] &= c \cdot E[g(X)] \\ E[g_1(X) + \dots + g_k(X)] &= E[g_1(X)] + \dots + E[g_k(X)] \end{aligned}$$

Variance, Standard Deviation, and Coefficient of Variation

$$\begin{aligned} \text{Var}[X] &= E[X^2] - (E[X])^2 \\ \text{Var}[aX + b] &= a^2 \cdot \text{Var}[X] \\ \text{Var}[c] &= 0 \\ SD[X] &= \sqrt{\text{Var}[X]} \\ CV[X] &= SD[X]/E[X] \end{aligned}$$

*Moment Generating Function (MGF)

$$\begin{aligned} M_X(t) &= E[e^{tX}] \\ M_{aX+b}(t) &= e^{bt} \cdot M_X(at) \\ M_X(0) &= 1 \\ M_{X+Y}(t) &= M_X(t) \cdot M_Y(t) \text{ (independent)} \\ \left. \frac{d^n}{dt^n} M_X(t) \right|_{t=0} &= E[X^n] \end{aligned}$$

Probability Generating Function (PGF)

$$\begin{aligned} P_X(t) &= E[t^X] \\ P_X(0) &= p_X(0) \\ \left. \frac{d^n}{dt^n} P_X(t) \right|_{t=0} &= p_X(n) \\ \left. \frac{d^n}{dt^n} P_X(t) \right|_{t=1} &= E[X(X-1) \dots (X-n+1)] \end{aligned}$$

Percentiles

The 100^pth percentile is the smallest value of π_p where $F_X(\pi_p) \geq p$.

Univariate Transformation

$$\begin{aligned} f_Y(y) &= f_X[g^{-1}(y)] \cdot \left| \frac{d}{dy} g^{-1}(y) \right| \\ \text{where } y &= g(x) \Leftrightarrow x = g^{-1}(y) \end{aligned}$$

| Discrete Distributions | | | | | | |
|---|--|-----------------------|------------------------------------|--|--|--|
| | PMF | Mean | Variance | MGF | PGF | Special Properties |
| Discrete Uniform | $\frac{1}{b-a+1}$ | $\frac{a+b}{2}$ | $\frac{(b-a+1)^2-1}{12}$ | $\frac{e^{at}-e^{(b+1)t}}{(1-e^t)(b-a+1)}$ | - | - |
| Binomial | $\binom{n}{x} p^x (1-p)^{n-x}$ | np | $np(1-p)$ | $(pe^t+q)^n$ | $(pt+q)^n$ | - |
| Hypergeometric | $\frac{\binom{m}{x} \cdot \binom{N-m}{n-x}}{\binom{N}{n}}$ | $n \cdot \frac{m}{N}$ | - | - | - | - |
| Geometric | $(1-p)^{x-1} p$ | $\frac{1}{p}$ | $\frac{1-p}{p^2}$ | $\frac{pe^t}{1-(1-p)e^t}$ | $\frac{pt}{1-(1-p)t}$ | Memoryless property |
| X : trials; Y : failures $X = Y + 1$ | $(1-p)^y p$ | $\frac{1}{p} - 1$ | | $\frac{p}{1-(1-p)e^t}$ | $\frac{p}{1-(1-p)t}$ | |
| Negative Binomial | $\binom{x-1}{r-1} p^r (1-p)^{x-r}$ | $\frac{r}{p}$ | $r \left(\frac{1-p}{p^2} \right)$ | $\left(\frac{pe^t}{1-(1-p)e^t} \right)^r$ | $\left(\frac{pt}{1-(1-p)t} \right)^r$ | Neg Bin($r=1, p$) ~ Geometric(p) |
| X : trials; Y : failures $X = Y + r$ | $\binom{y+r-1}{r-1} p^r (1-p)^y$ | $\frac{r}{p} - r$ | | $\left(\frac{p}{1-(1-p)e^t} \right)^r$ | $\left(\frac{p}{1-(1-p)t} \right)^r$ | |
| Poisson | $\frac{e^{-\lambda} \cdot \lambda^x}{x!}$ | λ | λ | $e^{\lambda(e^t-1)}$ | $e^{\lambda(t-1)}$ | Sum of independent Poissons ~ Poisson ($\lambda = \sum_{i=1}^n \lambda_i$) |

| Continuous Distributions | | | | | | |
|--------------------------|---|---|-----------------|----------------------|--|--|
| | PDF | CDF | Mean | Variance | MGF | Special Properties |
| Continuous Uniform | $\frac{1}{b-a}$ | $\frac{x-a}{b-a}$ | $\frac{a+b}{2}$ | $\frac{(b-a)^2}{12}$ | $\frac{e^{bt}-e^{at}}{t(b-a)}$ | $(X X > c) \sim \text{Uniform}(c, b)$ $(X-c X > c) \sim \text{Uniform}(0, b-c)$ |
| Exponential | $\frac{1}{\theta} e^{-\frac{x}{\theta}}$ | $1 - e^{-\frac{x}{\theta}}$ | θ | θ^2 | $\frac{1}{1-\theta t}$ | Memoryless property: $(X-a X > a) \sim X$ |
| Gamma | $\frac{x^{\alpha-1}}{\Gamma(\alpha) \cdot \theta^\alpha} \cdot e^{-\frac{x}{\theta}}$ | $1 - \sum_{k=0}^{\alpha-1} \Pr(Y=k),$ $Y \sim \text{Poisson}\left(\lambda = \frac{x}{\theta}\right)$ | $\alpha\theta$ | $\alpha\theta^2$ | $\left(\frac{1}{1-\theta t}\right)^\alpha$ | Sum of α independent exponentials(θ) ~ Gamma(α, θ) |
| Normal | $\frac{1}{\sigma\sqrt{2\pi}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}}$ | $Z = \frac{X-\mu}{\sigma}$ $\Pr(Z \leq z) = \Phi(z)$ | μ | σ^2 | $e^{\mu t + \frac{\sigma^2 t^2}{2}}$ | Symmetry: $\Pr(Z \leq z) = \Pr(Z \geq -z)$ $\Pr(Z \leq -z) = \Pr(Z \geq z)$ Sum of independent normals ~ Normal($\mu = \sum_{i=1}^n \mu_i, \sigma^2 = \sum_{i=1}^n \sigma_i^2$) |

MULTIVARIATE PROBABILITY DISTRIBUTIONS

*Learn both discrete and continuous cases

*Joint PMF and CDF

$$\sum_{\text{all } x} \sum_{\text{all } y} p_{X,Y}(x, y) = 1$$

$$F_{X,Y}(x, y) = \sum_{s \leq x} \sum_{t \leq y} p_{X,Y}(s, t)$$

$$\frac{\partial^2}{\partial x \partial y} F_{X,Y}(x, y) = f_{X,Y}(x, y) \text{ (continuous)}$$

*Marginal Distributions and Conditional Distributions

$$p_X(x) = \sum_{\text{all } y} p_{X,Y}(x, y)$$

$$p_Y(y) = \sum_{\text{all } x} p_{X,Y}(x, y)$$

$$p_{X|Y}(x|Y=y) = p_{X,Y}(x, y)/p_Y(y)$$

*Joint Expected Value and Conditional Expectation

$$E[g(X, Y)]$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) \cdot f_{X,Y}(x, y) dy dx$$

$$E[X|Y=y] = \int_{-\infty}^{\infty} x \cdot f_{X|Y}(x|Y=y) dx$$

Double Expectation and Law of Total Variance

$$E[X] = E[E[X|Y]]$$

$$Var[X] = E[Var[X|Y]] + Var[E[X|Y]]$$

Covariance and Correlation Coefficient

$$Cov[X, Y] = E[XY] - E[X]E[Y]$$

$$Cov[aX, bY] = ab \cdot Cov[X, Y]$$

$$Cov[X, X] = Var[X]$$

$$Var[aX + bY] = a^2 Var[X] + b^2 Var[Y] + 2ab \cdot Cov[X, Y]$$

$$\rho_{X,Y} = Corr[X, Y] = \frac{Cov[X, Y]}{\sqrt{Var[X]} \sqrt{Var[Y]}}$$

Independence

$$F_{X,Y}(x, y) = F_X(x) \cdot F_Y(y)$$

$$f_{X,Y}(x, y) = f_X(x) \cdot f_Y(y)$$

$$E[h(X) \cdot k(Y)] = E[h(X)] \cdot E[k(Y)]$$

$$M_{X,Y}(s, t) = M_X(s) \cdot M_Y(t)$$

$$Cov[X, Y] = 0$$

$$\rho_{X,Y} = 0$$

*Joint MGF

$$M_{X,Y}(s, t) = E[e^{sX+tY}]$$

$$E[X] = \left. \frac{\partial}{\partial s} M_{X,Y}(s, t) \right|_{s=t=0}$$

$$E[Y] = \left. \frac{\partial}{\partial t} M_{X,Y}(s, t) \right|_{s=t=0}$$

$$E[X^m Y^n] = \left. \frac{\partial^{m+n}}{\partial s^m \partial t^n} M_{X,Y}(s, t) \right|_{s=t=0}$$

$$M_{X,Y}(t, t) = M_{X+Y}(t)$$

Multivariate Transformation

$$f_{w_1, w_2}(w_1, w_2)$$

$$= f_{x_1, x_2}[h_1(w_1, w_2), h_2(w_1, w_2)] \cdot |J|$$

where

$$x_1 = h_1(w_1, w_2)$$

$$x_2 = h_2(w_1, w_2)$$

$$J = \begin{vmatrix} \frac{\partial x_1}{\partial w_1} & \frac{\partial x_1}{\partial w_2} \\ \frac{\partial x_2}{\partial w_1} & \frac{\partial x_2}{\partial w_2} \end{vmatrix}$$

Multinomial Distribution

$$\Pr(X_1 = x_1, \dots, X_k = x_k)$$

$$= \frac{n!}{x_1! \cdot \dots \cdot x_k!} \cdot p_1^{x_1} \cdot \dots \cdot p_k^{x_k}$$

$$E[X_i] = np_i$$

$$Var[X_i] = np_i(1 - p_i)$$

$$Cov[X_i, X_j] = -np_i p_j, \quad i \neq j$$

Bivariate Continuous Uniform

$$f_{X,Y}(x, y) = \frac{1}{\text{Area of domain}}$$

$$\Pr(\text{region}) = \frac{\text{Area of region}}{\text{Area of domain}}$$

Bivariate Normal

For $X \sim \text{Normal}(\mu_X, \sigma_X^2)$ and

$Y \sim \text{Normal}(\mu_Y, \sigma_Y^2)$,

$(Y|X=x) \sim \text{Normal}$

where

$$E[Y|X=x] = \mu_Y + \rho \cdot \sigma_Y \left(\frac{x - \mu_X}{\sigma_X} \right)$$

$$Var[Y|X=x] = \sigma_Y^2(1 - \rho^2)$$

Expectation and Variance for Sum and Average of I.I.D. Random Variables

$$S = X_1 + \dots + X_n$$

$$\bar{X} = [X_1 + \dots + X_n]/n$$

$$E[S] = n \cdot E[X_i]$$

$$E[\bar{X}] = E[X_i]$$

$$Var[S] = n \cdot Var[X_i]$$

$$Var[\bar{X}] = (1/n) \cdot Var[X_i]$$

Central Limit Theorem

The sum of a large number of identically and independently distributed (i.i.d.) random variables approximately follows a normal distribution.

Order Statistics

$$X_{(1)} = \min(X_1, X_2, \dots, X_n)$$

$$X_{(n)} = \max(X_1, X_2, \dots, X_n)$$

For i.i.d. random variables,

$$S_{X_{(1)}}(x) = [S_X(x)]^n$$

$$F_{X_{(n)}}(x) = [F_X(x)]^n$$

INSURANCE AND RISK MANAGEMENT

| Category | Definition of Payment, Y | $E[Y]$ | |
|---|--|---|---|
| Deductible | $Y = \begin{cases} 0, & X \leq d \\ X - d, & X > d \end{cases}$ | $\int_d^\infty (x - d) \cdot f_X(x) dx$ $\int_d^\infty S_X(x) dx$ | For exponential: $\theta \cdot \Pr(X > d)$ |
| Policy Limit | $Y = \begin{cases} X, & X < u \\ u, & X \geq u \end{cases}$ | $\int_0^u x \cdot f_X(x) dx + u \cdot S_X(u)$ $\int_0^u S_X(x) dx$ | For exponential: $\theta \cdot \Pr(X < u)$ |
| Deductible and Policy Limit (u is the policy limit/ maximum payment) | $Y = \begin{cases} 0, & X \leq d \\ X - d, & d < X < d + u \\ u, & X \geq d + u \end{cases}$ | $\int_d^{d+u} (x - d) \cdot f_X(x) dx + u \cdot S_X(d + u)$ $\int_d^{d+u} S_X(x) dx$ | For exponential: $\theta \cdot \Pr(d < X < d + u)$ |

Unreimbursed Loss, Z

If X is the loss and Y is the payment (i.e. reimbursed loss), then $X = Y + Z \Rightarrow Z = X - Y$, and $E[Z] = E[X] - E[Y]$.