

## **HANDOUT # 3**

### **One Way - Completely Randomized Design**

1. The Research Design
2. Randomization Procedures
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# The Research Design for CRD with 1-Way Treatment Structure

The description of an experiment consists of three components:

## 1. The Method of Randomization

The method by which the EU's are assigned to the Treatments

In a Completely Randomized Design (CRD), the  $n$  experimental units are considered to have no identifiable differences relative to the response. Thus, there is no restrictions on the randomization. The  $n_i$  EU's assigned to Treatment #  $i$  are  $n_i$  randomly selected EU's from the totality of  $n$  EU's.

## 2. The Treatment Structure

How the treatments are constructed

In a one-way treatment structure, the treatments are  $t$  distinct methods of performing a process or  $t$  distinct populations:

- (a)  $t$  populations ( $t$  suppliers of raw materials)
- (b)  $t$  methods of performing a process ( $t$  different ways to teach elementary students how to read)
- (c)  $t$  procedures for treating an illness ( $t$  drugs or  $t$  surgical techniques or  $t$  dose levels of the same drug)

## 3. The Measurement Process

The method by which the response is recorded on the EU after the EU has been randomly to a treatment

- (a) Single measurement on each of the experimental units
- (b) Repeated measurements on experimental unit over time (Longitudinal Measurements): EU (patient or lab animal) is randomly assigned one of 6 possible dose levels (treatment) of a drug . The amount of drug in the blood stream is measured every hour over the next 2 days. A total of 48 measurements per EU.
- (c) Repeated measurements at various locations on experimental unit (Spatial Measurements): Studying three electroplating processes( 3 treatments). Six specimens of metal (EU), all uniform in size and thickness, are randomly assigned to each of the 3 electroplating processes (treatments). After electroplating, the thickness of each specimen was measured at three specified locations on the specimen.
- (d) Sub sampling of experimental unit: Turfgrass specialist investigates four root growth stimulators (treatments). Eight similar plots of turfgrass on a golf course are randomly assigned to each of the four stimulators. After a period of time, twenty equally sized cores were randomly selected from the 32 plots and analyzed for root weight.

## Randomization Procedure

In a CRD with  $t$  treatments and  $n_i$  EU's per treatment, the procedure for assignment of EU's to treatments can be conducted as follows:

### Case I: For Randomized Treatments in a Designed Experiment

Suppose we have  $t$  treatments:  $A_1, \dots, A_t$  and  $n$  EU's

The  $n = n_1 + n_2 + \dots + n_t$  EU's are considered homogenous relative to characteristics which may affect the response after the treatments have been applied.

1. Assign the numbers 1 to  $n$  to the experimental units
2. Obtain a random permutation of the numbers 1 to  $n$

R code:  $y <- \text{sample}(n, \text{replace}=\text{F})$

3. Assign the first  $n_1$  EU's in the list to Treatment  $A_1$ , the next  $n_2$  EU's in the list to Treatment  $A_2$ , ..., the last  $n_t$  EU's to treatment  $A_t$ .

**Example:** Suppose  $n = 20$ ,  $t = 3$ ,  $n_1 = 7$ ,  $n_2 = 5$ ,  $n_3 = 8$ :

1.  $EU_1, EU_2, EU_3, EU_4, EU_5, EU_6, EU_7, EU_8, EU_9, EU_{10},$   
 $EU_{11}, EU_{12}, EU_{13}, EU_{14}, EU_{15}, EU_{16}, EU_{17}, EU_{18}, EU_{19}, EU_{20}$

2. Using the R code: **sample(20,replace=F)** yields

1 15 18 5 4 17 19    3 13 10 9 14    8 12 20 11 16 6 7 2

3.  $A_1 : EU_1, EU_{15}, EU_{18}, EU_5, EU_4, EU_{17}, EU_{19}$

$A_2 : EU_3, EU_{13}, EU_{10}, EU_9, EU_{14}$

$A_3 : EU_8, EU_{12}, EU_{20}, EU_{11}, EU_{16}, EU_6, EU_7, EU_2$

## Case II: For Comparative Observational Study

Suppose we have  $t$  existing populations that we want to compare. For example,

1. five manufacturers of fire alarm devices
2. six producers of a raw material in the manufacturer of paint
3. five types of landscapes in which birds may migrate.

The procedure is to take a simple randomly sample of  $n_i$  items (EU's) from Population  $i$ . That is, select the units such that every unit in the population has an equal chance of being selected. Then make observations or measurements on the  $n = n_1 + \cdots + n_t$  selected items.

**Example:** Suppose we have 3 manufacturers of fire alarms and we want to compare the reliability of their devices. We want to randomly select 35 devices from the warehouses of each manufacture and assess the reliability of the devices. From the 10,000 fire alarms in the warehouse of Manufacturer 1 randomly select 35 fire alarms.

1. Assign the numbers 1 to 10000 to the fire alarms.
2. Randomly generate 35 numbers between 1 and 10000.
3. Repeat the above for the other two Manufacturers.

SAS code:

```
data randdata;  
m=10000;  
do i = 1 to m;  
random = i;  
output;end;drop i;  
proc surveyselect data=randdata method = srs n=35 reps = 1 out = sample;  
run;  
proc print data = sample; var random; run;
```

Output from SAS:

Obs	random	Obs	random	Obs	random	Obs	random
1	392	11	3472	21	6206	31	8966
2	408	12	3511	22	6451	32	9404
3	418	13	3701	23	6764	33	9654
4	615	14	3810	24	7941	34	9753
5	735	15	4083	25	8240	35	9926
6	1102	16	4985	26	8315		
7	1186	17	5061	27	8502		
8	1578	18	5211	28	8677		
9	2197	19	5543	29	8753		
10	3457	20	5883	30	8866		

## Cell Means Model

The goals of the CRD are

1. To compare the response distributions for the  $t$  treatments
2. To estimate and place confidence intervals on the parameters for the response distributions for the  $t$  treatments:  $\mu_i$  and  $\sigma$
3. To estimate and place confidence intervals on the effects of the  $t$  treatments:

$$\mu_i - \mu_k \text{ for all } i \neq k = 1, \dots, t$$

To accomplish these goals, we set up the following model:

Let  $y_{ij}$  be the response from the  $j$ th EU observed from treatment  $i$

The Sources of variation in the data,  $y_{ij}$ , are

- **Between Treatment** Differences as measured by differences in the treatment means,  $\mu_i$   
Comparing relative sizes of  $\mu_1, \mu_2, \dots, \mu_t$
- **Within Treatment** Differences as measured by the Random variation about the treatment means, modeled by  $e_{ij}$

Variation in responses from EU's receiving the **same treatments**, size of  $\sigma_e$

**Model:**  $y_{ij} = \mu_i + e_{ij}$  for  $i = 1, \dots, t; j = 1, \dots, n_i$

where

1.  $\mu_i$  is the mean response for the  $i$ th treatment
2.  $e_{ij}$ 's are iid random variables with standard deviation  $\sigma_e$
3. We will develop tests and C.I.'s for the case where  $e_{ij}$ 's have a normal distribution. Alternative approaches will be discussed where the normality condition is not imposed.

A major goal is to test the hypotheses:

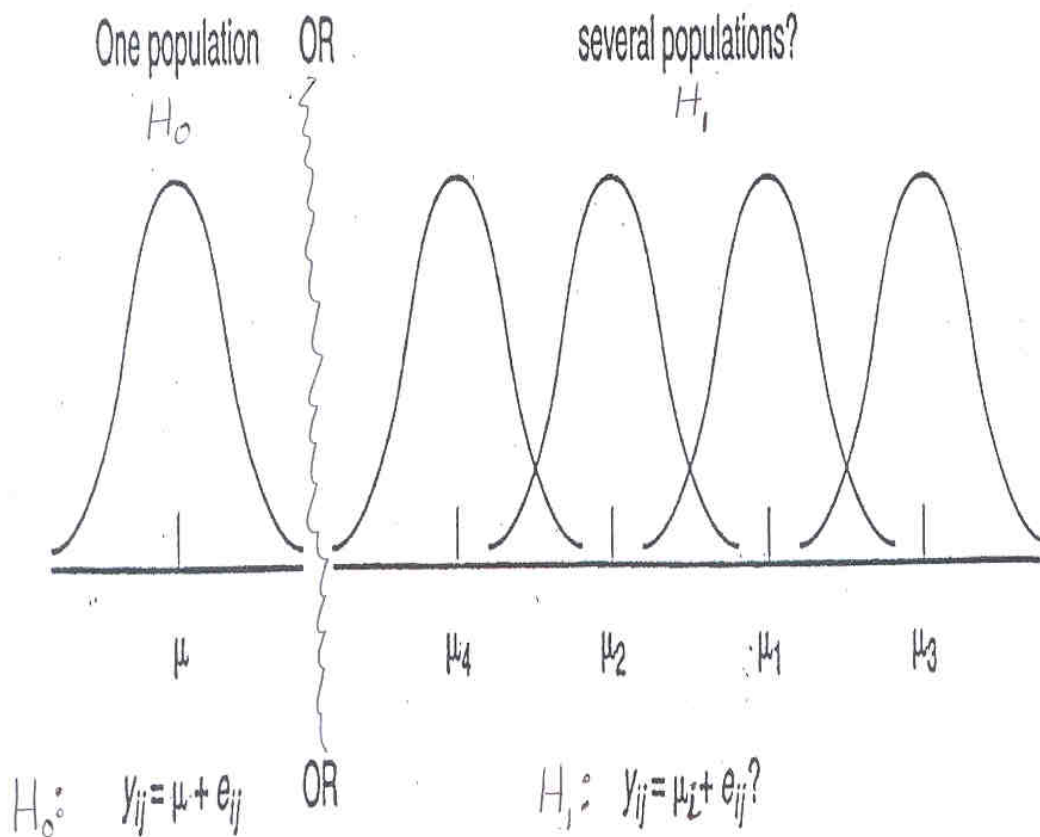
$$H_o : \mu_1 = \mu_2 = \dots = \mu_t = \mu \text{ versus } H_1 : \mu_i \neq \mu_k \text{ for at least one pair } i, k$$

We thus have two models depending on which of  $H_o$  or  $H_1$  is true:

Under  $H_o$ :  $y_{ij} = \mu + e_{ij}$  called the **Reduced Model**

Under  $H_1$ :  $y_{ij} = \mu_i + e_{ij}$  called the **Full Model**

We can display the difference in the two models when  $t = 4$  using the following graphic from *Design of Experiments*, by R.O. Kuehl:



$$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu \quad \text{versus} \quad H_1 : \mu_i \neq \mu_k \text{ for at least one pair } (\mu_i, \mu_k)$$

We will obtain estimators of the model parameters  $\mu$ ,  $\mu_i$ , and  $\sigma_e$  for both models. A test of hypotheses for  $H_0$  and  $H_1$  will then be developed. A regression and matrix formulation of these models will also be formulated for the two models.

## Parameter Estimation (LSE) and Sums of Squares

### Least Squares Estimation of Model Parameters (LSE) for the Full Model:

In the full model,  $y_{ij} = \mu_i + e_{ij}$  we have that the residuals are

$$e_{ij} = y_{ij} - \mu_i$$

To obtain the LSE, we select the estimators of  $\mu_i$ ,  $\hat{\mu}_i$  which minimizes the objective function, the sum of squares of the sample residuals:

$$Q(\mu_1, \mu_2, \dots, \mu_t) = \sum_{i=1}^t \sum_{j=1}^{n_i} [e_{ij}]^2 = \sum_{i=1}^t \sum_{j=1}^{n_i} [y_{ij} - \mu_i]^2$$

The minimum value of this sum of squares is denoted as the sum of squares error from the full model ( $SSE_{Full}$ ) :

$$SSE_{Full} = \sum_{i=1}^t \sum_{j=1}^{n_i} \hat{e}_{ij}^2 = \sum_{i=1}^t \sum_{j=1}^{n_i} [y_{ij} - \hat{\mu}_i]^2,$$

where  $\hat{e}_{ij} = y_{ij} - \hat{\mu}_i$  are called the *sample residuals* of the fitted model. The population residuals,  $e_{ij}$ 's, describe the distribution of the observed responses  $y_{ij}$  about the population (treatment) means  $\mu_i$ .

The LSE's are obtained by a direct application of calculus to the quantity  $Q(\mu_1, \dots, \mu_t) = \sum_{i=1}^t \sum_{j=1}^{n_i} [y_{ij} - \mu_i]^2$ ,

Take the partial derivative of  $Q(\mu_1, \dots, \mu_t)$  wrt  $\mu_i$ , set equal to 0, and solve for  $\hat{\mu}_i$ :

$$\frac{\partial Q(\mu_1, \dots, \mu_t)}{\partial \mu_i} = \frac{\partial}{\partial \mu_i} \sum_{j=1}^{n_i} [y_{ij} - \mu_i]^2 = -2 \sum_{j=1}^{n_i} [y_{ij} - \mu_i]$$

$$\begin{aligned} \frac{\partial Q(\mu_1, \dots, \mu_t)}{\partial \mu_i} = 0 &\Rightarrow -2 \sum_{j=1}^{n_i} [y_{ij} - \hat{\mu}_i] = 0 \\ \sum_{j=1}^{n_i} y_{ij} - \sum_{j=1}^{n_i} \hat{\mu}_i &= 0 \\ y_{i.} - n_i \hat{\mu}_i &= 0 \\ \hat{\mu}_i &= \frac{1}{n_i} y_{i.} = \bar{y}_i. \end{aligned}$$

### Least Squares Estimation of Model Parameters (LSE) for the Reduced Model:

In the reduced model,  $\mu_1 = \mu_2 = \dots = \mu_t = \mu$ , hence the model simplifies to  $y_{ij} = \mu + e_{ij}$  with corresponding residuals

$$e_{ij} = y_{ij} - \mu$$

To obtain the LSE, we select the estimator of  $\mu$ ,  $\hat{\mu}$  which minimizes sum of squares residuals from the reduced

$$Q(\mu) = \sum_{i=1}^t \sum_{j=1}^{n_i} [e_{ij}]^2 = \sum_{i=1}^t \sum_{j=1}^{n_i} [y_{ij} - \mu]^2$$

The minimum value of this sum of squares is denoted as the sum of squares error from the reduced model ( $SSE_{Red}$ ) :

$$SSE_{Red} = \sum_{i=1}^t \sum_{j=1}^{n_i} \hat{e}_{ij}^2 = \sum_{i=1}^t \sum_{j=1}^{n_i} [y_{ij} - \hat{\mu}]^2,$$

Take the partial derivative of  $Q(\mu)$  wrt  $\mu$ , set equal to 0, and solve for  $\hat{\mu}$ :

$$\frac{\partial Q(\mu)}{\partial \mu} = \frac{\partial}{\partial \mu} \sum_{i=1}^t \sum_{j=1}^{n_i} [y_{ij} - \mu]^2 = -2 \sum_{i=1}^t \sum_{j=1}^{n_i} [y_{ij} - \mu]$$

$$\frac{\partial Q(\mu)}{\partial \mu} = 0 \Rightarrow \quad -2 \sum_{i=1}^t \sum_{j=1}^{n_i} [y_{ij} - \hat{\mu}] = 0$$

$$\sum_{i=1}^t \sum_{j=1}^{n_i} y_{ij} - \sum_{i=1}^t \sum_{j=1}^{n_i} \hat{\mu} = 0$$

$$y_{..} - \hat{\mu} \sum_{i=1}^t n_i = 0$$

$$y_{..} - \hat{\mu} n = 0$$

$$\hat{\mu} = \frac{1}{n} y_{..} = \bar{y}_{..}$$



### Estimation of $\sigma_e$ for both models

Let  $\sigma_i^2$  be the variance of the responses from the  $i$ th distribution. We have imposed the restriction that  $\sigma_1 = \sigma_2 = \dots = \sigma_t = \sigma_e$ .

An estimator of  $\sigma_i^2$  is given by

$$\hat{\sigma}_i^2 = \frac{1}{n_i - 1} \sum_{j=1}^{n_i} [y_{ij} - \bar{y}_i.]^2 \quad i = 1, 2, \dots, t$$

These estimators are obtained separately from each of the  $t$  population distributions.

From results in STAT 641, we know that

$$E[\hat{\sigma}_i^2] = \sigma_i^2 = \sigma_e^2 \quad \text{for } i = 1, \dots, t$$

Therefore, an estimator of  $\sigma_e^2$  which is unbiased under both the full and reduced model is obtained by pooling the  $t$  estimators of  $\sigma_e^2$ . The  $t$  estimators  $\hat{\sigma}_i^2$  are all estimators of  $\sigma_e^2$ . Therefore, create a weighted average of the  $t$  estimators:

$$\hat{\sigma}_e^2 = \frac{\sum_{i=1}^t (n_i - 1) \hat{\sigma}_i^2}{\sum_{i=1}^t (n_i - 1)} = \frac{\sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_i.)^2}{n - t} = \hat{\sigma}_{pooled}^2$$

$\hat{\sigma}_e^2$  is a pooled measure of the dispersion of the observations about the population mean  $\mu_i$  in each of the  $t$  populations.

The estimator  $\hat{\sigma}_e^2$  is an unbiased estimator for  $\sigma_e^2$ :

$$E[\hat{\sigma}_e^2] = \frac{\sum_{i=1}^t (n_i - 1) E[\hat{\sigma}_i^2]}{\sum_{i=1}^t (n_i - 1)} = \frac{\sum_{i=1}^t (n_i - 1) \sigma_e^2}{n - t} = \frac{\sigma_e^2 \sum_{i=1}^t (n_i - 1)}{n - t} = \sigma_e^2$$

Note:

- If we impose the condition that the  $y_{ij}$ s are distributed independent  $N(\mu_i, \sigma_e^2)$ , then we have that

$(n - t) \hat{\sigma}_e^2 / \sigma_e^2$  has a Chi-square distribution with  $df = n - t$

- $\hat{\sigma}_e$  is a **biased** estimator of  $\sigma_e$ , in fact,

$$E[\hat{\sigma}_e] = \left[ \sqrt{\frac{2}{n - t}} \frac{\Gamma\left(\frac{n - t + 1}{2}\right)}{\Gamma\left(\frac{n - t}{2}\right)} \right] \sigma$$

## Sums of Squares

In developing a test statistic for testing

$$H_o : \mu_1 = \mu_2 = \cdots = \mu_t = \mu \quad \text{versus} \quad H_1 : \mu_i \neq \mu_k \quad \text{for some } i \neq k$$

we will use the ideas of Analysis of Variance (AOV). Although we are testing hypotheses about differences in means,  $\mu_i$ , we will examine the variation in the  $y_{ij}$ 's and create a partition of the total variation in the  $y_{ij}$ 's about the overall mean  $\bar{y}_{..}$  into two components.

$$SS_{TOT} = \sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{..})^2$$

The **first component** is the amount of variation in the treatment sample means which we obtain by comparing the change in the residual sum of squares from the full model,  $y_{ij} = \mu_i + e_{ij}$ , to the reduced model,  $y_{ij} = \mu_i + e_{ij}$ , that is, the sum of squares due to differences in the treatment means:

$$\begin{aligned} SS_{TRT} &= SSE_{RED} - SSE_{FULL} \\ &= \sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \hat{\mu})^2 - \sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \hat{\mu}_i)^2 \\ &= \sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{..})^2 - \sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{i.})^2 \\ &= \sum_{i=1}^t \sum_{j=1}^{n_i} [(y_{ij}^2 - 2y_{ij}\bar{y}_{..} + \bar{y}_{..}^2) - (y_{ij}^2 - 2y_{ij}\bar{y}_{i.} + \bar{y}_{i.}^2)] \\ &= \sum_{i=1}^t [-2\bar{y}_{..} \sum_{j=1}^{n_i} y_{ij} + n_i \bar{y}_{..}^2 + 2\bar{y}_{i.} \sum_{j=1}^{n_i} y_{ij} - n_i \bar{y}_{i.}^2] \\ &= \sum_{i=1}^t [-2\bar{y}_{..} n_i \bar{y}_{i.} + n_i \bar{y}_{..}^2 + 2n_i \bar{y}_{i.}^2 - n_i \bar{y}_{i.}^2] \\ &= \sum_{i=1}^t n_i [\bar{y}_{i.}^2 - 2\bar{y}_{i.} \bar{y}_{..} + \bar{y}_{..}^2] \\ &= \sum_{i=1}^t n_i (\bar{y}_{i.} - \bar{y}_{..})^2 \end{aligned}$$

$SS_{TRT}$  measures the amount of variation in the  $y_{ij}$  "explained" by the size of differences in

Treatment means:  $\mu_1, \mu_2, \cdots, \mu_t$

The **second component** in  $SS_{TOT}$  is the amount of variation **within** the  $t$  populations:

$$SSE = \sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{i.})^2 = SSE_{FULL}$$

SSE measures the amount of variation in  $y_{ij}$  "within" each of the  $t$  population. It is just the numerator of our estimator of  $\sigma_e^2$ .

The two sum of squares form the *Fundamental Partition* of the total sum of squares:

$$\begin{aligned} SS_{TOT} &= \sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{..})^2 \\ &= \sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{i.} + \bar{y}_{i.} - \bar{y}_{..})^2 \\ &= \sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{i.})^2 + \sum_{i=1}^t \sum_{j=1}^{n_i} (\bar{y}_{i.} - \bar{y}_{..})^2 + 2 \sum_{i=1}^t (\bar{y}_{i.} - \bar{y}_{..}) \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{i.}) \\ &= \sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{i.})^2 + \sum_{i=1}^t n_i (\bar{y}_{i.} - \bar{y}_{..})^2 + 0 \\ &= SSE + SS_{TRT} \end{aligned}$$

#### Remarks:

1.  $SS_{TRT}$  is often referred to as
  - (a) **Sum of Squares Model** in regression analysis
  - (b) **Sum of Squares Between** or **Sum of Squares Due to Treatments** in Analysis of Variance (AOV)
2. In regression analysis,  $SS_{TRT}$  measures the amount of variation in the data,  $y_{ij}$ s "explained by the model"
3. In AOV,  $SS_{TRT}$  evaluates the amount of difference in  $\mu_1, \mu_2, \dots, \mu_t$ :  $(\mu_i - \mu)$ ,  
 where  $\mu = \frac{1}{t} \sum_{i=1}^t \mu_i$ , because  $(\mu_i - \mu)$  is estimated by  $(\bar{y}_{i.} - \bar{y}_{..})$

4. *SSE* is referred to as **Sum of Squares Residuals** or **Sum of Squares Within** or **Sum of Squares Error**. It measures the size of the variation within each of the  $t$  populations,  $\sigma_i$ s, because we are working in the situation that  $\sigma_1 = \sigma_2 = \cdots = \sigma_t = \sigma_e$ .

Thus, *SSE* is just the pooled measure of the  $t$  measures of variation,  $\hat{\sigma}_i$ s:

$$\begin{aligned} SSE &= \sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{i.})^2 \\ &= \sum_{i=1}^t (n_i - 1) \hat{\sigma}_i^2, \text{ where} \end{aligned}$$

$$\hat{\sigma}_i^2 = \frac{1}{n_i - 1} \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{i.})^2$$

are the individual estimators of  $\sigma_e^2$  obtained from each of the  $t$  samples.

## Degrees of Freedom

The sums of squares have another component referred to as Degrees of Freedom (df). The value of df for a given sum of squares is thought as the number of independent components in the sum. We will consider df for the following four sum of squares:

1. Uncorrected Sum of Squares:  $\sum_{i=1}^t \sum_{j=1}^{n_i} y_{ij}^2$

Because the  $y_{ij}$ 's have no restrictions

- $df_{UTOT} = n$

2. Corrected Total Sum of Squares:  $\sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{..})^2$

There is a restriction on the terms, that is,  $\sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{..}) = 0$ .

This implies that  $(y_{tn_t} - \bar{y}_{..}) = -\sum_{i=1}^{t-1} \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{..}) - \sum_{j=1}^{n_{t-1}} (y_{tj} - \bar{y}_{..})$

Hence, there are only  $(n - 1)$  independent terms in the sum.

- $df_{TOT} = n - 1$

3. Sum of Squares Error:  $\sum_{i=1}^t \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{i.})^2$

There are t restriction on the terms, that is, for each  $i = 1, \dots, t$ :  $\sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{i.}) = 0$ .

We observe that  $(y_{i,n_i} - \bar{y}_{i.}) = -\sum_{j=1}^{n_i-1} (y_{ij} - \bar{y}_{i.})$ . Thus, there are only

$\sum_{i=1}^t (n_i - 1) = \sum_{i=1}^t n_i - \sum_{i=1}^t 1 = n - t$  independent terms in the sum.

- $df_E = n - t$

4. Sum of Squares Treatment:  $\sum_{i=1}^t n_i (\bar{y}_{i.} - \bar{y}_{..})^2$

There is a restriction on the terms since

$$\sum_{i=1}^t n_i (\bar{y}_{i.} - \bar{y}_{..}) = \sum_{i=1}^t n_i \bar{y}_{i.} - \sum_{i=1}^t n_i \bar{y}_{..} = \sum_{i=1}^t \sum_{j=1}^{n_i} y_{ij} - \bar{y}_{..} \sum_{i=1}^t n_i = n\bar{y}_{..} - n\bar{y}_{..} = 0.$$

Hence,  $n_t (\bar{y}_{t.} - \bar{y}_{..}) = -\sum_{i=1}^{t-1} n_i (\bar{y}_{i.} - \bar{y}_{..})$ .

Thus, there are only  $(t-1)$  independent terms in the sum.

- $df_{TRT} = t - 1$

- An alternative approach for determining  $df_{TRT} = t - 1$  is obtained using the fact that

$$SS_{TRT} = SSE_{RED} - SSE_{FULL} \text{ and noting that}$$

$$SSE_{RED} = SS_{TOT} \text{ with}$$

$$df_{TOT} = n - 1 \text{ and}$$

$$SSE_{FULL} = SSE$$

$$\text{with } df_E = n - t.$$

Thus,

$$df_{TRT} = (n - 1) - (n - t) = t - 1$$

## Expected Values of the Model Mean Squares

The **Mean Squares** for the terms in the Fundamental Decomposition of the sum of squares total are obtained by dividing the SS's by their corresponding df's. The MS's are in some sense the *average* sum of squares for the two components:

1. **Mean Square Treatment:**  $MS_{TRT} = SS_{TRT}/df_{TRT} = \frac{SS_{TRT}}{t-1}$

2. **Mean Square Error:**  $MSE = SSE/df_E = \frac{SSE}{n-t}$

Next we compute the expected value of the Mean Squares

$$y_{ij} = \mu_i + e_{ij} \Rightarrow \bar{y}_{i.} = \mu_i + \bar{e}_{i.} \quad \text{and} \quad \bar{y}_{..} = \bar{\mu}_{..} + \bar{e}_{..} \quad \text{with} \quad \bar{\mu}_{..} = \frac{1}{n} \sum_{i=1}^t n_i \mu_i$$

Recall the following from STAT 610 or 630:

1.  $E[X^2] = Var(X) + (E[X])^2 \Rightarrow E[X^2] = Var(X)$  when  $E[X] = 0$
2.  $Var[cX] = c^2 Var(X)$ , when  $c$  is a constant
3.  $E[e_{ij}] = 0 \Rightarrow E[e_{i.}] = E\left[\sum_{j=1}^{n_i} e_{ij}\right] = \sum_{i=1}^{n_i} E[e_{ij}] = 0$

$$\text{and similarly} \quad E[e_{..}] = E\left[\sum_{i=1}^t \sum_{j=1}^{n_i} e_{ij}\right] = 0$$

Using the fact that the  $e_{ij}$ 's are independent we have

4.  $E[e_{ij}] = 0 \Rightarrow E[e_{ij}^2] = Var(e_{ij}) = \sigma_e^2 \Rightarrow$

$$E[\bar{e}_{i.}^2] = Var(\bar{e}_{i.}) = Var\left(\frac{1}{n_i} \sum_{j=1}^{n_i} e_{ij}\right) = \frac{1}{n_i^2} \sum_{i=1}^{n_i} Var(e_{ij}) = \frac{1}{n_i^2} \sum_{i=1}^{n_i} \sigma_e^2 = \frac{1}{n_i^2} n_i \sigma_e^2 = \frac{\sigma_e^2}{n_i}$$

Similarly, we have

$$\begin{aligned} E[\bar{e}_{..}^2] &= Var(\bar{e}_{..}) = Var\left(\frac{1}{n} \sum_{i=1}^t \sum_{j=1}^{n_i} e_{ij}\right) = \frac{1}{n^2} \sum_{i=1}^t \sum_{j=1}^{n_i} Var(e_{ij}) \\ &= \frac{1}{n^2} \sum_{i=1}^t \sum_{j=1}^{n_i} \sigma_e^2 \\ &= \frac{1}{n^2} \sigma_e^2 \sum_{i=1}^t n_i \\ &= \frac{\sigma_e^2}{n} \end{aligned}$$

We will now use the above to obtain the expected mean squares.

**Expected Mean Square Error:**

$$\begin{aligned}
SSE &= \sum_{i=1}^t \sum_{j=1}^{n_i} [y_{ij} - \bar{y}_i.]^2 \\
&= \sum_{i=1}^t \sum_{j=1}^{n_i} [(\mu_i + e_{ij}) - (\mu_i + \bar{e}_i.)]^2 \\
&= \sum_{i=1}^t \sum_{j=1}^{n_i} [e_{ij} - \bar{e}_i.]^2 \\
&= \sum_{i=1}^t \sum_{j=1}^{n_i} [e_{ij}^2 - 2e_{ij}\bar{e}_i. + \bar{e}_i.^2] \\
&= \sum_{i=1}^t \sum_{j=1}^{n_i} e_{ij}^2 - 2 \sum_{i=1}^t \bar{e}_i. \sum_{j=1}^{n_i} e_{ij} + \sum_{i=1}^t \bar{e}_i.^2 \sum_{j=1}^{n_i} 1 \\
&= \sum_{i=1}^t \sum_{j=1}^{n_i} e_{ij}^2 - 2 \sum_{i=1}^t \bar{e}_i. n_i \bar{e}_i. + \sum_{i=1}^t \bar{e}_i.^2 n_i \\
&= \sum_{i=1}^t \sum_{j=1}^{n_i} e_{ij}^2 - \sum_{i=1}^t n_i \bar{e}_i.^2
\end{aligned}$$

$$\begin{aligned}
E[SSE] &= \sum_{i=1}^t \sum_{j=1}^{n_i} E[e_{ij}^2] - \sum_{i=1}^t n_i E[\bar{e}_i.^2] \\
&= \sum_{i=1}^t \sum_{j=1}^{n_i} \sigma_e^2 - \sum_{i=1}^t n_i \frac{\sigma_e^2}{n_i} \\
&= n\sigma_e^2 - t\sigma_e^2 \\
&= \sigma_e^2(n - t)
\end{aligned}$$

$$E[MSE] = \frac{1}{(n - t)} E[SSE] = \sigma_e^2$$

This result holds under both  $H_o$  and  $H_1$ .



### Expected Mean Square Treatment:

From the model:  $y_{ij} = \mu_i + e_{ij}$  implies  $\bar{y}_{i.} = \mu_i + \bar{e}_{i.}$  and  $\bar{y}_{..} = \mu_{..} + \bar{e}_{..}$ . Thus, we have

$$\begin{aligned} SS_{TRT} &= \sum_{i=1}^t n_i (\bar{y}_{i.} - \bar{y}_{..})^2 \\ &= \sum_{i=1}^t n_i [(\mu_i - \bar{\mu}_{..}) + (\bar{e}_{i.} - \bar{e}_{..})]^2 \\ &= \sum_{i=1}^t n_i (\mu_i - \bar{\mu}_{..})^2 + \sum_{i=1}^t n_i (\bar{e}_{i.} - \bar{e}_{..})^2 + 2 \sum_{i=1}^t n_i (\mu_i - \bar{\mu}_{..})(\bar{e}_{i.} - \bar{e}_{..}) \end{aligned}$$

We also note that  $\bar{e}_{..} = \frac{1}{n} \sum_{i=1}^t \sum_{j=1}^{n_i} e_{ij} = \frac{1}{n} \sum_{i=1}^t n_i \bar{e}_{i.} \Rightarrow n \bar{e}_{..} = \sum_{i=1}^t n_i \bar{e}_{i.} \Rightarrow \sum_{i=1}^t n_i (\bar{e}_{i.} - \bar{e}_{..})^2 = \sum_{i=1}^t n_i \bar{e}_{i.}^2 - n \bar{e}_{..}^2$

It then follows that

$$\begin{aligned} E[SS_{TRT}] &= \sum_{i=1}^t n_i (\mu_i - \bar{\mu}_{..})^2 + E \left[ \sum_{i=1}^t n_i (\bar{e}_{i.} - \bar{e}_{..})^2 \right] + 2E \left[ \sum_{i=1}^t n_i (\mu_i - \bar{\mu}_{..})(\bar{e}_{i.} - \bar{e}_{..}) \right] \\ &= \sum_{i=1}^t n_i (\mu_i - \bar{\mu}_{..})^2 + E \left[ \sum_{i=1}^t n_i \bar{e}_{i.}^2 - n \bar{e}_{..}^2 \right] + 2E \left[ \sum_{i=1}^t n_i (\mu_i - \bar{\mu}_{..})(\bar{e}_{i.} - \bar{e}_{..}) \right] \\ &= \sum_{i=1}^t n_i (\mu_i - \bar{\mu}_{..})^2 + \sum_{i=1}^t n_i E[\bar{e}_{i.}^2] - n E[\bar{e}_{..}^2] + 2 \left[ \sum_{i=1}^t n_i (\mu_i - \bar{\mu}_{..})(E(\bar{e}_{i.}) - E(\bar{e}_{..})) \right] \\ &= \sum_{i=1}^t n_i (\mu_i - \bar{\mu}_{..})^2 + \left( \sum_{i=1}^t n_i \frac{\sigma_e^2}{n_i} \right) - n \frac{\sigma_e^2}{n} + 2(0) \\ &= \sum_{i=1}^t n_i (\mu_i - \bar{\mu}_{..})^2 + (t-1) \sigma_e^2 \end{aligned}$$

$$E[MS_{TRT}] = \frac{1}{(t-1)} E[SS_{TRT}] = \sigma_e^2 + \theta_{TRT} \quad \text{where} \quad \theta_{TRT} = \frac{1}{t-1} \sum_{i=1}^t n_i (\mu_i - \bar{\mu}_{..})^2$$

Note that under  $H_0$ :  $\mu_i = \mu = \bar{\mu}_{..}$  which yields

$$\theta_{TRT} = \frac{1}{t-1} \sum_{i=1}^t n_i (\mu_i - \bar{\mu}_{..})^2 = 0$$

We have thus shown that

$$E_{H_0}[MS_{TRT}] = \sigma_e^2 \quad \text{and} \quad E_{H_1}[MS_{TRT}] = \sigma_e^2 + \theta_{TRT}$$

where  $\theta_{TRT} \geq 0$ .

Thus,

$$E_{H_1}[MS_{TRT}] \geq E_{H_0}[MS_{TRT}] = E[MSE]$$

Therefore, if  $MS_{TRT}$  and  $MSE$  are nearly the same in size we would tend to believe that  $H_o$  is true.

However, if  $MS_{TRT}$  is much larger than  $MSE$  then we would tend to believe that  $H_1$  is true.

With the above motivation our test statistic for testing

$$H_o : \mu_1 = \mu_2 = \cdots = \mu_t = \mu \text{ versus } H_1 : \mu_i \neq \mu_k \text{ for at least one pair } (i, k) \text{ is } F = \frac{MS_{TRT}}{MSE}$$

We will reject  $H_o$  in favor of  $H_1$  when  $F$  is large.

We must next determine the sampling distribution of  $F$  under both null and alternative hypotheses in order to set critical values, compute p-values, compute power curves, and determine an appropriate number of replications.

In STAT 630 or STAT 611, it will be shown that this ratio is essentially the Likelihood Ratio test statistic for this situation.

All the previous results concerning LSE, partition of sums of squares, expectation of sums of squares, and using the F-ratio only required that the  $e_{ij}$ 's were iid with mean 0 and finite variance  $\sigma_e^2$ .

The LSE of  $\mu_i$ 's,  $\hat{\mu}_i = \bar{y}_{i.}$ , are Best Linear Unbiased Estimators (BLUE). The author on page 47 in the class textbook states "If the experimental errors are independent with a mean of zero and have homogeneous variances, the LSE are unbiased with minimum variance (UMVUE). This is not true. The LSE are UMVUE only if the  $e_{ij}$ 's are iid with a normal distribution.

We will now impose the condition that  $e_{ij}$ 's have a  $N(0, \sigma_e^2)$  distribution. We will verify at a later point in this handout the following distributional results:

1.  $SSE/\sigma_e^2$  has a chi-square distribution with  $df = n - t$
2.  $SS_{TRT}/\sigma_e^2$  has a non-central Chi-square distribution with  $df = t - 1$  and non-centrality parameter

$$\lambda = \frac{\sum_{i=1}^t n_i(\mu_i - \bar{\mu}_{..})^2}{\sigma_e^2} = \frac{(t-1)\theta_{TRT}}{\sigma_e^2}$$

When  $H_o : \mu_1 = \mu_2 = \cdots = \mu_t = \mu$ , is true, we have  $\lambda = 0$  and  $SS_{TRT}/\sigma_e^2$  has a central chi-square distribution.

3. In many linear model books, the non-centrality parameter is given with a 2 in the denominator:

$$\lambda^* = \frac{\sum_{i=1}^t n_i(\mu_i - \bar{\mu}_{..})^2}{2\sigma_e^2}$$

To be consistent with our textbook and the software packages *SAS* and *R*, we will use the expression **without 2** in the denominator.

4. Note that the df associated with  $MSE$  and  $MS_{TRT}$  are the same as the df for the corresponding chi-square distribution.
5.  $\lambda = 0$  if and only if  $H_o : \mu_1 = \mu_2 = \dots = \mu_t = \mu$  is true.
6.  $SSE$  and  $SS_{TRT}$  are independently distributed
7. Under  $H_o$ :  $F = \frac{MS_{TRT}}{MSE}$  has a central F-distribution with  $df = t - 1; n - t$
8. Under  $H_1$ :  $F = \frac{MS_{TRT}}{MSE}$  has a noncentral F-distribution with  $df = t - 1; n - t$  and noncentrality parameter  $\lambda^* = \frac{\sum_{i=1}^t n_i(\mu_i - \bar{\mu})^2}{\sigma_e^2} = \frac{(t-1)\theta_{TRT}}{\sigma_e^2}$  with  $\bar{\mu} = \frac{1}{n} \sum_{i=1}^t n_i \mu_i$ .
9. Once we prove that  $SSE/\sigma_e^2$  and  $SS_{TRT}/\sigma_e^2$  have chisquare distributions, the expectations of  $MSE$  and  $MS_{TRT}$  can be obtained by noting that if  $G$  has a chisquare distribution with  $df = k$  and noncentrality parameter  $\lambda$  then

$$E[G] = k + \lambda$$

$$Var[G] = 2k + 4\lambda$$

Note: A non-central  $F$  distribution can defined as follows:

1. If  $X_1, \dots, X_{\nu_1}$  are independent  $N(\mu_i, \sigma_i^2)$  r.v.'s, then  $D = \sum_1^{\nu_1} X_i^2/\sigma_i^2$ , has a non-central chi-square distribution with  $df = \nu_1$  and noncentrality parameter (ncp)  $\lambda = \sum_1^{\nu_1} \frac{\mu_i^2}{\sigma_i^2}$
2. Let  $W$  have a central chi-square distribution with  $df = \nu_2$
3. If  $D$  and  $W$  are independent with distributions given in (1.) and (2.), then  $F = D/W$  has a non-central F distribution with  $df = \nu_1, \nu_2$  and ncp =  $\lambda$ .
4. If  $\lambda = 0$ , i.e.,  $\mu_i = 0$  for  $i = 1, 2, \dots, \nu_1$ , then
  - $D$  has a central chi-square distribution and hence
  - $F$  has a central F distribution

We can now set up the rejection region and compute the power function for a test of

$$H_o : \mu_1 = \mu_2 = \cdots = \mu_t = \mu \quad \text{versus} \quad H_1 : \mu_i \neq \mu_k \quad \text{for at least one pair } i, k$$

Test Statistic:

$$F = \frac{(SSE_{Red} - SSE_{Full}) / (df_{Red} - df_{Full})}{MSE_{Full}} = \frac{MS_{TRT}}{MSE}$$

The test statistic is measuring the average reduction in the sum of squares residuals obtained by including terms in the model which allow a difference in the treatment means relative to a model in which the means are constrained to be equal, that is,  $y_{ij} = \mu_i + e_{ij}$  vs  $y_{ij} = \mu + e_{ij}$

Decision Rule: Reject  $H_o$  in favor of  $H_1$  if  $F \geq F_{\alpha, \nu_1, \nu_2}$ , where  $\nu_1 = t - 1$  and  $\nu_2 = n - t$ .

We compute the p-value for the test statistic as

$$p - value = P[F_{\nu_1, \nu_2} \geq F] = 1 - G(F)$$

where  $F_{\nu_1, \nu_2}$  is a random variable with an F-distribution,  $df = \nu_1, \nu_2$ ,  $F$  is the value of the test statistic computed from the observed data, and  $G(\cdot)$  is the cdf of an F-distribution with  $df = \nu_1, \nu_2$ , where  $\nu_1 = t - 1, \nu_2 = n - t$ . To compute the p-value, there are tables in the back of the textbook, or

use the R function:  $1 - pf(F, \nu_1, \nu_2)$  or the SAS function:  $1 - PROBF(F, \nu_1, \nu_2)$ .

The above results are all summarized in an AOV table:

Source of Variation	df	Sum of Squares	Mean Square	F	p-value
Treatment	t-1	$SS_{TRT}$	$\frac{SS_{TRT}}{t-1}$	$\frac{MS_{TRT}}{MSE}$	1-G(F)
Error	n-t	$SSE$	$\frac{SSE}{n-t}$		
Total	n-1	$SS_{TOT}$			

In the special case where  $t = 2$ , the  $F$  test is equivalent to the pooled  $t$  test:

$$t = \frac{\bar{y}_{1.} - \bar{y}_{2.}}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$$

Verify that  $t^2 = F$  and that the rejection region:

$$|t| \geq t_{\alpha/2, n-t} \quad \text{is equivalent to} \quad F \geq F_{\alpha, 1, n-t}$$

## CRD AOV - EXAMPLE

The following example is modified from *Design of Experiments* by Kuehl, will be used to illustrate the SAS code and output needed to obtain the AOV for a CRD with a 1-way treatment structure.

The shelf life of stored meats is the time a prepackaged cut remains salable, safe, and nutritious. Standard packaging in ambient air atmosphere has a shelf life of about 48 hours after which the meat quality begins to deteriorate from microbial contamination, color degradation, and shrinkage. Vacuum packaging is effective in suppressing microbial growth; however, other quality losses remain a problem.

Recent studies suggested controlled gas atmospheres as possible alternatives to existing packagings. Two atmospheres which promise to combine the capability for suppressing microbial development while maintaining other meat qualities were (1) pure carbon dioxide (CO<sub>2</sub>), and (2) mixtures of carbon monoxide (CO), oxygen (O<sub>2</sub>), and nitrogen (N).

Based on this new information the investigator hypothesized that some form of controlled gas atmosphere would provide a more effective packaging environment for meat storage. The researcher decides to study the effectiveness of four packaging environments:

**Method I:** Ambient air in a commercial plastic wrap

**Method II:** A vacuum

**Method III:** Mixture of gases - 1% CO, 40% O<sub>2</sub>, and 59% N

**Method IV:** 100% CO<sub>2</sub>

A complete randomized design was used for the experiment. Three, four or five beef steaks of approximately the same size (75g) were randomly assigned to each of the packaging conditions. The randomization method is demonstrated in the following table. Each steak was packaged separately in its assigned conditions. The number of psychrotrophic bacteria found on the meat after nine days of storage at 4°C in a standard meat storage facility was recorded for each of the twelve packages. The response variable is the log of the bacteria concentration on the meat: log(count/cm<sup>2</sup>).

Steak	Treatment	Obser.	Log(count/cm <sup>2</sup> )	$y_{ij}$	Model value
1	M I	1	7.66	$y_{11}$	$\mu_1 + e_{11}$
12	M I	2	6.98	$y_{12}$	$\mu_1 + e_{12}$
7	M I	3	7.80	$y_{13}$	$\mu_1 + e_{13}$
13	M II	1	5.26	$y_{21}$	$\mu_2 + e_{21}$
5	M II	2	5.44	$y_{22}$	$\mu_2 + e_{22}$
3	M II	3	5.80	$y_{23}$	$\mu_2 + e_{23}$
10	M III	1	7.41	$y_{31}$	$\mu_3 + e_{31}$
9	M III	2	7.33	$y_{32}$	$\mu_3 + e_{32}$
2	M III	3	7.04	$y_{33}$	$\mu_3 + e_{33}$
15	M III	4	7.59	$y_{34}$	$\mu_3 + e_{34}$
8	M IV	1	3.51	$y_{41}$	$\mu_4 + e_{41}$
4	M IV	2	2.91	$y_{42}$	$\mu_4 + e_{42}$
11	M IV	3	3.66	$y_{43}$	$\mu_4 + e_{43}$
6	M IV	4	2.87	$y_{44}$	$\mu_4 + e_{44}$
14	M IV	5	3.04	$y_{45}$	$\mu_4 + e_{45}$

SAS Program: **storage.SAS**

```
ods html; ods graphics on;
option ls=75 ps=50 nocenter nodate;
title 'Storage of meat by four methods';
data old;
array Y Y1-Y5;
input T $ Y1-Y5;
do over Y;
TCOUNT=Y;
output; end; drop Y1-Y5;
cards;
COMM  7.66 6.98 7.80 .      .
VAC   5.26 5.44 5.80 .      .
MIXED 7.41 7.33 7.04 7.59 .
CO2    3.51 2.91 3.66 2.87 3.04
run;

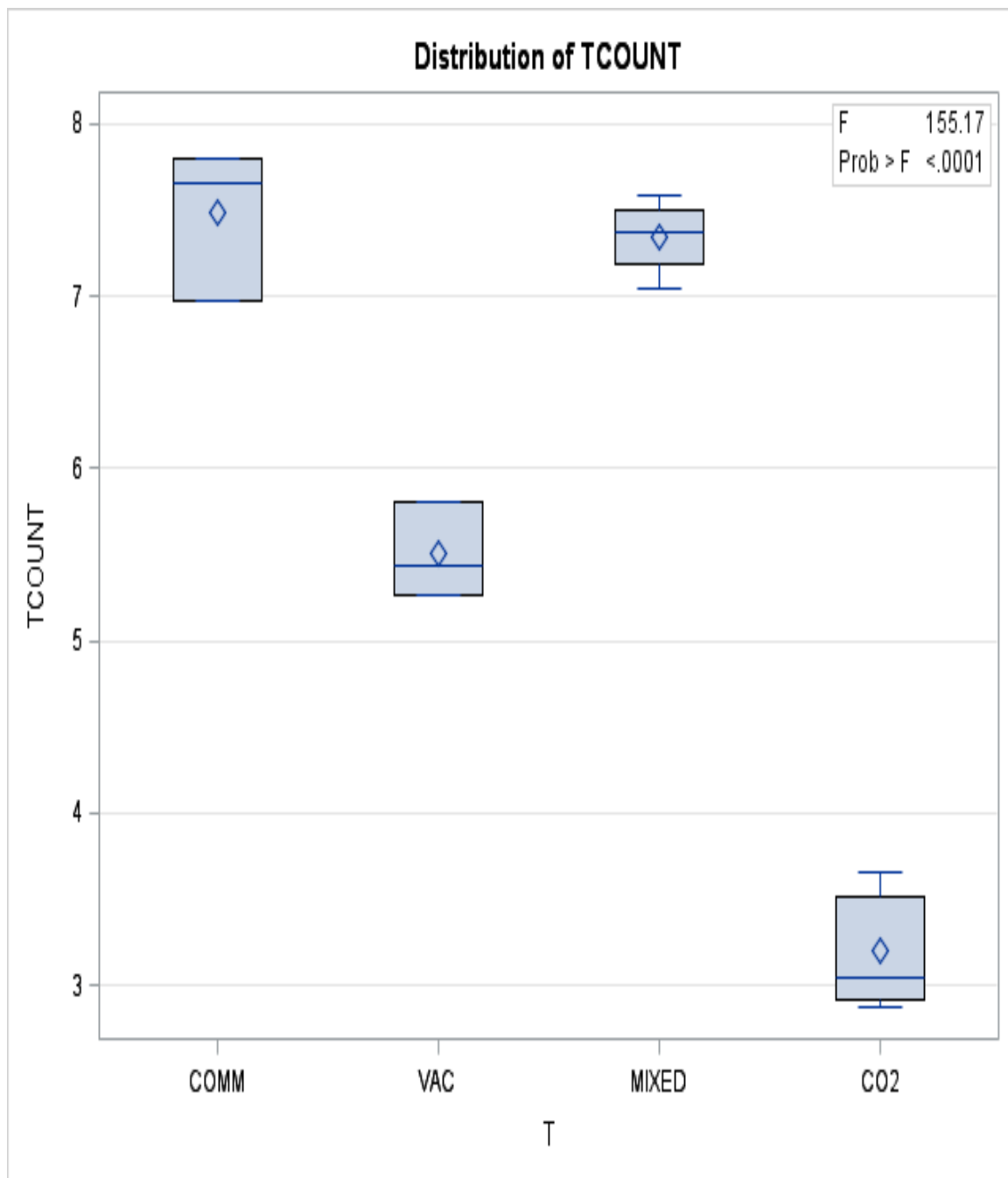
proc boxplot;
plot TCOUNT*T;
RUN;

proc glimmix data=old order=data;
class T;
model TCOUNT=T/solutions;
lsmeans T/plot = meanplot cl ;
run;

proc glm data=old order=data;
class T;
model TCOUNT=T/solutions;
lsmeans T/stderr cl ;

means T/HOVTTEST=bf;

output out=ASSUMP R=RESID P=PRED;
proc univariate def=5 plot normal; var RESID;
run;
ods graphics off; ods html close;
```



# Storage of meat by four methods

## The GLM Procedure

### Class Level Information

Class	Levels	Values
T	4	CO2 COMM MIXED VAC

Dependent Variable: TCOUNT

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	51.62044500	17.20681500	155.17	<.0001
Error	11	1.21975500	0.11088682		
Corrected Total	14	52.84020000			

R-Square	Coeff Var	Root MSE	TCOUNT Mean
0.976916	5.925209	0.332997	5.620000

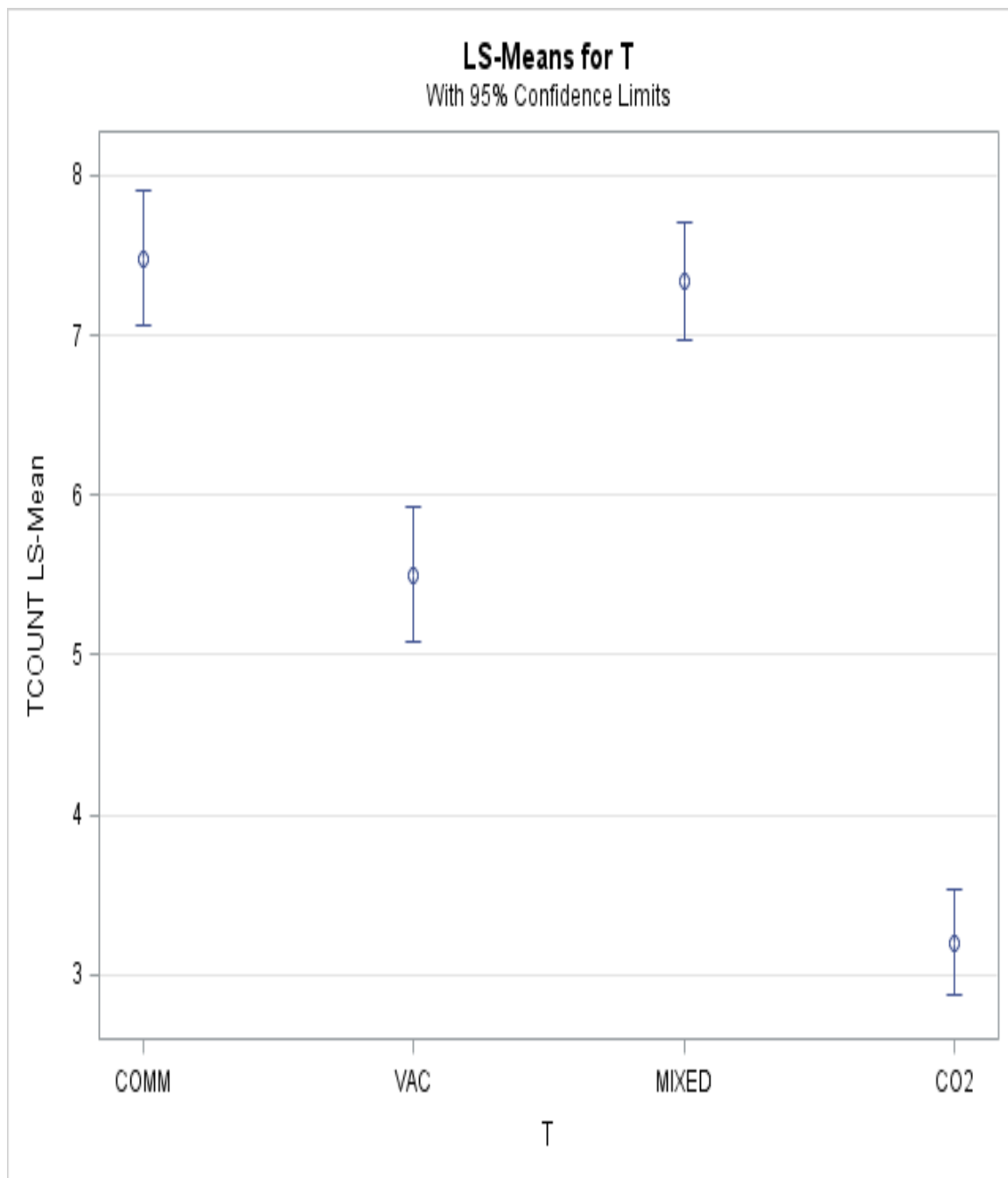
Parameter	Estimate	Standard Error	t Value	Pr >  t
Intercept	3.198000000 B	0.14892066	21.47	<.0001
T COMM	4.282000000 B	0.24318642	17.61	<.0001
T VAC	2.302000000 B	0.24318642	9.47	<.0001
T MIXED	4.144500000 B	0.22338099	18.55	<.0001
T CO2	0.000000000 B	.	.	.

Level of	-----TCOUNT-----		
T	N	Mean	Std Dev
CO2	5	3.19800000	0.36272579
COMM	3	7.48000000	0.43863424
MIXED	4	7.34250000	0.22911060
VAC	3	5.50000000	0.27495454

### Least Squares Means

T	TCOUNT LSMEAN	Standard Error	95% Confidence Limits	
COMM	7.480000	.1923	7.056848	7.903152
VAC	5.500000	.1923	5.076848	5.923152
MIXED	7.342500	.1665	6.976040	7.708960
CO2	3.198000	.1489	2.870228	3.525772





Brown and Forsythe's Test for Homogeneity of TCOUNT Variance  
ANOVA of Absolute Deviations from Group Medians

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
T	3	0.0454	0.0151	0.26	0.8552
Error	11	0.6486	0.0590		

The UNIVARIATE Procedure  
Variable: RESID

Moments

N	15	Sum Weights	15
Mean	0	Sum Observations	0
Std Deviation	0.29517005	Variance	0.08712536
Skewness	-0.0634278	Kurtosis	-1.2832322
Uncorrected SS	1.219755	Corrected SS	1.219755
Coeff Variation	.	Std Error Mean	0.07621258

Basic Statistical Measures

Location		Variability	
Mean	0.00000	Std Deviation	0.29517
Median	-0.01250	Variance	0.08713
Mode	.	Range	0.96200
		Interquartile Range	0.58800

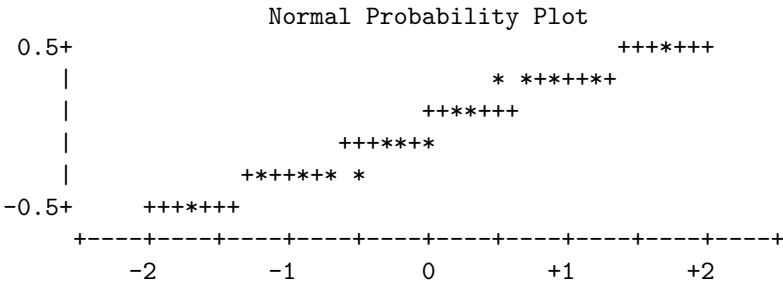
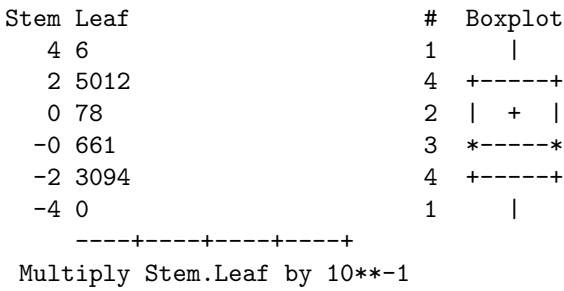
Tests for Location: Mu0=0

Test	-Statistic-	-----p Value-----
Student's t	t 0	Pr >  t  1.0000
Sign	M -0.5	Pr >=  M  1.0000
Signed Rank	S 1	Pr >=  S  0.9780

Tests for Normality

Test	--Statistic--	-----p Value-----
Shapiro-Wilk	W 0.946881	Pr < W 0.4767
Kolmogorov-Smirnov	D 0.132458	Pr > D >0.1500
Cramer-von Mises	W-Sq 0.053968	Pr > W-Sq >0.2500
Anderson-Darling	A-Sq 0.348094	Pr > A-Sq >0.2500

Variable: RESID



## R Code - AOV and LSMEAN with C.I.

```
install.packages("lsmeans")
install.packages("ggplot2")
library(lsmeans)
library(ggplot2)

# specify the treatments as a "stacked" data set
treatment = as.factor(c(rep("COMM", 3), rep("VAC", 3), rep("MIXED", 4), rep("C02", 5)))

# specify the counts as a "stacked" data set
counts = c(7.66,6.98,7.80,5.26,5.44,5.80,7.41,7.33,7.04,7.59,3.51,2.91,3.66,2.87,3.04)

# create a data frame of the treatments and counts
data = data.frame(T=treatment, TCOUNT=counts)

# produce a linear model of the counts as a function of treatment
model = lm(TCOUNT ~ T, data=data)
summary(model)

# produce the AOV table
A = aov(model)
summary(A)

# produce plot of lsmeans with 95% C.I. on Population Means
lsmeans(model, "T")
T.LSmeans = lsmeans(model, "T")
df.TLSmeans = as.data.frame(summary(T.LSmeans))
limits = aes(ymax = lsmean+qt(p=0.05/2,df=df)*SE, ymin = lsmean-qt(p=0.05/2,df=df)*SE)
qplot(data=df.TLSmeans, x=T, y=lsmean) + geom_errorbar(limits)
```

## Inferences About Model Parameters

After conducting the F-test, it is necessary to measure the size of the differences in the treatment means and to place confidence intervals on the various model parameters.

1. Estimation of  $\sigma_e^2$ :

(a) Point Estimator:  $\hat{\sigma}_e^2 = MSE$

(b) Confidence Interval: A  $100(1 - \alpha)\%$  confidence interval for  $\sigma_e$  is given by

$$\left( \sqrt{\frac{(n-t)\hat{\sigma}_e^2}{\chi_{\alpha/2, n-t}^2}}, \sqrt{\frac{(n-t)\hat{\sigma}_e^2}{\chi_{1-\alpha/2, n-t}^2}} \right),$$

where  $\chi_{\alpha/2, n-t}^2$  and  $\chi_{1-\alpha/2, n-t}^2$  are the upper  $\alpha/2$  and  $(1 - \alpha/2)$  percentiles from a chisquared distribution with  $df = n - t$ .

2. Estimation of  $\mu_i$ :

(a) Point Estimator:  $\hat{\mu}_i = \bar{y}_i$  with  $\widehat{SE}(\hat{\mu}_i) = \sqrt{Var(\hat{\mu}_i)} = \frac{\hat{\sigma}_e}{\sqrt{n_i}}$

•  $\hat{\mu}_i$  is BLUE in general and MLE & UMVUE if we assume  $e_{ij}$  are iid  $N(0, \sigma_e^2)$

(b) Confidence Interval: A  $100(1 - \alpha)\%$  confidence interval for  $\mu_i$  is given by

$$\hat{\mu}_i \pm t_{\alpha/2, n-t} \widehat{SE}(\hat{\mu}_i) = \bar{y}_i \pm t_{\alpha/2, n-t} \frac{\hat{\sigma}_e}{\sqrt{n_i}},$$

where  $t_{\alpha/2, n-t}$  is the upper  $\alpha/2$  percentile from a t-distribution with  $df = n - t$ .

3. Estimation of treatment effects:  $\mu_i - \mu_k$ :

(a) Point Estimator:  $\hat{\mu}_i - \hat{\mu}_k = \bar{y}_i - \bar{y}_k$  with  $\widehat{SE}(\hat{\mu}_i - \hat{\mu}_k) = \sqrt{\frac{\hat{\sigma}_e^2}{n_i} + \frac{\hat{\sigma}_e^2}{n_k}}$

(b) Confidence Interval: A  $100(1 - \alpha)\%$  confidence interval for  $\mu_i - \mu_k$  is given by

$$\hat{\mu}_i - \hat{\mu}_k \pm t_{\alpha/2, n-t} \widehat{SE}(\hat{\mu}_i - \hat{\mu}_k) = \bar{y}_i - \bar{y}_k \pm t_{\alpha/2, n-t} \hat{\sigma}_e \sqrt{\frac{1}{n_i} + \frac{1}{n_k}},$$

where  $t_{\alpha/2, n-t}$  is the upper  $\alpha/2$  percentile from a t-distribution with  $df = n - t$ .

One problem with the confidence intervals for  $\mu_i - \mu_k$  is that we have a large number of such intervals. In fact, there are  $\binom{t}{2} = \frac{t(t-1)}{2}$  such intervals. We will develop in Handout 4 **simultaneous confidence intervals** for  $\mu_i - \mu_k$  such that the level of confidence is  $100(1 - \alpha)\%$  for all such intervals not just for the individual intervals.

We will now demonstrate these methods using the meat storage example:

1. Estimation of  $\sigma_e^2$ :

(a) Point Estimator:  $\hat{\sigma}_e^2 = MSE = 0.11089 \Rightarrow \hat{\sigma}_e = \sqrt{0.11089} = 0.333$

(b) Confidence Interval: A 95% confidence interval for  $\sigma_e$  is given by

$$\left( \sqrt{\frac{(n-t)\hat{\sigma}_e^2}{\chi_{\alpha/2, n-t}^2}}, \sqrt{\frac{(n-t)\hat{\sigma}_e^2}{\chi_{1-\alpha/2, n-t}^2}} \right) = \left( \sqrt{\frac{(15-4)(.11089)}{21.920}}, \sqrt{\frac{(15-4)(.11089)}{3.816}} \right) = (.236, .565)$$

2. Estimation of  $\mu_i$ , Point Estimators and 95% Confidence Intervals for  $\mu_i$ :

$\hat{\mu}_i = \bar{y}_i$  and 95% C.I. is  $\bar{y}_i \pm t_{\alpha/2, n-t} \frac{\hat{\sigma}_e}{\sqrt{n_i}}$

$t_{.025, 11} = 2.201 \quad \hat{\sigma}_e = \sqrt{.11089} = .333$

	TREATMENT			
	CO2	COMM	MIXED	VAC
$n_i$	5	3	4	3
$\hat{\mu}_i$	3.198	7.480	7.3425	5.50
$t_{.025, .025} \frac{\hat{\sigma}_e}{\sqrt{n_i}}$	.328	.423	.366	.423
95% C.I.	$3.198 \pm .328$	$7.480 \pm .423$	$7.3425 \pm .366$	$5.50 \pm .423$
	(2.87, 3.53)	(7.06, 7.90)	(6.98, 7.71)	(5.08, 5.92)

3. Is there a significant difference in the 4 Treatment means?

From the AOV table we have  $F = 155.17$  with

$p - value = P[F_{3,11} \geq 155.17] = 1 - pf(155.17, 3, 11) = 2.78 \times 10^{-9}$ .

Thus, there is significant evidence of a difference in the four treatment means. The next step would be to determine what type of difference exists in the means. Handout 4 will deal with this subject.

## Power Calculations and Sample Size Determination

In order to assess whether the AOV F-test has sufficient ability to detect specified regions in the alternative hypothesis and to determine the appropriate number of replications we need to determine the power function for the AOV F-test.

We have stated that  $F = \frac{MS_{TRT}}{MSE}$  has a noncentral F-distribution with  $df = t - 1, n - t$  and noncentrality parameter

$$\lambda = \frac{\sum_{i=1}^t n_i(\mu_i - \bar{\mu}_{..})^2}{\sigma_e^2}$$

Thus, the power function is given by

$$\begin{aligned}\gamma(\lambda) &= P[\text{reject } H_0 \text{ for a specified value of } \lambda] \\ &= P[F \geq F_{\alpha, t-1, n-t}] \\ &= 1 - G_\lambda(F_{\alpha, t-1, n-t}) \\ &= 1 - pf(qf(1 - \alpha, t - 1, n - t), t - 1, n - t, \lambda)\end{aligned}$$

In order to make this calculation we need to specify the following values

1.  $\alpha$
2.  $n_i$ 's
3. values of  $\mu_1, \dots, \mu_t$  in  $H_1$  in order to calculate  $\lambda$
4.  $\sigma_e$  (obtain estimate from previous studies or pilot study)

Once these values have been specified, we can use SAS or R to compute the power.

Note: The probability of Type II errors at specified values of  $\lambda$  is given by

$$\beta(\lambda) = P[\text{Type II Error for specified value of } \lambda] = 1 - \gamma(\lambda)$$

### Example

Suppose  $t = 4$ ,  $\alpha = .05$   $n_1 = n_2 = n_3 = n_4 = 3$ ,  $\sigma_e^2 = 0.116$ ,  $F_{.05,3,8} = 4.0666$

Compute the power of the F-test when  $\mu_1 = 6.5$ ,  $\mu_2 = 6$ ,  $\mu_3 = 6$ ,  $\mu_4 = 5.5$

That is, what is the probability that the F-test will reject  $H_o$

if  $\mu_1 = 6.5$ ,  $\mu_2 = 6$ ,  $\mu_3 = 6$ ,  $\mu_4 = 5.5$ ?

$$\bar{\mu}_. = \frac{1}{n} \sum_{i=1}^t n_i \mu_i = \frac{1}{12} 3(6.5 + 6 + 6 + 5.5) = 6$$

$$\lambda = \frac{\sum_{i=1}^t n_i (\mu_i - \bar{\mu}_.)^2}{\sigma_e^2} = \frac{3[(6.5 - 6)^2 + (6 - 6)^2 + (6 - 6)^2 + (5.5 - 6)^2]}{.116} = 12.93$$

$$\gamma(12.93) = P[F \geq 4.0666] = 1 - G_{12.93}(4.0666) = .65066$$

where  $G_{12.93}(4.0666)$  is the cdf of a non-central F-distribution with  $df_1 = 3$ ,  $df_2 = 8$  and  $\lambda = 12.93$

The above calculation was obtained from R using the function:

$$1 - pf(F, \nu_1, \nu_2, \lambda) = 1 - pf(4.0666, 3, 8, 12.93) = .65066$$

Thus, there is approximately a 65% chance that an  $\alpha = .05$  F-test with  $df = 3, 8$  will reject  $H_o$  and determine that there is a difference in the  $\mu_i$ 's if the populations have

$\mu_1 = 6.5$ ,  $\mu_2 = 6$ ,  $\mu_3 = 6$ ,  $\mu_4 = 5.5$  or any other configuration of

$(\mu_1, \mu_2, \mu_3, \mu_4)$  such that  $\lambda = 12.93$

The probability that test will fail to reject  $H_o$  at  $\mu_1 = 6.5$ ,  $\mu_2 = 6$ ,  $\mu_3 = 6$ ,  $\mu_4 = 5.5$  or any other configuration of  $(\mu_1, \mu_2, \mu_3, \mu_4)$  such that  $\lambda = 12.93$  is

$$P[\text{Type II Error if } \lambda = 12.93] = 1 - .65 = .35$$

The book has tables for obtaining power (see pages 604-613). In this table, the author uses the parameter  $\Phi = \sqrt{\lambda/t}$ .

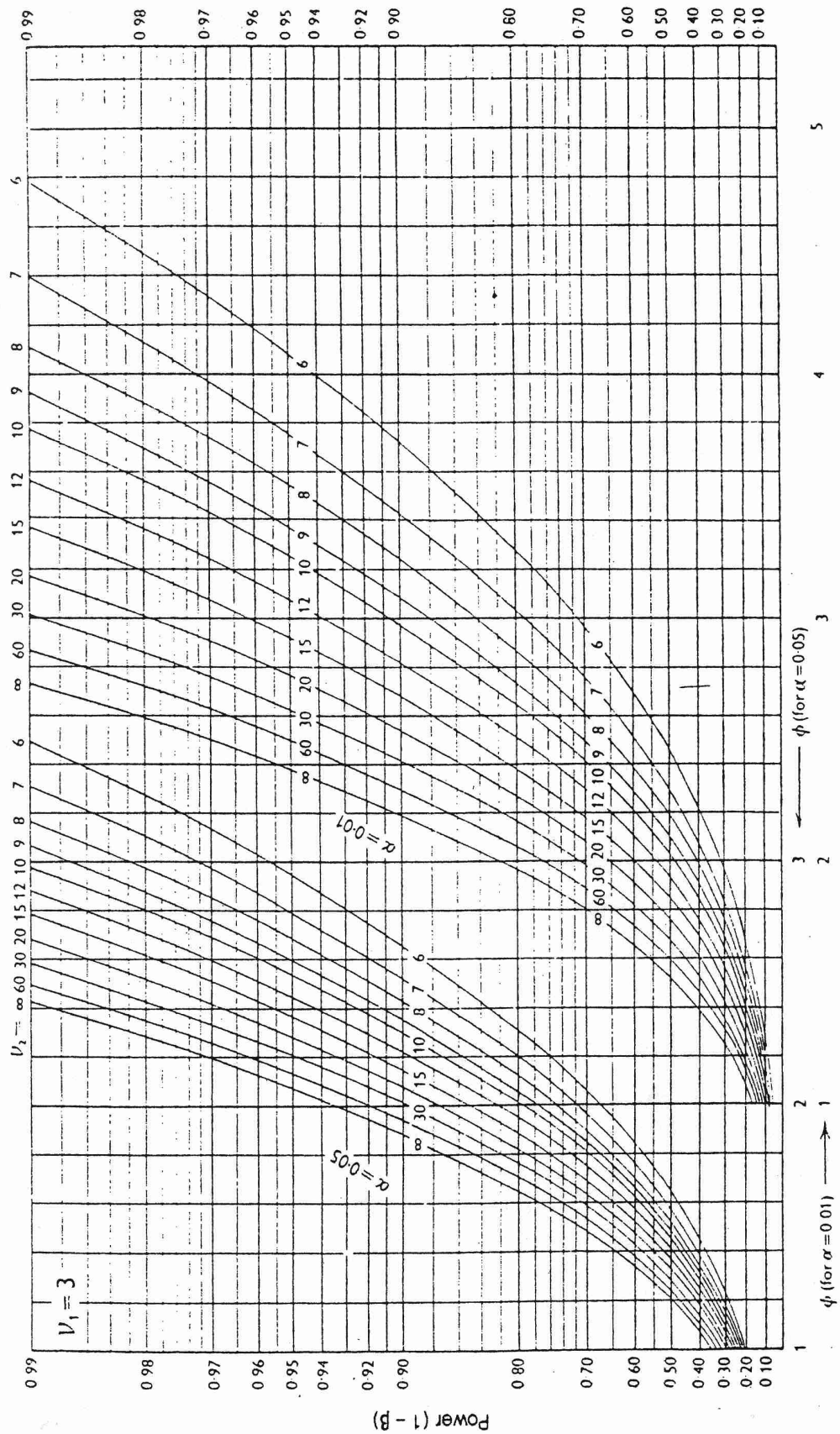
The appropriate graph for this calculation is given on the next page.

$$\Phi = \sqrt{\lambda/t} = \sqrt{12.93/4} = 1.80 \text{ with } \nu_1 = t - 1 = 3, \nu_2 = n - t = 12 - 4 = 8 \text{ and } \alpha = .05.$$

From the graph, power is approximately 0.65.



Table IX F test power curves for fixed effects model analysis of variance from "Design of Experiment" by R.O. Kuehn



There are infinitely many choices of  $(\mu_1, \mu_2, \mu_3, \mu_4)$  that will produce  $\lambda = 12.93$  or  $\Phi = 1.80$ . Therefore, in many situations, the power is computed just as a function of specified values of  $\lambda$  or  $\Phi$ :

For example, suppose  $t = 4$ ,  $n = 24$ ,  $\alpha = .05$ , then compute the power of the  $F$  test for specified values of  $\lambda$ :

$$\nu_1 = 4 - 1 = 3 \quad \nu_2 = 24 - 4 = 20 \quad F_{.05,3,20} = 3.098 \quad \Phi = \sqrt{\lambda/4}$$

In SAS and R we use  $\lambda$  not  $\Phi$ .

Using the following SAS code we obtain the following values for the power function:

(SAS Program: powerf\_specL.sas)

```
*SAS Program to Compute Power Curve for F-Test with t=4,
    alpha=.05, df1=3, df2=20, and
    for specified values of L=noncentrality parameter;
```

```
Data;
Input L @@;
t=4;
n=24;
df1=t-1;
df2=n-t;
alpha=.05;
Power=1-PROBF(finv(1-alpha,df1,df2),df1,df2,L);
phi=sqrt(L/4);
Cards;
0 .2 .4 .6 .8 1 1.5 2 2.5 3 3.5 4 4.5 5 6 8 10 12 14 16 19.36
23.04 27.04 31.36 35 40 45
run;
proc print;
var L Power phi;
run;
```

OUTPUT:

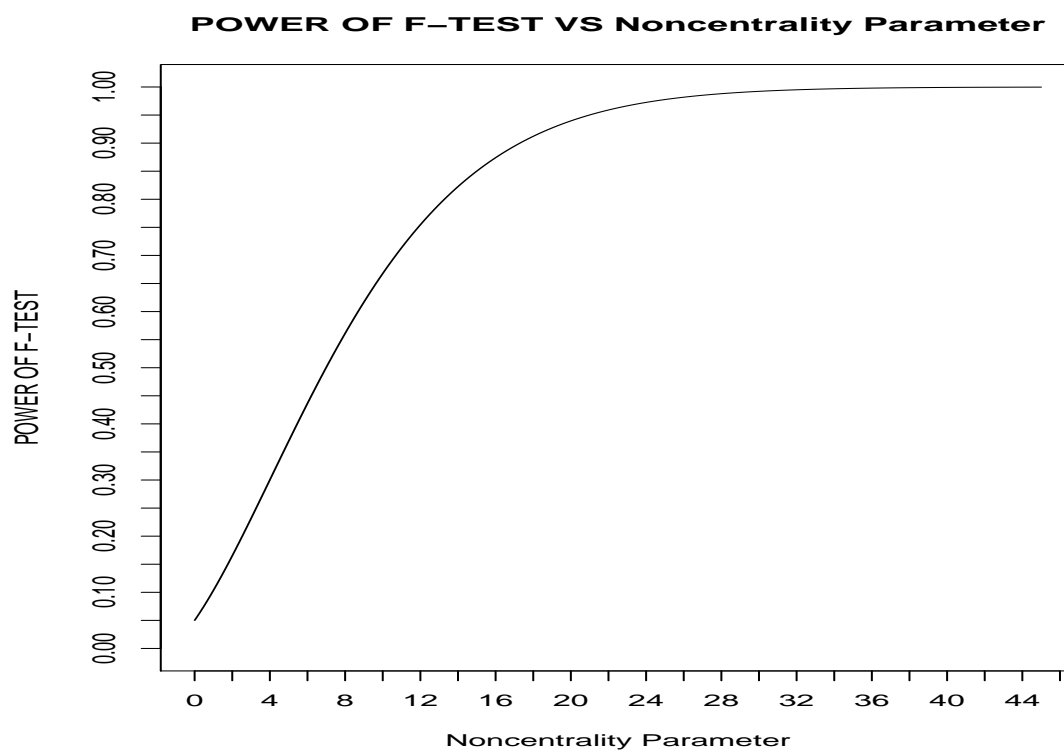
OBS	L	POWER	PHI
1	0.00	0.05000	0.00000
2	0.20	0.05992	0.22361
3	0.40	0.07025	0.31623
4	0.60	0.08098	0.38730
5	0.80	0.09208	0.44721
6	1.00	0.10352	0.50000
7	1.50	0.13346	0.61237
8	2.00	0.16501	0.70711
9	2.50	0.19780	0.79057
10	3.00	0.23148	0.86603
11	3.50	0.26574	0.93541
12	4.00	0.30028	1.00000
13	4.50	0.33485	1.06066
14	5.00	0.36921	1.11803
15	6.00	0.43648	1.22474
16	8.00	0.56110	1.41421
17	10.00	0.66775	1.58114
18	12.00	0.75459	1.73205
19	14.00	0.82256	1.87083
20	16.00	0.87409	2.00000
21	19.36	0.93179	2.20000
22	23.04	0.96667	2.40000
23	27.04	0.98536	2.60000
24	31.36	0.99423	2.80000
25	35.00	0.99745	2.95804
26	40.00	0.99920	3.16228
27	45.00	0.99976	3.35410

The following R code will yield the same data plus a plot of the power function:

(R Code : powerf.R)

```
t=4
r=7
n=t*(r-1)
alpha=.05
df1=t-1
df2=n-t
L=seq(0,45,.05)
phi = sqrt(L/t)
P=1-pf(qf(1-alpha,df1,df2),df1,df2,L)
output=cbind(L,P,phi)
postscript("u:/meth2/jpgfiles/powerf2.ps",width=6,horizontal=T)
plot(x,p,type="l",main="POWER OF F-TEST VS Noncentrality Parameter",
      xlab="Noncentrality Parameter",
      ylab="POWER OF F-TEST",lab=c(20,20,7),ylim=c(0,1))

graphics.off()
```



## How Many Replications?

### Approach #1A: Specify in Terms of Precision of Estimation of $\mu_i$ ( $\sigma$ known)

Determine the minimum  $n_i$  such that our estimator  $\hat{\mu}_i$  is within  $\delta$  units of  $\mu_i$  with  $100(1 - \alpha)\%$  confidence:

$$P[|\hat{\mu}_i - \mu_i| \leq \delta] = 1 - \alpha \Rightarrow P\left[\left|\frac{\bar{X}_i - \mu_i}{\sigma_e/\sqrt{n_i}}\right| \leq \frac{\delta}{\sigma_e/\sqrt{n_i}}\right] = P\left[|Z| \leq \frac{\sqrt{n_i}\delta}{\sigma_e}\right] = 1 - \alpha \Rightarrow$$
$$\frac{\sqrt{n_i}\delta}{\sigma_e} = Z_{\alpha/2} \Rightarrow n_i = \frac{\sigma_e^2 Z_{\alpha/2}^2}{\delta^2}$$

### Approach #1B: Specify in Terms of Precision of Estimation of $\mu_i$ ( $\sigma$ unknown)

In most cases it is necessary to replace  $\sigma_e$  with an estimator and then use an iterative procedure to find  $n_i$  involving the non-central  $t$  distribution. Use R-programs and Tables from STAT 641.

For reasonably large values of  $n_i$ , using the normal distribution in place of the interactive  $t$ -distribution process will yield approximately the same results.

### Approach #2: Specify in Terms of Precision of Estimation of $\mu_i - \mu_k$

Determine the minimum  $n_i$  such that our estimator  $(\hat{\mu}_i - \hat{\mu}_k)$  is within  $\delta$  units of  $(\mu_i - \mu_k)$  with  $100(1 - \alpha)\%$  confidence: (assume  $n_i = r$  for all  $i$ )

$$P[|(\hat{\mu}_i - \hat{\mu}_k) - (\mu_i - \mu_k)| \leq \delta] = 1 - \alpha \Rightarrow$$
$$P\left[\left|\frac{(\bar{Y}_i - \bar{Y}_k) - (\mu_i - \mu_k)}{\sigma_e \sqrt{\frac{1}{r} + \frac{1}{r}}}\right| \leq \frac{\delta}{\sigma_e \sqrt{\frac{1}{r} + \frac{1}{r}}}\right] = P\left[|Z| \leq \frac{\delta}{\sigma_e \sqrt{\frac{1}{r} + \frac{1}{r}}}\right] = 1 - \alpha \Rightarrow$$
$$\frac{\delta}{\sigma_e \sqrt{\frac{1}{r} + \frac{1}{r}}} = Z_{\alpha/2} \Rightarrow r = \frac{2\sigma_e^2 Z_{\alpha/2}^2}{\delta^2}$$

In most cases it is necessary to replace  $\sigma_e$  with an estimator and then use an iterative procedure to find  $r$  involving the non-central  $t$  distribution.

For unequal sample sizes we have:

When  $n_i \neq n_k$  but  $n_i = r$  and  $n_k = mr$ , we have that

$$\frac{\delta}{\sigma_e \sqrt{\frac{1}{r} + \frac{1}{mr}}} = Z_{\alpha/2} \Rightarrow r = \frac{\frac{m+1}{m} \sigma_e^2 Z_{\alpha/2}^2}{\delta^2}$$

### Approach #3: Specify in Terms of Power

Find the minimum value of  $r = n_1 = n_2 = \dots = n_t$  such that for specified values of  $\mu_1, \mu_2, \dots, \mu_t$  and  $\sigma_e$  the power of a level  $\alpha$   $F$  test is greater than or equal to  $\gamma_o$ .

From given information, compute

$$\lambda_r^{(3)} = \frac{r \sum_{i=1}^t (\mu_i - \bar{\mu}_.)^2}{\sigma_e^2}$$

Iteratively for specified values of  $r$  compute the power  $\gamma(\lambda_r^{(3)})$  and obtain the smallest value of  $r$  such that  $\gamma(\lambda_r^{(3)}) \geq \gamma_o$ .

In the case of equal sample sizes,

$$\nu_1 = t - 1, \quad \nu_2 = t(r - 1)$$

Thus, both the non-centrality parameter,  $\lambda_r^{(3)}$  and the critical value of the F-test,  $F_{\alpha, t-1, t(r-1)}$  depend on  $r$  in your iterations.

The problem is to find the minimum  $r$  such that

$$\gamma(\lambda_r^{(3)}) = 1 - G_{\lambda_r^{(3)}}(F_{\alpha, t-1, t(r-1)}) \geq \gamma_o$$

## Approach #4: Specify in Terms of Power with constraints on $\mu_i$

In most cases the researcher will not be able to provide particular values for  $\mu_i$ . However, they will be able to specify that they want a level  $\alpha$  test with probability of at least  $\gamma_o$  of rejecting  $H_o$  whenever all effects satisfy

$$|\mu_i - \bar{\mu}| > D$$

.

In this case, assuming  $\sigma_e$  is known or we have a good guess at its value, we can determine the minimum value of  $r$  to satisfy the specification.

$$|\mu_i - \bar{\mu}| > D \text{ for all } i \Rightarrow$$

$$\lambda_r^{(4)} = \frac{r \sum_{i=1}^t (\mu_i - \bar{\mu})^2}{\sigma_e^2} > \frac{rtD^2}{\sigma_e^2}$$

The problem then becomes to find the minimum  $r$  such that

$$\gamma(\lambda_r^{(4)}) = 1 - G_{\lambda_r^{(4)}}(F_{\alpha, t-1, t(r-1)}) \geq \gamma_o$$

This approach is very restrictive because it forces all values of  $\mu_i$  to be different from  $\bar{\mu}$ . Approach # 5, on the next page is a less restrictive approach to finding the necessary sample size but Approach 5 produces a larger value of  $r$ .

- Note that  $|\mu_j - \mu_k| > D$  for all choices of  $(j, k)$  does not in general imply

$$\sum_{i=1}^t (\mu_i - \bar{\mu})^2 > tD^2 \text{ but the following does hold.}$$

- $|\mu_j - \mu_k| > D$  for all choices of  $(j, k)$  implies that  $\sum_{i=1}^t (\mu_i - \bar{\mu})^2 > (t-1)D^2$  for  $t = 3, 4$
- $|\mu_j - \mu_k| > D$  for all choices of  $(j, k)$  implies that  $\sum_{i=1}^t (\mu_i - \bar{\mu})^2 > tD^2$  for  $t > 5$

## Distribution of the Non-Central F

The non-central F distribution with dfs  $\nu_1$ ,  $\nu_2$  and non-centrality parameter  $\lambda$  has pdf

$$g_{\lambda}(x) = \frac{C(x)}{B(\nu_1/2, \nu_2/2)} e^{-\lambda/2} \nu_1^{\nu_1/2} \nu_2^{\nu_2/2} (\nu_2 + \nu_1 x)^{-(\nu_1 + \nu_2)/2} x^{(\nu_1 - 2)/2}$$

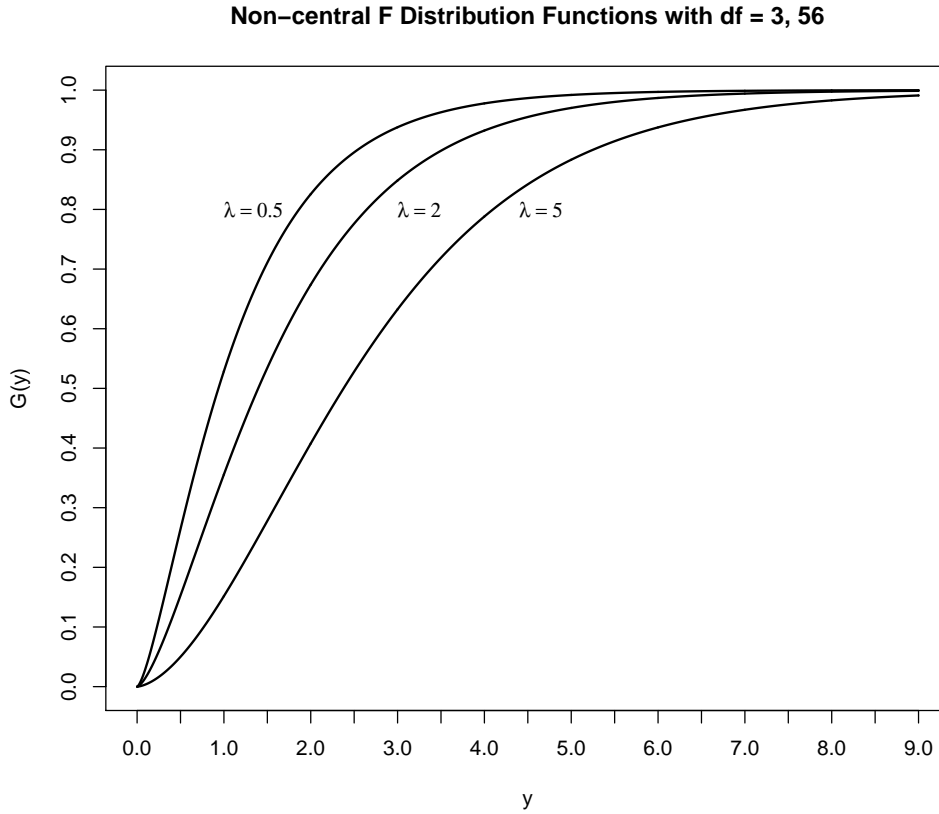
where  $B(\nu_1/2, \nu_2/2)$  is the beta function and

$$C(x) = 1 + \sum_{j=1}^{\infty} \left( \frac{(\nu_1 \lambda x)/2}{\nu_2 + \nu_1 x} \right)^j \frac{(\nu_1 + \nu_2)(\nu_1 + \nu_2 + 2)(\nu_1 + \nu_2 + 2j - 2)}{j! \nu_1(\nu_1 + 2) \cdots (\nu_1 + \nu_2 + 2j - 2)}$$

The cdf is then given by

$$G_{\lambda}(x) = \int_0^x g_{\lambda}(y) dy$$

Just by examining the function it is somewhat difficult to determine the relationship between  $G_{\lambda}(x)$  and  $\lambda$ . However, after considering numerous combinations values of  $\nu_1$ ,  $\nu_2$ ,  $\lambda$ , it was always true that for a fixed values of  $x$  as  $\lambda$  increases  $G_{\lambda}(x)$  decreases. See plot below as an illustration for  $\nu_1 = 3$ ,  $\nu_2 = 56$ ,  $\lambda = .5, 2, 5$ .





## Approach #5: Specify in Terms of Power with constraints on $\mu_i$

A less restrictive constraint on the  $\mu_i$ 's is to specify that they want a level  $\alpha$  test with probability of at least  $\gamma_o$  of rejecting  $H_o$  whenever at least one pair of treatment means differs by at least  $D$ .

That is, there exist at least one pair of means  $(\mu_j, \mu_k)$  such that  $|\mu_j - \mu_k| \geq D$ .

In this case, assuming  $\sigma_e$  is known or we have a good guess at its value, we can determine the minimum value of  $r$  to satisfy the specification. One approach is to determine the smallest possible value of  $\lambda$  to satisfy this constraint.

The minimum value of  $\lambda$  would be achieved when exactly one pair  $(\mu_j, \mu_k)$  satisfies  $(\mu_j - \mu_k) = D$  and with the remaining  $t - 2$   $\mu_i$ 's all equal to  $\frac{1}{2}(\mu_j + \mu_k)$ .

This would result in

$$\bar{\mu}_. = \frac{1}{n} \sum_{i=1}^t n_i \mu_i = \frac{r}{tr} [\mu_j + \mu_k + \frac{(t-2)}{2}(\mu_j + \mu_k)] = \frac{2(\mu_j + \mu_k) + (t-2)(\mu_j + \mu_k)}{2t} = \frac{1}{2}(\mu_j + \mu_k) \Rightarrow$$

$$\lambda_r^{(5)} = \frac{r \sum_{i=1}^t (\mu_i - \bar{\mu}_.)^2}{\sigma_e^2} = \frac{r[(t-2)0 + 2(\mu_j - \frac{1}{2}(\mu_j + \mu_k))^2]}{\sigma_e^2} \geq \frac{rD^2}{2\sigma_e^2}$$

The problem then becomes to find the minimum  $r$  such that

$$\gamma(\lambda_r^{(5)}) = 1 - G_{\lambda_r^{(5)}}(F_{\alpha, t-1, t(r-1)}) \geq \gamma_o$$

Note that

$$\lambda_r^{(4)} = \frac{rtD^2}{\sigma_e^2} > \frac{rD^2}{2\sigma_e^2} = \lambda_r^{(5)}$$

Also, for a fixed value of  $r$  the power increases as  $\lambda_r^{(*)}$  increases, therefore we will obtain a larger value for  $r$  in Approach 5 than in Approach 4.

Also, in Approach 4, we are requiring all  $t$  treatment effects to be at least  $D$  whereas in Approach 5 only one of more effects needs to exceed  $D$ .

Approach 5 in most cases is the more reasonable approach. Although, there may be cases in which the researcher will require the specification given in Approach 4.

Both approaches allow us to compute the sample size for specified parameters in the situation where the researcher can not completely specify the values of the population means,  $\mu_i$ 's in the alternative.

### Approach 3: SAScode: repsizeApproach3.sas

The following example using SAS code will illustrate Approaches 3 with the following specifications: Determine the sample size,  $r$ , such that the power of an  $\alpha = .05$  test is at least .90 when  $\mu_1 = 6.5$ ,  $\mu_2 = 6$ ,  $\mu_3 = 6$ ,  $\mu_4 = 5.5$ . The researcher specifies:

$$t = 4, \quad r_1 = \cdots = r_4 = r, \quad \alpha = .05, \quad \mu_1 = 6.5, \quad \mu_2 = 6, \quad \mu_3 = 6, \quad \mu_4 = 5.5, \quad \sigma_e^2 = .116, \quad \gamma_o \geq .90$$

```
Data;
Input r @@;
t=4;
alpha=.05;
s2=.116;
u1=6.5;
u2=6;
u3=6;
u4=5.5;
mean_u=(u1+u2+u3+u4)/t;
L=r*((u1-mean_u)**2 + (u2-mean_u)**2 + (u3-mean_u)**2 + (u4-mean_u)**2)/s2;
n1=t-1;
n2=t*(r-1);
Fcr=finv(1-alpha,n1,n2);
P=1-PROBF(Fcr,n1,n2,L);
Cards;
2 3 4 5 6 7 8 9 10
run;
proc print;
var r n1 n2 Fcr L P;
Run;
```

SAS Output:

Obs	r	n1	n2	Fcr	L	P
1	2	3	4	6.59138	8.6207	0.31843
2	3	3	8	4.06618	12.9310	0.65075
3	4	3	12	3.49029	17.2414	0.85194
4	5	3	16	3.23887	21.5517	0.94477
5	6	3	20	3.09839	25.8621	0.98127
6	7	3	24	3.00879	30.1724	0.99410
7	8	3	28	2.94669	34.4828	0.99825
8	9	3	32	2.90112	38.7931	0.99951
9	10	3	36	2.86627	43.1034	0.99987

Next we will illustrate the determination of rep sizes using Approaches 4 and 5:

#### APPROACH 4 - SAScode: repsizeApproach4.sas

SAS Program to compute sample size when the specification is that ALL EFFECTS ARE GREATER THAN D. Find the smallest  $r$  such that the power of an  $\alpha=.05$  test at  $\lambda_r$  exceeds .90 when  $|\mu_j - \mu_k| \geq .5$  for all choices of  $(j, k)$ . To solve the problem, it is necessary for the researcher to provide

$t$  = Number of Treatments = 4

$D$  = size of effect to be detected = .5

$S$  = an estimate of the experimental standard deviation(sigma) = .34

$\alpha$  = Maximum probability of Type I error = .05

$\gamma_o$  = Minimum acceptable power at  $D = .90$

```
data;
input  r @@;
t=4;    alpha=.05
u1=t-1;    u2=t*(r-1);
S=.34;
D=.5;
L=r*t*D**2/(S**2);
phi=sqrt(L/t);
C=finv(1-alpha,u1,u2);
p=1-probf(C,u1,u2,L);
cards;
3 4 5 6 7 8 9 10
run;
proc print; var D t r u2 L phi p;
run;
```

#### OUTPUT FROM APPROACH 4:

OBS	D	T	R	U2	L	PHI	P
1	0.5	4	2	4	17.3010	2.07973	0.56414
2	0.5	4	3	8	25.9516	2.54713	0.92625
3	0.5	4	4	12	34.6021	2.94118	0.99213
4	0.5	4	5	16	43.2526	3.28834	0.99936
5	0.5	4	6	20	51.9031	3.60219	0.99996
6	0.5	4	7	24	60.5536	3.89081	1.00000
7	0.5	4	8	28	69.2042	4.15945	1.00000
8	0.5	4	9	32	77.8547	4.41176	1.00000
9	0.5	4	10	36	86.5052	4.65041	1.00000

\*APPROACH 5 - SAScode: repsizeApproach5.sas

Program used to compute sample size  
when the specification is that  
AT LEAST ONE PAIR OF TREATMENT MEANS ARE AT LEAST D UNITS APART.  
It is necessary to provide  
t = Number of Treatments = 4  
D = size of effect to be detected = .5  
S = an estimate of the experimental standard deviation(sigma) =.34  
Alpha = .05; Desired Power = .90

```
data;
input  r @@;
t=4;      alpha=.05;
u1=t-1;    u2=t*(r-1);
S=.34;     D=.5;
L=r*D**2/(2*(S**2));
phi=sqrt(L/t);
c=finv(1-alpha,u1,u2);
p=1-probf(c,u1,u2,L);
cards;
2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
run;
proc print; var t r u2 L phi p;
run;
```

-----  
OUTPUT FROM APPROACH 5:

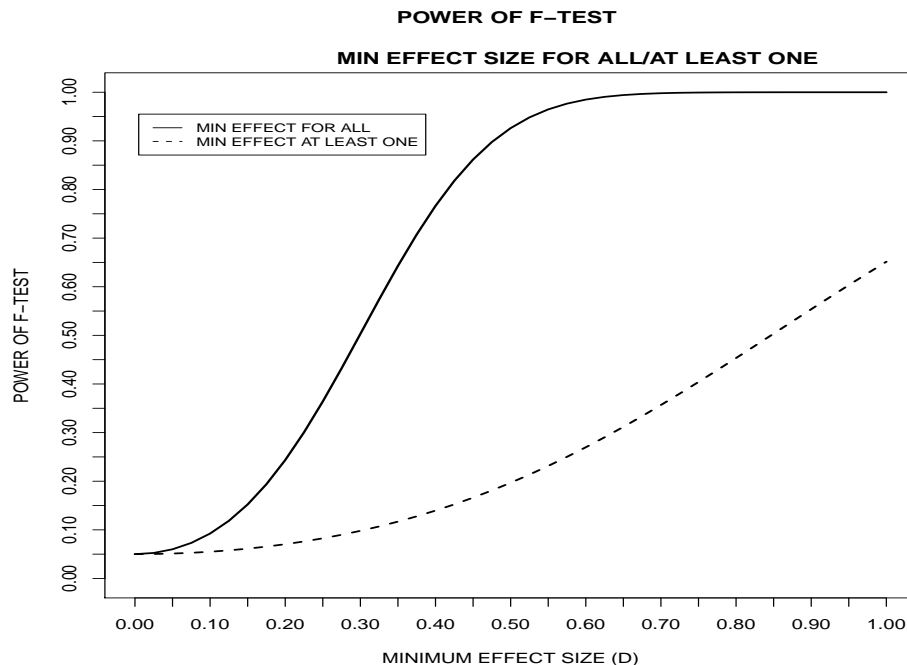
OBS	T	R	U2	L	PHI	P
1	4	2	4	2.1626	0.73529	0.11233
2	4	3	8	3.2439	0.90055	0.19718
3	4	4	12	4.3253	1.03986	0.28833
4	4	5	16	5.4066	1.16260	0.38004
5	4	6	20	6.4879	1.27357	0.46829
6	4	7	24	7.5692	1.37561	0.55032
7	4	8	28	8.6505	1.47059	0.62450
8	4	9	32	9.7318	1.55979	0.69003
9	4	10	36	10.8131	1.64417	0.74681
10	4	11	40	11.8945	1.72442	0.79518
11	4	12	44	12.9758	1.80110	0.83577
12	4	13	48	14.0571	1.87464	0.86940
13	4	14	52	15.1384	1.94541	0.89693
14	4	15	56	16.2197	2.01369	0.91923
15	4	16	60	17.3010	2.07973	0.93712

We can use Approaches 4 and 5 to compute the power of the  $F$ -test when the researcher is unable to supply specific values for the  $\mu_i$ 's. The graph given below illustrates the difference in the power curve under the specifications given in Approach 4 and 5:

( Rcode: powerf.R)

```
t=4
r=3
s=.34
df=t*(r-1)
D = seq(0,1.0,.025)
L1 = (D^2)*r*t/s^2
P1 = 1-pf(qf(.95,t-1,df),t-1,df,L1)
L2 = (D^2)*3/(2*0.11585)
P2 = 1-pf(qf(.95,t-1,df),t-1,df,L2)
postscript("u:\meth2\handouts\powerf.ps",height=8,horizontal=F)
P<-cbind(P1,P2)
matplot(D,P,type="l",main="POWER OF F-TEST \n
      MIN EFFECT SIZE FOR ALL/AT LEAST ONE",
      xlab="MINIMUM EFFECT SIZE (D)", ylab="POWER OF F-TEST",ylim=c(0,1),
      lab=c(20,20,7),col="black",lwd=2,
      cex=.5)
legend(.005,.955,lty=c(1,2),legend=
c("MIN EFFECT FOR ALL","MIN EFFECT AT LEAST ONE"),cex=.4)
graphics.off()
```

The following graph illustrates the power curve under the two types of specifications:



## Matrix Form of Cell Means and Effects Models

Background information on matrices is available:

PowerPoint

[http://dist.stat.tamu.edu/flash/Matrix%20Algebra/matrix\\_algebra\\_review.ppt](http://dist.stat.tamu.edu/flash/Matrix%20Algebra/matrix_algebra_review.ppt)

Video

[http://dist.stat.tamu.edu/flash/Matrix%20Algebra/matrix\\_algebra\\_review/matrix\\_algebra\\_review.html](http://dist.stat.tamu.edu/flash/Matrix%20Algebra/matrix_algebra_review/matrix_algebra_review.html)

**Cell Means Model:**  $y_{ij} = \mu_i + e_{ij}; \quad i = 1, \dots, t; \quad j = 1, \dots, n_i \quad n = \sum_{i=1}^t n_i$

Model in matrix form:  $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$ ,

where  $\mathbf{Y}$  is the  $n \times 1$  data vector,  $\mathbf{X}$  is the  $n \times t$  design matrix,  $\boldsymbol{\beta}$  is the  $t \times 1$  vector of parameters, and  $\mathbf{e}$  is the  $n \times 1$  vector of errors.

$$\mathbf{Y} = \begin{bmatrix} Y_{11} \\ Y_{12} \\ \vdots \\ Y_{1n_1} \\ Y_{21} \\ Y_{22} \\ \vdots \\ Y_{2n_2} \\ \vdots \\ Y_{t1} \\ Y_{t2} \\ \vdots \\ Y_{tn_t} \end{bmatrix}_{n \times 1} \quad \mathbf{X} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 \\ 0 & 0 & \cdots & 1 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix}_{n \times t} \quad \boldsymbol{\beta} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_t \end{bmatrix}_{t \times 1} \quad \mathbf{e} = \begin{bmatrix} e_{11} \\ e_{12} \\ \vdots \\ e_{1n_1} \\ e_{21} \\ e_{22} \\ \vdots \\ e_{2n_2} \\ \vdots \\ e_{t1} \\ e_{t2} \\ \vdots \\ e_{tn_t} \end{bmatrix}_{n \times 1}$$

For example,

$$Y_{12} = \mu_1 + e_{12} = (1, 0, 0, \dots, 0) \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_t \end{bmatrix} + e_{12}$$

The design matrix can also be written as:

$$\mathbf{X} = \text{Diag}[\mathbf{J}_{n_1}, \mathbf{J}_{n_2}, \dots, \mathbf{J}_{n_t}]; \quad \text{where } \mathbf{J}_{n_i} \text{ is a column vector of } n_i \text{ 1's}$$

The parameters in the matrix model are  $\beta_i = \mu_i$ , the treatment means.

## Regression Model:

The design matrix can also be obtained by considering  $t$  “explanatory variables” ( $\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_t$ ), as is done in regression models, with  $\mathbf{X}_i$  given by

$$X_{ij} = \begin{cases} 1 & \text{if } j\text{th EU receives Trt}\#i \\ 0 & \text{otherwise} \end{cases} \quad \text{for } j = 1, \dots, n; \quad i = 1, \dots, t$$

**Regression model:**  $y_j = \beta_1 X_{1j} + \beta_2 X_{2j} + \dots + \beta_t X_{tj} + e_j$ , where  $\beta_i = \mu_i$ .

Note that there is no intercept term so the design matrix to obtain the equivalence of the above model is given by

$$\text{Regression Model in matrix form: } \mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}, \quad \text{with } \mathbf{X} = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 1 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \\ 0 & 0 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix}_{n \times t}$$

The rank of  $(\mathbf{X}'\mathbf{X})$  is  $t$  because the rank of  $\mathbf{X}$  is  $t$ . Thus,  $(\mathbf{X}'\mathbf{X})^{-1}$  exists.

The least squares estimators of the model parameters are obtained from the equation:

$$\begin{aligned} \hat{\boldsymbol{\beta}} &= (\mathbf{X}'\mathbf{X})^{-1} (\mathbf{X}'\mathbf{Y}) = \begin{bmatrix} n_1 & 0 & \dots & 0 \\ 0 & n_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & n_t \end{bmatrix}^{-1} \begin{bmatrix} y_{1.} \\ y_{2.} \\ \vdots \\ y_{t.} \end{bmatrix} \\ &= \begin{bmatrix} 1/n_1 & 0 & \dots & 0 \\ 0 & 1/n_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1/n_t \end{bmatrix} \begin{bmatrix} y_{1.} \\ y_{2.} \\ \vdots \\ y_{t.} \end{bmatrix} \\ &= \begin{bmatrix} \bar{y}_{1.} \\ \bar{y}_{2.} \\ \vdots \\ \bar{y}_{t.} \end{bmatrix} = \begin{bmatrix} \hat{\mu}_1 \\ \hat{\mu}_2 \\ \vdots \\ \hat{\mu}_t \end{bmatrix} \end{aligned}$$

Thus, the LSE of the regression coefficients are identical to our AOV estimators of the cell means:

$$\hat{\beta}_i = \hat{\mu}_i$$

## Effects Model: The default model in most software packages

$$y_{ij} = \mu + \tau_i + e_{ij}; \quad i = 1, \dots, t; \quad j = 1, \dots, n_i$$

$$\text{Model in matrix form: } \mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$$

where  $\mathbf{Y}$  is the data vector,  $\mathbf{X}$  is the design matrix,  $\boldsymbol{\beta}$  is the vector of parameters, and  $\mathbf{e}$  is the vector of errors.

$$\mathbf{Y} = \begin{bmatrix} Y_{11} \\ Y_{12} \\ \vdots \\ Y_{1n_1} \\ Y_{21} \\ Y_{22} \\ \vdots \\ Y_{2n_2} \\ \vdots \\ Y_{t1} \\ Y_{t2} \\ \vdots \\ Y_{tn_t} \end{bmatrix}_{n \times 1}; \quad \mathbf{X} = \begin{bmatrix} 1 & 1 & 0 & \cdots & 0 \\ 1 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 1 & 0 & \cdots & 0 \\ 1 & 0 & 1 & \cdots & 0 \\ 1 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & \cdots & 1 \\ 1 & 0 & 0 & \cdots & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & \cdots & 1 \end{bmatrix}_{n \times (t+1)}; \quad \boldsymbol{\beta} = \begin{bmatrix} \mu \\ \tau_1 \\ \tau_2 \\ \vdots \\ \tau_t \end{bmatrix}_{(t+1) \times 1}; \quad \mathbf{e} = \begin{bmatrix} e_{11} \\ e_{12} \\ \vdots \\ e_{1n_1} \\ e_{21} \\ e_{22} \\ \vdots \\ e_{2n_2} \\ \vdots \\ e_{t1} \\ e_{t2} \\ \vdots \\ e_{tn_t} \end{bmatrix}_{n \times 1}$$

For example,

$$Y_{22} = \mu + \tau_2 + e_{22} = (1, 0, 1, \dots, 0) \begin{bmatrix} \mu \\ \tau_1 \\ \tau_2 \\ \vdots \\ \tau_t \end{bmatrix} + e_{22}$$

In this model, there are  $t + 1$  parameters:  $(\mu, \tau_1, \dots, \tau_t)$ , referred to as

- $\mu$  - the overall mean
- $(\tau_1, \dots, \tau_t)$  - treatment effects.

The effects model yields the following relationship between the treatment means and the model parameters:

$$\mu_i = E[Y_{ij}] = \mu + \tau_i$$

Thus, the effects model is using  $t + 1$  parameters,  $\mu, \tau_1, \dots, \tau_t$  to model the  $t$  treatment means  $\mu_1, \mu_2, \dots, \mu_t$ .



This results in an overparametrized model ( $t + 1$  parameters for only  $t$  treatment means) which produces the following problem. When we attempt to obtain the least squares of the model parameters, the design matrix is not of full column rank.

In fact, from examining the design matrix

$$\mathbf{X}'\mathbf{X} = \begin{bmatrix} n & n_1 & n_2 & \cdots & n_t \\ n_1 & n_1 & 0 & \cdots & 0 \\ n_2 & 0 & n_2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ n_{t-1} & 0 & \cdots & n_{t-1} & 0 \\ n_t & 0 & \cdots & 0 & n_t \end{bmatrix}_{(t+1) \times (t+1)}$$

it can be seen that the sum of columns 2 through  $t + 1$  equals column 1. Therefore, the rank of  $(\mathbf{X}'\mathbf{X})$  is  $t < t + 1$  because Columns 2 through  $t + 1$  are linearly independent.

Thus,  $(\mathbf{X}'\mathbf{X})^{-1}$  does not exist and the parameters are non-estimable.

In order to obtain the least squares estimators of the parameters, restrictions must be placed on the parameters. There are two such restrictions that are widely used, however, there are potentially many other feasible restrictions. This results in problems in the interpretation of the parameters in the effects model:

$\mu_i = \mu + \tau_i$  implies the “ $i$ th treatment effect” is given by  $\tau_i = \mu_i - \mu$ .

The sample estimates of  $\tau_i$  are interpreted as the difference between the  $i$ th treatment mean and the overall treatment mean. However, there are constraints on the  $\tau_i$ 's which are not consistent with this interpretation.

### Restriction 1: Set $\tau_t = 0$

With this restriction, there are now  $t$  parameters,  $(\mu, \tau_1, \dots, \tau_{t-1})$ .

The restriction requires a reparametrization of the model:

$$y_{ij} = \mu_i + e_{ij} = \mu + \tau_i + e_{ij}; \quad \text{for } i = 1, \dots, t-1; j = i, \dots, n_j; \quad \text{and}$$

$$\text{with } \tau_t = 0 \text{ we have } y_{tj} = \mu_t + e_{tj} = \mu + e_{tj} \quad \text{for } j = i, \dots, n_t$$

The identification of the treatment means has

$$\mu_i = \mu + \tau_i \quad \text{for } i = 1, \dots, t-1 \quad \text{and} \quad \mu_t = \mu \quad \Rightarrow$$

$$\mu = \mu_t; \quad \tau_i = \mu_i - \mu = \mu_i - \mu_t \quad \text{for } i = 1, \dots, t-1$$

The treatment effects,  $\tau_i$ 's are now the differences between the  $i$  th treatment mean and the  $t$  th treatment mean under this restriction.

The restrictions result in a new formulation of the matrix model:

$$\begin{aligned}
 \mathbf{Y} &= \begin{bmatrix} Y_{11} \\ Y_{12} \\ \vdots \\ Y_{1n_1} \\ Y_{21} \\ Y_{22} \\ \vdots \\ Y_{2n_2} \\ \vdots \\ Y_{tn_t} \end{bmatrix}_{n \times 1} &
 \mathbf{X} &= \begin{bmatrix} 1 & 1 & 0 & \cdots & 0 \\ 1 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 1 & 0 & \cdots & 0 \\ 1 & 0 & 1 & \cdots & 0 \\ 1 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & \cdots & 1 \\ 1 & 0 & 0 & \cdots & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & \cdots & 1 \\ 1 & 0 & 0 & \cdots & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & \cdots & 0 \\ 1 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & \cdots & 0 \end{bmatrix}_{n \times t} &
 \boldsymbol{\beta} &= \begin{bmatrix} \mu \\ \tau_1 \\ \tau_2 \\ \vdots \\ \tau_{t-1} \end{bmatrix}_{t \times 1} &
 \mathbf{e} &= \begin{bmatrix} e_{11} \\ e_{12} \\ \vdots \\ e_{1n_1} \\ e_{21} \\ e_{22} \\ \vdots \\ e_{2n_2} \\ \vdots \\ e_{t1} \\ e_{t2} \\ \vdots \\ e_{tn_t} \end{bmatrix}_{n \times 1}
 \end{aligned}$$

$$Y_{ij} = \mu + \tau_i + e_{ij} \quad \text{for } i = 1, 2, \dots, t-1; \quad j = 1, 2, \dots, n_i \Rightarrow \mu_i = \mu + \tau_i \quad \text{for } i < t$$

$$Y_{tj} = \mu + e_{tj} \quad \text{for } j = 1, 2, \dots, n_t \Rightarrow \mu_t = \mu$$

The design matrix is now of full column rank. The least squares estimators of the model parameters are obtained from the equation:

$$\begin{aligned}
 \hat{\boldsymbol{\beta}} &= (\mathbf{X}'\mathbf{X})^{-1} (\mathbf{X}'\mathbf{Y}) = \begin{bmatrix} n & n_1 & n_2 & \cdots & n_{t-1} \\ n_1 & n_1 & 0 & \cdots & 0 \\ n_2 & 0 & n_2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ n_{t-1} & 0 & \cdots & 0 & n_{t-1} \end{bmatrix}^{-1} \begin{bmatrix} y_{..} \\ y_{1.} \\ y_{2.} \\ \vdots \\ y_{t-1.} \end{bmatrix} \\
 &= \begin{bmatrix} \bar{y}_{t.} \\ \bar{y}_{1.} - \bar{y}_{t.} \\ \bar{y}_{2.} - \bar{y}_{t.} \\ \vdots \\ \bar{y}_{t-1.} - \bar{y}_{t.} \end{bmatrix} = \begin{bmatrix} \hat{\mu} \\ \hat{\tau}_1 \\ \hat{\tau}_2 \\ \vdots \\ \hat{\tau}_{t-1} \end{bmatrix}
 \end{aligned}$$

The estimated variances of  $\hat{\boldsymbol{\beta}}$  and  $\ell' \hat{\boldsymbol{\beta}}$  are given by

$$Var(\hat{\boldsymbol{\beta}}) = \hat{\sigma}^2 (\mathbf{X}'\mathbf{X})^{-1}; \quad Var(\ell' \hat{\boldsymbol{\beta}}) = \hat{\sigma}^2 \ell' (\mathbf{X}'\mathbf{X})^{-1} \ell$$

**EXAMPLE** An experiment consists of 4 treatments with number of reps given by

$$n_1 = 3, n_2 = 2, n_3 = 4, n_4 = 2$$

The matrix formulation of the effects model has  $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$  with

$$\mathbf{Y} = \begin{bmatrix} Y_{11} \\ Y_{12} \\ Y_{13} \\ Y_{21} \\ Y_{22} \\ Y_{31} \\ Y_{32} \\ Y_{33} \\ Y_{34} \\ Y_{41} \\ Y_{41} \end{bmatrix} \quad \mathbf{X} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \quad \boldsymbol{\beta} = \begin{bmatrix} \beta_o \\ \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} = \begin{bmatrix} \mu \\ \tau_1 \\ \tau_2 \\ \tau_3 \end{bmatrix} \quad \mathbf{e} = \begin{bmatrix} e_{11} \\ e_{12} \\ e_{13} \\ e_{21} \\ e_{22} \\ e_{31} \\ e_{32} \\ e_{33} \\ e_{34} \\ e_{41} \\ e_{41} \end{bmatrix}$$

Express the estimator of  $\mu_2$ ,  $\mu_1 - \mu_4$ , and  $\mu_1 - \mu_2$  in terms of the  $\hat{\beta}_i$ 's

- $\mu_2 = \mu + \tau_2 = \beta_o + \beta_2 = \ell' \boldsymbol{\beta}$  with  $\ell' = [1, 0, 1, 0] \Rightarrow \hat{\mu}_2 = \ell' \hat{\boldsymbol{\beta}}$  with

$$Var(\hat{\mu}_2) = \hat{\sigma}^2 \ell' (\mathbf{X}' \mathbf{X})^{-1} \ell = \hat{\sigma}^2 [1, 0, 1, 0] \begin{bmatrix} 11 & 3 & 2 & 4 \\ 3 & 3 & 0 & 0 \\ 2 & 0 & 2 & 0 \\ 4 & 0 & 0 & 4 \end{bmatrix}^{-1} \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

$$= \hat{\sigma}^2 [1, 0, 1, 0] \begin{bmatrix} .5 & -.5 & -.5 & -.5 \\ -.5 & .833 & .5 & .5 \\ -.5 & .5 & 1 & .5 \\ -.5 & .5 & .5 & .75 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

$$= \hat{\sigma}^2 (.5) = \hat{\sigma}^2 / 2 = \hat{\sigma}^2 / n_2$$

- $\mu_1 - \mu_4 = \mu + \tau_1 - \mu = \beta_1 = \ell' \boldsymbol{\beta}$  with  $\ell' = [0, 1, 0, 0] \Rightarrow \hat{\mu}_1 - \hat{\mu}_4 = \ell' \hat{\boldsymbol{\beta}}$  with

$$Var(\hat{\mu}_1 - \hat{\mu}_4) = \hat{\sigma}^2 \ell' (\mathbf{X}' \mathbf{X})^{-1} \ell = \hat{\sigma}^2 [0, 1, 0, 0] \begin{bmatrix} .5 & -.5 & -.5 & -.5 \\ -.5 & .833 & .5 & .5 \\ -.5 & .5 & 1 & .5 \\ -.5 & .5 & .5 & .75 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

$$= \hat{\sigma}^2(.833) = \hat{\sigma}^2(5/6) = \hat{\sigma}^2 \left( \frac{1}{n_1} + \frac{1}{n_4} \right)$$

- $\mu_1 - \mu_2 = \mu + \tau_1 - \mu - \tau_2 = \beta_1 - \beta_2 = \ell' \boldsymbol{\beta}$  with  $\ell' = [0, 1, -1, 0] \Rightarrow \hat{\mu}_1 - \hat{\mu}_2 = \ell' \hat{\boldsymbol{\beta}}$  with

$$Var(\hat{\mu}_1 - \hat{\mu}_2) = \hat{\sigma}^2 \ell' (\mathbf{X}' \mathbf{X})^{-1} \ell = \hat{\sigma}^2 [0, 1, -1, 0] \begin{bmatrix} .5 & -.5 & -.5 & -.5 \\ -.5 & .833 & .5 & .5 \\ -.5 & .5 & 1 & .5 \\ -.5 & .5 & .5 & .75 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ -1 \\ 0 \end{bmatrix}$$

$$= \hat{\sigma}^2(.833) = \hat{\sigma}^2(5/6) = \hat{\sigma}^2 \left( \frac{1}{n_1} + \frac{1}{n_2} \right)$$

**Restriction 2: Set**  $\sum_{i=1}^t n_i \tau_i = 0$

With this restriction, there are now  $t$  parameters,  $(\mu, \tau_1, \dots, \tau_{t-1})$  because

$$\sum_{i=1}^t n_i \tau_i = 0 \Rightarrow \tau_t = \frac{-1}{n_t} \sum_{i=1}^{t-1} n_i \tau_i.$$

The restriction requires a reparameterization of the model:

$$y_{ij} = \mu_i + e_{ij} = \mu + \tau_i + e_{ij}; \quad \text{for } i = 1, \dots, t-1; j = i, \dots, n_j; \quad \text{and}$$

$$y_{tj} = \mu_t + e_{tj} = \mu + \tau_t + e_{tj} = \mu - \frac{1}{n_t} \sum_{i=1}^{t-1} n_i \tau_i + e_{tj} \quad \text{for } j = i, \dots, n_t$$

The identification of the treatment means has

$$\mu_i = \mu + \tau_i \quad \text{for } i = 1, \dots, t-1 \quad \text{and} \quad \mu_t = \mu - \frac{1}{n_t} \sum_{i=1}^{t-1} n_i \tau_i.$$

$$\sum_{i=1}^t n_i \mu_i = n\mu + \sum_{i=1}^{t-1} n_i \tau_i - \sum_{i=1}^{t-1} n_i \tau_i \Rightarrow \mu = \frac{1}{n} \sum_{i=1}^t n_i \mu_i \Rightarrow \tau_i = \mu_i - \mu.$$

Under this restriction, the treatment effects,  $\tau_i$ 's are now the differences between the  $i$ th treatment mean and the weighted average of the treatment means. The population parameter  $\mu$  now depends on the sample sizes which is somewhat a limitation for this restriction.

The restrictions result in a new formulation of the matrix model:

$$\mathbf{Y} = \begin{bmatrix} Y_{11} \\ Y_{12} \\ \vdots \\ Y_{1n_1} \\ Y_{21} \\ Y_{22} \\ \vdots \\ Y_{2n_2} \\ \vdots \\ Y_{t1} \\ Y_{t2} \\ \vdots \\ Y_{tn_t} \end{bmatrix}_{n \times 1} \quad \mathbf{X} = \begin{bmatrix} 1 & 1 & 0 & \cdots & 0 \\ 1 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 1 & 0 & \cdots & 0 \\ 1 & 0 & 1 & \cdots & 0 \\ 1 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & \cdots & 1 \\ 1 & 0 & 0 & \cdots & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & \cdots & 1 \\ 1 & \frac{-n_1}{n_t} & \frac{-n_2}{n_t} & \cdots & \frac{-n_{t-1}}{n_t} \\ 1 & \frac{-n_1}{n_t} & \frac{-n_2}{n_t} & \cdots & \frac{-n_{t-1}}{n_t} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \frac{-n_1}{n_t} & \frac{-n_2}{n_t} & \cdots & \frac{-n_{t-1}}{n_t} \end{bmatrix}_{n \times t} \quad \boldsymbol{\beta} = \begin{bmatrix} \mu \\ \tau_1 \\ \tau_2 \\ \vdots \\ \tau_{t-1} \end{bmatrix}_{t \times 1} \quad \mathbf{e} = \begin{bmatrix} e_{11} \\ e_{12} \\ \vdots \\ e_{1n_1} \\ e_{21} \\ e_{22} \\ \vdots \\ e_{2n_2} \\ \vdots \\ e_{t1} \\ e_{t2} \\ \vdots \\ e_{tn_t} \end{bmatrix}_{n \times 1}$$

The design matrix is now of full column rank. The least squares estimators of the model parameters are obtained from the equation:

$$\begin{aligned}\hat{\beta} &= (\mathbf{X}'\mathbf{X})^{-1}(\mathbf{X}'\mathbf{Y}) \\ &= \begin{bmatrix} n & 0 & 0 & \cdots & 0 \\ 0 & n_1(1 + \frac{n_1}{n_t}) & n_1n_2/n_t & \cdots & n_1n_{t-1}/n_t \\ 0 & n_1n_2/n_t & n_2(1 + \frac{n_2}{n_t}) & \cdots & n_2n_{t-1}/n_t \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & n_1n_{t-1}/n_t & n_2n_{t-1}/n_t & \cdots & n_{t-1}(1 + \frac{n_{t-1}}{n_t}) \end{bmatrix}^{-1} \begin{bmatrix} y_{..} \\ y_{1.} - n_1y_t. \\ y_{2.} - n_2y_t. \\ \vdots \\ y_{t-1.} - n_{t-1}y_t. \end{bmatrix} \\ &= \begin{bmatrix} \bar{y}_{..} \\ \bar{y}_{1.} - \bar{y}_{..} \\ \bar{y}_{2.} - \bar{y}_{..} \\ \vdots \\ \bar{y}_{t-1.} - \bar{y}_{..} \end{bmatrix} = \begin{bmatrix} \hat{\mu} \\ \hat{\tau}_1 \\ \hat{\tau}_2 \\ \vdots \\ \hat{\tau}_{t-1} \end{bmatrix}\end{aligned}$$

Comments:

1. Under both Restriction 1,  $\tau_t = 0$  and Restriction 2,  $\sum_{i=1}^t n_i \tau_i = 0$ , we obtain the LSE of  $\mu_i$  by substituting in the LSE of  $\mu$  and  $\tau_i$ .
2. Restriction 2 is no longer widely used, although you will still find this restriction in a number of textbooks. This restriction involves defining a population parameter  $\mu = 1/n \sum_{i=1}^t n_i \mu_i$  which is a function of the sample sizes. Thus, it is difficult to interpret the meaning of the effect parameters,  $\tau_i = \mu_i - \mu$  because the values of  $\tau_i$ 's would vary across experiments depending on the values of the sample sizes even when the treatment means did not change.
3. When the experiments are balanced ( $n_1 = n_2 = \cdots = n_t$ ), the problem with the definition of  $\mu$  does not occur. Under a balanced experiment,  $\mu = \frac{1}{n} \sum_{i=1}^t n_i \mu_i = \frac{1}{t} \sum_{i=1}^t \mu_i$ , which would not depend on the sample sizes,  $n_1, \dots, n_t$ .
4. Restriction 1 does not have the definitional problem that was observed in Restriction 2. Also, most statistical software packages use Restriction 1. We will use Restriction 1 throughout this course.
5. When using various software packages to obtain the LSE of the  $\tau_i$ 's (effects), make sure to check which restriction has been imposed on the  $\tau_i$ 's so that the correct interpretation can be made about the estimates.

6. In the effects model, the LSE of  $\mu$ ,  $\tau_1$ ,  $\tau_2$ , ...,  $\tau_t$  are not uniquely determined because their solution to the normal equations will depend on which restriction is imposed on the parameters. This can be seen in the output from SAS:

The GLM Procedure

Class	Levels	Values
T	4	COMM VAC MIXED CO2

Number of Observations Read	20
Number of Observations Used	15

Dependent Variable: TCOUNT

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	51.62044500	17.20681500	155.17	<.0001
Error	11	1.21975500	0.11088682		
Corrected Total	14	52.84020000			

Parameter	Estimate	Standard Error	t Value	Pr >  t
Intercept	3.198000000 B	0.14892066	21.47	<.0001
T COMM	4.282000000 B	0.24318642	17.61	<.0001
T VAC	2.302000000 B	0.24318642	9.47	<.0001
T MIXED	4.144500000 B	0.22338099	18.55	<.0001
T CO2	0.000000000 B	.	.	.

NOTE: The X'X matrix has been found to be singular, and a generalized inverse was used to solve the normal equations. Terms whose estimates are followed by the letter 'B' are not uniquely estimable.

Least Squares Means

	TCOUNT	Standard Error	Pr >  t
T	LSMEAN		
COMM	7.48000000	0.19225575	<.0001
VAC	5.50000000	0.19225575	<.0001
MIXED	7.34250000	0.16649836	<.0001
CO2	3.19800000	0.14892066	<.0001
Overall	5.62000000		

## Derivation of Distribution of AOV F-Statistic

The following theorems will be stated without proof. (See STAT 612 or STAT 616 for proofs or one of the following textbooks.)

1. *Methods and Applications of Linear Models*, by Ronald Hocking.
2. *Linear Models for Unbalanced Data*, by Shayle Searle.
3. *Theory and Applications of Linear Models*, by Frank Graybill.

**Theorem 1** Let  $\mathbf{Y}' = [y_1, y_2, \dots, y_p]$  be distributed as a  $p$ -dimensional normal random vector,  $N_p(\boldsymbol{\mu}, \mathbf{V})$ , where  $\boldsymbol{\mu}' = [\mu_1, \mu_2, \dots, \mu_p]$ , with  $\mu_i = E[y_i]$  and  $\mathbf{V}$  is a  $p \times p$  variance-covariance matrix, that is,  $\mathbf{V} = (\sigma_{ij})$  with  $\sigma_{ij} = \text{Cov}(y_i, y_j)$ ,  $\sigma_{ii} = \text{Var}(y_i)$ . Let  $\mathbf{A}$  be a  $p \times p$  matrix. If  $\mathbf{AV}$  is an idempotent matrix, that is,  $\mathbf{AVAV} = \mathbf{AV}$ , then the quadratic form  $\mathbf{Y}'\mathbf{A}\mathbf{Y}$  has a noncentral chisquare distribution with  $df = r = \text{rank}(\mathbf{A})$  and noncentrality parameter,  $\lambda = \boldsymbol{\mu}'\mathbf{A}\boldsymbol{\mu}$ . It then follows that  $E[\mathbf{Y}'\mathbf{A}\mathbf{Y}] = r + \lambda$  and  $\text{Var}[\mathbf{Y}'\mathbf{A}\mathbf{Y}] = 2r + 4\lambda$ .

**Theorem 2** Let  $\mathbf{Y}$  be distributed  $N_p(\boldsymbol{\mu}, \mathbf{V})$  and denote the two quadratic forms  $W_1 = \mathbf{Y}'\mathbf{A}\mathbf{Y}$  and  $W_2 = \mathbf{Y}'\mathbf{B}\mathbf{Y}$ . If  $\mathbf{AVB} = \mathbf{0}$ , then  $W_1$  and  $W_2$  are independent.

We will now use Theorems 1 and 2 to obtain results concerning the distribution of the AOV F-test.

Model:  $y_{ij} = \mu_i + e_{ij}$  for  $i = 1, \dots, t$ ;  $j = 1, \dots, n_i$ ; and  $n = \sum_{i=1}^t n_i$ , where  $e_{ij}$ 's are iid  $N(0, \sigma_e^2)$ . Let  $\mathbf{Y}$  be the data vector,

$$\mathbf{Y}' = [Y_{11}, Y_{12}, \dots, Y_{1n_1}, Y_{21}, Y_{22}, \dots, Y_{2n_2}, \dots, Y_{t1}, Y_{t2}, \dots, Y_{tn_t}]_{n \times 1}$$

It is observed that  $\mathbf{Y}$  is distributed  $N_n(\boldsymbol{\mu}, \mathbf{V})$  with  $\mathbf{V} = \sigma_e^2 \mathbf{I}_n$ , where  $\mathbf{I}_n$  is a  $n$ -dimensional identity matrix.

**Notation** Let

1.  $\mathbf{J}_m$  be a  $m \times 1$  vector of all 1's
2.  $\mathbf{K}_m = \mathbf{J}_m \mathbf{J}_m'$ , a  $m \times m$  matrix of all 1's
3.  $\bar{\mathbf{K}}_m = \frac{1}{m} \mathbf{K}_m$ , a  $m \times m$  matrix with all values equal to  $\frac{1}{m}$
4.  $\mathbf{D}$  be a  $n \times n$  matrix with the  $t$  matrices  $\bar{\mathbf{K}}_{n_1}, \bar{\mathbf{K}}_{n_2}, \dots, \bar{\mathbf{K}}_{n_t}$  on its diagonal and 0's in all other cells.



## Express $SS_{TRT}$ and $SSE$ as Quadratic Forms

$$SS_{TRT} = \sum_{i=1}^t n_i [\bar{y}_{i.} - \bar{y}_{..}]^2 = \mathbf{Y}' \mathbf{A}_1 \mathbf{Y}, \text{ with } \mathbf{A}_1 = \mathbf{D} - \bar{\mathbf{K}}_n$$

$$SSE = \sum_{i=1}^t \sum_{j=1}^{n_i} [y_{ij} - \bar{y}_{i.}]^2 = \mathbf{Y}' \mathbf{A}_2 \mathbf{Y}, \text{ with } \mathbf{A}_2 = \mathbf{I}_n - \mathbf{D}$$

To obtain the sampling distribution of  $SS_{TRT}$  and  $SSE$ , we need to verify the following results:

Result 1.  $\mathbf{A}_1 \mathbf{I}_n$  is idempotent:

$$\begin{aligned} (\mathbf{A}_1 \mathbf{I}_n) (\mathbf{A}_1 \mathbf{I}_n) &= (\mathbf{D} - \bar{\mathbf{K}}_n) \mathbf{I}_n (\mathbf{D} - \bar{\mathbf{K}}_n) \mathbf{I}_n \\ &= \mathbf{D}\mathbf{D} - \mathbf{D}\bar{\mathbf{K}}_n - \bar{\mathbf{K}}_n\mathbf{D} + \bar{\mathbf{K}}_n\bar{\mathbf{K}}_n \\ &= \mathbf{D} - \bar{\mathbf{K}}_n - \bar{\mathbf{K}}_n + \bar{\mathbf{K}}_n = \mathbf{D} - \bar{\mathbf{K}}_n = \mathbf{A}_1 \mathbf{I}_n \end{aligned}$$

Result 2.  $\mathbf{A}_2 \mathbf{I}_n$  is idempotent:

$$\begin{aligned} (\mathbf{A}_2 \mathbf{I}_n) (\mathbf{A}_2 \mathbf{I}_n) &= (\mathbf{I}_n - \mathbf{D}) \mathbf{I}_n (\mathbf{I}_n - \mathbf{D}) \mathbf{I}_n \\ &= \mathbf{I}_n - \mathbf{D} - \mathbf{D} + \mathbf{D}\mathbf{D} = \mathbf{I}_n - \mathbf{D} = \mathbf{A}_2 \mathbf{I}_n \end{aligned}$$

Result 3.  $\text{Rank}(\mathbf{A}_1) = \text{rank}(\mathbf{D} - \bar{\mathbf{K}}_n) = t - 1$

Result 4. Let  $\boldsymbol{\mu}' = (\mu_1 \mathbf{J}'_{n_1}, \mu_2 \mathbf{J}'_{n_2}, \dots, \mu_t \mathbf{J}'_{n_t})$ , then

$$\begin{aligned} \boldsymbol{\mu}' \mathbf{A}_1 \boldsymbol{\mu} &= \boldsymbol{\mu}' (\mathbf{D} - \bar{\mathbf{K}}_n) \boldsymbol{\mu} \\ &= \boldsymbol{\mu}' \mathbf{D} \boldsymbol{\mu} - \boldsymbol{\mu}' \bar{\mathbf{K}}_n \boldsymbol{\mu} \\ &= \sum_{i=1}^t n_i \mu_i^2 - n \left( \frac{1}{n} \sum_{i=1}^t n_i \mu_i \right)^2 = \sum_{i=1}^t n_i (\mu_i - \bar{\mu}_{..})^2 \end{aligned}$$

Result 5.

$$\begin{aligned} \boldsymbol{\mu}' \mathbf{A}_2 \boldsymbol{\mu} &= \boldsymbol{\mu}' (\mathbf{I}_n - \mathbf{D}) \boldsymbol{\mu} \\ &= \boldsymbol{\mu}' \boldsymbol{\mu} - \boldsymbol{\mu}' \mathbf{D} \boldsymbol{\mu} \\ &= \sum_{i=1}^t n_i \mu_i^2 - \sum_{i=1}^t n_i \mu_i^2 = 0 \end{aligned}$$

Result 6.  $\text{Rank}(\mathbf{A}_2) = \text{rank}(\mathbf{I}_n - \mathbf{D}) = n - t$

Result 7.

$$\begin{aligned}\mathbf{A}_2 \mathbf{I}_n \mathbf{A}_1 &= (\mathbf{I}_n - \mathbf{D}) \mathbf{I}_n (\mathbf{D} - \bar{\mathbf{K}}_n) \\ &= \mathbf{D} - \bar{\mathbf{K}}_n - \mathbf{D}\mathbf{D} + \mathbf{D}\bar{\mathbf{K}}_n \\ &= \mathbf{D} - \bar{\mathbf{K}}_n - \mathbf{D} + \bar{\mathbf{K}}_n = 0\end{aligned}$$

Using Results 1-5 and the two theorems, the following distributional results are obtained:

**D1.**  $\frac{1}{\sigma_e^2} SS_{TRT} = \mathbf{Y}' \left( \frac{1}{\sigma_e^2} \mathbf{A}_1 \right) \mathbf{Y}$  has a noncentral chisquare distribution with  $df = t - 1$  and noncentrality paramter given by: let  $\boldsymbol{\mu}' = (\mu_1 \mathbf{J}'_{n_1}, \mu_2 \mathbf{J}'_{n_2}, \dots, \mu_t \mathbf{J}'_{n_t})$ , then

$$\lambda = \boldsymbol{\mu}' \left( \frac{1}{\sigma_e^2} \mathbf{A}_1 \right) \boldsymbol{\mu} = \frac{1}{\sigma_e^2} \boldsymbol{\mu}' (\mathbf{D} - \bar{\mathbf{K}}_n) \boldsymbol{\mu} = \frac{1}{\sigma_e^2} \sum_{i=1}^t n_i (\mu_i - \bar{\mu})^2$$

- Justification:  $\mathbf{Y}$  is distributed  $N_n(\boldsymbol{\mu}, \sigma_e^2 \mathbf{I}_n)$ .

$$\left( \frac{1}{\sigma_e^2} \mathbf{A}_1 \right) V = \left( \frac{1}{\sigma_e^2} \mathbf{A}_1 \right) (\sigma_e^2 \mathbf{I}_n) = \mathbf{A}_1 \mathbf{I}_n. \text{ Result 1 shows that } \mathbf{A}_1 \mathbf{I}_n \text{ is idempotent.}$$

Thus, Theorem 1 along with Results 3 and 4 yield the stated distributional result.

**D2.**  $\frac{1}{\sigma_e^2} SSE = \mathbf{Y}' \left( \frac{1}{\sigma_e^2} \mathbf{A}_2 \right) \mathbf{Y}$  has a central chisquare distribution with  $df = n - t$

- Justification:  $\mathbf{Y}$  is distributed  $N_n(\boldsymbol{\mu}, \sigma_e^2 \mathbf{I}_n)$ .

$$\left( \frac{1}{\sigma_e^2} \mathbf{A}_2 \right) V = \left( \frac{1}{\sigma_e^2} \mathbf{A}_2 \right) (\sigma_e^2 \mathbf{I}_n) = \mathbf{A}_2 \mathbf{I}_n. \text{ Result 2 shows that } \mathbf{A}_2 \mathbf{I}_n \text{ is idempotent .}$$

Thus, Theorem 1 along with Results 5 and 6 yield the stated distributional result.

**D3.**  $SSE$  and  $SS_{TRT}$  are independent

- Justification:  $SS_{TRT} = \mathbf{Y}' \mathbf{A}_1 \mathbf{Y}$  and  $SSE = \mathbf{Y}' \mathbf{A}_2 \mathbf{Y}$

$$\mathbf{A}_2 \mathbf{V} \mathbf{A}_1 = \mathbf{A}_2 \sigma_e^2 \mathbf{I}_n \mathbf{A}_1 = \sigma_e^2 \mathbf{A}_2 \mathbf{A}_1 = \mathbf{0}$$

The independence follows Theorem 2 and Result 7.

**D4.**  $F = \frac{MS_{TRT}}{MSE}$  has a noncentral F-distribution with  $df = t - 1, n - t$  and noncentrality parameter

$$\lambda = \frac{1}{\sigma_e^2} \sum_{i=1}^t n_i (\mu_i - \bar{\mu})^2$$

- Justification: Follows from D1-D3 after noting that

$$F = \frac{\frac{1}{\sigma_e^2} SS_{TRT} / (t - 1)}{\frac{1}{\sigma_e^2} SSE / (n - t)}$$

**D5.** Under  $H_o : \mu_1 = \dots = \mu_t$ ,  $F$  has a central F-distribution

- Justification: Follows from D1-D3.

**D6.** Let  $\mathbf{H}$  be a  $k \times t$  matrix with  $\text{rank}(\mathbf{H}) = k \leq t$ , define the Hypotheses:

$$H_o : \mathbf{H}\boldsymbol{\mu} = \mathbf{0} \text{ versus } H_1 : \mathbf{H}\boldsymbol{\mu} \neq \mathbf{0},$$

Let  $\hat{\boldsymbol{\mu}}' = (\bar{y}_{1.}, \dots, \bar{y}_{t.})$ . The test statistic

$$F = \frac{(\mathbf{H}\hat{\boldsymbol{\mu}})' \left( \mathbf{H} (\mathbf{X}'\mathbf{X})^{-1} \mathbf{H}' \right)^{-1} (\mathbf{H}\hat{\boldsymbol{\mu}}) / k}{MSE}$$

has, under  $H_o$ , an F-distribution with  $df = k, df_E$ .

- Justification:  $\mathbf{H}\hat{\boldsymbol{\mu}}$  is distributed  $N_k(\mathbf{H}\boldsymbol{\mu}, \mathbf{H}V\mathbf{H}')$ , where  $V = \sigma_e^2 \text{Diag}(\frac{1}{n_1}, \dots, \frac{1}{n_t})$ . The result then follows using arguments similar to those used to obtain D1-D3.