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Response surface designs using the generalized variance inflation factors

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using GVIF, the H310 design can be improved for the standard global optimality criteria of A, D, and E.

1. Introduction

We consider a linear regression $Y=X\beta+\varepsilon$ with X a full rank $n\times p$ matrix and $L(\varepsilon)=N(0,\sigma^2I_n)$. The variance inflation factor VIF, Belsley ([1986](#)), measures the penalty for adding one non-orthogonal additional explanatory variable to a linear regression model, and they can be computed as a ratio of determinants. The extension of VIF to a measure of the penalty for adding a subset of variables to a model is the generalized variance inflation factor GVIF of Fox and Monette ([1992](#)), which will be used to study response surface designs, in particular, as the penalty for adding the quadratic terms to the model.

2. Variance inflation factors

For our linear model $Y=X\beta+\varepsilon$, let D_X be the diagonal matrix with entries on the diagonal $D_X[i,i]=(X'X)^{-1}_{i,i}$. When the design has been standardized $X\rightarrow XDX$, the VIFs



$$VIF_p = [S(X^{-1})]_{p,p} = [DX^{-1}(X'X)^{-1}DX^{-1}]_{p,p} = (x_p'x_p)^{-1/2} \det(C_p) \det(X'X)$$

$$(x_p'x_p)^{-1/2} = \det(M_p) \det(X'X)$$

(1)

the ratio of the determinant of the idealized moment matrix M_p to the determinant of the moment matrix $X'X$. This definition extends naturally to subsets and is discussed in the next section.

For an alternate view of the how collinearities in the explanatory variables inflate the model variances of the regression coefficients when compared to a fictitious orthogonal reference design, consider the formula for the model variance

$$\text{Var}(\hat{\beta}_j) = \sigma^2 \sum_{i=1}^n (x_{ij} - \bar{x}_j)^2 (1 - R_j^2)^{-1}$$

where R_j^2 is the square of the multiple correlation from the regression of the j th column of $X = [x_{ij}]$ on the remaining columns as in Liao and Valliant (2012). The first term $\sigma^2 / \sum (x_{ij} - \bar{x}_j)^2$ is the model variance for $\hat{\beta}_j$ had the j th explanatory variable been orthogonal to the remaining variables. The second term $1/(1 - R_j^2)$ is a standard definition of the j th VIF as in Thiel (1971).

3. Generalized variance inflation factors

In this section we consider the variance inflation factors VIF_j for the regression coefficients with X_1 and X_2 as the n -dimensional explanatory matrix for

variance inflation factors VIF_j are partitioned into two components of the total moment



Following the regression of $X_2|X_1$, we

that is for

(2)

as in Equation 10 of Fox and Monette (1992), who compared the sizes of the joint confidence regions for β for partitioned designs and noted when $X=[X[p],x_p]$ that $G\text{VIF}[x_p|X[p]]=\text{VIF}_p$. Equation 2 is in the spirit of the efficiency comparisons in linear inferences introduced in Theorems 4 and 5 of Jensen and Ramirez (1993). A similar measure of collinearity is mentioned in Note 2 in Wichers (1975), Theorem 1 of Berk (1977), and Garcia, Garcia, and Soto (2011). For the simple linear regression model with $p=2$, Equation 2 gives $\text{VIF}=1/(1-\rho^2)$ with ρ the correlation coefficient as required. Fox and Monette (1992) suggested that X_1 contains the variables which are of “simultaneous interest,” while X_2 contains additional variables selected by the investigator. We will set X_1 for the constant and main effects and set X_2 the (optional) quadratic terms with values from X_1 .

Willan and Watts (1978) measured the effect of collinearity using the ratio of the volume of the actual joint confidence region for $\hat{\beta}$ to the volume of the joint confidence region in the fictitious orthogonal reference design. Their ratio is in the spirit of GVIF as $\det(X'X)$ is inversely proportional to the square of the volume of the joint confidence region for $\hat{\beta}$. They also introduced a measure of relative predictability and they note: “The existence of near linear relations in the independent variables of the actual data reduces the overall predictive efficiency by this factor.” For a simple case study, consider the simple linear regression model with $n=4$, $x_1=[-2,-1,1,2]'$, and $y=[4,1,1,4]'$. The 95% prediction interval for $x_1=0$ is 2.5 ± 10.20 . If the model also includes $x_2=[-2,0,0,2]'$, the 95% prediction interval for $(x_1,x_2)=(0,0)$ is 2.5 ± 46.4 . This illustrates the effect of collinearity on the prediction interval.

For the (3) design of dimension $n \times s$, set



and denoted by $R=D(1-1/2)I_s \times s$;

(3)

with det

$$\det(R) = \det(X'X) \det(X_1'X_1) \det(X_2'X_2) = 1 \text{GVIF}(X_2|X_1);$$

equivalently,

$$\det(R) = \det(I_r \times r - B_r \times s B_s \times r') = \det(I_s \times s - B_s \times r' B_r \times s)$$

where $B_r \times s = X_1'X_1^{-1/2}(X_1'X_2)X_2'X_2^{-1/2}$.

In the case $\{r=p-1, s=1\}$, $X_2=x_p$ is a $n \times 1$ vector and the partitioned design $X=[X_1, x_p]$ has $\det(R) = 1 - [x_p'X_1X_1'X_1^{-1}X_1'x_p]/x_p'x_p$. From standard facts for the inverse of a partitioned matrix, for example, Myers ([1990](#), p. 459), $\text{VIF}_p = [R^{-1}]_{p,p} = [D(p-1, 1)^{-1}(X'X)^{-1}D(p-1, 1)^{-1}]_{p,p}$ can be computed directly as

$$x_p'x_p^{1/2}(X'X)^{-1}_{p,p}x_p^{1/2} = x_p'x_p x_p'x_p - x_p'X_1X_1'X_1^{-1}X_1'x_p = 1 - [x_p'X_1X_1'X_1^{-1}X_1'x_p]/x_p'x_p = 1 - \det(R) = \text{GVIF}(X_2|X_1).$$

Table 1. CCD with parameter α , canonical index γ_{X_2} , and GVIF



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We study the eigenvalue structure of $M(r, s)$ in Appendix 1. Let $\{\lambda_1 > \lambda_2 > \dots \geq \lambda_{\min}(r, s)\}$ be the eigenvalues of $M(r, s)$. It is shown in

(4)

4. C



For the partitioned design $X=[X_1, x_p]$ as the identity $I_p = I_{p-1} \oplus 1$ and $X_1'X_2X_2'X_2^{-1/2}$ we have

From Equation 4, $\text{GVIF}(x_2|1,x) = (1-\lambda_2)^{-1}$ where $\lambda = \rho_1^2 + \rho_2^2$ is the unique positive singular value of $[\rho_1, \rho_2]'$. Denote

$$\gamma X^2 = \rho_1^2 + \rho_2^2$$

as the canonical index with $\text{GVIF}(x_2|1,x) = 1 - \gamma X^2 = 1/\det(R)$. Surprisingly, many higher order designs also have the off-diagonal entry of the canonical moment matrix with a unique positive singular value with $\text{GVIF}(X_2|X_1) = 1 - \gamma X^2$ with the collinearity between the lower order terms and the upper order terms as a function of the canonical index γX^2 .

5. Central composite and factorial designs for quadratic models ($p=6$)

In this section, we compare the central composite design (CCD) X of Box and Wilson (1951) and the factorial design Z . The design points are shown in Table A1 of Appendix 2. Both designs are 9×6 and use the quadratic response model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{12} x_1 x_2 + \varepsilon.$$

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6. Larger designs ($p=10$)

We consider the quadratic response surface designs for

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3 + \varepsilon \quad (5)$$

with n responses and with X partitioned into $X_1|X_2$ with X_1 the four lower order terms ($r=4$) and X_2 the six quadratic terms ($s=6$). Four popular designs are given in Appendix 2. They are the hybrid designs (H310 and H311B) of Roquemore (1976) Tables A2 and A3, the Box and Behnken (1960) (BBD) design Table A4, and the CCD of Box and Wilson (1951) Table A5.

For each design, we compute the 10×10 canonical moment matrix. It is striking that, for all these designs, the off-diagonal 4×6 array in R has only one non-zero singular value with its square the canonical index γX_2 . It follows that $\text{GVIF}(X_2|X_1) = 11 - \gamma X_2$.

Table 2. Hybrid designs H310, H311B, Box and Behnken BBD, and CCD

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Let X be

Table A6

for the quadratic response surface model ($r=4$ and $s=6$) as in Equation (5). Let $\alpha = \{\alpha_1 \geq \dots \geq \alpha_r \geq 0\}$ and $\beta = \{\beta_1 \geq \dots \geq \beta_r \geq 0\}$ be the non-negative singular values of the off-diagonal array for R_X and R_Z , respectively. As $\alpha_i \leq \beta_i (1 \leq i \leq r)$ in Table 3, it follows that $G\text{VIF}(X_2|X_1) \leq G\text{VIF}(Z_2|Z_1)$ showing less collinearity between the lower and higher order terms for the BDD design.

8. An improved H310 design

When the diagonal matrix $\Lambda_{r \times s}$ in Equation 6 in Appendix 1 has only one non-zero entry, we have denoted the square of this value the canonical index. We extend this definition to the case when $X_1'X_1^{-1/2}(X_1'X_2)X_2'X_2^{-1/2}$ has multiple positive singular values. The Frobenious norm for a rectangular matrix $A_{r \times s}$ is defined by $\|A\|_F^2 = \sum_{i=1}^r \sum_{j=1}^s a_{ij}^2 = \text{trace}(A'A)$. For a design matrix X , we extend the definition of the canonical index with $\gamma_{X_2} = \|\Lambda_{r \times s}\|_F^2$. Alternatively, $\gamma_{X_2} = \text{trace}(X_2'X_2^{-1}(X_2'X_1)X_1'X_1^{-1}(X_1'X_2))$ as in Equation 7.

We examine, in detail, the H310 design matrix $X_{11 \times 10}$, Table A2 in Appendix 2, with our attention to the value of -0.1360 in row 2 for x_3 . In succession, we will replace the values $\{1.1736, 0.6386, -0.9273, 1.0000, 1.2906, -0.1360\}$ by a free parameter and use γ_{X_2} to determine an optimal value. For example, replacing the four entries which are

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Appendix 1

We study the eigenvalue structure of $M(r,s)$. Let $\{\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_{\min(r,s)} \geq 0\}$ be the non-negative singular values of $X_1'X_1^{-1/2}(X_1'X_2)X_2'X_2^{-1/2}$.

As with the canonical correlation coefficients Eaton (1983), write the off-diagonal rectangular array $B_{r \times s}$ of R as $P\Lambda Q'$ with P and Q orthogonal matrices and $\Lambda_{r \times s}$ the rectangular diagonal matrix with the non-negative singular values down the diagonal. Set

$$L = \begin{bmatrix} P_{r \times r} & 0_{r \times s} \\ 0_{s \times r} & Q_{s \times s} \end{bmatrix}$$

For notational convenience, we assume $r \leq s$. The matrix L is orthogonal and transforms $R \rightarrow L'RL$ into diagonal matrices:

$$(A1) \quad \begin{bmatrix} \Lambda_{r \times s} & 0_{s \times r} \end{bmatrix} = \begin{bmatrix} S_{V_{r \times r}} & 0_{r \times (s-r)} \end{bmatrix} \begin{bmatrix} S_{V_{r \times r}} & 0_{r \times (s-r)} \end{bmatrix}' \begin{bmatrix} I_s \end{bmatrix}$$

with $\Lambda_{r \times s} = \begin{bmatrix} S_{V_{r \times r}} & 0_{r \times (s-r)} \end{bmatrix}$ where $S_{V_{r \times r}}$ is the diagonal matrix of the non-negative singular values. Since L is orthogonal, this transformation has not changed the eigenvalues. To compute the determinant of R , convert the matrix in Equation 6 into an upper diagonal matrix by Gauss Elimination on $\Lambda_{s \times r}'$. This changes r of the 1's on the diagonal

The singular values of R are the square roots of the eigenvalues of $R'R$.

(A2)  $\lambda_1(X_2'X_1)$.

If the trace of R is zero, note that

$\begin{bmatrix} \Lambda_{r \times s} & 0_{s \times r} \end{bmatrix}^{-1} \begin{bmatrix} I_s \end{bmatrix} = \begin{bmatrix} \Lambda_{r \times s}^{-1} & 0_{r \times (s-r)} \end{bmatrix}$

Table A1. The lower order matrix for the CCD with center run with $a=2$, $n=9$ and the lower order matrix for the factorial design with center run $n=9$



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Table A2. The lower order matrix for the hybrid (H310) design of Roquemore ([1976](#)) with center run, $n=11$



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Table A3. The lower order matrix for the hybrid (H311B) design of Roquemore ([1976](#)) with center run, $n=11$



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Table A6. The lower order matrix for the Box and Draper ([1974](#)) minimal design (BDD) with center run, $n=11$



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Table A7. The Lower order matrix for the small composite design of Hartley ([1959](#)) (SCD) for $\alpha=1.732$ with center run, $n=11$



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