ANOVA Table

Source	Sum of	df	Mean	Expected	
of Variation	Squares		Square	Mean Square	
Treatment	SSTR	<i>r</i> – 1	$\frac{\text{SSTR}}{r-1}$	$\sigma^2 + \frac{\sum n_i(\mu_i - \mu_{\cdot})^2}{r - 1}$	
Error	SSE	$n_T - r$	$\frac{SSE}{n_T - r}$	σ^2	
Total	SSTO	$n_{T} - 1$	1		

Kenton Food C	Company							MSTR
Source of Variation	Sum of Squares	df	Mean Square	F	Ρ	For	os =	MSE
Treatment	588.22	3	196.07	18.59	1 2.58	52105		196.02
Error	158.2	15	10.55					
Total	746.42	18						10.55
							r a li due	18.58 ittle off to rounding

P-value of the F test is area to the right of the observed statistic F_{obs} . *Ex: Kenton Food Company* P-value = $P(F_{3,15} > 18.591)$ Null distribution of the product of the observed statistic F_{obs} . > 1 - pf(18.591, df1=3, df2=15) Fr-1, ng-r [1] 2.585007e-05

Since P < .05, reject $H_0: \mu_1 = \mu_2 = \mu_3 = \mu_4$ at level $\alpha = .05$. Conclude that at least two of the package designs differ in number of packages sold on average.

${\it F}$ Test with pre-set Type I error probability α

For $\alpha = .05$ first find the .95 quantile of the appropriate *F* distribution.

> qf(.95,df1=3,df2=15)
[1] 3.287382

Decision Rule: For a level $\alpha = .05$ test, we will reject H_0 if $F_{obs} > 3.288$

Factor Effects Model (Section 16.7) Some one-way model $Y_{ij} = \mu_{.} + \tau_{i} + \epsilon_{ij}, i = 1, ..., r; j = 1, ..., n_{i}$ where: $\mu_{i} = \mu_{.} + \tau_{i} + \epsilon_{ij}, i = 1, ..., r; j = 1, ..., n_{i}$

µ_. is the "overall mean," more accurately described as a "constant component common to all observations"

- \succ τ_i is the effect of the *i*th factor level
- ▶ the errors, ϵ_{ij} , are independent $\mathcal{N}(0, \sigma^2)$

Usually take $\mu_{.}$ to be the unweighted mean of the factor level means:

i=1

$$\mu_{\cdot} = \frac{\sum_{i=1}^{r} \mu_{i}}{r}$$

This leads to the constraint on the τ_i 's: $\sum_{i=1}^{r} \tau_i = 0$ $\sum_{i=1}^{r} \tau_i = 0$ The *factor-effects model* is a different formulation of the one-way ANOVA model, that is, it looks different from the cell-means model, but it is the **same model**.

We will use the unweighted mean for the parameter μ_{\cdot} .

Weighted mean is sometimes appropriate:

1. A car rental company is interested in average fuel consumption for a population of vehicles which has 80 percent compacts, 15 percent mid-sized and 5 percent vans.

Let μ_1 = mean fuel consumption for the population of compacts, μ_2 = mean fuel consumption for the population of mid-sized vehicles, and μ_3 = mean fuel consumption for the population of vans.

The relevant parameter is $.8\mu_1 + .15\mu_2 + .05\mu_3$.

2. If random samples were used, weights proportional to sample size would make sense.

CAUTION: Recall the formula for **C**E(MSTR): **from lec 1**

$$E(MSTR) = \sigma^{2} + \frac{\sum n_{i}(\mu_{i} - \mu_{.})^{2}}{r - 1}$$

where $\mu_{.}$ is the weighted mean with weights proportional to the number of observations in the group (n_i) . This is a different definition of $\mu_{.}$.

Show $\sum_{i=1}^{r} \tau_i = 0$.

Keep straight which the to use from the situation.



The design matrix is **not full rank**

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Recall, this means that one of the columns can be expressed as a linear combination of the other columns; for example,

TAKE2 - WILL WORK Linear model approach to factor effects model

We will take the approach of solving for one of the τ 's in terms of the others. In the example, take $\tau_4 = -\tau_1 - \tau_2 - \tau_3$ Parameter vector:

 $oldsymbol{eta} = egin{pmatrix} & & & \ & au_1 \\ & & au_2 \end{bmatrix}$

Design matrix:

XB

Exercise (1) Cell means model
for a case of
$$r=3$$
 $n=2$
 $\beta = (\chi'\chi)^{-1} \chi' \gamma$ is the LS. estimate.
Show $\beta = \begin{pmatrix} \overline{Y_{1.}} \\ \overline{Y_{2.}} \\ \overline{Y_{3.}} \end{pmatrix}$
where $\overline{Y_{1.}} = \frac{Y_{\overline{u}} + Y_{\overline{12}}}{2}$.
(2) Do same thing for factor-effects
model.