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Deduction of PMSE in Predictive Mean Square Error and Stochastic Regressor Variables by SUBHASH C. NARULA

The response variable and the predictor variables follow a joint (k+ 1)-variate normal distribution with unknown mean vector $\boldsymbol{\mu}^* = [\mu_0, \boldsymbol{\mu}']'$, and unknown covariance matrix $\boldsymbol{\Sigma}^* = \begin{bmatrix} \sigma_{00} & \boldsymbol{\sigma}' \\ \boldsymbol{\sigma} & \boldsymbol{\Sigma} \end{bmatrix}$. Let $\boldsymbol{z_1}, \boldsymbol{z_2}, ..., \boldsymbol{z_n}$ be n independent (k-component vector) observations

on the predictor variables, $\mathbf{z}_i = \mathbf{z}_i - \bar{\mathbf{z}}$. Let $\mathbf{S}^* = \begin{bmatrix} s_{00} & \mathbf{s}' \\ \mathbf{s} & \mathbf{S} \end{bmatrix}$ be sample covariance matrix, where

$$s_{00} = \sum \frac{(y_i - \bar{y})^2}{n-1}, s = \sum \frac{(y_i - \bar{y})x_i}{n-1}, S = \sum \frac{x_i x_i'}{n-1}$$

For any given z_i ,

$$\begin{split} E(y_i|\boldsymbol{z_i}) &= \alpha + \boldsymbol{z_i'}\boldsymbol{\beta} & \text{wrong notation, not a scalar} \\ &= \mu_0 - \boldsymbol{\sigma'}\boldsymbol{\Sigma^{-1}}\boldsymbol{\mu} + \boldsymbol{z_i'}\boldsymbol{\sigma'}\boldsymbol{\Sigma^{-1}}^1 \\ &= \mu_0 + \boldsymbol{\sigma'}\boldsymbol{\Sigma^{-1}}(\boldsymbol{z_i - \mu}) \\ &= \mu_0 + \boldsymbol{\sigma'}\boldsymbol{\Sigma^{-1}}\boldsymbol{x_i} & \text{different, since x_i = z_i - \bar{z}} \end{split}$$

where $\alpha = \mu_0 - \sigma' \Sigma^{-1} \mu, \beta = \sigma' \Sigma^{-1}$. Thus $\hat{\alpha} = \bar{y} - s' S^{-1} \bar{x}, \hat{\beta} = S^{-1} s$.

The LSE prediction is given by

$$\hat{y}_i = \bar{y} + \boldsymbol{x}_i' \hat{\boldsymbol{\beta}}$$

and the conditional predictive mean square error by

$$\begin{split} E[(y_0-\hat{y_0})^2|\boldsymbol{z_0}] &= E[(\alpha+\boldsymbol{x_0'}\boldsymbol{\beta}+\epsilon_0-\bar{\boldsymbol{y}}-\boldsymbol{x_0'}\hat{\boldsymbol{\beta}}|\boldsymbol{z_0})^2] \\ &= E[(\alpha+\boldsymbol{x_0'}\boldsymbol{\beta}+\epsilon_0-\boldsymbol{\alpha}+\bar{\boldsymbol{x_0'}}\boldsymbol{\beta}-\bar{\boldsymbol{\epsilon}}-\boldsymbol{x_0'}\hat{\boldsymbol{\beta}}|\boldsymbol{z_0})^2] \\ &= E[(\boldsymbol{x_0'}\boldsymbol{\beta}+\bar{\boldsymbol{x}'}\boldsymbol{\beta}+\epsilon_0-\bar{\boldsymbol{\epsilon}}-\boldsymbol{x_0'}\hat{\boldsymbol{\beta}}|\boldsymbol{z_0})^2] \\ &= E[(\boldsymbol{x_0'}\boldsymbol{\beta}+\bar{\boldsymbol{x}'}\boldsymbol{\beta}+\epsilon_0-\bar{\boldsymbol{\epsilon}}-\boldsymbol{x_0'}\hat{\boldsymbol{\beta}}|\boldsymbol{z_0})^2] \\ &= E[(\boldsymbol{x_0'}\boldsymbol{\beta}+(\epsilon_0-\bar{\boldsymbol{\epsilon}})-\boldsymbol{x_0'}\hat{\boldsymbol{\beta}}|\boldsymbol{z_0})^2] \\ &= E[(\boldsymbol{x_0'}\boldsymbol{\beta}+(\epsilon_0-\bar{\boldsymbol{\epsilon}}))^2+(\boldsymbol{x_0'}\hat{\boldsymbol{\beta}})^2-2(\boldsymbol{x_0'}\boldsymbol{\beta}+(\epsilon_0-\bar{\boldsymbol{\epsilon}}))\boldsymbol{x_0'}\hat{\boldsymbol{\beta}}|\boldsymbol{z_0}] \\ &= E[(\boldsymbol{x_0'}\boldsymbol{\beta})^2+(\epsilon_0-\bar{\boldsymbol{\epsilon}})^2+(\boldsymbol{x_0'}\hat{\boldsymbol{\beta}})^2-2\boldsymbol{x_0'}\boldsymbol{\beta}\boldsymbol{x_0'}\hat{\boldsymbol{\beta}}|\boldsymbol{z_0}] \\ &= B'E(\boldsymbol{x_0}\boldsymbol{x_0'}|\boldsymbol{z_0})\boldsymbol{\beta}+E[(\epsilon_0-\bar{\boldsymbol{\epsilon}})^2|\boldsymbol{z_0}]+E[(\boldsymbol{x_0'}\hat{\boldsymbol{\beta}})^2|\boldsymbol{z_0}]-2\boldsymbol{\beta}'E[\boldsymbol{x_0}\boldsymbol{x_0'}\hat{\boldsymbol{\beta}}|\boldsymbol{z_0}] \end{split}$$

By Lemma A1, Lemma A3, Lemma A7

$$\begin{split} E(\tilde{\beta}_1|\boldsymbol{X}_1) &= \boldsymbol{\beta}_1 + \boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{12}\boldsymbol{\beta}_2 = \boldsymbol{\Phi}_1 \\ E(\boldsymbol{x}_{01}\boldsymbol{x}_{01}'|\boldsymbol{z}_0) &= (\boldsymbol{z}_{01} - \boldsymbol{\mu}_1)(\boldsymbol{z}_{01} - \boldsymbol{\mu}_1)' + \frac{\boldsymbol{\Sigma}_{11}}{n} \\ E(\boldsymbol{x}_0\boldsymbol{x}_0'|\boldsymbol{z}_0) &= (\boldsymbol{z}_0 - \boldsymbol{\mu})(\boldsymbol{z}_0 - \boldsymbol{\mu})' + \frac{\boldsymbol{\Sigma}}{n} \\ E[(\boldsymbol{x}_{01}'\tilde{\boldsymbol{\beta}}_1)^2|\boldsymbol{z}_0] &= \sigma_p^2 \left[(\boldsymbol{z}_{01} - \boldsymbol{\mu}_1)'\boldsymbol{\Sigma}_{11}^{-1}(\boldsymbol{z}_{01} - \boldsymbol{\mu}_1) + \frac{p}{n} \right] \frac{1}{n - p - 2} \\ &+ \boldsymbol{\Phi}_1'\boldsymbol{\Sigma}_{11}\boldsymbol{\Phi}_1 \frac{1}{n} + \boldsymbol{\Phi}_1'(\boldsymbol{z}_{01} - \boldsymbol{\mu}_1)(\boldsymbol{z}_{01} - \boldsymbol{\mu}_1)'\boldsymbol{\Phi}_1 \\ \boldsymbol{\sigma}'\boldsymbol{\Sigma}^{-1} \begin{bmatrix} \boldsymbol{\Sigma}_{11} \\ \boldsymbol{\Sigma}_{21} \end{bmatrix} &= \boldsymbol{\sigma}_1' \end{split}$$

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The conditional PMSE can be written as

$$E[(y_0 - \hat{y_0})^2 | \mathbf{z_0}] = \boldsymbol{\beta'} E(\mathbf{x_0} \mathbf{x_0'} | \mathbf{z_0}) \boldsymbol{\beta} + E[(\epsilon_0 - \bar{\epsilon})^2 | \mathbf{z_0}] + E[(\mathbf{x_0'} \hat{\boldsymbol{\beta}})^2 | \mathbf{z_0}] - 2\boldsymbol{\beta'} E[\mathbf{x_0} \mathbf{x_0'} \hat{\boldsymbol{\beta}} | \mathbf{z_0}]$$

$$= \boldsymbol{\beta'} \left[(\mathbf{z_0} - \boldsymbol{\mu}) (\mathbf{z_0} - \boldsymbol{\mu})' + \frac{\boldsymbol{\Sigma}}{n} \right] \boldsymbol{\beta} + \sigma_k^2 \left(1 + \frac{1}{n} \right)$$

$$+ \sigma_k^2 \left[(\mathbf{z_0} - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{z_0} - \boldsymbol{\mu}) + \frac{k}{n} \right] \frac{1}{n - k - 2}$$

$$+ \frac{1}{n} \boldsymbol{\Phi'} \boldsymbol{\Sigma} \boldsymbol{\Phi} + \boldsymbol{\Phi'} (\mathbf{z_0} - \boldsymbol{\mu}) (\mathbf{z_0} - \boldsymbol{\mu})' \boldsymbol{\Phi} - 2\boldsymbol{\beta'} \left[(\mathbf{z_0} - \boldsymbol{\mu}) (\mathbf{z_0} - \boldsymbol{\mu})' + \frac{\boldsymbol{\Sigma}}{n} \right] \boldsymbol{\beta}$$

$$= \sigma_k^2 \left(1 + \frac{1}{n} \right) + \sigma_k^2 \left[(\mathbf{z_0} - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{z_0} - \boldsymbol{\mu}) + \frac{k}{n} \right] \frac{1}{n - k - 2}$$

Since Φ is the notation of expactation of $\tilde{\beta}$, when we are using all preditors, the LSE is unbiased, which means $\Phi = \beta$.

The unconditional PMSE

$$E[(y_{0} - \hat{y_{0}})^{2}] = E\{E[(y_{0} - \hat{y_{0}})^{2} | \mathbf{z_{0}}]\}$$

$$= E\left[\sigma_{k}^{2}\left(1 + \frac{1}{n}\right) + \sigma_{k}^{2}\left[(\mathbf{z_{0}} - \boldsymbol{\mu})'\boldsymbol{\Sigma}^{-1}(\mathbf{z_{0}} - \boldsymbol{\mu}) + \frac{k}{n}\right] \frac{1}{n - k - 2}\right]$$

$$= \sigma_{k}^{2}\left(1 + \frac{1}{n}\right) + \sigma_{k}^{2}E\left[(\mathbf{z_{0}} - \boldsymbol{\mu})'\boldsymbol{\Sigma}^{-1}(\mathbf{z_{0}} - \boldsymbol{\mu}) + \frac{k}{n}\right] \frac{1}{n - k - 2}$$

$$= \sigma_{k}^{2}\left(1 + \frac{1}{n}\right) + \sigma_{k}^{2}E\left[k + \frac{k}{n}\right] \frac{1}{n - k - 2}$$

$$= \sigma_{k}^{2}\left(1 + \frac{1}{n}\right)\left(1 + \frac{1}{n - k - 2}\right)$$

$$= \sigma_{k}^{2}\left(1 + \frac{1}{n}\right)\left(\frac{n - 2}{n - k - 2}\right)$$

For subset, we partition the k-component vector of predictor variables into two parts, $Z = [Z_1, Z_2], X = [X_1, X_2], x'_1 = [x'_{i1}, x'_{i2}], \mu' = [\mu'_1, \mu'_2], \sigma' = [\sigma'_1, \sigma'_2], s' = [s'_1, s'_2],$ $\Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}, S = \begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix}$, so the subset prediction equation is given by

$$\tilde{y}_i = \bar{y} + \boldsymbol{x_{i1}'} \tilde{\boldsymbol{\beta}_1}$$

where $\tilde{\beta}_1 = S_{11}^{-1} s_1$. By LemmaA1, LemmaA3, LemmaA7, the conditional PMSE at z_0 is

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given by

\bar{y} contains \bar{z} instead of \bar{x}=0?

$$\begin{split} E[(y_0 - \tilde{y_0})^2 | \pmb{z_0}] &= E[(\pmb{x_0'}\boldsymbol{\beta} + \epsilon_0 - \boldsymbol{\hat{\epsilon}} - \pmb{x_{01}'}\tilde{\beta}_1 | \pmb{z_0})^2] \\ &= E[(\epsilon_0 - \bar{\epsilon})^2 + (\pmb{x_0'}\boldsymbol{\beta} - \pmb{x_{01}'}\tilde{\beta}_1)^2 | \pmb{z_0}] \\ &= E[(\epsilon_0 - \bar{\epsilon})^2 | \pmb{z_0}] + Var[(\pmb{x_0'}\boldsymbol{\beta} - \pmb{x_{01}'}\tilde{\beta}_1) | \pmb{z_0}] + \{E[(\pmb{x_0'}\boldsymbol{\beta} - \pmb{x_{01}'}\tilde{\beta}_1) | \pmb{z_0}]\}^2 \\ &= \sigma_k^2 + \frac{\sigma_p^2}{n} + Var(\pmb{x_0'}\boldsymbol{\beta}|\pmb{z_0}) + Var(\pmb{x_{01}'}\tilde{\beta}_1|\pmb{z_0}) + [(\pmb{z_0} - \pmb{\mu})'\boldsymbol{\beta} - (\pmb{z_{01}} - \pmb{\mu_1})'\boldsymbol{\Phi_1}]^2 \\ &= \sigma_k^2 + \frac{\sigma_p^2}{n} + \sigma_k^2 + \sigma_p^2 \left[(\pmb{z_{01}} - \pmb{\mu_1})'\boldsymbol{\Sigma_{11}^{-1}}(\pmb{z_{01}} - \pmb{\mu_1}) + \frac{p}{n} \right] \frac{1}{n - p - 2} + \boldsymbol{\Phi_1'}\boldsymbol{\Sigma_{11}}\boldsymbol{\Phi_1}/n \\ &+ [(\pmb{z_0} - \pmb{\mu})'\boldsymbol{\beta} - (\pmb{z_{01}} - \pmb{\mu_1})'\boldsymbol{\Phi_1}]^2 & \text{what happened to these two terms?} \\ &= \\ &= \\ &= \\ &= \\ &= \\ &= \\ &= \sigma_k^2 + \frac{\sigma_p^2}{n} + \sigma_p^2 \left[(\pmb{z_{01}} - \pmb{\mu_1})'\boldsymbol{\Sigma_{11}^{-1}}(\pmb{z_{01}} - \pmb{\mu_1}) + \frac{p}{n} \right] \frac{1}{n - p - 2} \\ &+ [(\pmb{z_0} - \pmb{\mu})'\boldsymbol{\beta} - (\pmb{z_{01}} - \pmb{\mu_1})'\boldsymbol{\Phi_1}]^2 \\ &= \sigma_k^2 + \frac{\sigma_p^2}{n} + \sigma_p^2 \left[(\pmb{z_{01}} - \pmb{\mu_1})'\boldsymbol{\Sigma_{11}^{-1}}(\pmb{z_{01}} - \pmb{\mu_1})' + \frac{p}{n} \right] \frac{1}{n - p - 2} \\ &+ [(\pmb{z_{02}} - \pmb{\mu_2})'\boldsymbol{\beta}_2 - (\pmb{z_{01}} - \pmb{\mu_1})'\boldsymbol{\Sigma_{11}^{-1}}\boldsymbol{\Sigma_{12}\boldsymbol{\beta_2}}]^2 \end{split}$$