MATH 829: Introduction to Data Mining and Analysis
Consistency of Linear Regression

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What is the distribution of $\hat{\beta}$?

Multivariate normal distribution

Recall: $X = (X_1, \ldots, X_p) \sim N(\mu, \Sigma)$ where

- $\mu \in \mathbb{R}^p$,
- $\Sigma = (\sigma_{ij}) \in \mathbb{R}^{p \times p}$ is positive definite,

if

$$P(X \in A) = \frac{1}{\sqrt{(2\pi)^p \det \Sigma}} \int_A e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1} (x-\mu)} \, dx_1 \ldots dx_p.$$

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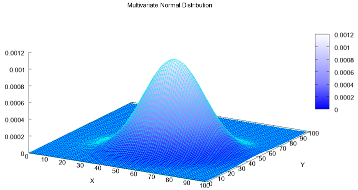
Bivariate case:



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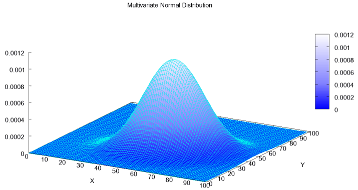

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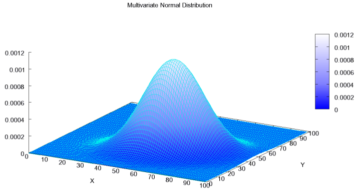

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If $Y = c + BX$, where $c \in \mathbb{R}^p$ and $B \in \mathbb{R}^{m \times p}$, then

$$Y \sim N(c + B\mu, B\Sigma B^T).$$

Back to our problem: $Y = X\beta + \epsilon$ where ϵ_i are iid $N(0, \sigma^2)$. We have

$$Y \sim N(X\beta, \sigma^2 I).$$

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In particular,

$$E(\hat{\beta}) = \beta.$$

Thus, $\hat{\beta}$ is **unbiased**.

Statistical consistency of least squares

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(Without any assumptions, nothing prevents the observations to be all the same for example...)

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We will **assume**:

1. $(\mathbf{x}_i)_{i=1}^n$ are iid random vectors.
2. $y_i = \beta_1 x_{i,1} + \cdots + \beta_p x_{i,p} + \epsilon_i$ where ϵ_i are iid $N(0, \sigma^2)$.
3. The error ϵ_i is independent of $\mathbf{x}_i$.
4. $E x_{ij}^2 < \infty$ (finite second moment).
5. $Q = E(\mathbf{x}_i \mathbf{x}_i^T) \in \mathbb{R}^{p \times p}$ is invertible.

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Under these assumptions, we have the following theorem.

Theorem: Let $\hat{\beta}_n = (X^T X)^{-1} X^T y$. Then, under the above assumptions, we have

$$\hat{\beta}_n \xrightarrow{p} \beta.$$

Recall:

Weak law of large numbers: Let $(X_i)_{i=1}^{\infty}$ be iid random variables with finite first moment $E(|X_i|) < \infty$. Let $\mu := E(X_i)$. Then

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Continuous mapping theorem: Let S, S' be metric spaces. Suppose $(X_i)_{i=1}^{\infty}$ are S-valued random variables such that $X_i \xrightarrow{p} X$. Let $g : S \to S'$. Denote by D_g the set of points in S where g is discontinuous and suppose $P(X \in D_g) = 0$. Then $g(X_n) \xrightarrow{p} g(X)$.

Proof of the theorem

We have

$$\hat{\beta} = (X^T X)^{-1} X^T y = \left(\frac{1}{n} \sum_{i=1}^{n} \mathbf{x}_i \mathbf{x}_i^T \right)^{-1} \left(\frac{1}{n} \sum_{i=1}^{n} \mathbf{x}_i y_i \right).$$

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By the weak law of large numbers, we obtain

$$\frac{1}{n} \sum_{i=1}^{n} \mathbf{x}_i \mathbf{x}_i^T \xrightarrow{p} E(\mathbf{x}_i \mathbf{x}_i^T) = Q,$$

$$\frac{1}{n} \sum_{i=1}^{n} \mathbf{x}_i y_i \xrightarrow{p} E(\mathbf{x}_i y_i).$$

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Using the continuous mapping theorem, we obtain

$$\hat{\beta}_n \xrightarrow{p} E(\mathbf{x}_i \mathbf{x}_i^T)^{-1} E(\mathbf{x}_i y_i).$$

(define $g : \mathbb{R}^{p \times p} \times \mathbb{R}^p \to \mathbb{R}^p$ by $g(A, b) = A^{-1}b$.)

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We conclude that

$$\beta = E(\mathbf{x}_i \mathbf{x}_i^T)^{-1} E(\mathbf{x}_i y_i)$$

and so $\hat{\beta}_n \xrightarrow{p} \beta$. $\square$