

Bailey, Sec.1.5

- The response on plot w is Y_w : a random variable, whose value denoted by Y_w
- collected data vector $Y_L = \{Y_w | w \in \Omega\}$ is a realization of the r.v. Y_L

- For plot w , assume treatment-plot additivity (no interaction effects between treatments & plots)

$$Y_w = T_{T(w)} + Z_w$$

- $T_{T(w)}$: (1) a constant (2) depend on the treatment $T(w)$
(3) can be thought of the contribution of treatment $T(w)$
- Z_w : (1) random variable (2) depend on w
(3) can be thought of the contribution of plot w

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- Z_w is a r.v. $\Rightarrow Z_w$ must have probability space \Rightarrow the set of occasions & uncontrolled conditions.
- Z_α & Z_β are different random variables for different plots α & β $\Rightarrow Z_\alpha$ & Z_β must have a joint distribution, including a correlation (may be zero)
- Q: What should be the joint dist. of $\{Z_w | w \in \Omega\} \equiv Z_\Omega$

1. simple textbook model

$$Z_w \text{ i.i.d } N(0, \sigma^2) \Rightarrow Z_\Omega \sim N(0, \sigma^2 I) \rightarrow \boxed{\text{often seen in completely randomized design}}$$

2. fixed effect model

Z_w are indep. Normal with variance σ^2 & mean $\mu_w \Rightarrow Z_\Omega \sim N(\mu_\Omega, \sigma^2 I)$

often seen in block design.

3. random effect model

Z_w have identical (marginal) distribution \Rightarrow $\text{cov}(Z_\alpha, Z_\beta)$ depends on how α, β related,

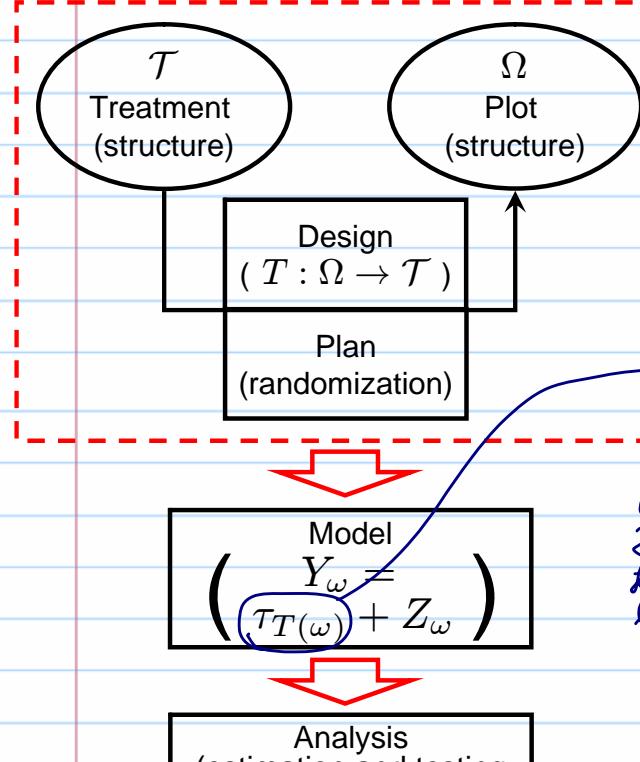
often seen in block design, split-plot design.

4. randomization model $\Rightarrow Z_\Omega \sim N(\Omega, \mathbf{I})$

Z_w have identical (marginal) distribution \Rightarrow $\text{cov}(Z_\alpha, Z_\beta)$ depends on the method of randomization.

non-parametric methods.

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Analysis: estimation & testing for function of T 's

↓
linear combinations
↑
depend on the treatment structure

Example: $(E(Y) = X\beta)$

1. treatment structure: no structure
e.g. 4 treatments.

$$\begin{matrix} i & \tau_i \\ j & \tau_j \\ k & \tau_k \\ l & \tau_l \end{matrix} \quad \begin{matrix} \beta_0 = \tau_i, \beta_1 = \tau_j, \beta_2 = \tau_k, \beta_3 = \tau_l \\ X = \begin{bmatrix} \beta_0 & \beta_1 & \beta_2 & \beta_3 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{matrix}$$

$$\begin{matrix} \beta_0 = (\tau_i + \tau_j + \tau_k + \tau_l)/4 = \bar{\tau} \\ \beta_1 = \tau_j - \bar{\tau} \\ \beta_2 = \tau_k - \bar{\tau} \\ \beta_3 = \tau_l - \bar{\tau} \end{matrix} \quad \begin{matrix} X = \begin{bmatrix} \beta_0 & \beta_1 & \beta_2 & \beta_3 \\ 1 & -1 & -1 & -1 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix} \end{matrix}$$

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2. several treatments v.s. a control

$$\begin{matrix} \text{control} \leftarrow i & \tau_i \\ j & \tau_j \\ k & \tau_k \\ l & \tau_l \end{matrix} \quad \begin{matrix} \beta_0 = \tau_i \\ \beta_1 = \tau_j - \tau_i \\ \beta_2 = \tau_k - \tau_i \\ \beta_3 = \tau_l - \tau_i \end{matrix}$$

$$X = \begin{bmatrix} \beta_0 & \beta_1 & \beta_2 & \beta_3 \\ 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix}$$

3. factorial structure

	A	B	AB
i τ_i	+	+	+
j τ_j	+	-	-
k τ_k	-	+	-
l τ_l	-	-	+

$$\begin{matrix} \beta_0 = (\tau_i + \tau_j + \tau_k + \tau_l)/4 \\ \beta_A = [(\tau_i + \tau_j) - (\tau_k + \tau_l)]/c \\ \beta_B = [(\tau_i + \tau_k) - (\tau_j + \tau_l)]/c \\ \beta_{AB} = [(\tau_i + \tau_l) - (\tau_j + \tau_k)]/c \end{matrix}$$

$$X = \begin{bmatrix} \beta_0 & \beta_A & \beta_B & \beta_{AB} \\ 1 & 1 & 1 & 1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & 1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix}$$

Note: all the X -matrices have same column space, i.e., the space spanned by the columns of X , which will be referred to as treatment space.

(Bailey) the data analysis should give

- minimum variance unbiased estimator of τ_i 's & linear combinations such as $\tau_i - \tau_j$
- estimate the variance of these estimators
- inference about present/absent of effects \Rightarrow test $H_0: \beta_i = 0$.

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