# D-optimal designs for correlated random vectors ${ }^{2 / 3}$ 

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#### Abstract

Suppose that $Y=\left(Y_{i}\right)$ is a normal random vector with mean $X b$ and covariance $\sigma^{2} I_{n}$, where $b$ is a $p$-dimensional vector $\left(b_{j}\right), X=\left(X_{i j}\right)$ is an $n \times p$ matrix. Given a family $\mathscr{D}$ of $D$-optimal designs, a design $Z$ in $\mathscr{D}$ is chosen that is robust in the sense that $Z$ is $D$-optimal in $\mathscr{D}$ when the components $Y_{i}$ are dependent: for $i \neq i^{\prime}$, the covariance of $Y_{i}, Y_{i^{\prime}}$ is $\rho \neq 0$. Such designs $Z$ merely depend on the sign of $\rho$. The general results are applied to the situation where $X_{i j} \in\{-1,1\}$; this corresponds to a factorial design with $-1,1$ representing low or high level, respectively, or corresponds to a weighing design with $-1,1$ representing an object $j$ with weight $b_{j}$ being placed on the left and right side of a chemical balance, respectively.


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## 1. Introduction

Let $Y=\left(Y_{i}\right)$ be a normal $n$-dimensional random vector with mean $\mu=X b$, where $X=\left(X_{i j}\right)$ is an $n \times p$ matrix of rank $p$ with each $X_{i j}$ in the set $\mathfrak{R}$ of real numbers, $b=\left(b_{j}\right)$ is a parameter in the $p$-dimensional Euclidean space $\mathfrak{R}^{p}$, and the covariance, $\Sigma_{Y}$, of $Y$ is $\sigma^{2} I_{n}$, where $\mathfrak{R}$ denotes the real line. To simplify our presentation, we assume that $\sigma=1$. The precision of the least square estimator $\tilde{b}(Y)$ and of the usual confidence ellipsoid of $b$ depends only on covariance, $\operatorname{cov}(\tilde{b}(Y))$, of $\tilde{b}(Y)$, where

$$
\begin{equation*}
\tilde{b}(Y)=\left(X^{\prime} X\right)^{-1} X^{\prime} Y \tag{1.1}
\end{equation*}
$$

and

$$
\begin{equation*}
\operatorname{cov}(\tilde{b}(Y))=\left(X^{\prime} X\right)^{-1} \tag{1.2}
\end{equation*}
$$

So we wish to choose an $X$ such that, among all admissible designs $X,\left(X^{\prime} X\right)^{-1}$ is smallest in some way, e.g., to choose $X$ such that $X$ is $D$-optimal, i.e., the generalized variance

$$
\begin{equation*}
|\operatorname{cov}(\tilde{b}(Y))|=\left|\left(X^{\prime} X\right)^{-1}\right| \tag{1.3}
\end{equation*}
$$

is smallest, where $|\bullet|$ denotes the determinant function.

[^0]Due to random effects or practical circumstance, $\operatorname{cov}\left(Y_{i}, Y_{i^{\prime}}\right)=\rho$ with $\rho$ positive or negative; see, e.g., Searle (1971) and Pukelsheim (1993). On the other hand, when $\rho=0$, there may exist more than one $D$-optimal design $X$. For example, for the weighing design model, there may be a large family of $D$-optimal designs (see Galil and Kiefer, 1980). Because of this, one may wish to set up a criterion to choose a particular one; see, e.g., Galil and Kiefer (1983). Consideration of $\rho \neq 0$ is such a criterion. Other authors have addressed similar problems (see Ceranka and Graczyk, 2004; Ceranka et al., 2006; Das et al., 2003; Evangelaras et al., 2002).

Now, the weighted least square estimator $\tilde{b}(Y)$ is given by

$$
\begin{equation*}
\tilde{b}(Y)=\left(X^{\prime} G^{-1} X\right)^{-1} X^{\prime} G^{-1} Y \tag{1.4}
\end{equation*}
$$

where $G=\Sigma_{Y}$ :

$$
\begin{align*}
& G=(1-\rho) I_{n}+\rho J_{n}, \quad \frac{-1}{n-1}<\rho<1,  \tag{1.5}\\
& J_{n}=e_{n} e_{n}^{\prime}, \quad e_{n}=(1,1, \ldots, 1)^{\prime} \in \mathfrak{R}^{n} . \tag{1.6}
\end{align*}
$$

Since

$$
\operatorname{cov}(\tilde{b})=\left(X^{\prime} G^{-1} X\right)^{-1}
$$

$X$ is $D$-optimal with respect to $\rho$ if it minimizes $\left|\left(X^{\prime} G^{-1} X\right)^{-1}\right|$, or equivalently, maximizes $\left|X^{\prime} G^{-1} X\right|$.
Although all of our main results in Section 2 are general, we shall merely apply them to the case where $X_{i j} \in\{-1,1\}$. More specifically, let $\mathscr{D}$ be the set of $D$-optimal designs obtained earlier for $\rho=0$, i.e., $X \in \mathscr{D}$ maximizes $\left|X^{\prime} X\right|$ for $X$ in $\mathscr{D}$. We shall choose a design $Z$ in $\mathscr{D}$ such that it is robust in the sense that it also maximizes $\left|X^{\prime} G^{-1} X\right|$ for all $X \in \mathscr{D}$ and all $\rho>0(<0)$. This definition of robustness guards against the situation where the experimenter assumes the observations $Y_{i}$ are uncorrelated when, in fact, there may be a positive (negative) correlation.

The models $Y$ considered here correspond to certain factorial designs with $-1,1$ representing low or high level, respectively, or correspond to weighing designs with $-1,1$ representing the object $j$ with weight $b_{j}$ being placed on the left and right side of a chemical balance, respectively; see, e.g., Cheng (1978, 1980, 1987), Cheng et al. (1985), Galil and Kiefer (1982, 1983), Jacroux et al. (1983), Pukelsheim (1993), Sathe and Shenoy (1991). The results on optimal designs in these papers are subject to the existence of an $m \times m$ Hadamard matrix, $H=\left(h_{i j}\right)$, of appropriate order $m$ :

$$
\begin{equation*}
\text { all } i, j \in\{-1,1\}, \quad H^{\prime} H=m I_{m} . \tag{1.7}
\end{equation*}
$$

The existence of such a matrix is still a conjecture for $m=268$ and many other $m>268$; see Hedayat and Wallis (1978). For other $D$-optimal designs, see, e.g., Chen and Huang (2000), Huang (1987), Huang et al. (1995), Pukelsheim (1993), Yeh and Huang (2005).

## 2. Main results

We begin by simplifying $\operatorname{cov}(\tilde{b})=\left(X^{\prime} G^{-1} X\right)^{-1}$. Let $M_{n \times p}$ be the set of all $n \times p$ matrices over $\mathfrak{R}$ equipped with the trace norm $\|\bullet\|:\|A\|=\left(\operatorname{tr}\left(A^{\prime} A\right)\right)^{1 / 2}$. Note that $M_{n \times p}=\mathfrak{\Re}^{n}$ if $p=1$. We shall first estimate $\|u(X)\|^{2}$, where

$$
\begin{equation*}
u(X)=\left(X^{\prime} X\right)^{-1 / 2} X^{\prime} e_{n} \tag{2.1}
\end{equation*}
$$

a very important vector in our presentation ( $e_{n}$ is as in (1.6)).
Lemma 1. Let $X \in M_{n \times p}$. Then:
(a)

$$
\begin{equation*}
\|u(X)\|^{2} \leqslant n \tag{2.2}
\end{equation*}
$$

(b) Suppose that $X^{\prime} X=n I_{p}$. Then $\left\|X^{\prime} e_{n}\right\| \leqslant n$. Hence if $e_{n}$ is a column of $X$, then $\left\|X^{\prime} e_{n}\right\|=n$.

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