

# Supplement to “Bayesian $D$ -Optimal Design of Experiments with Quantitative and Qualitative Responses”

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## S1 Proofs and Derivations

### Proof of (3.3)

*Proof.*

$$\begin{aligned}
 \Psi(\mathbf{X}|\mu_0, \sigma^2) &= \int p(\mathbf{y}, \mathbf{z}|\mu_0, \sigma^2) \int \log \left( p(\boldsymbol{\beta}^{(1)}, \boldsymbol{\beta}^{(2)}, \boldsymbol{\eta}|\mathbf{y}, \mathbf{z}, \mu_0, \sigma^2) \right) \\
 &\quad p(\boldsymbol{\beta}^{(1)}, \boldsymbol{\beta}^{(2)}, \boldsymbol{\eta}|\mathbf{y}, \mathbf{z}, \mu_0, \sigma^2) d\boldsymbol{\beta}^{(1)} d\boldsymbol{\beta}^{(2)} d\boldsymbol{\eta} d\mathbf{y} d\mathbf{z} \\
 &= \int p(\mathbf{y}, \mathbf{z}|\mu_0, \sigma^2) \left\{ \int \log(p(\boldsymbol{\eta}|\mathbf{z})) p(\boldsymbol{\eta}|\mathbf{z}) d\boldsymbol{\eta} \right. \\
 &\quad \left. + \sum_{i=1}^2 \int \log \left( p(\boldsymbol{\beta}^{(i)}|\mathbf{y}, \mathbf{z}, \mu_0, \sigma^2) \right) p(\boldsymbol{\beta}^{(i)}|\mathbf{y}, \mathbf{z}, \mu_0, \sigma^2) d\boldsymbol{\beta}^{(i)} \right\} d\mathbf{y} d\mathbf{z} \\
 &= \int p(\mathbf{y}, \mathbf{z}|\mu_0, \sigma^2) \left\{ \int \log(p(\boldsymbol{\eta}|\mathbf{z})) p(\boldsymbol{\eta}|\mathbf{z}) d\boldsymbol{\eta} \right. \\
 &\quad \left. - \frac{1}{2} \sum_{i=1}^2 \log \det \{ \sigma^{-2} (\mathbf{F}' \mathbf{V}_i \mathbf{F})^{-1} \} - n \log(2\pi) - n \right\} d\mathbf{y} d\mathbf{z} \\
 &= \int \log(p(\boldsymbol{\eta}|\mathbf{z})) p(\boldsymbol{\eta}|\mathbf{z}) p(\mathbf{z}) d\boldsymbol{\eta} d\mathbf{z} \\
 &\quad - \frac{1}{2} \sum_{i=1}^2 \int \log \det \{ \sigma^{-2} (\mathbf{F}' \mathbf{V}_i \mathbf{F})^{-1} \} p(\mathbf{z}) d\mathbf{z} + \text{constant} \\
 &= \int \log(p(\boldsymbol{\eta}|\mathbf{z})) p(\mathbf{z}, \boldsymbol{\eta}) d\boldsymbol{\eta} d\mathbf{z} \\
 &\quad + \frac{1}{2} \sum_{i=1}^2 \int \log \det \{ (\mathbf{F}' \mathbf{V}_i \mathbf{F}) \} p(\mathbf{z}|\boldsymbol{\eta}) p(\boldsymbol{\eta}) d\mathbf{z} d\boldsymbol{\eta} + \text{constant}.
 \end{aligned}$$

Write the integration into the form of expectation,

$$\begin{aligned}
 \Psi(\mathbf{X}|\mu_0, \sigma^2) &= \mathbb{E}_{\mathbf{z}, \boldsymbol{\eta}} \{ \log(p(\boldsymbol{\eta}|\mathbf{z})) \} \\
 &\quad + \frac{1}{2} \sum_{i=1}^2 \mathbb{E}_{\boldsymbol{\eta}} \mathbb{E}_{\mathbf{z}|\boldsymbol{\eta}} \{ \log \det(\mathbf{F}' \mathbf{V}_i \mathbf{F}) \} + \text{constant}.
 \end{aligned}$$

□

### Proof of Theorem 1

*Proof.* To show (3.6), we just need to show that  $\mathbb{E}_{\mathbf{z}|\boldsymbol{\eta}}(\log \det(\mathbf{F}'\mathbf{V}_i\mathbf{F})) \leq \log \det(\mathbf{F}'\mathbf{W}_i\mathbf{F}')$  for  $i = 1, 2$ .

First we need to show that  $\log \det(\mathbf{F}'\mathbf{A}\mathbf{F}) = \log \det(\sum_{i=1}^n a_i \mathbf{f}(\mathbf{x}_i)\mathbf{f}(\mathbf{x}_i)')$  with  $\mathbf{A} = \text{diag}\{a_1, \dots, a_n\}$  is a concave function of  $\mathbf{a} = (a_1, \dots, a_n)'$  for  $\mathbf{a} \in [0, 1]^n$ . Denote  $\mathbf{B} = \text{diag}\{b_1, \dots, b_n\}$  for  $\mathbf{b} = (b_1, \dots, b_n)' \in [0, 1]^n$ . We assume that  $\mathbf{F}'\mathbf{A}\mathbf{F}$  is nonsingular, thus  $\mathbf{F}'\mathbf{A}\mathbf{F}$  is positive definite. For any scalar value of  $t$ , define function  $g(t)$

$$\begin{aligned} g(t) &= \log \det(\mathbf{F}'\mathbf{A}\mathbf{F} + \mathbf{F}'(t\mathbf{B})\mathbf{F}) \\ &= \log \det(\mathbf{F}'\mathbf{A}\mathbf{F}) + \log \det(\mathbf{I}_q + t(\mathbf{F}'\mathbf{A}\mathbf{F})^{-1/2}(\mathbf{F}'\mathbf{B}\mathbf{F})(\mathbf{F}'\mathbf{A}\mathbf{F})^{-1/2}) \\ &= \log \det(\mathbf{F}'\mathbf{A}\mathbf{F}) + \sum_{i=1}^q \log(1 + t\lambda_i), \end{aligned}$$

where  $\lambda_i$ 's are the eigenvalues of the positive definite matrix  $(\mathbf{F}'\mathbf{A}\mathbf{F})^{-1/2}(\mathbf{F}'\mathbf{B}\mathbf{F})(\mathbf{F}'\mathbf{A}\mathbf{F})^{-1/2}$ . Thus  $g(t)$  is a concave function in  $t$  for any choice of  $\mathbf{a}$ , which is the sufficient and necessary condition that  $\log \det(\mathbf{F}'\mathbf{A}\mathbf{F})$  is a concave function of  $\mathbf{a}$ . According to Jensen's inequality, if  $\pi(\mathbf{x}_i, \boldsymbol{\eta}) \in (0, 1)$  for  $i = 1, \dots, n$ , then

$$\begin{aligned} \mathbb{E}_{\mathbf{z}|\boldsymbol{\eta}}(\log \det(\mathbf{F}'\mathbf{V}_1\mathbf{F})) &\leq \log \det\left(\sum_{i=1}^n \mathbb{E}(Z_i|\boldsymbol{\eta})\mathbf{f}(\mathbf{x}_i)\mathbf{f}(\mathbf{x}_i)'\right) \\ &= \log \det\left(\sum_{i=1}^n \pi(\mathbf{x}_i, \boldsymbol{\eta})\mathbf{f}(\mathbf{x}_i)\mathbf{f}(\mathbf{x}_i)'\right), \\ \mathbb{E}_{\mathbf{z}|\boldsymbol{\eta}}(\log \det(\mathbf{F}'\mathbf{V}_2\mathbf{F})) &\leq \log \det\left(\sum_{i=1}^n \mathbb{E}((1 - Z_i)|\boldsymbol{\eta})\mathbf{f}(\mathbf{x}_i)\mathbf{f}(\mathbf{x}_i)'\right) \\ &= \log \det\left(\sum_{i=1}^n (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))\mathbf{f}(\mathbf{x}_i)\mathbf{f}(\mathbf{x}_i)'\right). \end{aligned}$$

So we have proved (3.6). □

### Proof of Proposition 1

*Proof.*

$$m = \sum_{i=1}^m I\left(0 < \sum_{j=1}^{n_i} Z_{ij} < n_i\right) + \sum_{i=1}^m I\left(\sum_{j=1}^{n_i} Z_{ij} = 0\right) + \sum_{i=1}^m I\left(\sum_{j=1}^{n_i} Z_{ij} = n_i\right) \geq q$$

If  $m = q$ , (3.7) is equivalent to  $I\left(0 < \sum_{j=1}^{n_i} Z_{ij} < n_i\right) = 1$  for  $i = 1, 2, \dots, m$ . A sufficient condition

for any  $\Pr\left(0 < \sum_{j=1}^{n_i} Z_{ij} < n_i\right) \geq \kappa$  can be derived as follows.

$$\begin{aligned} \Pr\left(0 < \sum_{j=1}^{n_i} Z_{ij} < n_i\right) &= 1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})^{n_i} - (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))^{n_i} \geq \kappa \\ \iff \pi(\mathbf{x}_i, \boldsymbol{\eta})^{n_i} + (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))^{n_i} &\leq 1 - \kappa. \end{aligned}$$

Next develop an upper bound for  $\pi(\mathbf{x}_i, \boldsymbol{\eta})^{n_i} + (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))^{n_i}$ . If  $\pi(\mathbf{x}_i, \boldsymbol{\eta}) \geq 1/2$ , denote  $a = (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))/\pi(\mathbf{x}_i, \boldsymbol{\eta})$  and  $a \leq 1$ . Then

$$\pi(\mathbf{x}_i, \boldsymbol{\eta})^{n_i} + (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))^{n_i} = \frac{1 + a^{n_i}}{(1 + a)^{n_i}} \leq \frac{1 + a}{(1 + a)^{n_i}}.$$

If

$$\frac{1 + a}{(1 + a)^{n_i}} \leq 1 - \kappa \iff n_i \geq 1 + \frac{\log(1 - \kappa)}{\log \pi(\mathbf{x}_i, \boldsymbol{\eta})},$$

then  $\pi(\mathbf{x}_i, \boldsymbol{\eta})^{n_i} + (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))^{n_i} \leq 1 - \kappa$ . If  $\pi(\mathbf{x}_i, \boldsymbol{\eta}) < 1/2$ , denote  $a = \pi(\mathbf{x}_i, \boldsymbol{\eta})/(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))$  and  $a < 1$ . Then

$$\pi(\mathbf{x}_i, \boldsymbol{\eta})^{n_i} + (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))^{n_i} = \frac{1 + a^{n_i}}{(1 + a)^{n_i}} < \frac{1 + a}{(1 + a)^{n_i}}.$$

The sufficient condition becomes

$$\frac{1 + a}{(1 + a)^{n_i}} \leq 1 - \kappa \iff n_i \geq 1 + \frac{\log(1 - \kappa)}{\log(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))}.$$

Combining the two cases, the sufficient condition on  $n_i$  for  $i = 1, \dots, m$  is (3.8). It is known that

$$2(\pi(\mathbf{x}_i, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))^{n_i/2}) \leq \pi(\mathbf{x}_i, \boldsymbol{\eta})^{n_i} + (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))^{n_i} \leq 1 - \kappa.$$

The necessary condition is

$$2(\pi(\mathbf{x}_i, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))^{n_i/2}) \leq 1 - \kappa \iff n_i \geq \frac{2 \log\left(\frac{1 - \kappa}{2}\right)}{\log \pi(\mathbf{x}_i, \boldsymbol{\eta}) + \log(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))}.$$

□

## Proof of Proposition 2

*Proof.* If  $m > q$ , (3.7) is equivalent to

$$\sum_{i=1}^m I\left(\sum_{j=1}^{n_i} Z_{ij} = 0\right) \leq m - q, \text{ and } \sum_{i=1}^m I\left(\sum_{j=1}^{n_i} Z_{ij} = n_i\right) \leq m - q.$$

For the two inequalities to hold with large probability,

$$\sum_{i=1}^m \mathbb{E} \left\{ I \left( \sum_{j=1}^{n_i} Z_{ij} = 0 \right) \right\} = \sum_{i=1}^m (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))^{n_i} \leq m - q, \quad (1)$$

$$\text{and } \sum_{i=1}^m \mathbb{E} \left\{ I \left( \sum_{j=1}^{n_i} Z_{ij} = n_i \right) \right\} = \sum_{i=1}^m \pi(\mathbf{x}_i, \boldsymbol{\eta})^{n_i} \leq m - q. \quad (2)$$

It is known that

$$m \left( \prod_{i=1}^m (1 - \pi_{\max})^{n_i} \right)^{1/m} \leq \sum_{i=1}^m (1 - \pi_{\max})^{n_i} \leq \sum_{i=1}^m (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))^{n_i} \leq \sum_{i=1}^m (1 - \pi_{\min})^{n_i} \leq m(1 - \pi_{\min})^{n_0}.$$

Thus one sufficient condition for (1) is

$$m(1 - \pi_{\min})^{n_0} \leq m - q \iff n_0 \geq \frac{\log(1 - q/m)}{\log(1 - \pi_{\min})}.$$

One necessary condition for (1) is

$$m \left( \prod_{i=1}^m (1 - \pi_{\max})^{n_i} \right)^{1/m} \leq m - q \iff \sum_{i=1}^m n_i \geq m \frac{\log(1 - q/m)}{\log(1 - \pi_{\max})}.$$

Similarly,

$$m \left( \prod_{i=1}^m \pi_{\min}^{n_i} \right)^{1/m} \leq \sum_{i=1}^m \pi_{\min}^{n_i} \leq \sum_{i=1}^m \pi(\mathbf{x}_i, \boldsymbol{\eta})^{n_i} \leq \sum_{i=1}^m \pi_{\max}^{n_i} \leq m \cdot \pi_{\max}^{n_0}.$$

Thus one sufficient condition for (2) is

$$m \cdot \pi_{\max}^{n_0} \leq m - q \iff n_0 \geq \frac{\log(1 - q/m)}{\log \pi_{\max}}.$$

One necessary condition for (2) is

$$m \left( \prod_{i=1}^m \pi_{\min}^{n_i} \right)^{1/m} \leq m - q \iff \sum_{i=1}^m n_i \geq m \frac{\log(1 - q/m)}{\log \pi_{\min}}.$$

Thus the sufficient condition for (1) and (2) derived here is

$$n_0 \geq \max \left\{ 1, \frac{\log(1 - q/m)}{\log(1 - \pi_{\min})}, \frac{\log(1 - q/m)}{\log \pi_{\max}} \right\},$$

or equivalently,

$$\sum_{i=1}^m n_i \geq m \cdot n_0 \geq m \cdot \max \left\{ 1, \frac{\log(1 - q/m)}{\log(1 - \pi_{\min})}, \frac{\log(1 - q/m)}{\log \pi_{\max}} \right\}.$$

The necessary condition for (1) and (2) derived here is

$$\sum_{i=1}^n n_i \geq m \cdot \max \left\{ 1, \frac{\log(1 - q/m)}{\log(1 - \pi_{\max})}, \frac{\log(1 - q/m)}{\log \pi_{\min}} \right\}.$$

It is easy to see that this lower bound in the necessary condition is smaller than the one in the sufficient condition,

$$\sum_{i=1}^m n_i \geq m \cdot n_0 \geq m \cdot \max \left\{ 1, \frac{\log(1 - q/m)}{\log(1 - \pi_{\min})}, \frac{\log(1 - q/m)}{\log \pi_{\max}} \right\}.$$

□

### Proof of Theorem 2

*Proof.* We only need to show that  $\log \det(\mathbf{F}'\mathbf{A}\mathbf{F} + \rho\mathbf{R}_i^{-1}) = \log \det(\sum_{i=1}^n a_i \mathbf{f}(\mathbf{x}_i)\mathbf{f}(\mathbf{x}_i)' + \rho\mathbf{R}_i^{-1})$  with  $\mathbf{A} = \text{diag}\{a_1, \dots, a_n\}$  is a concave function of  $\mathbf{a} = (a_1, \dots, a_n)'$  for  $\mathbf{a} \in [0, 1]^n$ . Denote  $\mathbf{B} = \text{diag}\{b_1, \dots, b_n\}$  for  $\mathbf{b} = (b_1, \dots, b_n)' \in [0, 1]^n$  and  $\mathbf{K} = \mathbf{F}'\mathbf{A}\mathbf{F} + \rho\mathbf{R}_i^{-1}$ . Define  $g(t)$  as follows.

$$\begin{aligned} g(t) &= \log \det (\mathbf{F}'\mathbf{A}\mathbf{F} + \rho\mathbf{R}_i^{-1} + \mathbf{F}'(t\mathbf{B})\mathbf{F} + \rho\mathbf{R}_i^{-1}) \\ &= \log \det(\mathbf{F}'\mathbf{A}\mathbf{F} + \rho\mathbf{R}_i^{-1}) \\ &\quad + \log \det(\mathbf{I}_q + (\mathbf{F}'\mathbf{A}\mathbf{F} + \rho\mathbf{R}_i^{-1})^{-1/2}(\mathbf{F}'t\mathbf{B}\mathbf{F} + \rho\mathbf{R}_i^{-1})(\mathbf{F}'\mathbf{A}\mathbf{F} + \rho\mathbf{R}_i^{-1})^{-1/2}) \\ &= \log \det(\mathbf{F}'\mathbf{A}\mathbf{F} + \rho\mathbf{R}_i^{-1}) \\ &\quad + \log \det(\mathbf{I}_q + t\mathbf{K}^{-1/2}\mathbf{F}'\mathbf{B}\mathbf{F}\mathbf{K}^{-1/2} + \rho\mathbf{K}^{-1/2}\mathbf{R}_i^{-1}\mathbf{K}^{-1/2}) \\ &= \log \det(\mathbf{F}'\mathbf{A}\mathbf{F} + \rho\mathbf{R}_i^{-1}) + \log \det(\mathbf{I}_q + \rho\mathbf{K}^{-1/2}\mathbf{R}_i^{-1}\mathbf{K}^{-1/2}) + \sum_{i=1}^q \log(1 + t\lambda_i), \end{aligned}$$

where  $\lambda_i$ 's are the eigenvalues of

$$(\mathbf{I}_q + \rho\mathbf{K}^{-1/2}\mathbf{R}_i^{-1}\mathbf{K}^{-1/2})^{-1/2}\mathbf{K}^{-1/2}\mathbf{F}'\mathbf{B}\mathbf{F}\mathbf{K}^{-1/2}(\mathbf{I}_q + \rho\mathbf{K}^{-1/2}\mathbf{R}_i^{-1}\mathbf{K}^{-1/2})^{-1/2}.$$

Therefore,  $\lambda_i \geq 0$  for  $i = 1, \dots, q$ . Thus  $g(t)$  is a concave function in  $t$  for any choice of  $\mathbf{a} \in [0, 1]^n$ , which is the sufficient and necessary condition for  $\log \det(\mathbf{F}'\mathbf{A}\mathbf{F} + \rho\mathbf{R}_i^{-1})$  to be a concave function of  $\mathbf{a}$ . □

### Proof of the deletion function (5.1)

*Proof.* Denote  $\mathbf{F}_{-i}$  as the model matrix for  $\mathbf{X}_{-i}$ , which is the design matrix without the  $i$ th design point, and  $\mathbf{W}_{0,-i}$ ,  $\mathbf{W}_{1,-i}$ , and  $\mathbf{W}_{2,-i}$  the weight matrices accordingly. According to the properties of matrix determinants, we can show the following.

$$\begin{aligned} \det(\mathbf{F}'_{-i}\mathbf{W}_{0,-i}\mathbf{F}_{-i}) &= \det \left( \sum_{j \neq i} \pi(\mathbf{x}_j, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_j, \boldsymbol{\eta}))\mathbf{f}(\mathbf{x}_j)\mathbf{f}(\mathbf{x}_j)' \right) \\ &= \det(\mathbf{F}'\mathbf{W}_0\mathbf{F} - \pi(\mathbf{x}_i, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))\mathbf{f}(\mathbf{x}_i)\mathbf{f}(\mathbf{x}_i)') \\ &= \det(\mathbf{F}'\mathbf{W}_0\mathbf{F}) [1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))\mathbf{f}(\mathbf{x}_i)'(\mathbf{F}'\mathbf{W}_0\mathbf{F})^{-1}\mathbf{f}(\mathbf{x}_i)] \\ &= \det(\mathbf{F}'\mathbf{W}_0\mathbf{F}) [1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))v_0(\mathbf{x}_i)]. \end{aligned}$$

$$\begin{aligned}
& \det(\mathbf{F}'_{-i}\mathbf{W}_{1,-i}\mathbf{F}_{-i} + \rho\mathbf{R}^{-1}) \\
&= \det\left(\sum_{j \neq i} \pi(\mathbf{x}_j, \boldsymbol{\eta})\mathbf{f}(\mathbf{x}_j)\mathbf{f}(\mathbf{x}_j)' + \rho\mathbf{R}^{-1}\right) \\
&= \det(\mathbf{F}'\mathbf{W}_1\mathbf{F} + \rho\mathbf{R}^{-1} - \pi(\mathbf{x}_i, \boldsymbol{\eta})\mathbf{f}(\mathbf{x}_i)\mathbf{f}(\mathbf{x}_i)') \\
&= \det(\mathbf{F}'\mathbf{W}_1\mathbf{F} + \rho\mathbf{R}^{-1}) [1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})\mathbf{f}(\mathbf{x}_i)'(\mathbf{F}'\mathbf{W}_1\mathbf{F} + \rho\mathbf{R}^{-1})^{-1}\mathbf{f}(\mathbf{x}_i)] \\
&= \det(\mathbf{F}'\mathbf{W}_1\mathbf{F} + \rho\mathbf{R}^{-1}) [1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})v_1(\mathbf{x}_i)].
\end{aligned}$$

Similarly,

$$\det(\mathbf{F}'_{-i}\mathbf{W}_{2,-i}\mathbf{F}_{-i} + \rho\mathbf{R}_2^{-1}) = \det(\mathbf{F}'\mathbf{W}_2\mathbf{F} + \rho\mathbf{R}^{-1}) [1 - (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))v_2(\mathbf{x}_i)].$$

The deletion function (5.1) is then obtained.  $\square$

### Shortcut formulas for $\mathbf{M}_{i,-j}$ .

*Proof.* Denote  $\mathbf{M}_{i,-j}$  for  $i = 0, 1, 2$  as the updated  $\mathbf{M}_i$  when the  $j$ th design point is removed. The following shortcut formulas are used in constructing the initial design.

$$\mathbf{M}_{i,-j} = \mathbf{M}_i + \left[ \frac{\pi(\mathbf{x}_j, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_j, \boldsymbol{\eta}))}{1 - \pi(\mathbf{x}_j, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_j, \boldsymbol{\eta}))v_0(\mathbf{x}_j)} \right] \mathbf{M}_i \mathbf{f}(\mathbf{x}_j)\mathbf{f}(\mathbf{x}_j)' \mathbf{M}_i, \quad \text{for } i = 0, 1, 2.$$

$\square$

### Proof of $\Delta(\mathbf{x}, \mathbf{x}_i)$ in (5.2).

*Proof.* Denote  $\mathbf{F}^*$  as the updated model matrix for updated design  $\mathbf{X}^*$ , and  $\mathbf{W}_i^*$  for  $i = 0, 1, 2$  as the updated weight matrices accordingly. Let

$$\mathbf{G}_0 = [\sqrt{\pi(\mathbf{x}, \boldsymbol{\eta})(1 - \pi(\mathbf{x}, \boldsymbol{\eta}))}\mathbf{f}(\mathbf{x}), i\sqrt{\pi(\mathbf{x}_i, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))}\mathbf{f}(\mathbf{x}_i)],$$

where  $i = \sqrt{-1}$ .

$$\begin{aligned}
\det(\mathbf{F}^{*\prime}\mathbf{W}_0^*\mathbf{F}^*) &= \det\left(\sum_{j \neq i} \pi(\mathbf{x}_j, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_j, \boldsymbol{\eta}))\mathbf{f}(\mathbf{x}_j)\mathbf{f}(\mathbf{x}_j)'\right. \\
&\quad \left. - \pi(\mathbf{x}_i, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))\mathbf{f}(\mathbf{x}_i)\mathbf{f}(\mathbf{x}_i)' + \pi(\mathbf{x}, \boldsymbol{\eta})(1 - \pi(\mathbf{x}, \boldsymbol{\eta}))\mathbf{f}(\mathbf{x})\mathbf{f}(\mathbf{x})'\right) \\
&= \det(\mathbf{F}'\mathbf{W}_0\mathbf{F} + \mathbf{G}_0\mathbf{G}_0') \\
&= \det(\mathbf{F}'\mathbf{W}_0\mathbf{F}) \det(\mathbf{I}_2 + \mathbf{G}_0'\mathbf{M}_0\mathbf{G}_0).
\end{aligned}$$

It can be computed that

$$\det(\mathbf{I}_2 + \mathbf{G}_0'\mathbf{M}_0\mathbf{G}_0) = \Delta_0(\mathbf{x}, \mathbf{x}_i),$$

where  $\Delta_0(\mathbf{x}, \mathbf{x}_i)$  is

$$\begin{aligned}
\Delta_0(\mathbf{x}, \mathbf{x}_i) &= [1 + \pi(\mathbf{x}, \boldsymbol{\eta})(1 - \pi(\mathbf{x}, \boldsymbol{\eta}))v_0(\mathbf{x})] [1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))v_0(\mathbf{x}_i)] \\
&\quad + \pi(\mathbf{x}, \boldsymbol{\eta})(1 - \pi(\mathbf{x}, \boldsymbol{\eta}))\pi(\mathbf{x}_i, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))v_0(\mathbf{x}, \mathbf{x}_i)^2.
\end{aligned}$$

Similarly, define

$$\begin{aligned}\mathbf{G}_1 &= [\sqrt{\pi(\mathbf{x}, \boldsymbol{\eta})} \mathbf{f}(\mathbf{x}), i\sqrt{\pi(\mathbf{x}_i, \boldsymbol{\eta})} \mathbf{f}(\mathbf{x}_i)] \quad \text{and} \\ \mathbf{G}_2 &= [\sqrt{(1 - \pi(\mathbf{x}, \boldsymbol{\eta}))} \mathbf{f}(\mathbf{x}), i\sqrt{(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))} \mathbf{f}(\mathbf{x}_i)].\end{aligned}$$

Following a similar derivation,

$$\begin{aligned}\det(\mathbf{F}^{*\prime} \mathbf{W}_1^* \mathbf{F}^* + \rho \mathbf{R}) &= \det(\mathbf{F}' \mathbf{W}_1 \mathbf{F} + \rho \mathbf{R}) \Delta_1(\mathbf{x}, \mathbf{x}_i), \\ \det(\mathbf{F}^{*\prime} \mathbf{W}_2^* \mathbf{F}^* + \rho \mathbf{R}) &= \det(\mathbf{F}' \mathbf{W}_2 \mathbf{F} + \rho \mathbf{R}) \Delta_2(\mathbf{x}, \mathbf{x}_i),\end{aligned}$$

where  $\Delta_1(\mathbf{x}, \mathbf{x}_i)$  and  $\Delta_2(\mathbf{x}, \mathbf{x}_i)$  are

$$\begin{aligned}\Delta_1(\mathbf{x}, \mathbf{x}_i) &= [1 + \pi(\mathbf{x}, \boldsymbol{\eta})v_1(\mathbf{x})] [1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})v_1(\mathbf{x}_i)] + \pi(\mathbf{x}, \boldsymbol{\eta})\pi(\mathbf{x}_i, \boldsymbol{\eta})v_1(\mathbf{x}, \mathbf{x}_i)^2, \\ \Delta_2(\mathbf{x}, \mathbf{x}_i) &= [1 + (1 - \pi(\mathbf{x}, \boldsymbol{\eta}))v_2(\mathbf{x})] [1 - (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))v_2(\mathbf{x}_i)] \\ &\quad + (1 - \pi(\mathbf{x}, \boldsymbol{\eta}))(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))v_2(\mathbf{x}, \mathbf{x}_i)^2.\end{aligned}$$

Thus  $\Delta(\mathbf{x}, \mathbf{x}_i)$  is computed as in (5.2). □

**Proof of update formulas  $M_i^*$  for  $i = 0, 1, 2$**

*Proof.* Use the same notation of  $\mathbf{G}_i$  for  $i = 0, 1, 2$  as in the previous proof. Define the functions

$$\begin{aligned}\mathbf{S}_i(\mathbf{x}) &= \mathbf{M}_i \mathbf{f}(\mathbf{x}) \mathbf{f}(\mathbf{x})' \mathbf{M}_i, \quad \text{for } i = 0, 1, 2, \\ \mathbf{S}_i(\mathbf{x}_1, \mathbf{x}_2) &= \mathbf{M}_i \mathbf{f}(\mathbf{x}_1) \mathbf{f}(\mathbf{x}_2)' \mathbf{M}_i, \quad \text{for } i = 0, 1, 2.\end{aligned}$$

It is straightforward to derive

$$\begin{aligned}\mathbf{M}_0^* &= (\mathbf{F}' \mathbf{W}_0 \mathbf{F} + \mathbf{G}_0 \mathbf{G}_0')^{-1} \\ &= \mathbf{M}_0 - \mathbf{M}_0 \mathbf{G}_0 (\mathbf{I}_2 + \mathbf{G}_0' \mathbf{M}_0 \mathbf{G}_0)^{-1} \mathbf{G}_0' \mathbf{M}_0.\end{aligned}$$

For simpler notation, denote  $a(\mathbf{x}) = \pi(\mathbf{x}, \boldsymbol{\eta})(1 - \pi(\mathbf{x}, \boldsymbol{\eta}))$  and  $a(\mathbf{x}_i) = \pi(\mathbf{x}_i, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}))$ .

$$\begin{aligned}& (\mathbf{I}_2 + \mathbf{G}_0' \mathbf{M}_0 \mathbf{G}_0)^{-1} \\ &= \begin{pmatrix} 1 + a(\mathbf{x})v_0(\mathbf{x}), & i\sqrt{a(\mathbf{x})a(\mathbf{x}_i)}v_0(\mathbf{x}, \mathbf{x}_i) \\ i\sqrt{a(\mathbf{x})a(\mathbf{x}_i)}v_0(\mathbf{x}, \mathbf{x}_i), & 1 - a(\mathbf{x}_i)v_0(\mathbf{x}_i) \end{pmatrix}^{-1} \\ &= \frac{1}{\Delta_0(\mathbf{x}, \mathbf{x}_i)} \begin{pmatrix} 1 - a(\mathbf{x}_i)v_0(\mathbf{x}_i), & -i\sqrt{a(\mathbf{x})a(\mathbf{x}_i)}v_0(\mathbf{x}, \mathbf{x}_i) \\ -i\sqrt{a(\mathbf{x})a(\mathbf{x}_i)}v_0(\mathbf{x}, \mathbf{x}_i), & 1 + a(\mathbf{x})v_0(\mathbf{x}) \end{pmatrix}.\end{aligned}$$

$$\begin{aligned}
M_0^* &= M_0 - \frac{1}{\Delta_0(\mathbf{x}, \mathbf{x}_i)} M_0 \left[ \sqrt{a(\mathbf{x})} v_0(\mathbf{x}), i \sqrt{a(\mathbf{x}_i)} v_0(\mathbf{x}_i) \right] \\
&\times \begin{pmatrix} 1 - a(\mathbf{x}_i) v_0(\mathbf{x}_i), & -i \sqrt{a(\mathbf{x}) a(\mathbf{x}_i)} v_0(\mathbf{x}, \mathbf{x}_i) \\ -i \sqrt{a(\mathbf{x}) a(\mathbf{x}_i)} v_0(\mathbf{x}, \mathbf{x}_i), & 1 + a(\mathbf{x}) v_0(\mathbf{x}) \end{pmatrix} \times \begin{bmatrix} \sqrt{a(\mathbf{x})} \mathbf{f}'(\mathbf{x})' \\ i \sqrt{a(\mathbf{x}_i)} \mathbf{f}'(\mathbf{x}_i)' \end{bmatrix} M_0. \\
&= M_0 - \frac{1}{\Delta_0(\mathbf{x}, \mathbf{x}_i)} \{ \pi(\mathbf{x}, \boldsymbol{\eta})(1 - \pi(\mathbf{x}, \boldsymbol{\eta})) [1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})) v_0(\mathbf{x}_i)] \mathbf{S}_0(\mathbf{x}) \\
&\quad - \pi(\mathbf{x}_i, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})) [1 + \pi(\mathbf{x}, \boldsymbol{\eta})(1 - \pi(\mathbf{x}, \boldsymbol{\eta})) v_0(\mathbf{x})] \mathbf{S}_0(\mathbf{x}_i) \\
&\quad + \pi(\mathbf{x}_i, \boldsymbol{\eta})(1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})) \pi(\mathbf{x}, \boldsymbol{\eta})(1 - \pi(\mathbf{x}, \boldsymbol{\eta})) v_0(\mathbf{x}, \mathbf{x}_i) [\mathbf{S}_0(\mathbf{x}, \mathbf{x}_i) + \mathbf{S}_0(\mathbf{x}_i, \mathbf{x})] \}
\end{aligned}$$

Update formulas for  $M_1^*$  and  $M_2^*$  can be derived similarly as follows.

$$\begin{aligned}
M_1^* &= M_1 - \frac{1}{\Delta_1(\mathbf{x}, \mathbf{x}_i)} \{ \pi(\mathbf{x}, \boldsymbol{\eta}) [1 - \pi(\mathbf{x}_i, \boldsymbol{\eta}) v_1(\mathbf{x}_i)] \mathbf{S}_1(\mathbf{x}) - \pi(\mathbf{x}_i, \boldsymbol{\eta}) [1 + \pi(\mathbf{x}, \boldsymbol{\eta}) v_1(\mathbf{x})] \mathbf{S}_1(\mathbf{x}_i) \\
&\quad + \pi(\mathbf{x}_i, \boldsymbol{\eta}) \pi(\mathbf{x}, \boldsymbol{\eta}) v_1(\mathbf{x}, \mathbf{x}_i) [\mathbf{S}_1(\mathbf{x}, \mathbf{x}_i) + \mathbf{S}_1(\mathbf{x}_i, \mathbf{x})] \}, \\
M_2^* &= M_2 - \frac{1}{\Delta_2(\mathbf{x}, \mathbf{x}_i)} \{ (1 - \pi(\mathbf{x}, \boldsymbol{\eta})) [1 - (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})) v_2(\mathbf{x}_i)] \mathbf{S}_2(\mathbf{x}) \\
&\quad - (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})) [1 + (1 - \pi(\mathbf{x}, \boldsymbol{\eta})) v_2(\mathbf{x})] \mathbf{S}_2(\mathbf{x}_i) \\
&\quad + (1 - \pi(\mathbf{x}_i, \boldsymbol{\eta})) (1 - \pi(\mathbf{x}, \boldsymbol{\eta})) v_2(\mathbf{x}, \mathbf{x}_i) [\mathbf{S}_2(\mathbf{x}, \mathbf{x}_i) + \mathbf{S}_2(\mathbf{x}_i, \mathbf{x})] \}.
\end{aligned}$$

□

## S2 Table



Table S1: Local Bayesian  $D$ -optimal Designs for  $\rho = 0$  and 0.3 and other three alternative designs. The values in columns 7-11 are frequencies.

| Point | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | $D_{QQ} \rho = 0$ | $D_{QQ} \rho = 0.3$ | $D_G$ | $D_L$ | $D_n$ |
|-------|-------|-------|-------|-------|-------|-------------------|---------------------|-------|-------|-------|
| 1     | -1    | -1    | -1    | -1    | -1    | 1                 | 2                   | 1     | 1     | 2     |
| 2     | 1     | -1    | -1    | -1    | -1    | 1                 | 1                   | 2     | 1     | 1     |
| 3     | -1    | 1     | -1    | -1    | -1    | 1                 | 1                   | 2     | 1     | 1     |
| 4     | 1     | 1     | -1    | -1    | -1    | 2                 | 1                   | 2     | 1     | 2     |
| 5     | -1    | -1    | 1     | -1    | -1    | 1                 | 0                   | 2     | 1     | 1     |
| 6     | 1     | -1    | 1     | -1    | -1    | 1                 | 1                   | 0     | 1     | 1     |
| 7     | -1    | 1     | 1     | -1    | -1    | 2                 | 2                   | 1     | 1     | 2     |
| 8     | 1     | 1     | 1     | -1    | -1    | 1                 | 2                   | 1     | 1     | 1     |
| 9     | -1    | -1    | -1    | 0     | -1    | 2                 | 2                   | 1     | 1     | 1     |
| 10    | 1     | -1    | -1    | 0     | -1    | 0                 | 0                   | 1     | 1     | 1     |
| 11    | -1    | 1     | -1    | 0     | -1    | 1                 | 1                   | 2     | 1     | 2     |
| 12    | 1     | 1     | -1    | 0     | -1    | 1                 | 2                   | 1     | 1     | 1     |
| 13    | -1    | -1    | 1     | 0     | -1    | 1                 | 1                   | 1     | 1     | 2     |
| 14    | 1     | -1    | 1     | 0     | -1    | 2                 | 2                   | 1     | 1     | 1     |
| 15    | -1    | 1     | 1     | 0     | -1    | 1                 | 1                   | 0     | 1     | 0     |
| 16    | 1     | 1     | 1     | 0     | -1    | 1                 | 1                   | 1     | 1     | 2     |
| 17    | -1    | -1    | -1    | 1     | -1    | 1                 | 0                   | 1     | 1     | 2     |
| 18    | 1     | -1    | -1    | 1     | -1    | 2                 | 2                   | 1     | 1     | 1     |
| 19    | -1    | 1     | -1    | 1     | -1    | 2                 | 2                   | 1     | 1     | 1     |
| 20    | 1     | 1     | -1    | 1     | -1    | 1                 | 1                   | 1     | 1     | 1     |
| 21    | -1    | -1    | 1     | 1     | -1    | 2                 | 2                   | 1     | 1     | 1     |
| 22    | 1     | -1    | 1     | 1     | -1    | 0                 | 1                   | 1     | 1     | 1     |
| 23    | -1    | 1     | 1     | 1     | -1    | 0                 | 1                   | 1     | 1     | 2     |
| 24    | 1     | 1     | 1     | 1     | -1    | 2                 | 1                   | 1     | 1     | 1     |
| 25    | -1    | -1    | -1    | -1    | 0     | 1                 | 0                   | 1     | 1     | 0     |
| 26    | 1     | -1    | -1    | -1    | 0     | 0                 | 0                   | 1     | 1     | 1     |
| 27    | -1    | 1     | -1    | -1    | 0     | 0                 | 0                   | 0     | 1     | 0     |
| 28    | 1     | 1     | -1    | -1    | 0     | 0                 | 1                   | 1     | 1     | 0     |
| 29    | -1    | -1    | 1     | -1    | 0     | 0                 | 1                   | 1     | 1     | 1     |
| 30    | 1     | -1    | 1     | -1    | 0     | 0                 | 0                   | 0     | 1     | 0     |
| 31    | -1    | 1     | 1     | -1    | 0     | 0                 | 0                   | 0     | 1     | 0     |
| 32    | 1     | 1     | 1     | -1    | 0     | 1                 | 0                   | 1     | 1     | 0     |
| 33    | -1    | -1    | -1    | 0     | 0     | 0                 | 0                   | 1     | 1     | 0     |
| 34    | 1     | -1    | -1    | 0     | 0     | 1                 | 1                   | 1     | 1     | 1     |
| 35    | -1    | 1     | -1    | 0     | 0     | 0                 | 0                   | 0     | 1     | 0     |
| 36    | 1     | 1     | -1    | 0     | 0     | 1                 | 0                   | 1     | 1     | 0     |
| 37    | -1    | -1    | 1     | 0     | 0     | 1                 | 1                   | 1     | 1     | 0     |
| 38    | 1     | -1    | 1     | 0     | 0     | 0                 | 0                   | 1     | 1     | 0     |
| 39    | -1    | 1     | 1     | 0     | 0     | 0                 | 0                   | 0     | 1     | 0     |
| 40    | 1     | 1     | 1     | 0     | 0     | 0                 | 0                   | 1     | 1     | 0     |
| 41    | -1    | -1    | -1    | 1     | 0     | 0                 | 2                   | 1     | 0     | 0     |
| 42    | 1     | -1    | -1    | 1     | 0     | 0                 | 0                   | 1     | 1     | 0     |
| 43    | -1    | 1     | -1    | 1     | 0     | 0                 | 0                   | 0     | 1     | 0     |
| 44    | 1     | 1     | -1    | 1     | 0     | 1                 | 0                   | 1     | 0     | 0     |
| 45    | -1    | -1    | 1     | 1     | 0     | 0                 | 0                   | 1     | 1     | 0     |
| 46    | 1     | -1    | 1     | 1     | 0     | 1                 | 1                   | 1     | 0     | 0     |
| 47    | -1    | 1     | 1     | 1     | 0     | 1                 | 0                   | 1     | 0     | 0     |
| 48    | 1     | 1     | 1     | 1     | 0     | 0                 | 1                   | 1     | 1     | 1     |
| 49    | -1    | -1    | -1    | -1    | 1     | 1                 | 1                   | 1     | 1     | 1     |
| 50    | 1     | -1    | -1    | -1    | 1     | 2                 | 2                   | 1     | 1     | 2     |
| 51    | -1    | 1     | -1    | -1    | 1     | 1                 | 1                   | 0     | 1     | 1     |
| 52    | 1     | 1     | -1    | -1    | 1     | 1                 | 1                   | 1     | 1     | 1     |
| 53    | -1    | -1    | 1     | -1    | 1     | 2                 | 1                   | 1     | 1     | 2     |
| 54    | 1     | -1    | 1     | -1    | 1     | 0                 | 0                   | 0     | 1     | 0     |
| 55    | -1    | 1     | 1     | -1    | 1     | 1                 | 1                   | 1     | 1     | 1     |
| 56    | 1     | 1     | 1     | -1    | 1     | 1                 | 2                   | 1     | 1     | 2     |
| 57    | -1    | -1    | -1    | 0     | 1     | 1                 | 1                   | 1     | 1     | 2     |
| 58    | 1     | -1    | -1    | 0     | 1     | 1                 | 1                   | 1     | 1     | 0     |
| 59    | -1    | 1     | -1    | 0     | 1     | 2                 | 2                   | 1     | 1     | 1     |
| 60    | 1     | 1     | -1    | 0     | 1     | 1                 | 1                   | 1     | 1     | 2     |
| 61    | -1    | -1    | 1     | 0     | 1     | 2                 | 2                   | 1     | 0     | 1     |
| 62    | 1     | -1    | 1     | 0     | 1     | 1                 | 1                   | 1     | 1     | 2     |
| 63    | -1    | 1     | 1     | 0     | 1     | 0                 | 0                   | 1     | 1     | 1     |
| 64    | 1     | 1     | 1     | 0     | 1     | 2                 | 2                   | 1     | 0     | 1     |
| 65    | -1    | -1    | -1    | 1     | 1     | 2                 | 1                   | 1     | 1     | 2     |
| 66    | 1     | -1    | -1    | 1     | 1     | 1                 | 1                   | 1     | 1     | 1     |
| 67    | -1    | 1     | -1    | 1     | 1     | 1                 | 1                   | 1     | 1     | 1     |
| 68    | 1     | 1     | -1    | 1     | 1     | 1                 | 2                   | 1     | 1     | 2     |
| 69    | -1    | -1    | 1     | 1     | 1     | 1                 | 1                   | 1     | 1     | 1     |
| 70    | 1     | -1    | 1     | 1     | 1     | 1                 | 1                   | 0     | 1     | 1     |
| 71    | -1    | 1     | 1     | 1     | 1     | 2                 | 2                   | 1     | 1     | 2     |
| 72    | 1     | 1     | 1     | 1     | 1     | 1                 | 0                   | 1     | 1     | 1     |