

## Some Optimal Block-Factorial Designs\*

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The theory of optimal design plays a fundamental role in experimental design. Some of the results have been widely applied to the realistic world. In[1], Kiefer proved the optimality of some block designs. In this paper some block-factorial designs are discussed.

When a block design  $d_2(v_2, b, k)$  is superimposed on other block design  $d_1(v_1, b, k)$ , the resulting structure is called a block-factorial design and is abbreviated as  $d_1 * d_2$ . The collection of all such designs is denoted by  $\Omega(v_1, v_2, bk)$  or  $\Omega$ .

If  $d_1, d_2$  are uniform and they are orthogonal to each other, the structure can be considered as an orthogonal design with three factors. In[2] Cheng pointed out that the designs are universally optimal. If we remove the conditions of uniformity entirely or partly, optimality results of some block-factorial designs are proved.

For any  $d \in \Omega(v_1, v_2, bk)$ , we assume the linear model

$$EY_d = X_d\theta, \quad \text{Var}Y_d = \sigma^2 I_N \quad (1)$$

where  $Y_d = (y_1, y_2, \dots, y_N)'$  is the  $N \times 1$  vector of observations,  $X_d$  is an  $N \times p$  design matrix,  $\theta = (\rho_1, \rho_2, \dots, \rho_{v_1}, \tau_1, \tau_2, \dots, \tau_{v_2}, \beta_1, \beta_2, \dots, \beta_b)'$  is a vector of unknown parameters,  $\rho_i$  is the effect of  $i$ th level of 1st factor,  $\tau_j$  is the effect of  $j$ th level of 2nd factor,  $\beta_k$  is the effect of  $k$ th block,  $\sigma^2 > 0$  is known or unknown and  $I_N$  is the  $N \times N$  identity matrix. Then

$$X_d'X_d = \begin{pmatrix} \text{diag}(r_1^{(1)}, r_2^{(1)}, \dots, r_{v_1}^{(1)}) & N_{12} & N_{10} \\ N_{21} & \text{diag}(r_1^{(2)}, r_2^{(2)}, \dots, r_{v_2}^{(2)}) & N_{20} \\ N_{01} & N_{02} & kI_b \end{pmatrix} \quad (2)$$

where  $\text{diag}(a_1, a_2, \dots, a_k)$  is the diagonal matrix with diagonal elements  $a_1, a_2, \dots, a_k$ ,  $r_j^{(l)}$  is the number of times that the  $j$ th level of the  $l$ th factor appears in the design,  $N_{12}$  is the incidence matrix between the 1st and 2nd factors, i.e., the  $(s, u)$ th element of  $N_{12}$  is the number of times that the  $s$ th level of 1st factor and  $u$ th level of 2nd factor appear together in the design, and  $N_{10}$  is the incidence matrix between the  $l$ th factor and the block,  $l = 1, 2$ .

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From (1), the information matrix for estimating the effects of 1st factor and 2nd factor jointly is

$$\begin{pmatrix} \text{diag}(r_1^{(1)}, r_2^{(1)}, \dots, r_{v_1}^{(1)}) & N_{12} \\ N_{21} & \text{diag}(r_1^{(2)}, r_2^{(2)}, \dots, r_{v_2}^{(2)}) \end{pmatrix} - \begin{pmatrix} N_{10} \\ N_{20} \end{pmatrix} \frac{1}{k} I_b(N_{01}, N_{02}) \\ = \begin{pmatrix} C_{d11} & C_{d12} \\ C_{d21} & C_{d22} \end{pmatrix} \quad (3)$$

where  $C_{d11} = \text{diag}(r_1^{(1)}, r_2^{(1)}, \dots, r_{v_1}^{(1)}) - k^{-1}N_{10}N_{01}$ ,  $C_{d12} = N_{12} - k^{-1}N_{10}N_{02}$ ,  $C_{d22} = \text{diag}(r_1^{(2)}, r_2^{(2)}, \dots, r_{v_2}^{(2)}) - k^{-1}N_{20}N_{02}$ , and  $A^-$  denotes a generalized inverse of  $A$ .

If we are interested only in estimation of linear combinations  $\Sigma_i c_i \rho_i$ , we obtain  $C_d^{(1)} = C_{d11} - C_{d12}C_{d22}^{-1}C_{d21}$  for the information matrix of  $d$  for  $\rho = (\rho_1, \rho_2, \dots, \rho_{v_1})'$ . Similarly, we obtain  $C_d^{(2)} = C_{d22} - C_{d21}C_{d11}^{-1}C_{d12}$  for the information matrix of  $d$  for  $\tau = (\tau_1, \tau_2, \dots, \tau_{v_2})'$ .

An optimality criterion is a function  $\Phi: \mathcal{B}_{v,v} \rightarrow (-\infty, \infty]$ , where  $\mathcal{B}_{v,v}$  is the collection of  $v \times v$  nonnegative definite matrices with zero row and column sums. A design is called  $\Phi$ -optimal if it minimizes  $\Phi(C_d^{(1)})$  or  $\Phi(C_d^{(2)})$  over the competing designs depending on which effects we are interested in. Note that  $C_d^{(1)} \in \mathcal{B}_{v_1,0}$  and  $C_d^{(2)} \in \mathcal{B}_{v_2,0}$  in our setting.

Kiefer<sup>[3]</sup> introduced the notion of universal optimality. A design  $d^*$  is called universally optimal if it is  $\Phi$ -optimal for all  $\Phi$  satisfying (I)  $\Phi$  is convex, (II)  $\Phi(bC)$  is nonincreasing in the scalar  $b \geq 0$ , (III)  $\Phi$  is invariant under any simultaneous permutation of rows and columns of  $C$ . Using a tool due to Kiefer<sup>[3]</sup>, the following theorem is proved:

**Theorem 1** If there is a  $d^* \in \Omega$  satisfying the conditions: (I)  $d^* = d_1 * d_2$ , where  $d_1$  is uniform design with parameters  $(v_1, b, k)$ ,  $d_2$  is BIBD( $v_2, b, k, r^{(2)}, \lambda$ ), (II)  $N_{12} = (v_1 v_2)^{-1} N J$ , where  $J$  is a matrix with all its entries 1, then  $d^*$  is universally optimal for the estimation of the effect of 1st factor as well as 2nd factor over  $\Omega$ .

If we restrict the competing designs to a smaller class and utilize a result of Ehrenfeld<sup>[4]</sup>, then some stronger optimality results can be proved. Let  $\Omega^* = \Omega^*(v_1, v_2, bk) = \{d: d \in \Omega(v_1, v_2, bk), r_1^{(1)} = r_2^{(1)} = \dots = r_{v_1}^{(1)} = r^{(1)}\}$ , then we have

**Theorem 2** Under the assumptions of theorem 1,  $d^*$  minimizes the variance of the best linear unbiased estimator of any contrast among the effect of 1st factor  $\rho$  over  $\Omega^*$ .

Using Kiefer's methods, we also proved following theorems:

**Theorem 3** If there is a  $d^* \in \Omega$  satisfying the conditions: (I)  $d^* = d_1 * d_2$ , where  $d_1$  is uniform design,  $d_2$  is BBD( $v_2, b, k$ ), (II)  $N_{12} = (v_1 v_2)^{-1} N J$ , then  $d^*$  is universally optimal for the effect of 1st factor as well as 2nd factor over  $\Omega$ .

**Theorem 4** If there is a  $d^* \in \Omega$  satisfying the conditions: (I)  $d^* = d_1 * d_2$ , where  $d_1$  is BIBD  $(v_1, b, k, r^{(1)}, \lambda^{(1)})$ ,  $d_2$  is BIBD  $(v_2, b, k, r^{(2)}, \lambda^{(2)})$ , (II)  $N_{12} = (v_1 v_2)^{-1} N J$ , (III)  $N_{10} N_{02} = (v_1 v_2)^{-1} N k J$ , then  $d^*$  is universally optimal for the effect of 1st factor as well as 2nd factor over  $\Omega$ .

### References

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- [4] Ehrenfeld, S., *Proc. Third Berkeley Symposium* 1, Univ. of California Press (1955), 57—67.