## Two-Way ANOVA

- Two factors ${ }^{\text {a }} X_{1}$ has $I$ levels and $X_{2}$ has $J$ levels.
- Data $y_{i j l}$ can be displayed in a two-way table with $I$ rows and $J$ columns. The $(i, j)$ th cell contains $n_{i j}$ obs

$$
y_{i j 1}, \ldots, y_{i j n_{i j}} .
$$

- A balanced design has $n_{i j}=m$.

[^0]
## Possible Models

- The interaction model (the most general model) $\mathcal{M}_{R \times C}$

$$
y_{i j l}=\mu+\alpha_{i}+\beta_{j}+\gamma_{i j}+e_{i j l} .
$$

- The additive model $\mathcal{M}_{R+C}$

$$
y_{i j l}=\mu+\alpha_{i}+\beta_{j}+e_{i j l} .
$$

- The row-effect model $\mathcal{M}_{R} \quad y_{i j l}=\mu+\alpha_{i}+e_{i j l}$.
- The column-effect model $\mathcal{M}_{C} \quad y_{i j l}=\mu+\beta_{j}+e_{i j l}$.
- The intercept-only model $\mathcal{M}_{0} \quad y_{i j l}=\mu+e_{i j l}$.


## The LS Estimates

- We can write the (element-wise) models in matrix form.
- Yes, some are over-parameterized. There are multiple ways to reduce parameters, .e.g., we can remove some columns. But no matter which approach we take, the resulting LS estimates should be the same.
- $\mathcal{M}_{R \times C} \quad \hat{y}_{i j l}=\bar{y}_{i j}$.
- $\mathcal{M}_{R+C} \quad \hat{y}_{i j l}=\bar{y}_{i . .}+\bar{y}_{. j .}-\bar{y}_{. . .}$回
- $\mathcal{M}_{R} \quad \hat{y}_{i j l}=\bar{y}_{i}$.
- $M_{C} \quad \hat{y}_{i j l}=\bar{y} \cdot j$.
- $M_{0} \quad \hat{y}_{i j l}=\bar{y} .$.
${ }^{\text {a}}$ This is true only for balanced design. For unbalanced design, the LS for $\mathcal{M}_{R+C}$ does not have a closed-form expression.


## Which model to pick?

- Recall the partial $F$-test for comparing two nested models:
$H_{0}$ : a smaller model with $p_{0}$ coefficients
$H_{a}$ : a large model with $p_{a}$ coefficients

$$
\begin{aligned}
F & =\frac{\left(\mathrm{RSS}_{0}-\mathrm{RSS}_{a}\right) /\left(p_{a}-p_{0}\right)}{\hat{\sigma}_{a}^{2}} \\
& \sim F_{p_{a}-p_{0}, n-p_{a}} \text { under the null. }
\end{aligned}
$$

- Suppose we are comparing three nested models:

$$
\mathcal{M}_{1} \subset \mathcal{M}_{2} \subset \mathcal{M}_{3} \text { with } \operatorname{dim} p_{1}<p_{2}<p_{3}
$$

- We make our decision through the following path:

1) Compare $\mathcal{M}_{2}$ vs $\mathcal{M}_{3}$. If $\mathcal{M}_{3}$ is selected, stop;
2) otherwise, compare $\mathcal{M}_{1}$ vs $\mathcal{M}_{2}$.

- When calculating the $F$-stat at step 2 , we could use $\hat{\sigma}^{2}$ from $\mathcal{M}_{2}$, i.e., the $F$-test $\sim F_{p_{2}-p_{1}, n-p_{2}}$ or we could calculate the two $F$-stats simultaneously using $\hat{\sigma}^{2}$ from $\mathcal{M}_{3}$ (the largest model), so the $F$-test for the comparison at step 2 would be $F_{p_{2}-p_{1}, n-p_{3}}$.
- Back to the two-way ANOVA model. Due to the hierarchical structure, we make our decision through the following path:

1) Compare $\mathcal{M}_{R \times C}$ vs $\mathcal{M}_{R+C}$. If select the interaction model, stop; otherwise, go to the next step.
2) Pick one among the remaining four models,

$$
\mathcal{M}_{R+C}, \quad \mathcal{M}_{R}, \quad \mathcal{M}_{C}, \quad \mathcal{M}_{0}
$$

depending on whether the row or column effect is significant.
Step 2 is much easier for the balanced design.

## The Balanced Design ( $n_{i j}=m>1$ )

|  | $\mathrm{SS}(\mathrm{Sum} \operatorname{Sq})$ | df |
| :--- | :---: | :--- |
| Interaction | $\operatorname{RSS}\left(\mathcal{M}_{R+C}\right)-\operatorname{RSS}\left(\mathcal{M}_{R \times C}\right)$ | $(I-1)(J-1)$ |
| Row | $\operatorname{RSS}\left(\mathcal{M}_{0}\right)-\operatorname{RSS}\left(\mathcal{M}_{R}\right)$ | $I-1$ |
| Col | $\operatorname{RSS}\left(\mathcal{M}_{0}\right)-\operatorname{RSS}\left(\mathcal{M}_{C}\right)$ | $J-1$ |
| Err | $\operatorname{RSS}\left(\mathcal{M}_{R \times C}\right)$ | $n-I J$ |

Three F-tests: $\mathrm{SS} / \mathrm{df}$ is the numerator, and the dominator is $\mathrm{SS} / \mathrm{df}$, i.e., $\hat{\sigma}^{2}$ from the interaction model

$$
\hat{\sigma}^{2}=\frac{\operatorname{RSS}\left(\mathcal{M}_{R \times C}\right)}{(m-1) I J} .
$$

| Selected Model | Interaction | Row | Col |
| :---: | :---: | :---: | :---: |
| $\mathcal{M}_{R \times C}$ | Sig | - | - |
| $\mathcal{M}_{R+C}$ | No | Sig | Sig |
| $\mathcal{M}_{R}$ | No | Sig | No |
| $\mathcal{M}_{C}$ | No | No | Sig |
| $\mathcal{M}_{0}$ | No | No | No |

## The Balanced Design ( $n_{i j}=m=1$ )

- Only one observation in each cell, so we cannot fit the interaction model.
- $\operatorname{RSS}\left(\mathcal{M}_{R \times C}\right)=0$, i.e., the corresponding error variance is 0 .
- Then consider $\mathcal{M}_{R+C}$, instead of $\mathcal{M}_{R \times C}$, to be the largest model. All the $F$-tests are the same except that the interaction model is not a candidate model.


## The Unbalanced Design

- Compare $\mathcal{M}_{R \times C}$ vs $\mathcal{M}_{R+C}$ : if the $F$-test is significant, stop.
- If the interaction is not significant, we need to pick one model from

$$
\mathcal{M}_{R+C}, \quad \mathcal{M}_{R}, \quad \mathcal{M}_{C}, \quad \mathcal{M}_{0}
$$

- The difficulty: to decide whether the column effect is significant, we can
a) compare $\mathcal{M}_{R+C}$ vs $\mathcal{M}_{R}$ (test the column effect given that the row effect has been included), or
b) compare $\mathcal{M}_{C}$ vs $\mathcal{M}_{0}$ (test the column effect given that the row effect is not included).
- For a balanced design, these two tests turn out to be the same, but that's not the case for the unbalanced design.
- In most cases, it is not difficult to make a consensus decision.
- Let's take a look of the two ANOVA tables.

|  | $\mathrm{SS}(\mathrm{Sum} \mathrm{Sq})$ | df |
| :--- | :---: | :--- |
| $C$ | $\operatorname{RSS}\left(\mathcal{M}_{0}\right)-\operatorname{RSS}\left(\mathcal{M}_{C}\right)$ | $J-1$ |
| $R \mid C$ | $\operatorname{RSS}\left(\mathcal{M}_{C}\right)-\operatorname{RSS}\left(\mathcal{M}_{R+C}\right)$ | $I-1$ |
| Interaction | $\operatorname{RSS}\left(\mathcal{M}_{R+C}\right)-\operatorname{RSS}\left(\mathcal{M}_{R \times C}\right)$ | $(I-1)(J-1)$ |
| Err | $\operatorname{RSS}\left(\mathcal{M}_{R \times C}\right)$ | $n-I J$ |
| TSS | $\operatorname{RSS}\left(\mathcal{M}_{0}\right)$ | $n-1$ |


|  | $\mathrm{SS}(\mathrm{Sum} \operatorname{Sq})$ | df |
| :--- | :---: | :--- |
| $R$ | $\operatorname{RSS}\left(\mathcal{M}_{0}\right)-\operatorname{RSS}\left(\mathcal{M}_{R}\right)$ | $I-1$ |
| $C \mid R$ | $\operatorname{RSS}\left(\mathcal{M}_{R}\right)-\operatorname{RSS}\left(\mathcal{M}_{R+C}\right)$ | $J-1$ |
| Interaction | $\operatorname{RSS}\left(\mathcal{M}_{R+C}\right)-\operatorname{RSS}\left(\mathcal{M}_{R \times C}\right)$ | $(I-1)(J-1)$ |
| Err | $\operatorname{RSS}\left(\mathcal{M}_{R \times C}\right)$ | $n-I J$ |
| TSS | $\operatorname{RSS}\left(\mathcal{M}_{0}\right)$ | $n-1$ |


| Selected Model | $R$ | $R \mid C$ | $C$ | $C \mid R$ |
| :---: | :---: | :---: | :---: | :---: |
| $\mathcal{M}_{0}$ | $\times$ | $\times$ | $\times$ | $\times$ |
| $\mathcal{M}_{R+C}$ | - | $\sqrt{ }$ | - | $\sqrt{ }$ |
|  | $\sqrt{ }$ | - | - | $\sqrt{ }$ |
|  | - | $\sqrt{ }$ | $\sqrt{ }$ | - |
| $\mathcal{M}_{R}$ | $\sqrt{ }$ | $\sqrt{ }$ | - | $\times$ |
|  | $\sqrt{ }$ | $\times$ | $\times$ | $\times$ |
| $\mathcal{M}_{C}$ | - | $\times$ | $\sqrt{ }$ | $\sqrt{ }$ |
|  | $\times$ | $\times$ | $\times$ | $\sqrt{ }$ |
| $\mathcal{M}_{R+C}$ | $\times$ | $\sqrt{ }$ | $\times$ | $\times$ |
|  | $\times$ | $\times$ | $\times$ | $\sqrt{ }$ |


|  | SS(Sum Sq) | df | $F$-stat |
| :--- | :---: | :---: | :---: |
| $R$ | 20 | 10 | $2 \sim F_{10,50}$ |
| $C \mid R$ | 16 | 8 | $2 \sim F_{8,50}$ |
| $C$ | 11 | 8 | $1.375 \sim F_{8,50}$ |
| $R \mid C$ | 25 | 10 | $2.5 \sim F_{10,50}$ |
| $R+C$ | 36 | 18 | $2 \sim F_{18,50}$ |
| Err | 50 | 50 | $\hat{\sigma}^{2}=1$ |


[^0]:    ${ }^{\mathrm{a}} \mathrm{A}$ factor is a categorical predictor with possible values called levels.

