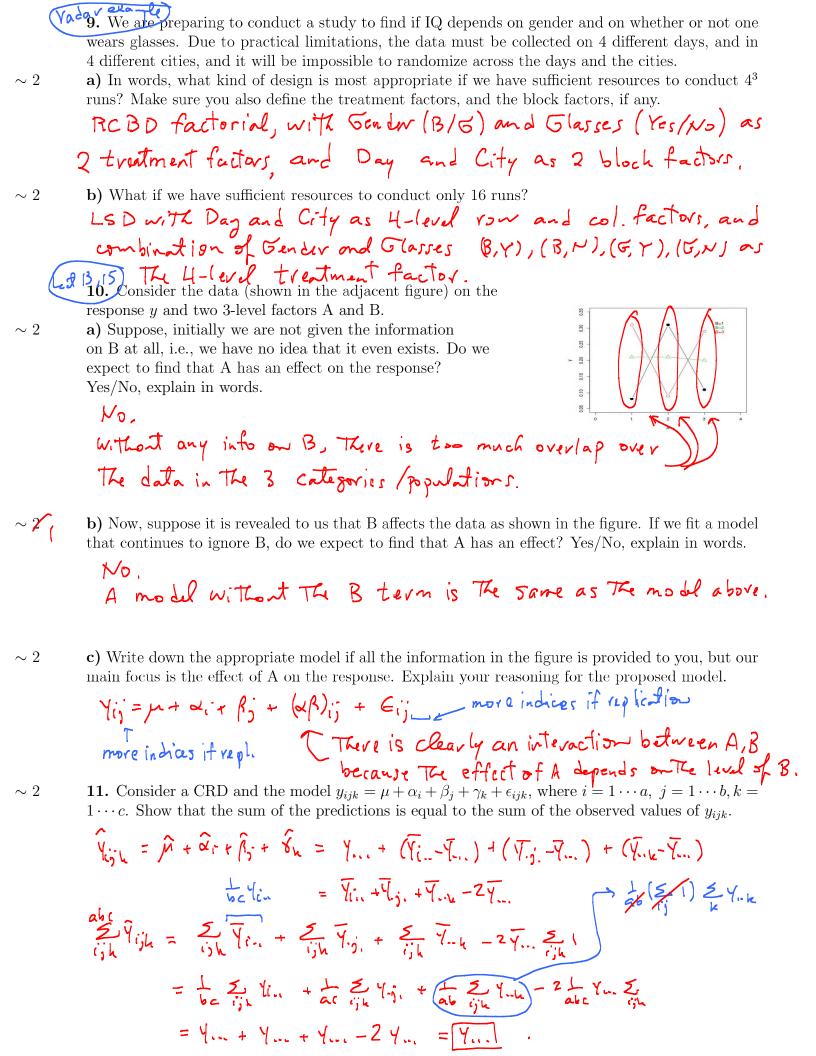
| | Name: ID: |
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| Points | Stat 421, Test 2, Fall, Nov. 16, 2015; Marzban ONLY a half-size "cheat sheet" is allowed Multiple choice: Circle all the correct answers; there is wrong-answer penalty For rest, SHOW answer & work; NO CREDIT for correct answer without explanation |
| | 1. Which of the following statements is/are true regarding contrasts? a) All comparisons of μ_i can be written in terms of zero-sum contrasts constructed from the μ_i . b) A specific comparison between several μ_i , constructed from a zero-sum contrast, can be written in terms of a zero-sum contrast constructed from the corresponding effects $\alpha_i = \mu - \mu_i$. c) For a treatment levels, there exists a unique set of $(a-1)$ orthogonal contrasts. d) If an anova F-test has led to the rejection of the null hypothesis of equal means, then testing a set of orthogonal contrasts can help in identifying a specific combination of means that is "responsible" for the rejection. |
| ~ 1 | 2. In using the maximum likelihood criterion for estimating model parameters, if we change the constraints, then of the parameter estimates will change. a) none b) some c) all |
| ~ 1 | 3. In using the maximum likelihood criterion for estimating model parameters, if we change the constraints, then functions of the parameters will change. a) no b) some c) all |
| 1 | 4. Suppose we have developed the model $y_{ij} = \mu + \alpha_i + \epsilon_{ij} i = 1 \cdots a$, $j = 1 \cdots n$ based on a CRD. Circle all of the following quantities that will be different in an RCBD model $y_{ij} = \mu + \alpha_i + \beta_j + \epsilon_{ij}$ of the same data. a) SST b) SSA b) SSA c) SSE |
| ~ 1 | In the model $y_{ij} = \mu + \alpha_i + \beta_j + \epsilon_{ij} i = 1 \cdots a$, $j = 1 \cdots b$ based on an RCBD design, how does F_A generally change with increasing b ? a) Generally decreases b) Generally remains constant c Generally increases d) None of the above. |
| 2 | 6. In which of the following models should we be concerned if the "grand mean" of the residuals turns out to be nonzero? (a) $y_{ij} = \mu + \alpha_i + \epsilon_{ij}$ (b) $y_{ij} = \mu + \alpha_i + \beta_j + \epsilon_{ij}$ (c) $y_{ijk} = \mu + \alpha_i + \beta_j + \epsilon_{ijk}$ (e) $y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_k + \epsilon_{ijk}$ |
| | The which of the following models should we not be surprised if some "conditional mean" of the residuals turns out to be nonzero? a) $y_{ij} = \mu + \alpha_i + \epsilon_{ij}$ b) $y_{ij} = \mu + \alpha_i + \beta_j + \epsilon_{ij}$ c) $y_{ijk} = \mu + \alpha_i + \beta_j + \epsilon_{ijk}$ d) $y_{ijk} = \mu + \alpha_i + \beta_j + \alpha_{ijk} + \epsilon_{ijk}$ e) $y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_k + \epsilon_{ijk}$ 8. In a problem with quantitative factors, one can develop a regression model that has a comparable number of parameters as the anova model. This statement is |
| ~1 (| 8. In a problem with quantitative factors, one can develop a regression model that has a comparable number of parameters as the anova model. This statement is a) always true, period. b) true, but the highest possible order depends on the number of factors in the problem. |
| | Cotrue, but the highest possible order depends on the number of levels in the factors. d) never true, period. $ \begin{array}{cccccccccccccccccccccccccccccccccc$ |
| | Le mace lavelein K Thelasiu to End A litted |



12. Show that
$$y_{1..} + y_{2..} + y_{3..} = y_{...}$$
 where all "dots" refer to restricted sums over the LSD given by $y_{1..} = y_{1|1} + y_{2|2} + y_{3|3}$
$$y_{2..} = y_{2|1} + y_{2|2} + y_{2|3}$$

$$y_{3..} = y_{3|1} + y_{3|2} + y_{3|2}$$

$$y_{3..} = y_{3|1} + y_{3|2} + y_{3|2}$$
 where all "dots" refer to restricted sums over the LSD given by
$$y_{1..} = y_{1|1} + y_{2..} + y_{3|.} = y_{3|1} + y_{3|2} + y_{3|3}$$

$$y_{3|1} = y_{3|1} + y_{3|2} + y_{3|2} + y_{3|2}$$

$$y_{3|1} = y_{3|1} + y_{3|2} + y_{3|2} + y_{3|2}$$

Lut (U **13.** Consider the model $y_{ij} = \mu + \alpha_i + \beta_j + \alpha \beta_{ij} + \epsilon_{ij}$, where $i = 1 \cdots a$, $j = 1 \cdots b$, and $\epsilon_{ij} \sim N(0, \sigma_{\epsilon}^2)$. a) Starting from the expression for the Likelihood of data, compute the maximum-likelihood (ML) estimate of the interaction term. You may use the fact that the ML estimates of μ , α_i , β_i are, respectively, $\overline{y_{..}}$, $(\overline{y_{i.}} - \overline{y_{..}})$ and $(\overline{y_{.j}} - \overline{y_{..}})$.

$$L = \frac{777}{1000} \frac{1}{\sqrt{27000}} e^{-\frac{1}{2}\left(\frac{4(2)^{2} - 1000}{2000} (40)^{2} - \frac{1}{2000} (40)^{2}\right)^{2}} = e^{-\frac{1}{2}\left(\frac{4(2)^{2} - 1000}{2000} (40)^{2}\right)^{2}} = e^{-\frac{1}{2}\left(\frac{4(2)^{2} - 1000$$

$$\frac{\partial}{\partial (A\beta)_{kl}}: \frac{\partial}{\partial (A\beta)_{kl}}: \frac{\partial}{\partial (A\beta)_{kl}} \frac{\partial}{\partial ($$

 ~ 2 **b)** Find the expression for the predictions \hat{y}_{ij} .

$$\widehat{Y}_{ij} = \widehat{\mathcal{M}} + \widehat{\mathcal{L}}_i + \widehat{\mathcal{B}}_j + (\widehat{\mathcal{L}}_i \widehat{\mathcal{B}}_i)_{ij}$$

$$= \widehat{\mathcal{M}} + \widehat{\mathcal{L}}_i + \widehat{\mathcal{B}}_j + (\widehat{\mathcal{L}}_i \widehat{\mathcal{B}}_i)_{ij}$$

$$= \widehat{\mathcal{M}} + \widehat{\mathcal{L}}_i + \widehat{\mathcal{B}}_j + (\widehat{\mathcal{L}}_i \widehat{\mathcal{B}}_i)_{ij}$$

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$$= \widehat{\mathcal{M}}_i + \widehat{\mathcal{L}}_i + \widehat{\mathcal{B}}_j + (\widehat{\mathcal{L}}_i \widehat{\mathcal{B}}_i)_{ij}$$

$$= \widehat{\mathcal{M}}_i + \widehat{\mathcal{L}}_i + \widehat{\mathcal{B}}_j + \widehat{\mathcal{L}}_i + \widehat{\mathcal{B}}_j + (\widehat{\mathcal{L}}_i \widehat{\mathcal{B}}_i)_{ij}$$

$$= \widehat{\mathcal{M}}_i + \widehat{\mathcal{L}}_i + \widehat{\mathcal{B}}_j + \widehat{\mathcal{L}}_i + \widehat{\mathcal{L}}$$

~ 3 Consider a CRD with a single qualitative factor A, and the model $y_{ij} = \mu + \alpha_i + \epsilon_{ij}$, $i = 1 \cdots a$, $j = 1 \cdots n$. We want to test whether A has an effect on the response. We know that $MS_{Tr} = \sum_{i,j} (\overline{y_{i.}} - \overline{y_{..}})^2$. Compute $SSE_{reduced}$ and SSE_{full} , and then show that $MS_{Tr} = SSE_{reduced} - SSE_{full}$. You may use the anova decomposition without deriving/proving it.

Reduced:
$$Y_{ij} = p + \epsilon_{ij} \implies \hat{p} = \overline{Y}_{ii}$$

$$\therefore \hat{Y}_{ij} = \hat{p} = \overline{Y}_{ii} \implies SSE_{\text{reduced}} = \underbrace{S}_{ij} (Y_{ij} - \overline{Y}_{ii})^{2}$$

Full: $Y_{ij} = p + \alpha_{i} + \epsilon_{ij} \implies \hat{p} = \overline{Y}_{ii}$, $\hat{Q}_{i} = \overline{Y}_{ii} - \overline{Y}_{ii}$

$$\therefore \hat{Y}_{ij} = p + \hat{\alpha}_{i} + \epsilon_{ij} \implies \hat{p} = \underline{Y}_{ii}$$

$$SSE_{\text{red}} - SSE_{\text{full}} = \underbrace{SSE}_{\text{full}} = \underbrace{SSE}_{\text{ful$$

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- 15. Consider the following data on a response y (numbers in the table) from two treatement levels of a factor A.
- ~ 2 a) Suppose the data have been collected in a CRD. Use an appropriate model and report the numerical value of SSE. Hint: find $\overline{y_i}$ first.

$$Y_{i,j} = \bigwedge + \alpha_{i} + \epsilon_{i,j} \qquad \alpha = 2, \ n = 3 \implies \hat{Y}_{i,j} = \overline{Y}_{i} = \begin{cases} \frac{1}{3} (1+2+3) = 2 & i = 1 \\ \frac{1}{3} (2+3+4) = 3 & i = 2 \end{cases}$$

$$SSE = \frac{5}{i,j} \left(Y_{i,j} - \overline{Y}_{i,j} \right)^{2} = (1-2)^{2} + (2-2)^{2} + (3-2)^{2} \iff i = 1 \\ + (2-3)^{2} + (3-3) + (4-3)^{2} \iff i = 2 \end{cases}$$

$$= 1 + 0 + (1+1+0+1) = \boxed{4}$$

 ~ 2 b) Now, suppose the 3 Runs occurred on 3 different days, and there was no randomization between days. Use an appropriate RCBD model and report the numerical value of SSE. Hint: find $\overline{y_{ij}}, \overline{y_{ii}}$.

$$\begin{aligned}
Y_{ij} &= M + di + \beta_j + C_{ij} &\implies \widehat{Y}_{ij} &= \overline{Y}_{i}, + \overline{Y}_{ij} - \overline{Y}_{i}, & \overline{Y}_{ij} = \begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix} = 3 / 2 \\ \frac{1}{2} (2 + 3) &= 5 / 2 \end{cases} \\
SSE &= \underbrace{\sum_{ij} (Y_{ij} - \overline{Y}_{i}, -\overline{Y}_{i})}_{(ij)} + \underbrace{Y_{ij}}_{(ij)}^{2} &\qquad \widehat{Y}_{ii} = \frac{15}{C} = \frac{5}{2} / 2 \\ &= (1 - 2 - \frac{3}{2} + \frac{5}{2})^{2} + (2 - 2 - \frac{5}{2} + \frac{5}{2})^{2} + (3 - 2 - \frac{7}{2} + \frac{5}{2})^{2} &\qquad \widehat{Y}_{ij} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \\ \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \\ \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \\ \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 \end{aligned}}_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 }_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac{1}{2} / 1 + 2 \end{pmatrix}}_{\frac{1}{2}} = 3 / 2 }_{\frac{1}{2}} &\qquad \widehat{Y}_{ii} = \underbrace{\begin{cases} \frac$$