

Note 1:

$$p(y) = (\sigma^2 \pi)^{-n/2} \exp \left\{ -\frac{1}{2\sigma^2} \|y - X\beta\|^2 \right\}$$

$$\log p(y) = -\frac{n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \|y - X\beta\|^2$$

Note 2:

$$\frac{\partial \log p(y)}{\partial \beta} = -\frac{1}{2\sigma^2} (-2X^T y + 2X^T X \beta) = 0$$

$$X^T X \beta = X^T y \rightarrow \text{normal equation.}$$

Note 3:

$$H = X(X^T X)^{-1} X^T$$

$$H^2 = X(X^T X)^{-1} X^T X(X^T X)^{-1} X^T = X(X^T X)^{-1} X^T = H$$

$$H^T = X(X^T X)^{-1} X^T = H$$

H orthogonal projector.

why:

$$\begin{aligned} \text{cov}(\beta, y - X\hat{\beta}) &= \text{cov}(X^T X)^{-1} X^T y, (I - H)y \\ &= (X^T X)^{-1} X^T \text{cov}(y) (I - H)^T \\ &= \sigma^2 (X^T X)^{-1} X^T (I - H) = 0 \end{aligned}$$

$$y - X\hat{\beta} = y - X(X^T X)^{-1} X^T y = (I - H)y$$

$$(X^T X)^{-1} X^T H = (X^T X)^{-1} X^T X (X^T X)^{-1} X^T = (X^T X)^{-1} X^T$$

Note 4:

$$RSS_1 = (N - p_1 - 1) \hat{\sigma}_1^2 \sim \sigma^2 \chi_{N-p_1-1}^2$$

$$RSS_0 = (N - p_0 - 1) \hat{\sigma}_0^2 \sim \sigma^2 \chi_{N-p_0-1}^2$$

$$RSS_0 - RSS_1 \sim \sigma^2 \chi_{p_1-p_0}^2$$

$RSS_0 - RSS_1$ independent of RSS_1 .

$$\frac{(RSS_0 - RSS_1) / (p_1 - p_0)}{RSS_1 / (N - p_1 - 1)} \sim F_{p_1 - p_0, N - p_1 - 1}$$

Note 4:

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$$\beta \sim N(\beta, \sigma^2 (X'X)^{-1})$$

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$$\frac{(X'X)^{\frac{1}{2}}}{\sigma} (\hat{\beta} - \beta) \sim N(0, I_{p+1})$$

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$$(\hat{\beta} - \beta)' \frac{X'X}{\sigma} (\hat{\beta} - \beta) \sim \chi_{p+1}^2$$

$$\frac{\hat{\beta}_j - \beta_j}{\sigma \sqrt{\hat{\sigma}_j^2}} \sim N(0, 1)$$

$$\frac{N - p - 1}{\sigma^2} \sim \chi_{N-p-1}^2$$

$$H_0: \beta_j = 0 \rightarrow \frac{\hat{\beta}_j}{\sigma \sqrt{\hat{\sigma}_j^2}} \sim t_{N-p-1}$$

Note 5: $y_0 = f(x_0) + \xi_0$

$$\begin{aligned} E[y_0 - \tilde{f}(x_0)]^2 &= E[(f(x_0) + \xi - \tilde{f}(x_0))^2] \\ &= E[\xi^2] + E[\xi(f(x_0) - \tilde{f}(x_0))] + E[(f(x_0) - \tilde{f}(x_0))^2] \\ &= \sigma^2 + E[(f(x_0) - \tilde{f}(x_0))^2] = \sigma^2 + \text{MSE}[\tilde{f}(x_0)] \\ E[\xi(f(x_0) - \tilde{f}(x_0))] &= 0 \text{ by independence of the error.} \end{aligned}$$

Note 6:

$$p(y) = \frac{1}{\sqrt{(2\pi)^p |\Sigma|}} \exp\left\{-\frac{1}{2}(y - \mu)^T \Sigma^{-1}(y - \mu)\right\}$$

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→ taking the log and ignoring the terms independent of β .

Note 7:

$$\text{Var}(\hat{\beta}_j) = \frac{\sigma^2}{1 - R_j^2}$$

where $\hat{\beta}_j$ are estimated from the centered & scaled predictor.

$$\text{VIF}(\hat{\beta}_j) = \frac{\text{Var}(\hat{\beta}_j)}{\sigma^2}$$

$$\text{Var} \hat{\beta}_j = \sigma^2 (X'X)^{-1}_{jj} = \sigma^2 \sum_{l=1}^p b_{jl} d_l^{-1}$$

where $\sum_{l=1}^p b_{jl}^2 = 1$ $X'X = T \Lambda T'$, $T = [t_{11}, \dots, t_{pp}]$.

$$\text{VIF}_j \leq \sum_{l=1}^p b_{jl}^2 \lambda_{\min}^{-1} \leq \lambda_{\min}^{-1} \leq \lambda_{\max} \lambda_{\min}^{-1} = K(X)^2$$

Note 8:

For a success event is an instance of β_1 .

Note 9:

$$y_i = f(x_i, \beta) + \varepsilon_i, \quad i=1, \dots, N$$

$$L(\beta) = \sum_{i=1}^n (y_i - f(x_i, \beta))^2$$

Note 10:

H: orthogonal projector $Hx = x$

$$E[e] = E[(I - H)y] = (I - H)E[y] = (I - H)(X\beta + \varepsilon) = (I - H)\varepsilon$$

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Note 11:

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$$y_i = \alpha_0 + \beta_1(x_{i1} - \bar{x}_1) + \dots + \beta_p(x_{ip} - \bar{x}_p) + \varepsilon_i$$

$$\alpha_0 = \beta_0 + \beta_1 \bar{x}_1 + \dots + \beta_p \bar{x}_p \quad \bar{x}_j = \sum_i x_{ij} / n$$

The model becomes: $y = X_c \alpha + \varepsilon$, $X_c = (\mathbf{1}_n, \tilde{X})$

\tilde{X} has element $\tilde{x}_{ij} = x_{ij} - \bar{x}_j$ and $\tilde{X}' \mathbf{1}_n = 0$ (mean).

$$H = X_c (X_c' X_c)^{-1} X_c' = \begin{pmatrix} \mathbf{1}_n & \tilde{X} \end{pmatrix} \begin{pmatrix} n & 0' \\ 0 & \tilde{X}' \tilde{X} \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{1}_n & \tilde{X} \end{pmatrix}'$$
$$= \frac{1}{n} \mathbf{1}_n \mathbf{1}_n' + \tilde{X} (\tilde{X}' \tilde{X})^{-1} \tilde{X}'$$

$$h_{ii} = \frac{1}{n} + \frac{1}{n-1} (x_i - \bar{x})' S^{-1} (x_i - \bar{x})$$

h_{ii} increase with the distance of x_i from \bar{x}

Note 11:

Using the multivariate Gaussian density \rightarrow take the log
 \rightarrow ignore the terms independent of B .

Note 12:

This leads to a computational complexity problem.

Note 14:

Similar to Note 5 where $P_1 = 1$ & $P_0 = 1$, $i = k+1$.

Note 15:

$$F = \frac{RSS(B) - RSS(\hat{B})}{RSS(B) / (N - k - 1)}$$

Note 16:

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After standardizing:

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$$L(B) = (y - XB)^T (y - XB) + \lambda B^T B$$

$$\frac{\partial L(B)}{\partial B} = -X^T (y - XB) + \lambda B = -X^T y + (X^T X + \lambda I) B$$
$$B = (X^T X + \lambda I)^{-1} X^T y.$$

Note 17:

orthogonal predictors: $X^T X = I$, $B_{LS} = X^T y$, $\lambda = \frac{1}{1+\alpha}$.

Note 18:

By decomposing the right term of the last equation we can relate the solution to CCA.