

PROBABILITY AND STATISTICS

CHEAT SHEET

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6th March, 2011

This cheat sheet integrates a variety of topics in probability theory and statistics. It is based on literature [1, 6, 3] and in-class material from courses of the statistics department at the University of California in Berkeley but also influenced by other sources [4, 5]. If you find errors or have suggestions for further topics, I would appreciate if you send me an email. The most recent version of this document is available at <http://bit.ly/probstat>. To reproduce, please contact me.

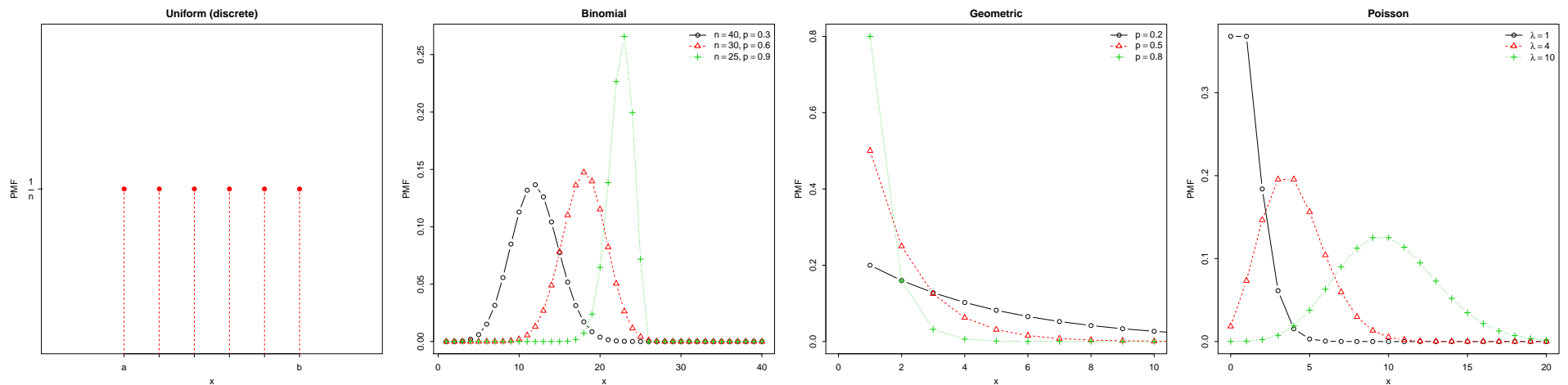
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1 Distribution Overview

1.1 Discrete Distributions

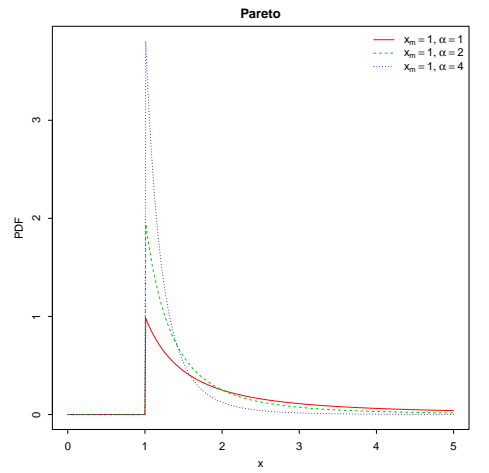
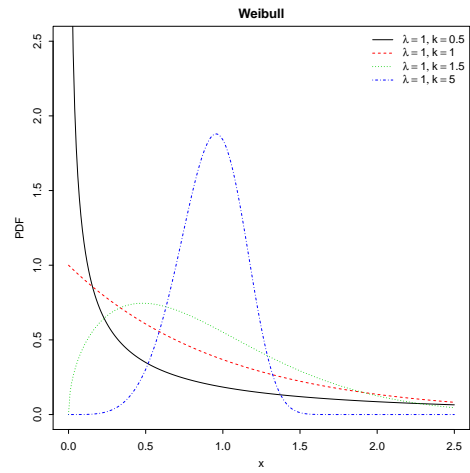
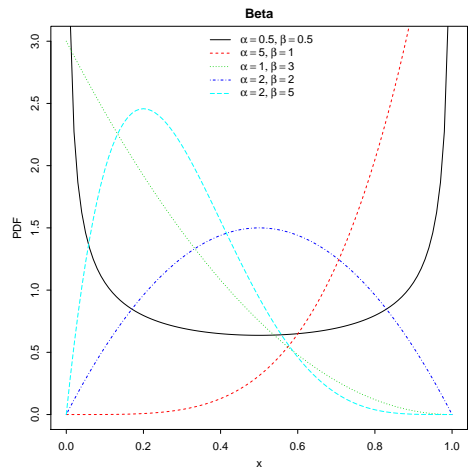
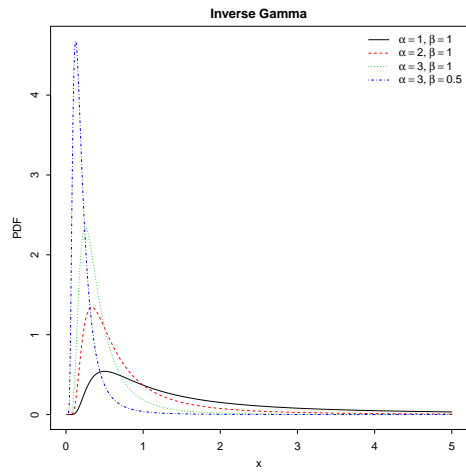
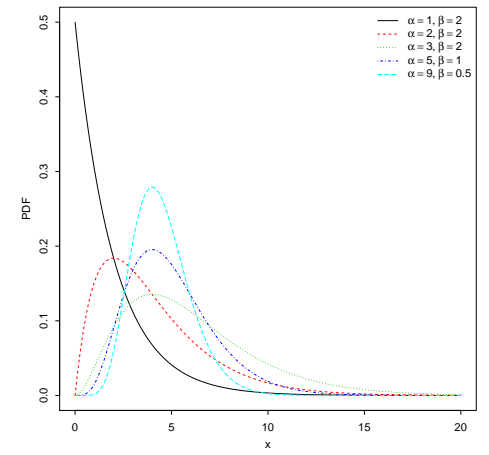
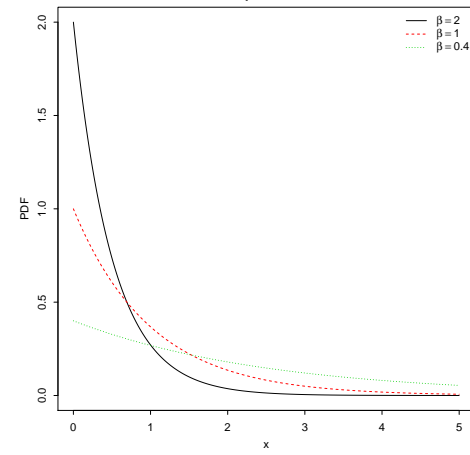
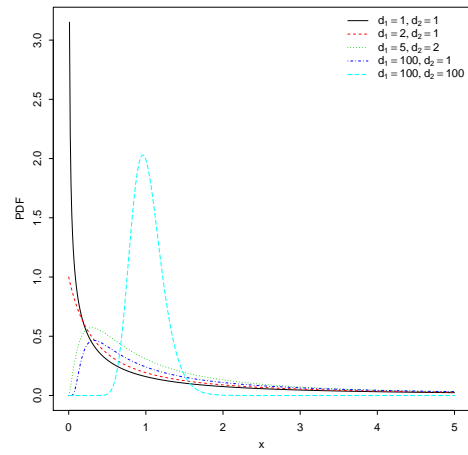
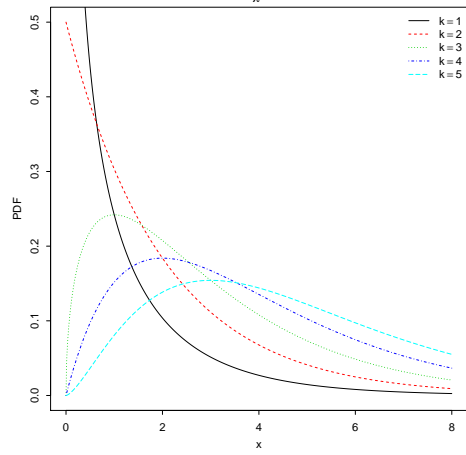
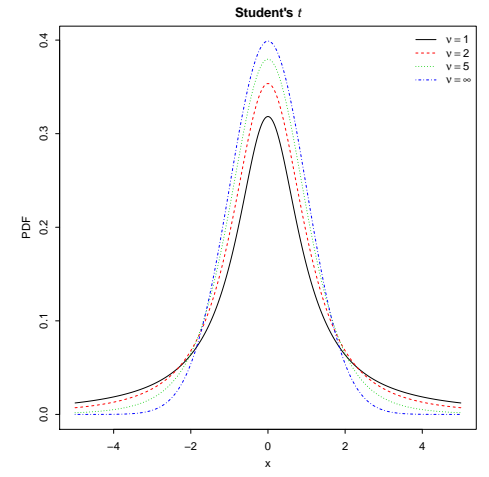
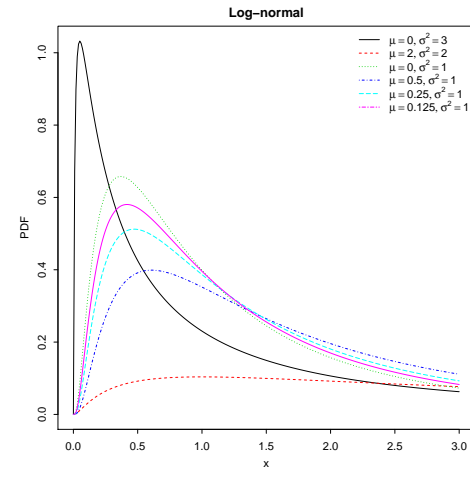
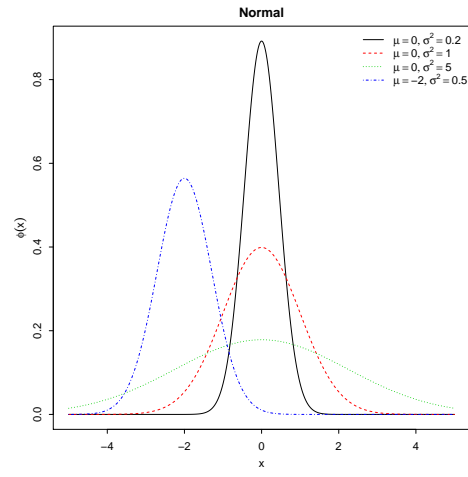
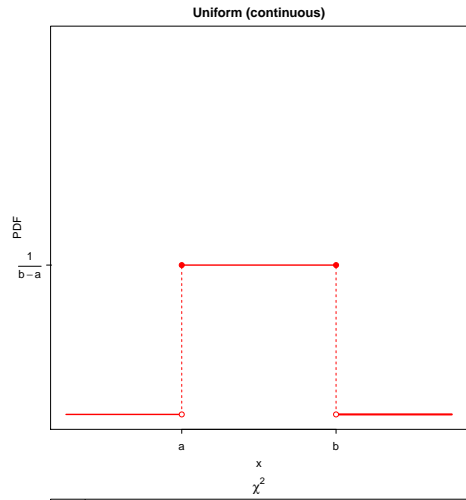
	Notation ¹	$F_X(x)$	$f_X(x)$	$\mathbb{E}[X]$	$\mathbb{V}[X]$	$M_X(s)$
Uniform	$\text{Unif}\{a, \dots, b\}$	$\begin{cases} 0 & x < a \\ \frac{\lfloor x \rfloor - a + 1}{b - a} & a \leq x \leq b \\ 1 & x > b \end{cases}$	$\frac{I(a < x < b)}{b - a + 1}$	$\frac{a + b}{2}$	$\frac{(b - a + 1)^2 - 1}{12}$	$\frac{e^{as} - e^{-(b+1)s}}{s(b - a)}$
Bernoulli	$\text{Bern}(p)$	$(1 - p)^{1-x}$	$p^x (1 - p)^{1-x}$	p	$p(1 - p)$	$1 - p + pe^s$
Binomial	$\text{Bin}(n, p)$	$I_{1-p}(n - x, x + 1)$	$\binom{n}{x} p^x (1 - p)^{n-x}$	np	$np(1 - p)$	$(1 - p + pe^s)^n$
Multinomial	$\text{Mult}(n, p)$		$\frac{n!}{x_1! \dots x_k!} p_1^{x_1} \dots p_k^{x_k} \quad \sum_{i=1}^k x_i = n$	np_i	$np_i(1 - p_i)$	$\left(\sum_{i=0}^k p_i e^{s_i} \right)^n$
Hypergeometric	$\text{Hyp}(N, m, n)$	$\approx \Phi\left(\frac{x - np}{\sqrt{np(1-p)}}\right)$	$\frac{\binom{m}{x} \binom{m-x}{n-x}}{\binom{N}{n}}$	$\frac{nm}{N}$	$\frac{nm(N-n)(N-m)}{N^2(N-1)}$	N/A
Negative Binomial	$\text{NBin}(n, p)$	$I_p(r, x + 1)$	$\binom{x+r-1}{r-1} p^r (1-p)^x$	$r \frac{1-p}{p}$	$r \frac{1-p}{p^2}$	$\left(\frac{p}{1 - (1-p)e^s} \right)^r$
Geometric	$\text{Geo}(p)$	$1 - (1-p)^x \quad x \in \mathbb{N}^+$	$p(1-p)^{x-1} \quad x \in \mathbb{N}^+$	$\frac{1}{p}$	$\frac{1-p}{p^2}$	$\frac{p}{1 - (1-p)e^s}$
Poisson	$\text{Po}(\lambda)$	$e^{-\lambda} \sum_{i=0}^x \frac{\lambda^i}{i!}$	$\frac{\lambda^x e^{-\lambda}}{x!}$	λ	λ	$e^{\lambda(e^s - 1)}$



¹We use the notation $\gamma(s, x)$ and $\Gamma(x)$ to refer to the Gamma functions (see §22.1), and use $B(x, y)$ and I_x to refer to the Beta functions (see §22.2).

1.2 Continuous Distributions

	Notation	$F_X(x)$	$f_X(x)$	$\mathbb{E}[X]$	$\mathbb{V}[X]$	$M_X(s)$
Uniform	$\text{Unif}(a, b)$	$\begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a < x < b \\ 1 & x > b \end{cases}$	$\frac{I(a < x < b)}{b-a}$	$\frac{a+b}{2}$	$\frac{(b-a)^2}{12}$	$\frac{e^{sb} - e^{sa}}{s(b-a)}$
Normal	$\mathcal{N}(\mu, \sigma^2)$	$\Phi(x) = \int_{-\infty}^x \phi(t) dt$	$\phi(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\}$	μ	σ^2	$\exp\left\{\mu s + \frac{\sigma^2 s^2}{2}\right\}$
Log-Normal	$\ln \mathcal{N}(\mu, \sigma^2)$	$\frac{1}{2} + \frac{1}{2} \operatorname{erf}\left[\frac{\ln x - \mu}{\sqrt{2}\sigma}\right]$	$\frac{1}{x\sqrt{2\pi}\sigma^2} \exp\left\{-\frac{(\ln x - \mu)^2}{2\sigma^2}\right\}$	$e^{\mu + \sigma^2/2}$	$(e^{\sigma^2} - 1)e^{2\mu + \sigma^2}$	
Multivariate Normal	$\text{MVN}(\mu, \Sigma)$		$(2\pi)^{-k/2} \Sigma ^{-1/2} e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)}$	μ	Σ	$\exp\left\{\mu^T s + \frac{1}{2} s^T \Sigma s\right\}$
Student's t	$\text{Student}(\nu)$	$I_x\left(\frac{\nu}{2}, \frac{\nu}{2}\right)$	$\frac{\Gamma(\frac{\nu+1}{2})}{\sqrt{\nu\pi}\Gamma(\frac{\nu}{2})} \left(1 + \frac{x^2}{\nu}\right)^{-(\nu+1)/2}$	0	0	
Chi-square	χ_k^2	$\frac{1}{\Gamma(k/2)} \gamma\left(\frac{k}{2}, \frac{x}{2}\right)$	$\frac{1}{2^{k/2}\Gamma(k/2)} x^{k/2} e^{-x/2}$	k	$2k$	$(1-2s)^{-k/2} s < 1/2$
F	$F(d_1, d_2)$	$I_{\frac{d_1 x}{d_1 x + d_2}}\left(\frac{d_1}{2}, \frac{d_1}{2}\right)$	$\frac{\sqrt{\frac{(d_1 x)^{d_1} d_2^{d_2}}{(d_1 x + d_2)^{d_1 + d_2}}}}{x \text{B}\left(\frac{d_1}{2}, \frac{d_1}{2}\right)}$	$\frac{d_2}{d_2 - 2}$	$\frac{2d_2^2(d_1 + d_2 - 2)}{d_1(d_2 - 2)^2(d_2 - 4)}$	
Exponential	$\text{Exp}(\beta)$	$1 - e^{-x/\beta}$	$\frac{1}{\beta} e^{-x/\beta}$	β	β^2	$\frac{1}{1 - \beta s} (s < 1/\beta)$
Gamma	$\text{Gamma}(\alpha, \beta)$	$\frac{\gamma(\alpha, x/\beta)}{\Gamma(\alpha)}$	$\frac{1}{\Gamma(\alpha)\beta^\alpha} x^{\alpha-1} e^{-x/\beta}$	$\alpha\beta$	$\alpha\beta^2$	$\left(\frac{1}{1 - \beta s}\right)^\alpha (s < 1/\beta)$
Inverse Gamma	$\text{InvGamma}(\alpha, \beta)$	$\frac{\Gamma(\alpha, \frac{\beta}{x})}{\Gamma(\alpha)}$	$\frac{\beta^\alpha}{\Gamma(\alpha)} x^{-\alpha-1} e^{-\beta/x}$	$\frac{\beta}{\alpha - 1} \alpha > 1$	$\frac{\beta^2}{(\alpha - 1)^2(\alpha - 2)^2} \alpha > 2$	$\frac{2(-\beta s)^{\alpha/2}}{\Gamma(\alpha)} K_\alpha(\sqrt{-4\beta s})$
Dirichlet	$\text{Dir}(\alpha)$		$\frac{\Gamma(\sum_{i=1}^k \alpha_i)}{\prod_{i=1}^k \Gamma(\alpha_i)} \prod_{i=1}^k x_i^{\alpha_i - 1}$	$\frac{\alpha_i}{\sum_{i=1}^k \alpha_i}$	$\frac{\mathbb{E}[X_i](1 - \mathbb{E}[X_i])}{\sum_{i=1}^k \alpha_i + 1}$	
Beta	$\text{Beta}(\alpha, \beta)$	$I_x(\alpha, \beta)$	$\frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1}$	$\frac{\alpha}{\alpha + \beta}$	$\frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)}$	$1 + \sum_{k=1}^{\infty} \left(\prod_{r=0}^{k-1} \frac{\alpha + r}{\alpha + \beta + r}\right) \frac{s^k}{k!}$
Weibull	$\text{Weibull}(\lambda, k)$	$1 - e^{-(x/\lambda)^k}$	$\frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k}$	$\lambda\Gamma\left(1 + \frac{1}{k}\right)$	$\lambda^2\Gamma\left(1 + \frac{2}{k}\right) - \mu^2$	$\sum_{n=0}^{\infty} \frac{s^n \lambda^n}{n!} \Gamma\left(1 + \frac{n}{k}\right)$
Pareto	$\text{Pareto}(x_m, \alpha)$	$1 - \left(\frac{x_m}{x}\right)^\alpha \quad x \geq x_m$	$\frac{\alpha x_m^\alpha}{x^{\alpha+1}} \quad x \geq x_m$	$\frac{\alpha x_m}{\alpha - 1} \alpha > 1$	$\frac{x_m^\alpha}{(\alpha - 1)^2(\alpha - 2)} \alpha > 2$	$\alpha(-x_m s)^\alpha \Gamma(-\alpha, -x_m s) \quad s < 0$



2 Probability Theory

Definitions

- Sample space Ω
- Outcome (point or element) $\omega \in \Omega$
- Event $A \subseteq \Omega$
- σ -algebra \mathcal{A}
 1. $\emptyset \in \mathcal{A}$
 2. $A_1, A_2, \dots \in \mathcal{A} \implies \bigcup_{i=1}^{\infty} A_i \in \mathcal{A}$
 3. $A \in \mathcal{A} \implies \neg A \in \mathcal{A}$
- Probability distribution \mathbb{P}
 1. $\mathbb{P}[A] \geq 0$ for every A
 2. $\mathbb{P}[\Omega] = 1$
 3. $\mathbb{P}\left[\bigcup_{i=1}^{\infty} A_i\right] = \sum_{i=1}^{\infty} \mathbb{P}[A_i]$
- Probability space $(\Omega, \mathcal{A}, \mathbb{P})$

Properties

- $\mathbb{P}[\emptyset] = 0$
- $B = \Omega \cap B = (A \cup \neg A) \cap B = (A \cap B) \cup (\neg A \cap B)$
- $\mathbb{P}[\neg A] = 1 - \mathbb{P}[A]$
- $\mathbb{P}[B] = \mathbb{P}[A \cap B] + \mathbb{P}[\neg A \cap B]$
- $\mathbb{P}[\Omega] = 1 \quad \mathbb{P}[\emptyset] = 0$
- $\neg(\bigcup_n A_n) = \bigcap_n \neg A_n \quad \neg(\bigcap_n A_n) = \bigcup_n \neg A_n \quad \text{DEMORGAN}$
- $\mathbb{P}[\bigcup_n A_n] = 1 - \mathbb{P}[\bigcap_n \neg A_n]$
- $\mathbb{P}[A \cup B] = \mathbb{P}[A] + \mathbb{P}[B] - \mathbb{P}[A \cap B]$
 $\implies \mathbb{P}[A \cup B] \leq \mathbb{P}[A] + \mathbb{P}[B]$
- $\mathbb{P}[A \cup B] = \mathbb{P}[A \cap \neg B] + \mathbb{P}[\neg A \cap B] + \mathbb{P}[A \cap B]$
- $\mathbb{P}[A \cap \neg B] = \mathbb{P}[A] - \mathbb{P}[A \cap B]$

Continuity of Probabilities

- $A_1 \subset A_2 \subset \dots \implies \lim_{n \rightarrow \infty} \mathbb{P}[A_n] = \mathbb{P}[A]$ where $A = \bigcup_{i=1}^{\infty} A_i$
- $A_1 \supset A_2 \supset \dots \implies \lim_{n \rightarrow \infty} \mathbb{P}[A_n] = \mathbb{P}[A]$ where $A = \bigcap_{i=1}^{\infty} A_i$

Independence $\perp\!\!\!\perp$

$$A \perp\!\!\!\perp B \iff \mathbb{P}[A \cap B] = \mathbb{P}[A] \mathbb{P}[B]$$

Conditional Probability

$$\mathbb{P}[A|B] = \frac{\mathbb{P}[A \cap B]}{\mathbb{P}[B]} \quad \text{if } \mathbb{P}[B] > 0$$

Law of Total Probability

$$\mathbb{P}[B] = \sum_{i=1}^n \mathbb{P}[B|A_i] \mathbb{P}[A_i] \quad \Omega = \bigsqcup_{i=1}^n A_i$$

Bayes' Theorem

$$\mathbb{P}[A_i|B] = \frac{\mathbb{P}[B|A_i] \mathbb{P}[A_i]}{\sum_{j=1}^n \mathbb{P}[B|A_j] \mathbb{P}[A_j]} \quad \Omega = \bigsqcup_{i=1}^n A_i$$

Inclusion-Exclusion Principle

$$\left| \bigcup_{i=1}^n A_i \right| = \sum_{r=1}^n (-1)^{r-1} \sum_{i_1 < \dots < i_r \leq n} \left| \bigcap_{j=1}^r A_{i_j} \right|$$

3 Random Variables

Random Variable

$$X : \Omega \rightarrow \mathbb{R}$$

Probability Mass Function (PMF)

$$f_X(x) = \mathbb{P}[X = x] = \mathbb{P}[\{\omega \in \Omega : X(\omega) = x\}]$$

Probability Density Function (PDF)

$$\mathbb{P}[a \leq X \leq b] = \int_a^b f(x) dx$$

Cumulative Distribution Function (CDF):

$$F_X : \mathbb{R} \rightarrow [0, 1] \quad F_X(x) = \mathbb{P}[X \leq x]$$

1. Nondecreasing: $x_1 < x_2 \implies F(x_1) \leq F(x_2)$
2. Normalized: $\lim_{x \rightarrow -\infty} F(x) = 0$ and $\lim_{x \rightarrow \infty} F(x) = 1$
3. Right-continuous: $\lim_{y \downarrow x} F(y) = F(x)$

$$\mathbb{P}[a \leq Y \leq b | X = x] = \int_a^b f_{Y|X}(y|x) dy \quad a \leq b$$

$$f_{Y|X}(y|x) = \frac{f(x, y)}{f_X(x)}$$

Independence

1. $\mathbb{P}[X \leq x, Y \leq y] = \mathbb{P}[X \leq x] \mathbb{P}[Y \leq y]$
2. $f_{X,Y}(x, y) = f_X(x) f_Y(y)$

3.1 Transformations

Transformation function

$$Z = \varphi(X)$$

Discrete

$$f_Z(z) = \mathbb{P}[\varphi(X) = z] = \mathbb{P}[\{x : \varphi(x) = z\}] = \mathbb{P}[X \in \varphi^{-1}(z)] = \sum_{x \in \varphi^{-1}(z)} f(x)$$

Continuous

$$F_Z(z) = \mathbb{P}[\varphi(X) \leq z] = \int_{A_z} f(x) dx \quad \text{with } A_z = \{x : \varphi(x) \leq z\}$$

Special case if φ strictly monotone

$$f_Z(z) = f_X(\varphi^{-1}(z)) \left| \frac{d}{dz} \varphi^{-1}(z) \right| = f_X(x) \left| \frac{dx}{dz} \right| = f_X(x) \frac{1}{|J|}$$

The Rule of the Lazy Statistician

$$\mathbb{E}[Z] = \int \varphi(x) dF_X(x)$$

$$\mathbb{E}[I_A(x)] = \int I_A(x) dF_X(x) = \int_A dF_X(x) = \mathbb{P}[X \in A]$$

Convolution

- $Z := X + Y \quad f_Z(z) = \int_{-\infty}^{\infty} f_{X,Y}(x, z-x) dx \stackrel{X, Y \geq 0}{=} \int_0^z f_{X,Y}(x, z-x) dx$
- $Z := |X - Y| \quad f_Z(z) = 2 \int_0^{\infty} f_{X,Y}(x, z+x) dx$
- $Z := \frac{X}{Y} \quad f_Z(z) = \int_{-\infty}^{\infty} |x| f_{X,Y}(x, xz) dx \stackrel{\perp}{=} \int_{-\infty}^{\infty} x f_x(x) f_X(x) f_Y(xz) dx$

4 Expectation

Expectation

- $\mathbb{E}[X] = \mu_X = \begin{cases} \sum_x x f_X(x) & X \text{ discrete} \\ \int x f_X(x) & X \text{ continuous} \end{cases}$

- $\mathbb{P}[X = c] = 1 \implies \mathbb{E}[c] = c$
- $\mathbb{E}[cX] = c \mathbb{E}[X]$
- $\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$

- $\mathbb{E}[XY] = \int_{X,Y} xy f_{X,Y}(x, y) dF_X(x) dF_Y(y)$
- $\mathbb{E}[\varphi(Y)] \neq \varphi(\mathbb{E}[X])$ (cf. **JENSEN inequality**)
- $\mathbb{P}[X \geq Y] = 0 \implies \mathbb{E}[X] \geq \mathbb{E}[Y] \wedge \mathbb{P}[X = Y] = 1 \implies \mathbb{E}[X] = \mathbb{E}[Y]$
- $\mathbb{E}[X] = \sum_{x=1}^{\infty} \mathbb{P}[X \geq x]$

Sample mean

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$$

Conditional Expectation

- $\mathbb{E}[Y | X = x] = \int y f(y | x) dy$
- $\mathbb{E}[X] = \mathbb{E}[\mathbb{E}[X | Y]]$
- $E[\varphi(X, Y) | X = x] = \int_{-\infty}^{\infty} \varphi(x, y) f_{Y|X}(y | x) dx$
- $\mathbb{E}[\varphi(Y, Z) | X = x] = \int_{-\infty}^{\infty} \varphi(y, z) f_{(Y,Z)|X}(y, z | x) dy dz$
- $\mathbb{E}[Y + Z | X] = \mathbb{E}[Y | X] + \mathbb{E}[Z | X]$
- $\mathbb{E}[\varphi(X)Y | X] = \varphi(X)\mathbb{E}[Y | X]$
- $E[Y | X] = c \implies \text{Cov}[X, Y] = 0$

5 Variance

Variance

- $\mathbb{V}[X] = \sigma_X^2 = \mathbb{E}[(X - \mathbb{E}[X])^2] = \mathbb{E}[X^2] - \mathbb{E}[X]^2$
- $\mathbb{V}\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n \mathbb{V}[X_i] + 2 \sum_{i \neq j} \text{Cov}[X_i, X_j]$
- $\mathbb{V}\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n \mathbb{V}[X_i] \quad \text{iff } X_i \perp X_j$

Standard deviation

$$\text{sd}[X] = \sqrt{\mathbb{V}[X]} = \sigma_X$$

Covariance

- $\text{Cov}[X, Y] = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$
- $\text{Cov}[X, a] = 0$
- $\text{Cov}[X, X] = \mathbb{V}[X]$
- $\text{Cov}[X, Y] = \text{Cov}[Y, X]$
- $\text{Cov}[aX, bY] = ab \text{Cov}[X, Y]$
- $\text{Cov}[X + a, Y + b] = \text{Cov}[X, Y]$

- $\text{Cov} \left[\sum_{i=1}^n X_i, \sum_{j=1}^m Y_j \right] = \sum_{i=1}^n \sum_{j=1}^m \text{Cov} [X_i, Y_j]$

Correlation

$$\rho [X, Y] = \frac{\text{Cov} [X, Y]}{\sqrt{\mathbb{V} [X] \mathbb{V} [Y]}}$$

Independence

$$X \perp\!\!\!\perp Y \implies \rho [X, Y] = 0 \iff \text{Cov} [X, Y] = 0 \iff \mathbb{E} [XY] = \mathbb{E} [X] \mathbb{E} [Y]$$

Sample variance

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X}_n)^2$$

Conditional Variance

- $\mathbb{V} [Y | X] = \mathbb{E} [(Y - \mathbb{E} [Y | X])^2 | X] = \mathbb{E} [Y^2 | X] - \mathbb{E} [Y | X]^2$
- $\mathbb{V} [Y] = \mathbb{E} [\mathbb{V} [Y | X]] + \mathbb{V} [\mathbb{E} [Y | X]]$

6 Inequalities

CAUCHY-SCHWARZ

$$\mathbb{E} [XY]^2 \leq \mathbb{E} [X^2] \mathbb{E} [Y^2]$$

MARKOV

$$\mathbb{P} [\varphi(X) \geq t] \leq \frac{\mathbb{E} [\varphi(X)]}{t}$$

CHEBYSHEV

$$\mathbb{P} [|X - \mathbb{E} [X]| \geq t] \leq \frac{\mathbb{V} [X]}{t^2}$$

CHERNOFF

$$\mathbb{P} [X \geq (1 + \delta)\mu] \leq \left(\frac{e^\delta}{(1 + \delta)^{1 + \delta}} \right) \quad \delta > -1$$

JENSEN

$$\mathbb{E} [\varphi(X)] \geq \varphi(\mathbb{E} [X]) \quad \varphi \text{ convex}$$

7 Distribution Relationships

Binomial

- $X_i \sim \text{Bern} (p) \implies \sum_{i=1}^n X_i \sim \text{Bin} (n, p)$
- $X \sim \text{Bin} (n, p), Y \sim \text{Bin} (m, p) \implies X + Y \sim \text{Bin} (n + m, p)$
- $\lim_{n \rightarrow \infty} \text{Bin} (n, p) = \text{Po} (np) \quad (n \text{ large, } p \text{ small})$

- $\lim_{n \rightarrow \infty} \text{Bin} (n, p) = \mathcal{N} (np, np(1 - p)) \quad (n \text{ large, } p \text{ far from 0 and 1})$

Negative Binomial

- $X \sim \text{NBin} (1, p) = \text{Geo} (p)$
- $X \sim \text{NBin} (r, p) = \sum_{i=1}^r \text{Geo} (p)$
- $X_i \sim \text{NBin} (r_i, p) \implies \sum X_i \sim \text{NBin} (\sum r_i, p)$
- $X \sim \text{NBin} (r, p) \cdot Y \sim \text{Bin} (s + r, p) \implies \mathbb{P} [X \leq s] = \mathbb{P} [Y \geq r]$

Poisson

- $X_i \sim \text{Po} (\lambda_i) \wedge X_i \perp\!\!\!\perp X_j \implies \sum_{i=1}^n X_i \sim \text{Po} \left(\sum_{i=1}^n \lambda_i \right)$
- $X_i \sim \text{Po} (\lambda_i) \wedge X_i \perp\!\!\!\perp X_j \implies X_i \left| \sum_{j=1}^n X_j \sim \text{Bin} \left(\sum_{j=1}^n X_j, \frac{\lambda_i}{\sum_{j=1}^n \lambda_j} \right)$

Exponential

- $X_i \sim \text{Exp} (\beta) \wedge X_i \perp\!\!\!\perp X_j \implies \sum_{i=1}^n X_i \sim \text{Gamma} (n, \beta)$
- Memoryless property: $\mathbb{P} [X > x + y | X > y] = \mathbb{P} [X > x]$

Normal

- $X \sim \mathcal{N} (\mu, \sigma^2) \implies \left(\frac{X - \mu}{\sigma} \right) \sim \mathcal{N} (0, 1)$
- $X \sim \mathcal{N} (\mu, \sigma^2) \wedge Z = aX + b \implies Z \sim \mathcal{N} (a\mu + b, a^2\sigma^2)$
- $X \sim \mathcal{N} (\mu_1, \sigma_1^2) \wedge Y \sim \mathcal{N} (\mu_2, \sigma_2^2) \implies X + Y \sim \mathcal{N} (\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$
- $X_i \sim \mathcal{N} (\mu_i, \sigma_i^2) \implies \sum_i X_i \sim \mathcal{N} (\sum_i \mu_i, \sum_i \sigma_i^2)$
- $\mathbb{P} [a < X \leq b] = \Phi \left(\frac{b - \mu}{\sigma} \right) - \Phi \left(\frac{a - \mu}{\sigma} \right)$
- $\Phi(-x) = 1 - \Phi(x) \quad \phi'(x) = -x\phi(x) \quad \phi''(x) = (x^2 - 1)\phi(x)$
- Upper quantile of $\mathcal{N} (0, 1)$: $z_\alpha = \Phi^{-1}(1 - \alpha)$

Gamma

- $X \sim \text{Gamma} (\alpha, \beta) \iff X/\beta \sim \text{Gamma} (\alpha, 1)$
- $\text{Gamma} (\alpha, \beta) \sim \sum_{i=1}^\alpha \text{Exp} (\beta)$
- $X_i \sim \text{Gamma} (\alpha_i, \beta) \wedge X_i \perp\!\!\!\perp X_j \implies \sum_i X_i \sim \text{Gamma} (\sum_i \alpha_i, \beta)$
- $\frac{\Gamma(\alpha)}{\lambda^\alpha} = \int_0^\infty x^{\alpha-1} e^{-\lambda x} dx$

Beta

- $\frac{1}{\text{B}(\alpha, \beta)} x^{\alpha-1} (1-x)^{\beta-1} = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1}$
- $\mathbb{E} [X^k] = \frac{\text{B}(\alpha + k, \beta)}{\text{B}(\alpha, \beta)} = \frac{\alpha + k - 1}{\alpha + \beta + k - 1} \mathbb{E} [X^{k-1}]$
- $\text{Beta} (1, 1) \sim \text{Unif} (0, 1)$

8 Probability and Moment Generating Functions

- $G_X(t) = \mathbb{E}[t^X] \quad |t| < 1$
- $M_X(t) = G_X(e^t) = \mathbb{E}[e^{Xt}] = \mathbb{E}\left[\sum_{i=0}^{\infty} \frac{(Xt)^i}{i!}\right] = \sum_{i=0}^{\infty} \frac{\mathbb{E}[X^i]}{i!} \cdot t^i$
- $\mathbb{P}[X = 0] = G_X(0)$
- $\mathbb{P}[X = 1] = G'_X(0)$
- $\mathbb{P}[X = i] = \frac{G_X^{(i)}(0)}{i!}$
- $\mathbb{E}[X] = G'_X(1^-)$
- $\mathbb{E}[X^k] = M_X^{(k)}(0)$
- $\mathbb{E}\left[\frac{X!}{(X-k)!}\right] = G_X^{(k)}(1^-)$
- $\mathbb{V}[X] = G''_X(1^-) + G'_X(1^-) - (G'_X(1^-))^2$
- $G_X(t) = G_Y(t) \implies X \stackrel{d}{=} Y$

9 Multivariate Distributions

9.1 Standard Bivariate Normal

Let $X, Y \sim \mathcal{N}(0, 1) \wedge X \perp\!\!\!\perp Z$ with $Y = \rho X + \sqrt{1 - \rho^2}Z$

Joint density

$$f(x, y) = \frac{1}{2\pi\sqrt{1 - \rho^2}} \exp\left\{-\frac{x^2 + y^2 - 2\rho xy}{2(1 - \rho^2)}\right\}$$

Conditionals

$$(Y | X = x) \sim \mathcal{N}(\rho x, 1 - \rho^2) \quad \text{and} \quad (X | Y = y) \sim \mathcal{N}(\rho y, 1 - \rho^2)$$

Independence

$$X \perp\!\!\!\perp Y \iff \rho = 0$$

9.2 Bivariate Normal

Let $X \sim \mathcal{N}(\mu_x, \sigma_x^2)$ and $Y \sim \mathcal{N}(\mu_y, \sigma_y^2)$.

$$f(x, y) = \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1 - \rho^2}} \exp\left\{-\frac{z}{2(1 - \rho^2)}\right\}$$

$$z = \left[\left(\frac{x - \mu_x}{\sigma_x}\right)^2 + \left(\frac{y - \mu_y}{\sigma_y}\right)^2 - 2\rho\left(\frac{x - \mu_x}{\sigma_x}\right)\left(\frac{y - \mu_y}{\sigma_y}\right)\right]$$

Conditional mean and variance

$$\mathbb{E}[X | Y] = \mathbb{E}[X] + \rho \frac{\sigma_X}{\sigma_Y} (Y - \mathbb{E}[Y])$$

$$\mathbb{V}[X | Y] = \sigma_X \sqrt{1 - \rho^2}$$

9.3 Multivariate Normal

Covariance Matrix Σ (Precision Matrix Σ^{-1})

$$\Sigma = \begin{pmatrix} \mathbb{V}[X_1] & \cdots & \text{Cov}[X_1, X_k] \\ \vdots & \ddots & \vdots \\ \text{Cov}[X_k, X_1] & \cdots & \mathbb{V}[X_k] \end{pmatrix}$$

If $X \sim \mathcal{N}(\mu, \Sigma)$,

$$f_X(x) = (2\pi)^{-n/2} |\Sigma|^{-1/2} \exp\left\{-\frac{1}{2}(x - \mu)^T \Sigma^{-1} (x - \mu)\right\}$$

Properties

- $Z \sim \mathcal{N}(0, 1) \wedge X = \mu + \Sigma^{1/2}Z \implies X \sim \mathcal{N}(\mu, \Sigma)$
- $X \sim \mathcal{N}(\mu, \Sigma) \implies \Sigma^{-1/2}(X - \mu) \sim \mathcal{N}(0, 1)$
- $X \sim \mathcal{N}(\mu, \Sigma) \implies AX \sim \mathcal{N}(A\mu, A\Sigma A^T)$
- $X \sim \mathcal{N}(\mu, \Sigma) \wedge a$ is vector of length $k \implies a^T X \sim \mathcal{N}(a^T \mu, a^T \Sigma a)$

10 Convergence

Let $\{X_1, X_2, \dots\}$ be a sequence of RV's and let X be another RV. Let F_n denote the CDF of X_n and let F denote the CDF of X .

Types of Convergence

1. In distribution (weakly, in law): $X_n \xrightarrow{D} X$

$$\lim_{n \rightarrow \infty} F_n(t) = F(t) \quad \forall t \text{ where } F \text{ continuous}$$

2. In probability: $X_n \xrightarrow{P} X$

$$(\forall \varepsilon > 0) \lim_{n \rightarrow \infty} \mathbb{P}[|X_n - X| > \varepsilon] = 0$$

3. Almost surely (strongly): $X_n \xrightarrow{as} X$

$$\mathbb{P}\left[\lim_{n \rightarrow \infty} X_n = X\right] = \mathbb{P}\left[\omega \in \Omega : \lim_{n \rightarrow \infty} X_n(\omega) = X(\omega)\right] = 1$$

4. In quadratic mean (L_2): $X_n \xrightarrow{qm} X$

$$\lim_{n \rightarrow \infty} \mathbb{E} [(X_n - X)^2] = 0$$

Relationships

- $X_n \xrightarrow{qm} X \implies X_n \xrightarrow{p} X \implies X_n \xrightarrow{d} X$
- $X_n \xrightarrow{as} X \implies X_n \xrightarrow{p} X$
- $X_n \xrightarrow{d} X \wedge (\exists c \in \mathbb{R}) \mathbb{P}[X = c] = 1 \implies X_n \xrightarrow{p} X$
- $X_n \xrightarrow{p} X \wedge Y_n \xrightarrow{p} Y \implies X_n + Y_n \xrightarrow{p} X + Y$
- $X_n \xrightarrow{qm} X \wedge Y_n \xrightarrow{qm} Y \implies X_n + Y_n \xrightarrow{qm} X + Y$
- $X_n \xrightarrow{p} X \wedge Y_n \xrightarrow{p} Y \implies X_n Y_n \xrightarrow{p} XY$
- $X_n \xrightarrow{p} X \implies \varphi(X_n) \xrightarrow{p} \varphi(X)$
- $X_n \xrightarrow{d} X \implies \varphi(X_n) \xrightarrow{d} \varphi(X)$
- $X_n \xrightarrow{qm} b \iff \lim_{n \rightarrow \infty} \mathbb{E}[X_n] = b \wedge \lim_{n \rightarrow \infty} \mathbb{V}[X_n] = 0$
- $X_1, \dots, X_n \text{ IID} \wedge \mathbb{E}[X] = \mu \wedge \mathbb{V}[X] < \infty \iff \bar{X}_n \xrightarrow{qm} \mu$

Slutzky's Theorem

- $X_n \xrightarrow{d} X$ and $Y_n \xrightarrow{p} c \implies X_n + Y_n \xrightarrow{d} X + c$
- $X_n \xrightarrow{d} X$ and $Y_n \xrightarrow{p} c \implies X_n Y_n \xrightarrow{d} cX$
- In general: $X_n \xrightarrow{d} X$ and $Y_n \xrightarrow{d} Y \not\implies X_n + Y_n \xrightarrow{d} X + Y$

10.1 Law of Large Numbers (LLN)

Let $\{X_1, \dots, X_n\}$ be a sequence of IID RV's, $\mathbb{E}[X_1] = \mu$, and $\mathbb{V}[X_1] < \infty$.

Weak (WLLN)

$$\bar{X}_n \xrightarrow{p} \mu \quad \text{as } n \rightarrow \infty$$

Strong (SLLN)

$$\bar{X}_n \xrightarrow{as} \mu \quad \text{as } n \rightarrow \infty$$

10.2 Central Limit Theorem (CLT)

Let $\{X_1, \dots, X_n\}$ be a sequence of IID RV's, $\mathbb{E}[X_1] = \mu$, and $\mathbb{V}[X_1] = \sigma^2$.

$$Z_n := \frac{\bar{X}_n - \mu}{\sqrt{\mathbb{V}[\bar{X}_n]}} = \frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \xrightarrow{d} Z \quad \text{where } Z \sim \mathcal{N}(0, 1)$$

$$\lim_{n \rightarrow \infty} \mathbb{P}[Z_n \leq z] = \Phi(z) \quad z \in \mathbb{R}$$

CLT Notations

$$\begin{aligned} Z_n &\approx \mathcal{N}(0, 1) \\ \bar{X}_n &\approx \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right) \\ \bar{X}_n - \mu &\approx \mathcal{N}\left(0, \frac{\sigma^2}{n}\right) \\ \sqrt{n}(\bar{X}_n - \mu) &\approx \mathcal{N}(0, \sigma^2) \\ \frac{\sqrt{n}(\bar{X}_n - \mu)}{n} &\approx \mathcal{N}(0, 1) \end{aligned}$$

Continuity Correction

$$\begin{aligned} \mathbb{P}[\bar{X}_n \leq x] &\approx \Phi\left(\frac{x + \frac{1}{2} - \mu}{\sigma/\sqrt{n}}\right) \\ \mathbb{P}[\bar{X}_n \geq x] &\approx 1 - \Phi\left(\frac{x - \frac{1}{2} - \mu}{\sigma/\sqrt{n}}\right) \end{aligned}$$

Delta Method

$$Y_n \approx \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right) \implies \varphi(Y_n) \approx \mathcal{N}\left(\varphi(\mu), (\varphi'(\mu))^2 \frac{\sigma^2}{n}\right)$$

11 Statistical Inference

Let $X_1, \dots, X_n \stackrel{iid}{\sim} F$ if not otherwise noted.

11.1 Point Estimation

- Point estimator $\hat{\theta}_n$ of θ is a RV: $\hat{\theta}_n = g(X_1, \dots, X_n)$
- $\text{bias}(\hat{\theta}_n) = \mathbb{E}[\hat{\theta}_n] - \theta$
- Consistency: $\hat{\theta}_n \xrightarrow{p} \theta$
- Sampling distribution: $F(\hat{\theta}_n)$
- Standard error: $\text{se}(\hat{\theta}_n) = \sqrt{\mathbb{V}[\hat{\theta}_n]}$
- Mean squared error: $\text{MSE} = \mathbb{E}[(\hat{\theta}_n - \theta)^2] = \text{bias}(\hat{\theta}_n)^2 + \mathbb{V}[\hat{\theta}_n]$
- $\lim_{n \rightarrow \infty} \text{bias}(\hat{\theta}_n) = 0 \wedge \lim_{n \rightarrow \infty} \text{se}(\hat{\theta}_n) = 0 \implies \hat{\theta}_n$ is consistent
- Asymptotic normality: $\frac{\hat{\theta}_n - \theta}{\text{se}} \xrightarrow{d} \mathcal{N}(0, 1)$
- SLUTZKY'S THEOREM often lets us replace $\text{se}(\hat{\theta}_n)$ by some (weakly) consistent estimator $\hat{\sigma}_n$.

11.2 Normal-based Confidence Interval

Suppose $\hat{\theta}_n \approx \mathcal{N}(\theta, \hat{\sigma}_e^2)$. Let $z_{\alpha/2} = \Phi^{-1}(1 - (\alpha/2))$, i.e., $\mathbb{P}[Z > z_{\alpha/2}] = \alpha/2$ and $\mathbb{P}[-z_{\alpha/2} < Z < z_{\alpha/2}] = 1 - \alpha$ where $Z \sim \mathcal{N}(0, 1)$. Then

$$C_n = \hat{\theta}_n \pm z_{\alpha/2} \hat{\sigma}_e$$

11.3 Empirical Distribution Function

Empirical Distribution Function (ECDF)

$$\hat{F}_n(x) = \frac{\sum_{i=1}^n I(X_i \leq x)}{n}$$

$$I(X_i \leq x) = \begin{cases} 1 & X_i \leq x \\ 0 & X_i > x \end{cases}$$

Properties (for any fixed x)

- $\mathbb{E}[\hat{F}_n] = F(x)$
- $\mathbb{V}[\hat{F}_n] = \frac{F(x)(1-F(x))}{n}$
- $\text{MSE} = \frac{F(x)(1-F(x))}{n} \xrightarrow{p} 0$
- $\hat{F}_n \xrightarrow{p} F(x)$

DVORETZKY-KIEFER-WOLFOWITZ (DKW) Inequality ($X_1, \dots, X_n \sim F$)

$$\mathbb{P}\left[\sup_x |F(x) - \hat{F}_n(x)| > \varepsilon\right] = 2e^{-2n\varepsilon^2}$$

Nonparametric $1 - \alpha$ confidence band for F

$$L(x) = \max\{\hat{F}_n - \varepsilon_n, 0\}$$

$$U(x) = \min\{\hat{F}_n + \varepsilon_n, 1\}$$

$$\varepsilon = \sqrt{\frac{1}{2n} \log\left(\frac{2}{\alpha}\right)}$$

$$\mathbb{P}[L(x) \leq F(x) \leq U(x) \forall x] \geq 1 - \alpha$$

11.4 Statistical Functionals

- Statistical functional: $T(F)$
- Plug-in estimator of $\theta = T(F)$: $\hat{\theta}_n = T(\hat{F}_n)$
- Linear functional: $T(F) = \int \varphi(x) dF_X(x)$
- Plug-in estimator for linear functional:

$$T(\hat{F}_n) = \int \varphi(x) d\hat{F}_n(x) = \frac{1}{n} \sum_{i=1}^n \varphi(X_i)$$

- Often: $T(\hat{F}_n) \approx \mathcal{N}(T(F), \hat{\sigma}_e^2) \implies T(\hat{F}_n) \pm z_{\alpha/2} \hat{\sigma}_e$
- p^{th} quantile: $F^{-1}(p) = \inf\{x : F(x) \geq p\}$
- $\hat{\mu} = \bar{X}_n$
- $\hat{\sigma}^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X}_n)^2$
- $\hat{\kappa} = \frac{\frac{1}{n} \sum_{i=1}^n (X_i - \hat{\mu})^3}{\hat{\sigma}^3}$
- $\hat{\rho} = \frac{\sum_{i=1}^n (X_i - \bar{X}_n)(Y_i - \bar{Y}_n)}{\sqrt{\sum_{i=1}^n (X_i - \bar{X}_n)^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y}_n)^2}}$

12 Parametric Inference

Let $\mathfrak{F} = \{f(x; \theta : \theta \in \Theta)\}$ be a parametric model with parameter space $\Theta \subset \mathbb{R}^k$ and parameter $\theta = (\theta_1, \dots, \theta_k)$.

12.1 Method of Moments

j^{th} moment

$$\alpha_j(\theta) = \mathbb{E}[X^j] = \int x^j dF_X(x)$$

j^{th} sample moment

$$\hat{\alpha}_j = \frac{1}{n} \sum_{i=1}^n X_i^j$$

Method of Moments Estimator (MoM)

$$\alpha_1(\theta) = \hat{\alpha}_1$$

$$\alpha_2(\theta) = \hat{\alpha}_2$$

$$\vdots = \vdots$$

$$\alpha_k(\theta) = \hat{\alpha}_k$$

Properties of the MoM estimator

- $\widehat{\theta}_n$ exists with probability tending to 1
- Consistency: $\widehat{\theta}_n \xrightarrow{P} \theta$
- Asymptotic normality:

$$\sqrt{n}(\widehat{\theta} - \theta) \xrightarrow{D} \mathcal{N}(0, \Sigma)$$

where $\Sigma = g\mathbb{E}[YY^T]g^T$, $Y = (X, X^2, \dots, X^k)^T$,
 $g = (g_1, \dots, g_k)$ and $g_j = \frac{\partial}{\partial \theta} \alpha_j^{-1}(\theta)$

12.2 Maximum Likelihood

Likelihood: $\mathcal{L}_n : \Theta \rightarrow [0, \infty)$

$$\mathcal{L}_n(\theta) = \prod_{i=1}^n f(X_i; \theta)$$

Log-likelihood

$$\ell_n(\theta) = \log \mathcal{L}_n(\theta) = \sum_{i=1}^n \log f(X_i; \theta)$$

Maximum Likelihood Estimator (MLE)

$$\mathcal{L}_n(\widehat{\theta}_n) = \sup_{\theta} \mathcal{L}_n(\theta)$$

Score Function

$$s(X; \theta) = \frac{\partial}{\partial \theta} \log f(X; \theta)$$

Fisher Information

$$I(\theta) = \mathbb{V}_{\theta} [s(X; \theta)]$$

$$I_n(\theta) = nI(\theta)$$

Fisher Information (exponential family)

$$I(\theta) = \mathbb{E}_{\theta} \left[-\frac{\partial}{\partial \theta} s(X; \theta) \right]$$

Observed Fisher Information

$$I_n^{obs}(\theta) = -\frac{\partial^2}{\partial \theta^2} \sum_{i=1}^n \log f(X_i; \theta)$$

Properties of the MLE

- Consistency: $\widehat{\theta}_n \xrightarrow{P} \theta$

- Equivariance: $\widehat{\theta}_n$ is the MLE $\implies \varphi(\widehat{\theta}_n)$ is the MLE of $\varphi(\theta)$

- Asymptotic normality:

$$1. \text{ se} \approx \sqrt{1/I_n(\theta)}$$

$$\frac{(\widehat{\theta}_n - \theta)}{\text{se}} \xrightarrow{D} \mathcal{N}(0, 1)$$

$$2. \widehat{\text{se}} \approx \sqrt{1/I_n(\widehat{\theta}_n)}$$

$$\frac{(\widehat{\theta}_n - \theta)}{\widehat{\text{se}}} \xrightarrow{D} \mathcal{N}(0, 1)$$

- Asymptotic optimality (or efficiency), i.e., smallest variance for large samples. If $\widetilde{\theta}_n$ is any other estimator, the asymptotic relative efficiency is

$$\text{ARE}(\widetilde{\theta}_n, \widehat{\theta}_n) = \frac{\mathbb{V}[\widehat{\theta}_n]}{\mathbb{V}[\widetilde{\theta}_n]} \leq 1$$

- Approximately the Bayes estimator

12.2.1 Delta Method

If $\tau = \varphi(\widehat{\theta})$ where φ is differentiable and $\varphi'(\theta) \neq 0$:

$$\frac{(\widehat{\tau}_n - \tau)}{\widehat{\text{se}}(\widehat{\tau})} \xrightarrow{D} \mathcal{N}(0, 1)$$

where $\widehat{\tau} = \varphi(\widehat{\theta})$ is the MLE of τ and

$$\widehat{\text{se}} = \left| \varphi'(\widehat{\theta}) \right| \widehat{\text{se}}(\widehat{\theta}_n)$$

12.3 Multiparameter Models

Let $\theta = (\theta_1, \dots, \theta_k)$ and $\widehat{\theta} = (\widehat{\theta}_1, \dots, \widehat{\theta}_k)$ be the MLE.

$$H_{jj} = \frac{\partial^2 \ell_n}{\partial \theta_j^2} \quad H_{jk} = \frac{\partial^2 \ell_n}{\partial \theta_j \partial \theta_k}$$

Fisher Information Matrix

$$I_n(\theta) = - \begin{bmatrix} \mathbb{E}_{\theta} [H_{11}] & \cdots & \mathbb{E}_{\theta} [H_{1k}] \\ \vdots & \ddots & \vdots \\ \mathbb{E}_{\theta} [H_{k1}] & \cdots & \mathbb{E}_{\theta} [H_{kk}] \end{bmatrix}$$

Under appropriate regularity conditions

$$(\widehat{\theta} - \theta) \approx \mathcal{N}(0, J_n)$$

with $J_n(\theta) = I_n^{-1}$. Further, if $\hat{\theta}_j$ is the j^{th} component of θ , then

$$\frac{(\hat{\theta}_j - \theta_j)}{\widehat{\text{se}}_j} \xrightarrow{D} \mathcal{N}(0, 1)$$

where $\widehat{\text{se}}_j^2 = J_n(j, j)$ and $\text{Cov}[\hat{\theta}_j, \hat{\theta}_k] = J_n(j, k)$

12.3.1 Multiparameter Delta Method

Let $\tau = \varphi(\theta_1, \dots, \theta_k)$ be a function and let the gradient of φ be

$$\nabla\varphi = \begin{pmatrix} \frac{\partial\varphi}{\partial\theta_1} \\ \vdots \\ \frac{\partial\varphi}{\partial\theta_k} \end{pmatrix}$$

Suppose $\nabla\varphi|_{\theta=\hat{\theta}} \neq 0$ and $\hat{\tau} = \varphi(\hat{\theta})$. Then,

$$\frac{(\hat{\tau} - \tau)}{\widehat{\text{se}}(\hat{\tau})} \xrightarrow{D} \mathcal{N}(0, 1)$$

where

$$\widehat{\text{se}}(\hat{\tau}) = \sqrt{(\hat{\nabla}\varphi)^T \hat{J}_n(\hat{\nabla}\varphi)}$$

and $\hat{J}_n = J_n(\hat{\theta})$ and $\hat{\nabla}\varphi = \nabla\varphi|_{\theta=\hat{\theta}}$.

12.4 Parametric Bootstrap

Sample from $f(x; \hat{\theta}_n)$ instead of from \hat{F}_n , where $\hat{\theta}_n$ could be the MLE or method of moments estimator.

13 Hypothesis Testing

$$H_0 : \theta \in \Theta_0 \quad \text{versus} \quad H_1 : \theta \in \Theta_1$$

Definitions

- Null hypothesis H_0
- Alternative hypothesis H_1
- Simple hypothesis $\theta = \theta_0$
- Composite hypothesis $\theta > \theta_0$ or $\theta < \theta_0$
- Two-sided test: $H_0 : \theta = \theta_0$ versus $H_1 : \theta \neq \theta_0$
- One-sided test: $H_0 : \theta \leq \theta_0$ versus $H_1 : \theta > \theta_0$
- Critical value c
- Test statistic T
- Rejection Region $R = \{x : T(x) > c\}$
- Power function $\beta(\theta) = \mathbb{P}[X \in R]$
- Power of a test: $1 - \mathbb{P}[\text{Type II error}] = 1 - \beta = \inf_{\theta \in \Theta_1} \beta(\theta)$
- Test size: $\alpha = \mathbb{P}[\text{Type I error}] = \sup_{\theta \in \Theta_0} \beta(\theta)$

	Retain H_0	Reject H_0
H_0 true	✓	Type I error (α)
H_1 true	Type II error (β)	✓ (power)

p-value

- p-value = $\sup_{\theta \in \Theta_0} \mathbb{P}_\theta [T(X) \geq T(x)] = \inf\{\alpha : T(x) \in R_\alpha\}$
- p-value = $\sup_{\theta \in \Theta_0} \underbrace{\mathbb{P}_\theta [T(X^*) \geq T(X)]}_{1 - F_\theta(T(X)) \text{ since } T(X^*) \sim F_\theta} = \inf\{\alpha : T(X) \in R_\alpha\}$

p-value	evidence
< 0.01	very strong evidence against H_0
0.01 – 0.05	strong evidence against H_0
0.05 – 0.1	weak evidence against H_0
> 0.1	little or no evidence against H_0

Wald Test

- Two-sided test
- Reject H_0 when $|W| > z_{\alpha/2}$ where $W = \frac{\hat{\theta} - \theta_0}{\widehat{\text{se}}}$
- $\mathbb{P}[|W| > z_{\alpha/2}] \rightarrow \alpha$
- p-value = $\mathbb{P}_{\theta_0}[|W| > |w|] \approx \mathbb{P}[|Z| > |w|] = 2\Phi(-|w|)$

Likelihood Ratio Test (LRT)

- $T(X) = \frac{\sup_{\theta \in \Theta} \mathcal{L}_n(\theta)}{\sup_{\theta \in \Theta_0} \mathcal{L}_n(\theta)} = \frac{\mathcal{L}_n(\hat{\theta}_n)}{\mathcal{L}_n(\hat{\theta}_{n,0})}$

- $\lambda(X) = 2 \log T(X) \xrightarrow{D} \chi_{r-q}^2$ where $\sum_{i=1}^k Z_i^2 \sim \chi_k^2$ with $Z_1, \dots, Z_k \stackrel{iid}{\sim} \mathcal{N}(0, 1)$
- p-value = $\mathbb{P}_{\theta_0} [\lambda(X) > \lambda(x)] \approx \mathbb{P} [\chi_{r-q}^2 > \lambda(x)]$

Multinomial LRT

- Let $\hat{p}_n = \left(\frac{X_1}{n}, \dots, \frac{X_k}{n} \right)$ be the MLE
- $T(X) = \frac{\mathcal{L}_n(\hat{p}_n)}{\mathcal{L}_n(p_0)} = \prod_{j=1}^k \left(\frac{\hat{p}_j}{p_{0j}} \right)^{X_j}$
- $\lambda(X) = 2 \sum_{j=1}^k X_j \log \left(\frac{\hat{p}_j}{p_{0j}} \right) \xrightarrow{D} \chi_{k-1}^2$
- The approximate size α LRT rejects H_0 when $\lambda(X) \geq \chi_{k-1, \alpha}^2$

Pearson χ^2 Test

- $T = \sum_{j=1}^k \frac{(X_j - \mathbb{E}[X_j])^2}{\mathbb{E}[X_j]}$ where $\mathbb{E}[X_j] = np_{0j}$ under H_0
- $T \xrightarrow{D} \chi_{k-1}^2$
- p-value = $\mathbb{P} [\chi_{k-1}^2 > T(x)]$
- Faster $\xrightarrow{D} \chi_{k-1}^2$ than LRT, hence preferable for small n

Independence Testing

- I rows, J columns, \mathbf{X} multinomial sample of size $n = I * J$
- MLEs unconstrained: $\hat{p}_{ij} = \frac{X_{ij}}{n}$
- MLEs under H_0 : $\hat{p}_{0ij} = \hat{p}_{i \cdot} \hat{p}_{\cdot j} = \frac{X_{i \cdot}}{n} \frac{X_{\cdot j}}{n}$
- LRT: $\lambda = 2 \sum_{i=1}^I \sum_{j=1}^J X_{ij} \log \left(\frac{n X_{ij}}{X_{i \cdot} X_{\cdot j}} \right)$
- Pearson χ^2 : $T = \sum_{i=1}^I \sum_{j=1}^J \frac{(X_{ij} - \mathbb{E}[X_{ij}])^2}{\mathbb{E}[X_{ij}]}$
- LRT and Pearson $\xrightarrow{D} \chi_k^2 \nu$, where $\nu = (I - 1)(J - 1)$

14 Bayesian Inference

BAYES' THEOREM

$$f(\theta | x) = \frac{f(x | \theta) f(\theta)}{f(x^n)} = \frac{f(x | \theta) f(\theta)}{\int f(x | \theta) f(\theta) d\theta} \propto \mathcal{L}_n(\theta) f(\theta)$$

Definitions

- $X^n = (X_1, \dots, X_n)$

- $x^n = (x_1, \dots, x_n)$
- Prior density $f(\theta)$
- Likelihood $f(x^n | \theta)$: joint density of the data

In particular, $X^n \text{ IID} \implies f(x^n | \theta) = \prod_{i=1}^n f(x_i | \theta) = \mathcal{L}_n(\theta)$

- Posterior density $f(\theta | x^n)$
- Normalizing constant $c_n = f(x^n) = \int f(x | \theta) f(\theta) d\theta$
- Kernel: part of a density that depends on θ
- Posterior Mean $\bar{\theta}_n = \int \theta f(\theta | x^n) d\theta = \frac{\int \theta \mathcal{L}_n(\theta) f(\theta) d\theta}{\int \mathcal{L}_n(\theta) f(\theta) d\theta}$

14.1 Credible Intervals

$1 - \alpha$ Posterior Interval

$$\mathbb{P} [\theta \in (a, b) | x^n] = \int_a^b f(\theta | x^n) d\theta = 1 - \alpha$$

$1 - \alpha$ Equal-tail Credible Interval

$$\int_{-\infty}^a f(\theta | x^n) d\theta = \int_b^{\infty} f(\theta | x^n) d\theta = \alpha/2$$

$1 - \alpha$ Highest Posterior Density (HPD) region R_n

1. $\mathbb{P} [\theta \in R_n] = 1 - \alpha$
2. $R_n = \{\theta : f(\theta | x^n) > k\}$ for some k

R_n is unimodal $\implies R_n$ is an interval

14.2 Function of Parameters

Let $\tau = \varphi(\theta)$ and $A = \{\theta : \varphi(\theta) \leq \tau\}$.

Posterior CDF for τ

$$H(\tau | x^n) = \mathbb{P} [\varphi(\theta) \leq \tau | x^n] = \int_A f(\theta | x^n) d\theta$$

Posterior Density

$$h(\tau | x^n) = H'(\tau | x^n)$$

Bayesian Delta Method

$$\tau | X^n \approx \mathcal{N} \left(\varphi(\hat{\theta}), \widehat{\text{se}} \left| \varphi'(\hat{\theta}) \right| \right)$$

14.3 Priors

Choice

- Subjective Bayesianism: prior should incorporate as much detail as possible the research's a priori knowledge — via *prior elicitation*.
- Objective Bayesianism: prior should incorporate as little detail as possible (*non-informative* prior).
- Robust Bayesianism: consider various priors and determine *sensitivity* of our inferences to changes in the prior.

Types

- Flat: $f(\theta) \propto \text{constant}$
- Proper: $\int_{-\infty}^{\infty} f(\theta) d\theta = 1$
- Improper: $\int_{-\infty}^{\infty} f(\theta) d\theta = \infty$
- JEFFREYS' prior (transformation-invariant):

$$f(\theta) \propto \sqrt{I(\theta)} \quad f(\theta) \propto \sqrt{\det(I(\theta))}$$

- Conjugate: $f(\theta)$ and $f(\theta | x^n)$ belong to the same parametric family

14.3.1 Conjugate Priors

Discrete likelihood		
Likelihood	Conjugate Prior	Posterior hyperparameters
Bernoulli(p)	Beta(α, β)	$\alpha + \sum_{i=1}^n x_i, \beta + n - \sum_{i=1}^n x_i$
Binomial(p)	Beta(α, β)	$\alpha + \sum_{i=1}^n x_i, \beta + \sum_{i=1}^n N_i - \sum_{i=1}^n x_i$
Negative Binomial(p)	Beta(α, β)	$\alpha + rn, \beta + \sum_{i=1}^n x_i$
Poisson(λ)	Gamma(α, β)	$\alpha + \sum_{i=1}^n x_i, \beta + n$
Multinomial(\mathbf{p})	Dirichlet(α)	$\alpha + \sum_{i=1}^n \mathbf{x}^{(i)}$
Geometric(p)	Beta(α, β)	$\alpha + n, \beta + \sum_{i=1}^n x_i$

Continuous likelihood (subscript c denotes constant)		
Likelihood	Conjugate Prior	Posterior hyperparameters
Uniform($0, \theta$)	Pareto(x_m, k)	$\max\{x_{(n)}, x_m\}, k + n$
Exponential(λ)	Gamma(α, β)	$\alpha + n, \beta + \sum_{i=1}^n x_i$
Normal(μ, σ_c^2)	Normal(μ_0, σ_0^2)	$\left(\frac{\mu_0}{\sigma_0^2} + \frac{\sum_{i=1}^n x_i}{\sigma_c^2}\right) / \left(\frac{1}{\sigma_0^2} + \frac{n}{\sigma_c^2}\right),$ $\left(\frac{1}{\sigma_0^2} + \frac{n}{\sigma_c^2}\right)^{-1}$
Normal(μ_c, σ^2)	Scaled Inverse Chi-square(ν, σ_0^2)	$\nu + n, \frac{\nu\sigma_0^2 + \sum_{i=1}^n (x_i - \mu)^2}{\nu + n}$
Normal(μ, σ^2)	Normal-scaled Inverse Gamma($\lambda, \nu, \alpha, \beta$)	$\frac{\nu\lambda + n\bar{x}}{\nu + n}, \quad \nu + n, \quad \alpha + \frac{n}{2},$ $\beta + \frac{1}{2} \sum_{i=1}^n (x_i - \bar{x})^2 + \frac{\gamma(\bar{x} - \lambda)^2}{2(n + \gamma)}$
MVN(μ, Σ_c)	MVN(μ_0, Σ_0)	$(\Sigma_0^{-1} + n\Sigma_c^{-1})^{-1} (\Sigma_0^{-1}\mu_0 + n\Sigma_c^{-1}\bar{x}),$ $(\Sigma_0^{-1} + n\Sigma_c^{-1})^{-1}$
MVN(μ_c, Σ)	Inverse-Wishart(κ, Ψ)	$n + \kappa, \Psi + \sum_{i=1}^n (x_i - \mu_c)(x_i - \mu_c)^T$
Pareto(x_{m_c}, k)	Gamma(α, β)	$\alpha + n, \beta + \sum_{i=1}^n \log \frac{x_i}{x_{m_c}}$
Pareto(x_m, k_c)	Pareto(x_0, k_0)	$x_0, k_0 - kn$ where $k_0 > kn$
Gamma(α_c, β)	Gamma(α_0, β_0)	$\alpha_0 + n\alpha_c, \beta_0 + \sum_{i=1}^n x_i$

14.4 Bayesian Testing

If $H_0 : \theta \in \Theta_0$:

$$\text{Prior probability } \mathbb{P}[H_0] = \int_{\Theta_0} f(\theta) d\theta$$

$$\text{Posterior probability } \mathbb{P}[H_0 | x^n] = \int_{\Theta_0} f(\theta | x^n) d\theta$$

Let H_0, \dots, H_{K-1} be K hypotheses. Suppose $\theta \sim f(\theta | H_k)$,

$$\mathbb{P}[H_k | x^n] = \frac{f(x^n | H_k)\mathbb{P}[H_k]}{\sum_{k=1}^K f(x^n | H_k)\mathbb{P}[H_k]}$$

Marginal Likelihood

$$f(x^n | H_i) = \int_{\Theta} f(x^n | \theta, H_i) f(\theta | H_i) d\theta$$

Posterior Odds (of H_i relative to H_j)

$$\frac{\mathbb{P}[H_i | x^n]}{\mathbb{P}[H_j | x^n]} = \underbrace{\frac{f(x^n | H_i)}{f(x^n | H_j)}}_{\text{Bayes Factor } BF_{ij}} \times \underbrace{\frac{\mathbb{P}[H_i]}{\mathbb{P}[H_j]}}_{\text{prior odds}}$$

Bayes Factor

$\log_{10} BF_{10}$	BF_{10}	evidence
0 – 0.5	1 – 1.5	Weak
0.5 – 1	1.5 – 10	Moderate
1 – 2	10 – 100	Strong
> 2	> 100	Decisive

$p^* = \frac{p}{1-p} BF_{10}$ where $p = \mathbb{P}[H_1]$ and $p^* = \mathbb{P}[H_1 | x^n]$

15 Exponential Family

Scalar parameter

$$\begin{aligned} f_X(x | \theta) &= h(x) \exp \{ \eta(\theta) T(x) - A(\theta) \} \\ &= h(x) g(\theta) \exp \{ \eta(\theta) T(x) \} \end{aligned}$$

Vector parameter

$$\begin{aligned} f_X(x | \theta) &= h(x) \exp \left\{ \sum_{i=1}^s \eta_i(\theta) T_i(x) - A(\theta) \right\} \\ &= h(x) \exp \{ \eta(\theta) \cdot T(x) - A(\theta) \} \\ &= h(x) g(\theta) \exp \{ \eta(\theta) \cdot T(x) \} \end{aligned}$$

Natural form

$$\begin{aligned} f_X(x | \eta) &= h(x) \exp \{ \eta \cdot \mathbf{T}(x) - A(\eta) \} \\ &= h(x) g(\eta) \exp \{ \eta \cdot \mathbf{T}(x) \} \\ &= h(x) g(\eta) \exp \{ \eta^T \mathbf{T}(x) \} \end{aligned}$$

16 Sampling Methods

16.1 The Bootstrap

Let $T_n = g(X_1, \dots, X_n)$ be a statistic.

1. Estimate $\mathbb{V}_F [T_n]$ with $\mathbb{V}_{\hat{F}_n} [T_n]$.

2. Approximate $\mathbb{V}_{\hat{F}_n} [T_n]$ using simulation:

(a) Repeat the following B times to get $T_{n,1}^*, \dots, T_{n,B}^*$, an IID sample from the sampling distribution implied by \hat{F}_n

i. Sample uniformly $X_1^*, \dots, X_n^* \sim \hat{F}_n$.

ii. Compute $T_n^* = g(X_1^*, \dots, X_n^*)$.

(b) Then

$$v_{boot} = \hat{\mathbb{V}}_{\hat{F}_n} = \frac{1}{B} \sum_{b=1}^B \left(T_{n,b}^* - \frac{1}{B} \sum_{r=1}^B T_{n,r}^* \right)^2$$

16.1.1 Bootstrap Confidence Intervals

Normal-based Interval

$$T_n \pm z_{\alpha/2} \hat{se}_{boot}$$

Pivotal Interval

1. Location parameter $\theta = T(F)$

2. Pivot $R_n = \hat{\theta}_n - \theta$

3. Let $H(r) = \mathbb{P}[R_n \leq r]$ be the CDF of R_n

4. Let $R_{n,b}^* = \hat{\theta}_{n,b}^* - \hat{\theta}_n$. Approximate H using bootstrap:

$$\hat{H}(r) = \frac{1}{B} \sum_{b=1}^B I(R_{n,b}^* \leq r)$$

5. Let θ_β^* denote the β sample quantile of $(\hat{\theta}_{n,1}^*, \dots, \hat{\theta}_{n,B}^*)$

6. Let r_β^* denote the β sample quantile of $(R_{n,1}^*, \dots, R_{n,B}^*)$, i.e., $r_\beta^* = \theta_\beta^* - \hat{\theta}_n$

7. Then, an approximate $1 - \alpha$ confidence interval is $C_n = (\hat{a}, \hat{b})$ with

$$\begin{aligned} \hat{a} &= \hat{\theta}_n - \hat{H}^{-1} \left(1 - \frac{\alpha}{2} \right) = \hat{\theta}_n - r_{1-\alpha/2}^* = 2\hat{\theta}_n - \theta_{1-\alpha/2}^* \\ \hat{b} &= \hat{\theta}_n - \hat{H}^{-1} \left(\frac{\alpha}{2} \right) = \hat{\theta}_n - r_{\alpha/2}^* = 2\hat{\theta}_n - \theta_{\alpha/2}^* \end{aligned}$$

Percentile Interval

$$C_n = \left(\theta_{\alpha/2}^*, \theta_{1-\alpha/2}^* \right)$$

16.2 Rejection Sampling

Setup

- We can easily sample from $g(\theta)$
- We want to sample from $h(\theta)$, but it is difficult
- We know $h(\theta)$ up to proportional constant: $h(\theta) = \frac{k(\theta)}{\int k(\theta) d\theta}$
- Envelope condition: we can find $M > 0$ such that $k(\theta) \leq Mg(\theta) \quad \forall \theta$

Algorithm

1. Draw $\theta^{cand} \sim g(\theta)$
2. Generate $u \sim \text{Unif}(0, 1)$
3. Accept θ^{cand} if $u \leq \frac{k(\theta^{cand})}{Mg(\theta^{cand})}$
4. Repeat until B values of θ^{cand} have been accepted

Example

- We can easily sample from the prior $g(\theta) = f(\theta)$
- Target is the posterior with $h(\theta) \propto k(\theta) = f(x^n | \theta)f(\theta)$
- Envelope condition: $f(x^n | \theta) \leq f(x^n | \hat{\theta}_n) = \mathcal{L}_n(\hat{\theta}_n) \equiv M$
- Algorithm
 1. Draw $\theta^{cand} \sim f(\theta)$
 2. Generate $u \sim \text{Unif}(0, 1)$
 3. Accept θ^{cand} if $u \leq \frac{\mathcal{L}_n(\theta^{cand})}{\mathcal{L}_n(\hat{\theta}_n)}$

16.3 Importance Sampling

Sample from an importance function g rather than target density h .

Algorithm to obtain an approximation to $\mathbb{E}[q(\theta) | x^n]$:

1. Sample from the prior $\theta_1, \dots, \theta_n \stackrel{iid}{\sim} f(\theta)$
2. For each $i = 1, \dots, B$, calculate $w_i = \frac{\mathcal{L}_n(\theta_i)}{\sum_{i=1}^B \mathcal{L}_n(\theta_i)}$
3. $\mathbb{E}[q(\theta) | x^n] \approx \sum_{i=1}^B q(\theta_i)w_i$

17 Decision Theory

Definitions

- Unknown quantity affecting our decision: $\theta \in \Theta$

- Decision rule: synonymous for an estimator $\hat{\theta}$
- Action $a \in \mathcal{A}$: possible value of the decision rule. In the estimation context, the action is just an estimate of θ , $\hat{\theta}(x)$.
- Loss function L : consequences of taking action a when true state is θ or discrepancy between θ and $\hat{\theta}$, $L : \Theta \times \mathcal{A} \rightarrow [-k, \infty)$.

Loss functions

- Squared error loss: $L(\theta, a) = (\theta - a)^2$
- Linear loss: $L(\theta, a) = \begin{cases} K_1(\theta - a) & a - \theta < 0 \\ K_2(a - \theta) & a - \theta \geq 0 \end{cases}$
- Absolute error loss: $L(\theta, a) = |\theta - a|$ (linear loss with $K_1 = K_2$)
- L_p loss: $L(\theta, a) = |\theta - a|^p$
- Zero-one loss: $L(\theta, a) = \begin{cases} 0 & a = \theta \\ 1 & a \neq \theta \end{cases}$

17.1 Risk

Posterior Risk

$$r(\hat{\theta} | x) = \int L(\theta, \hat{\theta}(x))f(\theta | x) d\theta = \mathbb{E}_{\theta | X} [L(\theta, \hat{\theta}(x))]$$

(Frequentist) Risk

$$R(\theta, \hat{\theta}) = \int L(\theta, \hat{\theta}(x))f(x | \theta) dx = \mathbb{E}_{X | \theta} [L(\theta, \hat{\theta}(X))]$$

Bayes Risk

$$r(f, \hat{\theta}) = \iint L(\theta, \hat{\theta}(x))f(x, \theta) dx d\theta = \mathbb{E}_{\theta, X} [L(\theta, \hat{\theta}(X))]$$

$$r(f, \hat{\theta}) = \mathbb{E}_{\theta} [\mathbb{E}_{X | \theta} [L(\theta, \hat{\theta}(X))]] = \mathbb{E}_{\theta} [R(\theta, \hat{\theta})]$$

$$r(f, \hat{\theta}) = \mathbb{E}_X [\mathbb{E}_{\theta | X} [L(\theta, \hat{\theta}(X))]] = \mathbb{E}_X [r(\hat{\theta} | X)]$$

17.2 Admissibility

- $\hat{\theta}'$ dominates $\hat{\theta}$ if

$$\forall \theta : R(\theta, \hat{\theta}') \leq R(\theta, \hat{\theta})$$

$$\exists \theta : R(\theta, \hat{\theta}') < R(\theta, \hat{\theta})$$

- $\hat{\theta}$ is inadmissible if there is at least one other estimator $\hat{\theta}'$ that dominates it. Otherwise it is called admissible.

17.3 Bayes Rule

Bayes Rule (or Bayes Estimator)

- $r(f, \hat{\theta}) = \inf_{\tilde{\theta}} r(f, \tilde{\theta})$
- $\hat{\theta}(x) = \inf r(\hat{\theta} | x) \forall x \implies r(f, \hat{\theta}) = \int r(\hat{\theta} | x) f(x) dx$

Theorems

- Squared error loss: posterior mean
- Absolute error loss: posterior median
- Zero-one loss: posterior mode

17.4 Minimax Rules

Maximum Risk

$$\bar{R}(\hat{\theta}) = \sup_{\theta} R(\theta, \hat{\theta}) \quad \bar{R}(a) = \sup_{\theta} R(\theta, a)$$

Minimax Rule

$$\sup_{\theta} R(\theta, \hat{\theta}) = \inf_{\tilde{\theta}} \bar{R}(\tilde{\theta}) = \inf_{\tilde{\theta}} \sup_{\theta} R(\theta, \tilde{\theta})$$

$$\hat{\theta} = \text{Bayes rule} \wedge \exists c : R(\theta, \hat{\theta}) = c$$

Least Favorable Prior

$$\hat{\theta}^f = \text{Bayes rule} \wedge R(\theta, \hat{\theta}^f) \leq r(f, \hat{\theta}^f) \forall \theta$$

18 Linear Regression

Definitions

- Response variable Y
- Covariate X (aka predictor variable or feature)

18.1 Simple Linear Regression

Model

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i \quad \mathbb{E}[\epsilon_i | X_i] = 0, \quad \mathbb{V}[\epsilon_i | X_i] = \sigma^2$$

Fitted Line

$$\hat{r}(x) = \hat{\beta}_0 + \hat{\beta}_1 x$$

Predicted (Fitted) Values

$$\hat{Y}_i = \hat{r}(X_i)$$

Residuals

$$\hat{\epsilon}_i = Y_i - \hat{Y}_i = Y_i - (\hat{\beta}_0 + \hat{\beta}_1 X_i)$$

Residual Sums of Squares (RSS)

$$\text{RSS}(\hat{\beta}_0, \hat{\beta}_1) = \sum_{i=1}^n \hat{\epsilon}_i^2$$

Least Square Estimates

$$\hat{\beta}^T = (\hat{\beta}_0, \hat{\beta}_1)^T : \min_{\hat{\beta}_0, \hat{\beta}_1} \text{RSS}$$

$$\hat{\beta}_0 = \bar{Y}_n - \hat{\beta}_1 \bar{X}_n$$

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (X_i - \bar{X}_n)(Y_i - \bar{Y}_n)}{\sum_{i=1}^n (X_i - \bar{X}_n)^2} = \frac{\sum_{i=1}^n X_i Y_i - n \bar{X} \bar{Y}}{\sum_{i=1}^n X_i^2 - n \bar{X}^2}$$

$$\mathbb{E}[\hat{\beta} | X^n] = \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix}$$

$$\mathbb{V}[\hat{\beta} | X^n] = \frac{\sigma^2}{n s_X} \begin{pmatrix} n^{-1} \sum_{i=1}^n X_i^2 & -\bar{X}_n \\ -\bar{X}_n & 1 \end{pmatrix}$$

$$\widehat{\text{se}}(\hat{\beta}_0) = \frac{\hat{\sigma}}{s_X \sqrt{n}} \sqrt{\frac{\sum_{i=1}^n X_i^2}{n}}$$

$$\widehat{\text{se}}(\hat{\beta}_1) = \frac{\hat{\sigma}}{s_X \sqrt{n}}$$

where $s_X^2 = n^{-1} \sum_{i=1}^n (X_i - \bar{X}_n)^2$ and $\hat{\sigma}^2 = \frac{1}{n-2} \sum_{i=1}^n \hat{\epsilon}_i^2$ an (unbiased) estimate of σ . Further properties:

- Consistency: $\hat{\beta}_0 \xrightarrow{P} \beta_0$ and $\hat{\beta}_1 \xrightarrow{P} \beta_1$
- Asymptotic normality:

$$\frac{\hat{\beta}_0 - \beta_0}{\widehat{\text{se}}(\hat{\beta}_0)} \xrightarrow{D} \mathcal{N}(0, 1) \quad \text{and} \quad \frac{\hat{\beta}_1 - \beta_1}{\widehat{\text{se}}(\hat{\beta}_1)} \xrightarrow{D} \mathcal{N}(0, 1)$$

- Approximate $1 - \alpha$ confidence intervals for β_0 and β_1 are

$$\hat{\beta}_0 \pm z_{\alpha/2} \widehat{\text{se}}(\hat{\beta}_0) \quad \text{and} \quad \hat{\beta}_1 \pm z_{\alpha/2} \widehat{\text{se}}(\hat{\beta}_1)$$

- The Wald test for testing $H_0 : \beta_1 = 0$ vs. $H_1 : \beta_1 \neq 0$ is: reject H_0 if $|W| > z_{\alpha/2}$ where $W = \hat{\beta}_1 / \widehat{\text{se}}(\hat{\beta}_1)$.

R^2

$$R^2 = \frac{\sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} = 1 - \frac{\sum_{i=1}^n \hat{\epsilon}_i^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} = 1 - \frac{\text{RSS}}{\text{TSS}}$$

Likelihood

$$\begin{aligned}\mathcal{L} &= \prod_{i=1}^n f(X_i, Y_i) = \prod_{i=1}^n f_X(X_i) \times \prod_{i=1}^n f_{Y|X}(Y_i | X_i) = \mathcal{L}_1 \times \mathcal{L}_2 \\ \mathcal{L}_1 &= \prod_{i=1}^n f_X(X_i) \\ \mathcal{L}_2 &= \prod_{i=1}^n f_{Y|X}(Y_i | X_i) \propto \sigma^{-n} \exp \left\{ -\frac{1}{2\sigma^2} \sum_i (Y_i - (\beta_0 + \beta_1 X_i))^2 \right\}\end{aligned}$$

Under the assumption of Normality, the least squares estimator is also the MLE

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n \hat{\epsilon}_i^2$$

18.2 Prediction

Observe $X = x_*$ of the covariate and want to predict their outcome Y_* .

$$\begin{aligned}\hat{Y}_* &= \hat{\beta}_0 + \hat{\beta}_1 x_* \\ \mathbb{V}[\hat{Y}_*] &= \mathbb{V}[\hat{\beta}_0] + x_*^2 \mathbb{V}[\hat{\beta}_1] + 2x_* \text{Cov}[\hat{\beta}_0, \hat{\beta}_1]\end{aligned}$$

Prediction Interval

$$\begin{aligned}\hat{\xi}_n^2 &= \hat{\sigma}^2 \left(\frac{\sum_{i=1}^n (X_i - X_*)^2}{n \sum_i (X_i - \bar{X})^2} + 1 \right) \\ \hat{Y}_* &\pm z_{\alpha/2} \hat{\xi}_n\end{aligned}$$

18.3 Multiple Regression

$$Y = X\beta + \epsilon$$

where

$$X = \begin{pmatrix} X_{11} & \cdots & X_{1k} \\ \vdots & \ddots & \vdots \\ X_{n1} & \cdots & X_{nk} \end{pmatrix} \quad \beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_k \end{pmatrix} \quad \epsilon = \begin{pmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{pmatrix}$$

Likelihood

$$\mathcal{L}(\mu, \Sigma) = (2\pi\sigma^2)^{-n/2} \exp \left\{ -\frac{1}{2\sigma^2} \text{RSS} \right\}$$

$$\text{RSS} = (y - X\beta)^T (y - X\beta) = \|Y - X\beta\|^2 = \sum_{i=1}^n (Y_i - x_i^T \beta)^2$$

If the $(k \times k)$ matrix $X^T X$ is invertible,

$$\begin{aligned}\hat{\beta} &= (X^T X)^{-1} X^T Y \\ \mathbb{V}[\hat{\beta} | X^n] &= \sigma^2 (X^T X)^{-1} \\ \hat{\beta} &\approx \mathcal{N}(\beta, \sigma^2 (X^T X)^{-1})\end{aligned}$$

Estimate regression function

$$\hat{r}(x) = \sum_{j=1}^k \hat{\beta}_j x_j$$

Unbiased estimate for σ^2

$$\hat{\sigma}^2 = \frac{1}{n-k} \sum_{i=1}^n \hat{\epsilon}_i^2 \quad \hat{\epsilon} = X\hat{\beta} - Y$$

MLE

$$\hat{\mu} = \bar{X} \quad \hat{\sigma}^2 = \frac{n-k}{n} \sigma^2$$

$1 - \alpha$ Confidence Interval

$$\hat{\beta}_j \pm z_{\alpha/2} \widehat{\text{se}}(\hat{\beta}_j)$$

18.4 Model Selection

Consider predicting a new observation Y^* for covariates X^* and let $S \subset J$ denote a subset of the covariates in the model, where $|S| = k$ and $|J| = n$. Issues

- Underfitting: too few covariates yields high bias
- Overfitting: too many covariates yields high variance

Procedure

1. Assign a score to each model
2. Search through all models to find the one with the highest score

Hypothesis Testing

$$H_0 : \beta_j = 0 \text{ vs. } H_1 : \beta_j \neq 0 \quad \forall j \in J$$

Mean Squared Prediction Error (MSPE)

$$\text{MSPE} = \mathbb{E} \left[(\hat{Y}(S) - Y^*)^2 \right]$$

Prediction Risk

$$R(S) = \sum_{i=1}^n \text{MSPE}_i = \sum_{i=1}^n \mathbb{E} \left[(\hat{Y}_i(S) - Y_i^*)^2 \right]$$

Training Error

$$\widehat{R}_{tr}(S) = \sum_{i=1}^n (\widehat{Y}_i(S) - Y_i)^2$$

R^2

$$R^2(S) = 1 - \frac{\text{RSS}(S)}{\text{TSS}} = 1 - \frac{\widehat{R}_{tr}(S)}{\text{TSS}} = 1 - \frac{\sum_{i=1}^n (\widehat{Y}_i(S) - \bar{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2}$$

The training error is a downward-biased estimate of the prediction risk.

$$\mathbb{E} \left[\widehat{R}_{tr}(S) \right] < R(S)$$

$$\text{bias}(\widehat{R}_{tr}(S)) = \mathbb{E} \left[\widehat{R}_{tr}(S) \right] - R(S) = -2 \sum_{i=1}^n \text{Cov} \left[\widehat{Y}_i, Y_i \right]$$

Adjusted R^2

$$R^2(S) = 1 - \frac{n-1}{n-k} \frac{\text{RSS}}{\text{TSS}}$$

MALLOW'S C_p statistic

$$\widehat{R}(S) = \widehat{R}_{tr}(S) + 2k\widehat{\sigma}^2 = \text{lack of fit} + \text{complexity penalty}$$

Akaike Information Criterion (AIC)

$$\text{AIC}(S) = \ell_n(\widehat{\beta}_S, \widehat{\sigma}_S^2) - k$$

Bayesian Information Criterion (BIC)

$$\text{BIC}(S) = \ell_n(\widehat{\beta}_S, \widehat{\sigma}_S^2) - \frac{k}{2} \log n$$

Validation and Training

$$\widehat{R}_V(S) = \sum_{i=1}^m (\widehat{Y}_i^*(S) - Y_i^*)^2 \quad m = |\{\text{validation data}\}|, \text{ often } \frac{n}{4} \text{ or } \frac{n}{2}$$

Leave-one-out Cross-validation

$$\widehat{R}_{CV}(S) = \sum_{i=1}^n (Y_i - \widehat{Y}_{(i)})^2 = \sum_{i=1}^n \left(\frac{Y_i - \widehat{Y}_i(S)}{1 - U_{ii}(S)} \right)^2$$

$$U(S) = X_S (X_S^T X_S)^{-1} X_S \text{ ("hat matrix")}$$

19 Non-parametric Function Estimation

19.1 Density Estimation

Estimate $f(x)$, where $f(x) = \mathbb{P}[X \in A] = \int_A f(x) dx$.

Integrated Square Error (ISE)

$$L(f, \widehat{f}_n) = \int \left(f(x) - \widehat{f}_n(x) \right)^2 dx = J(h) + \int f^2(x) dx$$

Frequentist Risk

$$R(f, \widehat{f}_n) = \mathbb{E} \left[L(f, \widehat{f}_n) \right] = \int b^2(x) dx + \int v(x) dx$$

$$b(x) = \mathbb{E} \left[\widehat{f}_n(x) \right] - f(x)$$

$$v(x) = \mathbb{V} \left[\widehat{f}_n(x) \right]$$

19.1.1 Histograms

Definitions

- Number of bins m
- Binwidth $h = \frac{1}{m}$
- Bin B_j has ν_j observations
- Define $\widehat{p}_j = \nu_j/n$ and $p_j = \int_{B_j} f(u) du$

Histogram Estimator

$$\widehat{f}_n(x) = \sum_{j=1}^m \frac{\widehat{p}_j}{h} I(x \in B_j)$$

$$\mathbb{E} \left[\widehat{f}_n(x) \right] = \frac{p_j}{h}$$

$$\mathbb{V} \left[\widehat{f}_n(x) \right] = \frac{p_j(1-p_j)}{nh^2}$$

$$R(\widehat{f}_n, f) \approx \frac{h^2}{12} \int (f'(u))^2 du + \frac{1}{nh}$$

$$h^* = \frac{1}{n^{1/3}} \left(\frac{6}{\int (f'(u))^2 du} \right)^{1/3}$$

$$R^*(\widehat{f}_n, f) \approx \frac{C}{n^{2/3}} \quad C = \left(\frac{3}{4} \right)^{2/3} \left(\int (f'(u))^2 du \right)^{1/3}$$

Cross-validation estimate of $\mathbb{E}[J(h)]$

$$\widehat{J}_{CV}(h) = \int \widehat{f}_n^2(x) dx - \frac{2}{n} \sum_{i=1}^n \widehat{f}_{(-i)}(X_i) = \frac{2}{(n-1)h} - \frac{n+1}{(n-1)h} \sum_{j=1}^m \widehat{p}_j^2$$

19.1.2 Kernel Density Estimator (KDE)

Kernel K

- $K(x) \geq 0$
- $\int K(x) dx = 1$
- $\int xK(x) dx = 0$
- $\int x^2 K(x) dx \equiv \sigma_K^2 > 0$

KDE

$$\hat{f}_n(x) = \frac{1}{n} \sum_{i=1}^n \frac{1}{h} K\left(\frac{x - X_i}{h}\right)$$

$$R(f, \hat{f}_n) \approx \frac{1}{4} (h\sigma_K)^4 \int (f''(x))^2 dx + \frac{1}{nh} \int K^2(x) dx$$

$$h^* = \frac{c_1^{-2/5} c_2^{-1/5} c_3^{-1/5}}{n^{1/5}} \quad c_1 = \sigma_K^2, \quad c_2 = \int K^2(x) dx, \quad c_3 = \int (f''(x))^2 dx$$

$$R^*(f, \hat{f}_n) = \frac{c_4}{n^{4/5}} \quad c_4 = \underbrace{\frac{5}{4} (\sigma_K^2)^{2/5} \left(\int K^2(x) dx \right)^{4/5}}_{C(K)} \left(\int (f'')^2 dx \right)^{1/5}$$

Epanechnikov Kernel

$$K(x) = \begin{cases} \frac{3}{4\sqrt{5}(1-x^2/5)} & |x| < \sqrt{5} \\ 0 & \text{otherwise} \end{cases}$$

Cross-validation estimate of $\mathbb{E}[J(h)]$

$$\hat{J}_{CV}(h) = \int \hat{f}_n^2(x) dx - \frac{2}{n} \sum_{i=1}^n \hat{f}_{(-i)}(X_i) \approx \frac{1}{hn^2} \sum_{i=1}^n \sum_{j=1}^n K^*\left(\frac{X_i - X_j}{h}\right) + \frac{2}{nh} K(0)$$

$$K^*(x) = K^{(2)}(x) - 2K(x) \quad K^{(2)}(x) = \int K(x-y)K(y) dy$$

19.2 Non-parametric Regression

Estimate $f(x)$, where $f(x) = \mathbb{E}[Y | X = x]$. Consider pairs of points $(x_1, Y_1), \dots, (x_n, Y_n)$ related by

$$\begin{aligned} Y_i &= r(x_i) + \epsilon_i \\ \mathbb{E}[\epsilon_i] &= 0 \\ \mathbb{V}[\epsilon_i] &= \sigma^2 \end{aligned}$$

k -nearest Neighbor Estimator

$$\hat{r}(x) = \frac{1}{k} \sum_{i: x_i \in N_k(x)} Y_i \quad \text{where } N_k(x) = \{k \text{ values of } x_1, \dots, x_n \text{ closest to } x\}$$

Nadaraya-Watson Kernel Estimator

$$\hat{r}(x) = \sum_{i=1}^n w_i(x) Y_i$$

$$w_i(x) = \frac{K\left(\frac{x-x_i}{h}\right)}{\sum_{j=1}^n K\left(\frac{x-x_j}{h}\right)} \in [0, 1]$$

$$R(\hat{r}_n, r) \approx \frac{h^4}{4} \left(\int x^2 K^2(x) dx \right)^4 \int \left(r''(x) + 2r'(x) \frac{f'(x)}{f(x)} \right)^2 dx + \int \frac{\sigma^2 \int K^2(x) dx}{nhf(x)} dx$$

$$h^* \approx \frac{c_1}{n^{1/5}}$$

$$R^*(\hat{r}_n, r) \approx \frac{c_2}{n^{4/5}}$$

Cross-validation estimate of $\mathbb{E}[J(h)]$

$$\hat{J}_{CV}(h) = \sum_{i=1}^n (Y_i - \hat{r}_{(-i)}(x_i))^2 = \sum_{i=1}^n \frac{(Y_i - \hat{r}(x_i))^2}{\left(1 - \frac{K(0)}{\sum_{j=1}^n K\left(\frac{x-x_j}{h}\right)}\right)^2}$$

19.3 Smoothing Using Orthogonal Functions

Approximation

$$r(x) = \sum_{j=1}^{\infty} \beta_j \phi_j(x) \approx \sum_{i=1}^J \beta_j \phi_j(x)$$

Multivariate Regression

$$Y = \Phi\beta + \eta$$

$$\text{where } \eta_i = \epsilon_i \quad \text{and} \quad \Phi = \begin{pmatrix} \phi_0(x_1) & \cdots & \phi_J(x_1) \\ \vdots & \ddots & \vdots \\ \phi_0(x_n) & \cdots & \phi_J(x_n) \end{pmatrix}$$

Least Squares Estimator

$$\begin{aligned} \hat{\beta} &= (\Phi^T \Phi)^{-1} \Phi^T Y \\ &\approx \frac{1}{n} \Phi^T Y \quad (\text{for equally spaced observations only}) \end{aligned}$$

Cross-validation estimate of $\mathbb{E}[J(h)]$

$$\widehat{R}_{CV}(J) = \sum_{i=1}^n \left(Y_i - \sum_{j=1}^J \phi_j(x_i) \widehat{\beta}_{j,(-i)} \right)^2$$

20 Stochastic Processes

Stochastic Process

$$\{X_t : t \in T\} \quad T = \begin{cases} \{0, \pm 1, \dots\} = \mathbb{Z} & \text{discrete} \\ [0, \infty) & \text{continuous} \end{cases}$$

- Notations: $X_t, X(t)$
- State space \mathcal{X}
- Index set T

20.1 Markov Chains

Markov Chain

$$\mathbb{P}[X_n = x | X_0, \dots, X_{n-1}] = \mathbb{P}[X_n = x | X_{n-1}] \quad \forall n \in T, x \in \mathcal{X}$$

Transition probabilities

$$p_{ij} \equiv \mathbb{P}[X_{n+1} = j | X_n = i]$$

$$p_{ij}(n) \equiv \mathbb{P}[X_{m+n} = j | X_m = i] \quad \text{n-step}$$

Transition matrix \mathbf{P} (n-step: \mathbf{P}_n)

- (i, j) element is p_{ij}
- $p_{ij} > 0$
- $\sum_i p_{ij} = 1$

CHAPMAN-KOLMOGOROV

$$p_{ij}(m+n) = \sum_k p_{ik}(m) p_{kj}(n)$$

$$\mathbf{P}_{m+n} = \mathbf{P}_m \mathbf{P}_n$$

$$\mathbf{P}_n = \mathbf{P} \times \dots \times \mathbf{P} = \mathbf{P}^n$$

Marginal probability

$$\mu_n = (\mu_n(1), \dots, \mu_n(N)) \quad \text{where} \quad \mu_i(i) = \mathbb{P}[X_n = i]$$

$$\mu_0 \triangleq \text{initial distribution}$$

$$\mu_n = \mu_0 \mathbf{P}^n$$

20.2 Poisson Processes

Poisson Process

- $\{X_t : t \in [0, \infty)\}$ – number of events up to and including time t
- $X_0 = 0$
- Independent increments:

$$\forall t_0 < \dots < t_n : X_{t_1} - X_{t_0} \perp\!\!\!\perp \dots \perp\!\!\!\perp X_{t_n} - X_{t_{n-1}}$$

- Intensity function $\lambda(t)$

$$- \mathbb{P}[X_{t+h} - X_t = 1] = \lambda(t)h + o(h)$$

$$- \mathbb{P}[X_{t+h} - X_t = 2] = o(h)$$

- $X_{s+t} - X_s \sim \text{Po}(m(s+t) - m(s))$ where $m(t) = \int_0^t \lambda(s) ds$

Homogeneous Poisson Process

$$\lambda(t) \equiv \lambda \implies X_t \sim \text{Po}(\lambda t) \quad \lambda > 0$$

Waiting Times

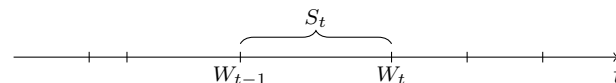
$W_t :=$ time at which X_t occurs

$$W_t \sim \text{Gamma}\left(t, \frac{1}{\lambda}\right)$$

Interarrival Times

$$S_t = W_{t+1} - W_t$$

$$S_t \sim \text{Exp}\left(\frac{1}{\lambda}\right)$$



21 Time Series

Mean function

$$\mu_{x_t} = \mathbb{E}[x_t] = \int_{-\infty}^{\infty} x f_t(x) dx$$

Autocovariance function

$$\gamma_x(s, t) = \mathbb{E}[(x_s - \mu_s)(x_t - \mu_t)] = \mathbb{E}[x_s x_t] - \mu_s \mu_t$$

$$\gamma_x(t, t) = \mathbb{E}[(x_t - \mu_t)^2] = \mathbb{V}[x_t]$$

Autocorrelation function (ACF)

$$\rho(s, t) = \frac{\text{Cov}[x_s, x_t]}{\sqrt{\mathbb{V}[x_s] \mathbb{V}[x_t]}} = \frac{\gamma(s, t)}{\sqrt{\gamma(s, s) \gamma(t, t)}}$$

Cross-covariance function (CCV)

$$\gamma_{xy}(s, t) = \mathbb{E}[(x_s - \mu_{x_s})(y_t - \mu_{y_t})]$$

Cross-correlation function (CCF)

$$\rho_{xy}(s, t) = \frac{\gamma_{xy}(s, t)}{\sqrt{\gamma_x(s, s) \gamma_y(t, t)}}$$

Backshift operator

$$B^k(x_t) = x_{t-k}$$

Difference operator

$$\nabla^d = (1 - B)^d$$

White Noise

- $w_t \sim wn(0, \sigma_w^2)$
- Gaussian: $w_t \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_w^2)$
- $\mathbb{E}[w_t] = 0 \quad t \in T$
- $\mathbb{V}[w_t] = \sigma^2 \quad t \in T$
- $\gamma_w(s, t) = 0 \quad s \neq t \wedge s, t \in T$

Random Walk

- Drift δ
- $x_t = \delta t + \sum_{j=1}^t w_j$
- $\mathbb{E}[x_t] = \delta t$

Symmetric Moving Average

$$m_t = \sum_{j=-k}^k a_j x_{t-j} \quad \text{where } a_j = a_{-j} \geq 0 \text{ and } \sum_{j=-k}^k a_j = 1$$

21.1 Stationary Time Series

Strictly stationary

$$\mathbb{P}[x_{t_1} \leq c_1, \dots, x_{t_k} \leq c_k] = \mathbb{P}[x_{t_1+h} \leq c_1, \dots, x_{t_k+h} \leq c_k]$$

$$\forall k \in \mathbb{N}, t_k, c_k, h \in \mathbb{Z}$$

Weakly stationary

- $\mathbb{E}[x_t^2] < \infty \quad \forall t \in \mathbb{Z}$
- $\mathbb{E}[x_t^2] = m \quad \forall t \in \mathbb{Z}$
- $\gamma_x(s, t) = \gamma_x(s+r, t+r) \quad \forall r, s, t \in \mathbb{Z}$

Autocovariance function

- $\gamma(h) = \mathbb{E}[(x_{t+h} - \mu)(x_t - \mu)] \quad \forall h \in \mathbb{Z}$
- $\gamma(0) = \mathbb{E}[(x_t - \mu)^2]$
- $\gamma(0) \geq 0$
- $\gamma(0) \geq |\gamma(h)|$
- $\gamma(h) = \gamma(-h)$

Autocorrelation function (ACF)

$$\rho_x(h) = \frac{\text{Cov}[x_{t+h}, x_t]}{\sqrt{\mathbb{V}[x_{t+h}] \mathbb{V}[x_t]}} = \frac{\gamma(t+h, t)}{\sqrt{\gamma(t+h, t+h) \gamma(t, t)}} = \frac{\gamma(h)}{\gamma(0)}$$

Jointly stationary time series

$$\gamma_{xy}(h) = \mathbb{E}[(x_{t+h} - \mu_x)(y_t - \mu_y)]$$

$$\rho_{xy}(h) = \frac{\gamma_{xy}(h)}{\sqrt{\gamma_x(0) \gamma_y(h)}}$$

Linear Process

$$x_t = \mu + \sum_{j=-\infty}^{\infty} \psi_j w_{t-j} \quad \text{where } \sum_{j=-\infty}^{\infty} |\psi_j| < \infty$$

$$\gamma(h) = \sigma_w^2 \sum_{j=-\infty}^{\infty} \psi_{j+h} \psi_j$$

21.2 Estimation of Correlation

Sample mean

$$\bar{x} = \frac{1}{n} \sum_{t=1}^n x_t$$

Sample variance

$$\mathbb{V}[\bar{x}] = \frac{1}{n} \sum_{h=-n}^n \left(1 - \frac{|h|}{n}\right) \gamma_x(h)$$

Sample autocovariance function

$$\hat{\gamma}(h) = \frac{1}{n} \sum_{t=1}^{n-h} (x_{t+h} - \bar{x})(x_t - \bar{x})$$

Sample autocorrelation function

$$\hat{\rho}(h) = \frac{\hat{\gamma}(h)}{\hat{\gamma}(0)}$$

Sample cross-variance function

$$\hat{\gamma}_{xy}(h) = \frac{1}{n} \sum_{t=1}^{n-h} (x_{t+h} - \bar{x})(y_t - \bar{y})$$

Sample cross-correlation function

$$\hat{\rho}_{xy}(h) = \frac{\hat{\gamma}_{xy}(h)}{\sqrt{\hat{\gamma}_x(0)\hat{\gamma}_y(0)}}$$

Properties

- $\sigma_{\hat{\rho}_x(h)} = \frac{1}{\sqrt{n}}$ if x_t is white noise
- $\sigma_{\hat{\rho}_{xy}(h)} = \frac{1}{\sqrt{n}}$ if x_t or y_t is white noise

21.3 Non-Stationary Time Series

Classical decomposition model

$$x_t = \mu_t + s_t + w_t$$

- μ_t = trend
- s_t = seasonal component
- w_t = random noise term

21.3.1 Detrending

Least Squares

1. Choose trend model, e.g., $\mu_t = \beta_0 + \beta_1 t + \beta_2 t^2$
2. Minimize RSS to obtain trend estimate $\hat{\mu}_t = \hat{\beta}_0 + \hat{\beta}_1 t + \hat{\beta}_2 t^2$
3. Residuals \triangleq noise w_t

Moving average

- The *low-pass* filter v_t is a symmetric moving average m_t with $a_j = \frac{1}{2k+1}$:

$$v_t = \frac{1}{2k+1} \sum_{i=-k}^k x_{t-i}$$

- If $\frac{1}{2k+1} \sum_{i=-k}^k w_{t-j} \approx 0$, a linear trend function $\mu_t = \beta_0 + \beta_1 t$ passes without distortion

Differencing

- $\mu_t = \beta_0 + \beta_1 t \implies \nabla x_t = \beta_1$

21.4 ARIMA models

Autoregressive polynomial

$$\phi(z) = 1 - \phi_1 z - \dots - \phi_p z^p \quad z \in \mathbb{C} \wedge \phi_p \neq 0$$

Autoregressive operator

$$\phi(B) = 1 - \phi_1 B - \dots - \phi_p B^p$$

Autoregressive model order p , AR(p)

$$x_t = \phi_1 x_{t-1} + \dots + \phi_p x_{t-p} + w_t \iff \phi(B)x_t = w_t$$

AR(1)

$$x_t = \phi^k(x_{t-k}) + \sum_{j=0}^{k-1} \phi^j(w_{t-j}) \stackrel{k \rightarrow \infty, |\phi| < 1}{=} \underbrace{\sum_{j=0}^{\infty} \phi^j(w_{t-j})}_{\text{linear process}}$$

- $\mathbb{E}[x_t] = \sum_{j=0}^{\infty} \phi^j(\mathbb{E}[w_{t-j}]) = 0$
- $\gamma(h) = \text{Cov}[x_{t+h}, x_t] = \frac{\sigma_w^2 \phi^h}{1 - \phi^2}$
- $\rho(h) = \frac{\gamma(h)}{\gamma(0)} = \phi^h$
- $\rho(h) = \phi \rho(h-1) \quad h = 1, 2, \dots$

Moving average polynomial

$$\theta(z) = 1 + \theta_1 z + \cdots + \theta_q z^q \quad z \in \mathbb{C} \wedge \theta_q \neq 0$$

Moving average operator

$$\theta(B) = 1 + \theta_1 B + \cdots + \theta_p B^p$$

MA(q) (moving average model order q)

$$x_t = w_t + \theta_1 w_{t-1} + \cdots + \theta_q w_{t-q} \iff x_t = \theta(B)w_t$$

$$\mathbb{E}[x_t] = \sum_{j=0}^q \theta_j \mathbb{E}[w_{t-j}] = 0$$

$$\gamma(h) = \text{Cov}[x_{t+h}, x_t] = \begin{cases} \sigma_w^2 \sum_{j=0}^{q-h} \theta_j \theta_{j+h} & 0 \leq h \leq q \\ 0 & h > q \end{cases}$$

MA(1)

$$x_t = w_t + \theta w_{t-1}$$

$$\gamma(h) = \begin{cases} (1 + \theta^2)\sigma_w^2 & h = 0 \\ \theta\sigma_w^2 & h = 1 \\ 0 & h > 1 \end{cases}$$

$$\rho(h) = \begin{cases} \frac{\theta}{(1+\theta^2)} & h = 1 \\ 0 & h > 1 \end{cases}$$

ARMA(p, q)

$$x_t = \phi_1 x_{t-1} + \cdots + \phi_p x_{t-p} + w_t + \theta_1 w_{t-1} + \cdots + \theta_q w_{t-q}$$

$$\phi(B)x_t = \theta(B)w_t$$

Partial autocorrelation function (PACF)

- $x_i^{h-1} \triangleq$ regression of x_i on $\{x_{h-1}, x_{h-2}, \dots, x_1\}$
- $\phi_{hh} = \text{corr}(x_h - x_h^{h-1}, x_0 - x_0^{h-1}) \quad h \geq 2$
- E.g., $\phi_{11} = \text{corr}(x_1, x_0) = \rho(1)$

ARIMA(p, d, q)

$$\nabla^d x_t = (1 - B)^d x_t \text{ is ARMA}(p, q)$$

$$\phi(B)(1 - B)^d x_t = \theta(B)w_t$$

Exponentially Weighted Moving Average (EWMA)

$$x_t = x_{t-1} + w_t - \lambda w_{t-1}$$

$$x_t = \sum_{j=1}^{\infty} (1 - \lambda)\lambda^{j-1} x_{t-j} + w_t \quad \text{when } |\lambda| < 1$$

$$\tilde{x}_{n+1} = (1 - \lambda)x_n + \lambda \tilde{x}_n$$

Seasonal ARIMA

- Denoted by ARIMA(p, d, q) \times (P, D, Q) _{s}
- $\Phi_P(B^s)\phi(B)\nabla_s^D \nabla^d x_t = \delta + \Theta_Q(B^s)\theta(B)w_t$

21.4.1 Causality and Invertibility

ARMA(p, q) is causal (future-independent) $\iff \exists \{\psi_j\} : \sum_{j=0}^{\infty} \psi_j < \infty$ such that

$$x_t = \sum_{j=0}^{\infty} w_{t-j} = \psi(B)w_t$$

ARMA(p, q) is invertible $\iff \exists \{\pi_j\} : \sum_{j=0}^{\infty} \pi_j < \infty$ such that

$$\pi(B)x_t = \sum_{j=0}^{\infty} X_{t-j} = w_t$$

Properties

- ARMA(p, q) causal \iff roots of $\phi(z)$ lie outside the unit circle

$$\psi(z) = \sum_{j=0}^{\infty} \psi_j z^j = \frac{\theta(z)}{\phi(z)} \quad |z| \leq 1$$

- ARMA(p, q) invertible \iff roots of $\theta(z)$ lie outside the unit circle

$$\pi(z) = \sum_{j=0}^{\infty} \pi_j z^j = \frac{\phi(z)}{\theta(z)} \quad |z| \leq 1$$

Behavior of the ACF and PACF for causal and invertible ARMA models

	AR(p)	MA(q)	ARMA(p, q)
ACF	tails off	cuts off after lag q	tails off
PACF	cuts off after lag p	tails off q	tails off

21.5 Spectral Analysis

Periodic process

$$x_t = A \cos(2\pi\omega t + \phi)$$

$$= U_1 \cos(2\pi\omega t) + U_2 \sin(2\pi\omega t)$$

- Frequency index ω (cycles per unit time), period $1/\omega$

- Amplitude A
- Phase ϕ
- $U_1 = A \cos \phi$ and $U_2 = A \sin \phi$ often normally distributed RV's

Periodic mixture

$$x_t = \sum_{k=1}^q (U_{k1} \cos(2\pi\omega_k t) + U_{k2} \sin(2\pi\omega_k t))$$

- U_{k1}, U_{k2} , for $k = 1, \dots, q$, are independent zero-mean RV's with variances σ_k^2
- $\gamma(h) = \sum_{k=1}^q \sigma_k^2 \cos(2\pi\omega_k h)$
- $\gamma(0) = \mathbb{E} [x_t^2] = \sum_{k=1}^q \sigma_k^2$

Spectral representation of a periodic process

$$\begin{aligned} \gamma(h) &= \sigma^2 \cos(2\pi\omega_0 h) \\ &= \frac{\sigma^2}{2} e^{-2\pi i\omega_0 h} + \frac{\sigma^2}{2} e^{2\pi i\omega_0 h} \\ &= \int_{-1/2}^{1/2} e^{2\pi i\omega h} dF(\omega) \end{aligned}$$

Spectral distribution function

$$F(\omega) = \begin{cases} 0 & \omega < -\omega_0 \\ \sigma^2/2 & -\omega \leq \omega < \omega_0 \\ \sigma^2 & \omega \geq \omega_0 \end{cases}$$

- $F(-\infty) = F(-1/2) = 0$
- $F(\infty) = F(1/2) = \gamma(0)$

Spectral density

$$f(\omega) = \sum_{h=-\infty}^{\infty} \gamma(h) e^{-2\pi i\omega h} \quad -\frac{1}{2} \leq \omega \leq \frac{1}{2}$$

- Needs $\sum_{h=-\infty}^{\infty} |\gamma(h)| < \infty \implies \gamma(h) = \int_{-1/2}^{1/2} e^{2\pi i\omega h} f(\omega) d\omega \quad h = 0, \pm 1, \dots$
- $f(\omega) \geq 0$
- $f(\omega) = f(-\omega)$
- $f(\omega) = f(1 - \omega)$
- $\gamma(0) = \mathbb{V} [x_t] = \int_{-1/2}^{1/2} f(\omega) d\omega$
- White noise: $f_w(\omega) = \sigma_w^2$
- ARMA (p, q) , $\phi(B)x_t = \theta(B)w_t$:

$$f_x(\omega) = \sigma_w^2 \frac{|\theta(e^{-2\pi i\omega})|^2}{|\phi(e^{-2\pi i\omega})|^2}$$

where $\phi(z) = 1 - \sum_{k=1}^p \phi_k z^k$ and $\theta(z) = 1 + \sum_{k=1}^q \theta_k z^k$

Discrete Fourier Transform (DFT)

$$d(\omega_j) = n^{-1/2} \sum_{i=1}^n x_i e^{-2\pi i\omega_j t}$$

Fourier/Fundamental frequencies

$$\omega_j = j/n$$

Inverse DFT

$$x_t = n^{-1/2} \sum_{j=0}^{n-1} d(\omega_j) e^{2\pi i\omega_j t}$$

Periodogram

$$I(j/n) = |d(j/n)|^2$$

Scaled Periodogram

$$\begin{aligned} P(j/n) &= \frac{4}{n} I(j/n) \\ &= \left(\frac{2}{n} \sum_{t=1}^n x_t \cos(2\pi t j/n) \right)^2 + \left(\frac{2}{n} \sum_{t=1}^n x_t \sin(2\pi t j/n) \right)^2 \end{aligned}$$

22 Math

22.1 Gamma Function

- Ordinary: $\Gamma(s) = \int_0^{\infty} t^{s-1} e^{-t} dt$
- Upper incomplete: $\Gamma(s, x) = \int_x^{\infty} t^{s-1} e^{-t} dt$
- Lower incomplete: $\gamma(s, x) = \int_0^x t^{s-1} e^{-t} dt$
- $\Gamma(\alpha + 1) = \alpha \Gamma(\alpha) \quad \alpha > 1$
- $\Gamma(n) = (n-1)! \quad n \in \mathbb{N}$
- $\Gamma(1/2) = \sqrt{\pi}$

22.2 Beta Function

- Ordinary: $B(x, y) = B(y, x) = \int_0^1 t^{x-1} (1-t)^{y-1} dt = \frac{\Gamma(x)\Gamma(y)}{\Gamma(x+y)}$
- Incomplete: $B(x; a, b) = \int_0^x t^{a-1} (1-t)^{b-1} dt$
- Regularized incomplete: $I_x(a, b) = \frac{B(x; a, b)}{B(a, b)} \stackrel{a, b \in \mathbb{N}}{=} \sum_{j=a}^{a+b-1} \frac{(a+b-1)!}{j!(a+b-1-j)!} x^j (1-x)^{a+b-1-j}$

- $I_0(a, b) = 0 \quad I_1(a, b) = 1$
- $I_x(a, b) = 1 - I_{1-x}(b, a)$

22.3 Series

Finite

- $\sum_{k=1}^n k = \frac{n(n+1)}{2}$
- $\sum_{k=1}^n (2k-1) = n^2$
- $\sum_{k=1}^n k^2 = \frac{n(n+1)(2n+1)}{6}$
- $\sum_{k=1}^n k^3 = \left(\frac{n(n+1)}{2}\right)^2$
- $\sum_{k=0}^n c^k = \frac{c^{n+1}-1}{c-1} \quad c \neq 1$

Infinite

- $\sum_{k=0}^{\infty} p^k = \frac{1}{1-p}, \quad \sum_{k=1}^{\infty} p^k = \frac{p}{1-p} \quad |p| < 1$
- $\sum_{k=0}^{\infty} k p^{k-1} = \frac{d}{dp} \left(\sum_{k=0}^{\infty} p^k \right) = \frac{d}{dp} \left(\frac{1}{1-p} \right) = \frac{1}{1-p^2} \quad |p| < 1$
- $\sum_{k=0}^{\infty} \binom{r+k-1}{k} x^k = (1-x)^{-r} \quad r \in \mathbb{N}^+$
- $\sum_{k=0}^{\infty} \binom{\alpha}{k} p^k = (1+p)^\alpha \quad |p| < 1, \alpha \in \mathbb{C}$

22.4 Combinatorics

Sampling

k out of n	w/o replacement	w/ replacement
ordered	$n^k = \prod_{i=0}^{k-1} (n-i) = \frac{n!}{(n-k)!}$	n^k
unordered	$\binom{n}{k} = \frac{n^k}{k!} = \frac{n!}{k!(n-k)!}$	$\binom{n-1+r}{r} = \binom{n-1+r}{n-1}$

Binomial

- $\sum_{k=0}^n \binom{n}{k} = 2^n$
- $\sum_{k=0}^n \binom{r+k}{k} = \binom{r+n+1}{n}$
- $\sum_{k=0}^n \binom{k}{m} = \binom{n+1}{m+1}$
- VANDERMONDE'S Identity:
 $\sum_{k=0}^r \binom{m}{k} \binom{n}{r-k} = \binom{m+n}{r}$
- Binomial Theorem:
 $\sum_{k=0}^n \binom{n}{k} a^{n-k} b^k = (a+b)^n$

Stirling numbers, 2nd kind

$$\left\{ \begin{matrix} n \\ k \end{matrix} \right\} = k \left\{ \begin{matrix} n-1 \\ k \end{matrix} \right\} + \left\{ \begin{matrix} n-1 \\ k-1 \end{matrix} \right\} \quad 1 \leq k \leq n \quad \left\{ \begin{matrix} n \\ 0 \end{matrix} \right\} = \begin{cases} 1 & n=0 \\ 0 & \text{else} \end{cases}$$

Partitions

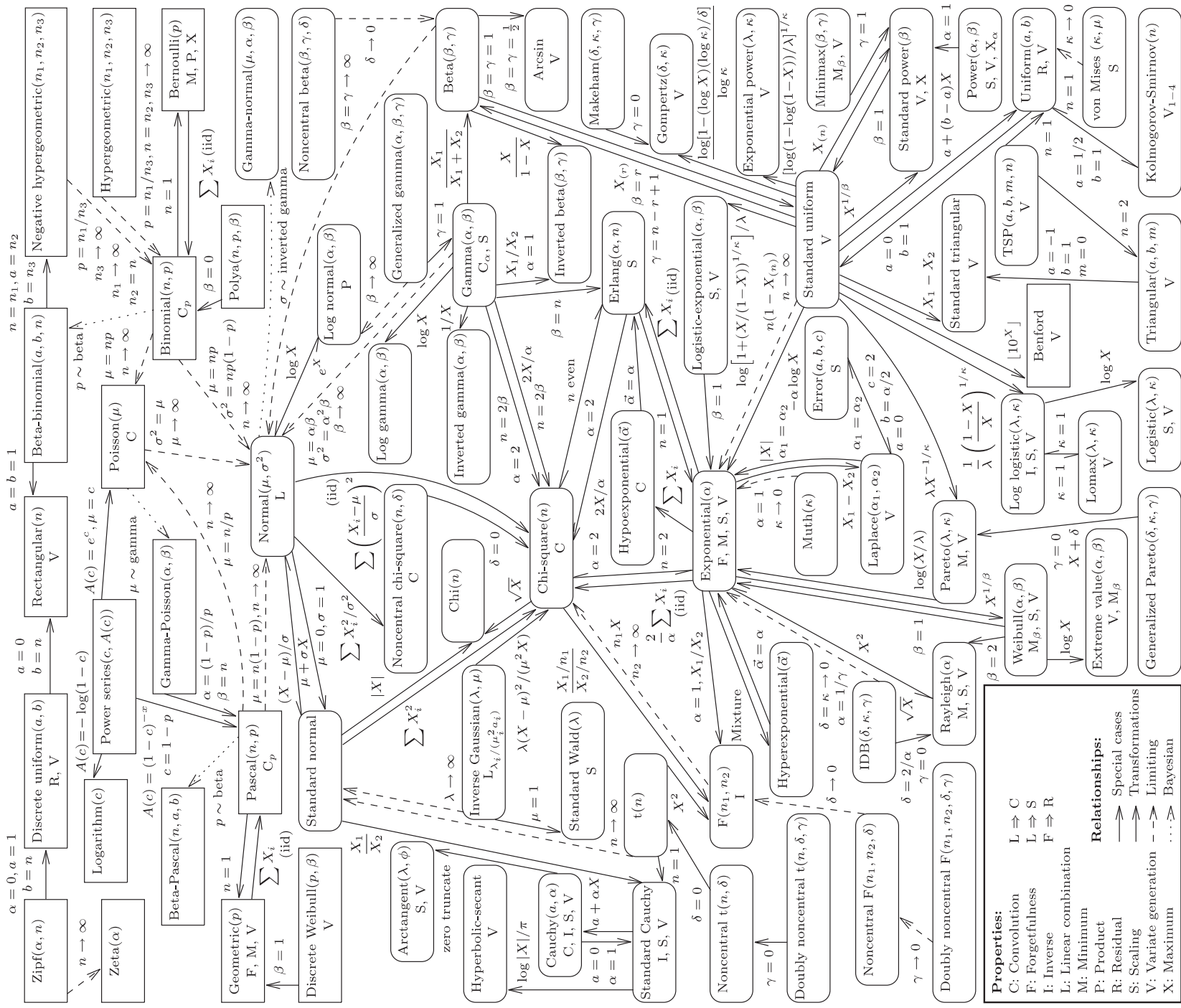
$$P_{n+k,k} = \sum_{i=1}^n P_{n,i} \quad k > n : P_{n,k} = 0 \quad n \geq 1 : P_{n,0} = 0, P_{0,0} = 1$$

Balls and Urns $f : B \rightarrow U \quad D = \text{distinguishable}, \neg D = \text{indistinguishable}.$

$ B = n, U = m$	f arbitrary	f injective	f surjective	f bijective
$B : D, U : \neg D$	m^n	$\begin{cases} m^{\underline{m}} & m \geq n \\ 0 & \text{else} \end{cases}$	$m! \left\{ \begin{matrix} n \\ m \end{matrix} \right\}$	$\begin{cases} n! & m = n \\ 0 & \text{else} \end{cases}$
$B : \neg D, U : D$	$\binom{n+n-1}{n}$	$\binom{m}{n}$	$\binom{n-1}{m-1}$	$\begin{cases} 1 & m = n \\ 0 & \text{else} \end{cases}$
$B : D, U : \neg D$	$\sum_{k=1}^m \left\{ \begin{matrix} n \\ k \end{matrix} \right\}$	$\begin{cases} 1 & m \geq n \\ 0 & \text{else} \end{cases}$	$\left\{ \begin{matrix} n \\ m \end{matrix} \right\}$	$\begin{cases} 1 & m = n \\ 0 & \text{else} \end{cases}$
$B : \neg D, U : \neg D$	$\sum_{k=1}^m P_{n,k}$	$\begin{cases} 1 & m \geq n \\ 0 & \text{else} \end{cases}$	$P_{n,m}$	$\begin{cases} 1 & m = n \\ 0 & \text{else} \end{cases}$

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Univariate distribution relationships, courtesy of Leemis and McQueston [2].