Repeated Measurement Designs under Subject Dropout

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Repeated Measurement Design (Crossover Design): A number of experimental units (subjects) are used to compare treatments of interest and each subject is assigned to a sequence of treatments over a number of time periods. Heavily used in various practices, ranging from psychology and human factor engineering to medical and agricultural applications.

Example

1 2 3 0

n: the number of subjects; t: the number of treatments; p: the number of periods.

 $\Omega(t, n, p)$: the class of designs with t treatments, n subjects and p periods.

Repeated Measurement Design **Optimality Theory** Subject Dropout Problem Questions

Traditional fixed-effects model:

$$y_{ij} = \alpha_i + \beta_j + \tau_{d(i,j)} + \rho_{d(i-1,j)} + \epsilon_{ij}$$

 $i = 1, 2, \dots, p \text{ and } j = 1, 2, \dots, n.$

 α_i : period effect.

 β_i : subject effect,

 $\tau_{d(i,j)}$: treatment direct effect,

 $\rho_{d(i-1,j)}$: carryover effect,

 ϵ_{ii} : random error with $E(\epsilon_{ii}) = 0$ and $Var(\epsilon_{ii}) = \sigma^2$,

 $Cov(\epsilon_{ii}, \epsilon_{i'i'}) = 0$ for any $(i, j) \neq (i', j')$.

For any design d:

$$Y^d = X_1^d \theta_1 + X_2^d \theta_2 + \varepsilon.$$

The Fisher Information Matrix:

Maximum Information Loss for Two Other Models

$$C^d = (X_1^d)'(Pr^{\perp}X_2^d)X_1^d = (X_1^d)'X_1^d - (X_1^d)'X_2^d((X_2^d)'X_2^d)^{-}(X_2^d)'X_1^d.$$

A-criterion: $tr(C^d)^+$.

$\mathsf{Theorem}$

(Kiefer (1975)) Suppose a class $\{C^d, d \in \Omega(t, n, p)\}\$ of matrices contains a Cd* for which

- C^{d*} is completely symmetric,
- $2 trC^{d^*} = \max_{d \in \Omega(t,n,p)} trC^d.$

Then d^* is universally optimal in $\Omega(t, n, p)$.

There is an **implicit**, **but critical**, assumption that the experiment will yield all the planned observations.

Example

* means that observation is not available

Repeated Measurement Design **Optimality Theory** Subject Dropout Problem Questions

- What statistical properties are maintained in the design at the end of the experiment? Here we choose to study UBRMD.
- Whether and how can we measure the goodness of a planned design in terms of precision loss due to subject dropouts? We suggest using two quantities: the expected precision loss and the maximum precision loss.

Assumption:

Subjects drop out independently with a probability λ .

The case:

Dropouts occur in the final period.

 d_{plan} : the starting design,

 d_{min} : the starting design without the final period,

 d_{imp} : the design actually observed; inbetween d_{plan} and d_{min} .

The loss of d_{imp} with respect to d_{plan} is measured by

$$L_{d_{imp}:d_{plan}} = \frac{H^{d_{plan}} - H^{d_{imp}}}{H^{d_{plan}}} = 1 - \frac{H^{d_{imp}}}{H^{d_{plan}}}$$

where
$$H^d = \frac{t-1}{tr(C^d)^+}$$
.



Uniformly Balanced Repeated Measure Designs (UBRMDs):

A design is uniform if

- for each subject, each treatment is allocated to the same number of periods
- for each period, each treatment is allocated to the same number of subjects

A design is called **balanced for carryover effects** (**balanced, in short**) if, in the order application, each treatment is preceded by every other treatment the same number of times and is not preceded by itself.

A UBRMD with t = 4, p = 4 and n = 4:

It is universally optimal in $\Omega(4, 4, 4)$.

The construction of UBRMDs are provided in Williams (1949), called **Williams Designs (WDs)**:

- (Family One) t is even, a UBRMD with n = p = t
- (Family Two) t is odd, a UBRMD with n = 2t and p = t



We suggest a type of design: **UBRMD Balanced for Loss**, denoted by d^* .

- d^* is a UBRMD,
- d* covers all ordered pairs of distinct treatments the same number times in the last two periods.

This requires $n \ge t(t-1)$.

Example

A UBRMD Balance for Loss with t = p = 4, n = 12

This UBRMD is universally optimal in $\Omega(4, 12, 4)$.



Theorem

In the class of designs $\Omega(t, n, t-1)$, for which $z_d \geq \left[\frac{2n}{t(t-2)}\right]$ or $z_d = 0$, n is a multiple of t(t-1), d_{min}^* is universally optimal.

Corollary

If n=t(t-1) and $t\geq 5$, d_{min}^* is universally optimal in the class of designs $\Omega(t,n,t-1)$ for which $z_d\geq 2$ or $z_d=0$. When t=4, d_{min}^* is universally optimal in $\Omega(4,12,3)$ for which $z_d\geq 3$ or $z_d=0$. When t=3, d_{min}^* is universally optimal in $\Omega(3,6,2)$ for which $z_d\geq 4$ or $z_d=0$.

Using the bound in Stufken(1991) that is generalized to the entire class by Hedayat and Yang (2004), the lower bound to efficiency of d_{min}^*

Order t	d_{min}^*	WD		
4	0.9967427	*		
5	0.9995917	0.898608		
6	0.9999083	0.8953254		
7	0.9999718	0.973486		
8	0.9999894	0.9631566		
9	0.9999954	0.9881278		
10	0.9999978	0.9811		

Proved that the lower bound to efficiency of $d_{min}^* \ge 99.63\%$ for $t \ge 4$. Thus d_{min}^* is nearly optimal.



Maximum Loss Table:

Order t=	4	5	6	7	8	9	10
d*	0.41	0.28	0.21	0.18	0.15	0.13	0.11
WD	*	0.35	0.30	0.20	0.18	0.14	0.13

Proved the maximum loss of d^* is an decreasing function of t.

Expected Loss =
$$\sum_{d_{imp}} L_{d_{imp}:d_{plan}} \times P(d_{imp}),$$

where $P(d_{imp})$ is the probability to observe d_{imp} .

A UBRMD with t = p = 5 and n = 20

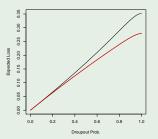


Figure: t=5, d^* (red) and two copies of WD(black)

UBRMD and WD
UBRMD Balanced for Loss
Optimality and Efficiency of the Minimal Design
Information Loss Due to Subject Dropout
Construction Methods

Definition

The subject dropout pattern of a implemented design is a $t \times t$ matrix with (i,j) entry 1 if treatment i lost due to subject dropout in the last period is preceded by treatment j; 0 otherwise. It is denoted by $DPM_{d_{imp}}$. Two implemented designs d_{imp1} and d_{imp2} from the same planned design which is a UBRMD is said to have the same dropout pattern if there exits a permutation matrix P such that $DPM_{d_{imp1}} = P \cdot DPM_{d_{imp2}} \cdot P'$.

Theorem

If two implemented designs from the same planned design which is a UBRMD have the same subject dropout pattern, then they have the same information loss. Constructions of UBRMD Balanced for Loss with n = t(t - 1):

- Complete set of mutually orthogonal Latin squares.
- Union of WDs using permutations.
- **3** Case t = 6 (Amusement in Mathematics, 1958).
- Methods by Bose and Bagchi(Utilitas Mathematica).

MOLS Method

Suppose x is a primitive root of the field GF(t). Express all the elements in the field as a power of x:

$$\alpha_0=0, \alpha_1=1, \alpha_2=x, \alpha_3=x^2, \cdots, \alpha_{t-1}=x^{t-2}$$
. The following $t-1$ pairwise orthogonal squares L_1, \cdots, L_{t-1} are constructed as: $L_i=(l_{jk})=(\alpha_j+\alpha_i\alpha_k)$ for $i=1,\cdots,t-1; j=0,\cdots,t-1; k=0,\cdots,t-1$. To get L , juxtapose L_1',\cdots,L_{t-1}' in the following way:

$$\left[L_1' \ L_2' \ \cdots \ L_{t-1}'\right].$$

$\mathsf{Theorem}$

L is a UBRMD Balanced for Loss.



t=4. Use an irreducible polynomial of order 2 which is x^2+x+1 on \mathbf{Z}_2 to construct a GF(4) having elements 0,1,x,1+x. Relabel 0,1,x,1+x by 0,1,2,3, the following 4×12 array is our type of design:

```
0 1 2 3 0 1 2 3 0 1 2 3
1 0 3 2 2 3 0 1 3 2 1 0
2 3 0 1 3 2 1 0 1 0 3 2
3 2 1 0 1 0 3 2 2 3 0 1
```

Union of WDs Using Permutation Method

- ① Start with a WD of order t, call it W_0 .
- ② Find a permutation matrix of order t P_1 , such that W_1 obtained from W_0 by applying P_1 , and W_0 covers totally different pairs of treatments in the last two rows.
- **3** Find a permutation matrix of order t again P_2 , such that W_2 obtained from W_0 by applying P_2 , covers pairs totally different from those covered by W_1 and W_0 in the last two rows.
- Continue in this fashion till all designs obtained together constitute a design with t(t-1) sequences and every pair of distinct treatments is represented once in the final two rows.

$$t = 5$$
,

 $L_2(\text{right WD})$ obtained from $L_1(\text{left WD})$ by permutating treatments. Permutation is (0,3,1,4,2)

Case t = 6 and Methods by Bose and Bagchi

In Dudeney (1958), a *UBRMD* Balanced for Loss with t=6,10 was provided. One can construct *UBRMD*s Balanced for Loss for t=3,4,5,7,8,9,11 using either *MOLS* method or permutation algorithm. For t=12, the existence of a *UBRMD* Balanced for Loss is still unclear. In Bose and Bagchi (2006), a different construction method for *UBRMD*s Balanced for Loss was suggested for t is an odd prime. They started with the initial columns of WD and expanded each column mod(t) to get a UBRMD Balanced for Loss in $\Omega(t, n=t(t-1), p=t)$.

Random Subject Effect Model:

$$E(y_{ij}) = \alpha_i + \tau_{d(i,j)} + \rho_{d(i-1,j)},$$

$$Var(y_{ij}) = \sigma^2 + \sigma_{\beta}^2,$$

and

$$Cov(y_{ij}, y_{i'j'}) = \begin{cases} 0 & \text{if } j \neq j' \\ \sigma_{\beta}^2 & \text{if } j = j' \text{ and } i \neq i' \end{cases}$$

$$i=1,2,\cdots,p$$
 and $j=1,2,\cdots,n$. Let $\theta=rac{\sigma_{eta}^2}{\sigma^2}$

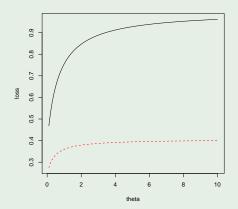


Figure: Maximum loss for $t=4,d^*$ (red) and WD(black)

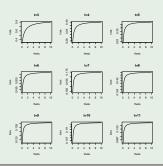
Theorem

The maximum loss of a UBRMD Balanced for Loss is monotonically increasing in θ , for any given $t \ge 3$.

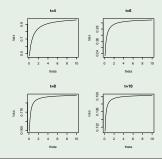
$\mathsf{Theorem}$

The maximum loss for WD is monotonically increasing in θ , for any given $t \geq 3$.

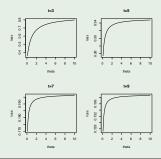
Maximum information loss for d^* :



Maximum information loss for WD:



Maximum information loss for WD:



Autoregressive Variance Model:

$$E(y_{ij}) = \alpha_i + \tau_{d(i,j)} + \rho_{d(i-1,j)},$$
$$Var(y_{ij}) = \sigma^2 + \sigma_{\beta}^2,$$

$$Cov(y_{ij}, y_{i'j'}) = \begin{cases} 0 & \text{if } j \neq j' \\ \sigma_{\beta}^2 \rho^{|i-i'|} & \text{if } j = j' \text{ and } i \neq i' \end{cases}$$

$$i = 1, 2, \dots, p \text{ and } j = 1, 2, \dots, n.$$

$$Var(Y_{\cdot j}) = \sigma_{\beta}^{2} \begin{pmatrix} 1 & \rho & \cdots & \rho^{p-1} \\ \rho & 1 & \cdots & \rho^{p-2} \\ \vdots & \vdots & \vdots & \vdots \\ \rho^{p-1} & \rho^{p-2} & \cdots & 1 \end{pmatrix}$$

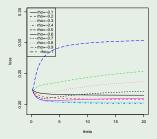


Figure: Maximum Loss of WD t = 5, $\rho < 0$

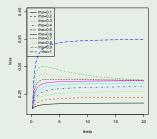


Figure: Maximum Loss of WD t = 5, $\rho > 0$

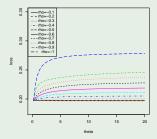


Figure: Maximum Loss of d^* t = 5, $\rho < 0$

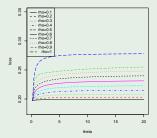


Figure: Maximum Loss of d^* t = 5, $\rho > 0$

Random Subject Effect Model Autoregressive Variance AR(1) Model

Thank you!