

$$\hat{x}_M = -\frac{1}{2}B^{-1}\vec{b}$$

Stat 526  
5-14-15  
①

But is this a max, min, or saddle point?

Evaluate  $y$  at  $\hat{x}_M$

$$\begin{aligned}\hat{y}_M &= b_0 + \hat{x}_M' \vec{b} + \hat{x}_M' B \hat{x}_M \\ &= b_0 + \left(-\frac{1}{2}\right) \vec{b}' B^{-1} \vec{b} + \left(-\frac{1}{2}\right) \vec{b}' B^{-1} B \left(-\frac{1}{2}\right) B^{-1} \vec{b} \\ &= b_0 - \frac{1}{2} \vec{b}' B^{-1} \vec{b} + \frac{1}{4} \vec{b}' B^{-1} \vec{b} \\ &= b_0 - \frac{1}{4} \vec{b}' B^{-1} \vec{b}\end{aligned}$$

Let  $x$  be a value close to  $\hat{x}_M$

And let  $\hat{y}$  be the corresponding  $y$ -value.

$$\begin{aligned}\text{Write } \hat{y} &= \hat{y}_M + (\hat{y} - \hat{y}_M) \\ &= \hat{y}_M + \left( \frac{1}{4} b_0 + x' \vec{b} + x' B x - \left( \frac{1}{4} b_0 - \frac{1}{4} \vec{b}' B^{-1} \vec{b} \right) \right) \\ &= \hat{y}_M + \left( x' \vec{b} + \underbrace{\frac{1}{4} \vec{b}' B^{-1} \vec{b}}_{-\frac{1}{2} \vec{b}' \hat{x}_M} + x' B x \right) \\ &= \hat{y}_M + \left( x' - \frac{1}{2} \hat{x}_M' \right) \vec{b} + x' B x\end{aligned}$$

②

$$= \hat{y}_M + (x - \frac{1}{2} \hat{x}_M)' \bar{b} + (x - \hat{x}_M)' B (x - \hat{x}_M) \quad (3)$$

$$+ x' B \hat{x}_M + \hat{x}_M' B x - \hat{x}_M' B \hat{x}_M$$

$$= \hat{y}_M + (x - \frac{1}{2} \hat{x}_M)' \bar{b} + (x - \hat{x}_M)' B (x - \hat{x}_M)$$

$$+ x' B (-\frac{1}{2} B' \bar{b}) + (-\frac{1}{2} B' \bar{b})' B x$$

$$- (-\frac{1}{2} B' \bar{b})' B (-\frac{1}{2} B' \bar{b})$$

$$= \hat{y}_M + \cancel{(x - \frac{1}{2} \hat{x}_M)' \bar{b}} + \cancel{(x - \hat{x}_M)' B (x - \hat{x}_M)}$$

$$\cancel{-\frac{1}{2} x' B' \bar{b}} - \cancel{\frac{1}{2} \bar{b}' B' x} - \frac{1}{4} \bar{b}' B' \bar{b}$$

$$= \hat{y}_M - \frac{1}{2} \underbrace{\hat{x}_M' \bar{b}}_{(-\frac{1}{2} B' \bar{b})'} + (x - \hat{x}_M)' B (x - \hat{x}_M) \quad (4)$$

$$- \frac{1}{4} \bar{b}' B' \bar{b}$$

$$\hat{y} = \hat{y}_M + (x - \hat{x}_M)' B (x - \hat{x}_M)$$

Write  $B = P \Lambda P^{-1}$  Spectral decomposition

$$= P \Lambda P'$$

since  $B$  is symmetric

its columns are the eigenvectors of  $B$

↑

diagonal matrix of eigenvalues

$$\hat{y} = \hat{y}_\mu + \underbrace{(x - \hat{x}_\mu)'}_{w'} \underbrace{P \Delta P'}_w (x - \hat{x}_\mu) \quad (5)$$

$$= \hat{y}_\mu + w' \Delta w$$

$$= \hat{y}_\mu + [w_1, w_2, \dots, w_k] \begin{bmatrix} \lambda_1 & & 0 \\ & \lambda_2 & \\ 0 & & \ddots \\ & & & \lambda_k \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_k \end{bmatrix}$$

$$\hat{y} = \hat{y}_\mu + \lambda_1 w_1^2 + \lambda_2 w_2^2 + \dots + \lambda_k w_k^2$$

$\Rightarrow$  If  $B$  is pos. def,  $\lambda_i > 0 \forall i$  so  $\hat{y} > \hat{y}_\mu$   
+  $\hat{y}_\mu$  is a minimum

$\Rightarrow$  If  $B$  is neg def,  $\lambda_i < 0 \forall i$ ,  
so  $\hat{y} < \hat{y}_\mu$  &  $\hat{y}_\mu$  a maximum (6)

$\Rightarrow$  If  $B$  is neither pos or neg def,  
then some  $\lambda_i$ 's  $> 0$  + other  $\lambda_i$ 's  $< 0$   
+  $\hat{y}_\mu$  is a saddle point

$E(f(X)) \neq f(E(X))$  unless  $f$  is linear

⑦

In an ANOVA, if you are willing to test

$$H_0: E_1(f(y)) = E_2(f(y)) = \dots = E_k(f(y))$$

instead of  $H_0: E_1(y) = E_2(y) = \dots = E_k(y)$

then you can do transformations.

One-way ANOVA

$$y_{ij} = \mu + \tau_i + \varepsilon_{ij},$$

$$\varepsilon_{ij} \sim \text{iid}(N(0, \sigma^2))$$

⑧

Box-Cox transformation:

$$x_{ij} = \frac{y_{ij}^\lambda - 1}{\lambda}$$

New model  $x_{ij} = \mu + \tau_i + \varepsilon_{ij}$  (completely new  $\mu, \tau_i, \varepsilon_{ij}$ )

$$\underset{\substack{\uparrow \\ \text{prob. density} \\ \text{function}}}{f(y_{ij})} = g(x_{ij}) \left| \frac{\partial x_{ij}}{\partial y_{ij}} \right|$$

Our goal is to choose  $\lambda$  so that the  $x_{ij}$ 's are as normal as possible.

(9)

Then

$$f(y_{ij}) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{y_{ij} - \mu - \tau_i}{\sigma}\right)^2} \underbrace{\left| \frac{\partial}{\partial y_{ij}} \frac{y_{ij}^\lambda - 1}{\lambda} \right|}_{\frac{1}{2} \lambda y_{ij}^{\lambda-1}}$$

$$f(\vec{y}) = \prod_{i=1}^a \prod_{j=1}^n f(y_{ij})$$

HW #6 15.21

a) wine fixed	} judges random
b) wine random	

$$\left[ MS_E \left( \frac{1}{n} + \frac{(\bar{x}_{i.} - \bar{x}_{..})^2}{E_{xx}} \right) \right]^{1/2}$$

Using this formula, calculate a 95 percent confidence interval on the adjusted mean of machine 1 in Example 15.5.

**15.19.** Show that in a single-factor analysis of covariance with a single covariate, the standard error of the difference between any two adjusted treatment means is

$$S_{\text{Adj}\bar{y}_{i.} - \text{Adj}\bar{y}_{j.}} = \left[ MS_E \left( \frac{2}{n} + \frac{(\bar{x}_{i.} - \bar{x}_{j.})^2}{E_{xx}} \right) \right]^{1/2}$$

**15.20.** Discuss how the operating characteristic curves for the analysis of variance can be used in the analysis of covariance.

**15.21.** Three different Pinot Noir wines were evaluated by a panel of eight judges. The judges are considered a random panel of all possible judges. The wines are evaluated on a 100-point scale. The wines were presented in random order to each judge, and the following results obtained.

Judge	Wine		
	1	2	3
1	85	88	93
2	90	89	94
3	88	90	98
4	91	93	96
5	92	92	95
6	89	90	95
7	90	91	97
8	91	89	98

Analyze the data from this experiment. Is there a difference in wine quality? Analyze the residuals and comment on model adequacy.