

1 Basics

Distributions

Normal: $\phi(x) = (2\pi)^{-1/2} \exp(-\frac{1}{2}x^2)$

Normal CDF: $\Phi(\mathbf{x}) = \int_{-\infty}^x \phi(y)dy$

Moments

Continuous: $m_k(X) \equiv \int_{-\infty}^{\infty} x^k f(x)dx$

Central:

$\mu_k \equiv E(X - E(X))^k = \int_{-\infty}^{\infty} (x - \mu)^k f(x)dx$

Discrete Central:

$\mu_k \equiv E(X - E(X))^k = \sum_{i=1}^m p(x)(x_i - \mu)^k$

Multivariate

Joint Density Func: $f(x_1, x_2) = \frac{\partial^2 F(x_1, x_2)}{\partial x_1 \partial x_2}$

Independence:

$F(x_1, x_2) = F(x_1, \infty)F(\infty, x_2)$

or $f(x_1, x_2) = f(x_1)f(x_2)$

Marginal Density:

$f(x_1) \equiv F_1(x_1, \infty) = \int_{-\infty}^{\infty} f(x_1, x_2)dx_2$

Conditional Density: $f(x_1|x_2) = \frac{f(x_1, x_2)}{f(x_2)}$

Law Iterate Expec: $E(E(X_1|X_2)) = E(X_1)$

Any Deterministic Func h :

$E(X_1 h(X_2) | X_2) = h(X_2)E(X_1 | X_2)$

Matrix Algebra

Dot Product: $\mathbf{a}^T \mathbf{b} = \sum_{i=1}^n a_i b_i$

Matrix Multiplication: $C_{ij} = \sum_{k=1}^m A_{ik} B_{ki}$

Transpose: $(\mathbf{AB})^T = \mathbf{B}^T \mathbf{A}^T$

$\|\mathbf{x}\| = (\mathbf{x}^T \mathbf{y})^{1/2} = \left(\sum_{i=1}^n x_i^2 \right)^{1/2}$

$\langle \mathbf{x}, \mathbf{y} \rangle = \|\mathbf{x}\| \|\mathbf{y}\| \cos(\theta)$

Cauchy-Schwartz: $\langle \mathbf{x}, \mathbf{y} \rangle \leq \|\mathbf{x}\| \|\mathbf{y}\|$

Linear Indep: $\mathbf{X}^T \mathbf{X} \mathbf{b} = \mathbf{0}, \mathbf{b} \neq \mathbf{0}$

2 Linear Regression

OLS

Estimator: $\hat{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$

$E(x_{ti} u_t) = 0 \implies \mathbf{X}^T (\mathbf{y} - \mathbf{X} \hat{\beta}) = \mathbf{0}$

SSR(β): $= \sum_{t=1}^n (y_i - \mathbf{X}_t \beta)^2$

$\mathbf{y}^T \mathbf{y} = \hat{\beta}^T \mathbf{X}^T \mathbf{X} \hat{\beta} + (\mathbf{y} - \mathbf{X} \hat{\beta})^T (\mathbf{y} - \mathbf{X} \hat{\beta})$

Projection: $\mathbf{P}_X = \mathbf{X}(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T$

$\mathbf{M}_X = \mathbf{I} - \mathbf{P}_X = \mathbf{I} - \mathbf{X}(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T$

$\mathbf{P}_X \mathbf{y} = \mathbf{X}((\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y})$; $\mathbf{P}_X \mathbf{P}_X = \mathbf{P}_X$

$\mathbf{M}_X \mathbf{y} = \hat{\mathbf{u}}$; $\mathbf{M}_X \mathbf{X} = \mathbf{0}$; $\mathbf{M}_X \mathbf{M}_X = \mathbf{M}_X$

$\mathbf{P}_X + \mathbf{M}_X = \mathbf{I}$; $\mathbf{P}_X \mathbf{M}_X = \mathbf{0}$; $\mathbf{P}_X^T = \mathbf{P}_X$

$\|\mathbf{y}\|^2 = \|\mathbf{P}_X \mathbf{y}\|^2 + \|\mathbf{M}_X \mathbf{y}\|^2$; $\|\mathbf{P}_X \mathbf{y}\| \leq \|\mathbf{y}\|$

Centering: $\mathbf{M}_1 \mathbf{x} = \mathbf{z} = \mathbf{x} - \bar{x} \mathbf{i}$; $\mathbf{i}^T \mathbf{z} = 0$

$\mathbf{P}_1 \equiv \mathbf{P}_{X_1}$; $\mathbf{P}_1 \mathbf{P}_X = \mathbf{P}_X \mathbf{P}_1 = \mathbf{P}_1$

FWL: β_2 from $\mathbf{y} = \mathbf{X}_1 \beta_1 + \mathbf{X}_2 \beta_2 + \mathbf{u}$ and

$\mathbf{M}_1 \mathbf{y} = \mathbf{M}_1 \mathbf{X}_2 \beta_2 + \text{res}$ are the same. (+ res)

Seasonal w const: $\mathbf{s}'_i = \mathbf{s}_i - \mathbf{s}_4$, $i = 1, 2, 3$.

Avg is const coeff. $\mathbf{M}_S \mathbf{y}$ is deseasonalized. Bias: $E(\hat{\theta}) - \theta_0$