

MATH 4720 / MSSC 5720

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Chapter 9



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MULTIPLE COMPARISON (POST HOC ANOVA)

- In the ANOVA we test

$$H_0: \mu_1 = \mu_2 = \cdots = \mu_t$$

$$H_a: \mu_i \neq \mu_j \text{ for some pairs } (i, j)$$

- If we reject H_0 in favor of H_a , then the question arises that for what pairs $\mu_i \neq \mu_j$.

- **Now**, we want to test

$$H_0^{ij}: \mu_i = \mu_j$$

$$H_a^{ij}: \mu_i \neq \mu_j$$

- for all pairs using, say, two-sample t-statistics.

MULTIPLE COMPARISON CONT'D

- $$t_{ij} = \frac{\bar{y}_i - \bar{y}_j}{s_p \sqrt{\left(\frac{1}{n_i} + \frac{1}{n_j}\right)}} \text{ for all pairs } (i, j)$$
- We will be testing many hypotheses. For example, if there are 5 treatments, there will be 10 hypotheses.
- If each hypothesis is tested at $\alpha = 0.05$, there is a good chance that one hypothesis will be falsely rejected.
- For illustration, suppose you are testing 100 hypothesis each at $\alpha = 0.05$, and suppose null H_0 is true for all hypotheses, then 5 (i.e. 5%) hypothesis will be falsely rejected.
- This problem always arises due to multiplicity of hypotheses.

MULTIPLE COMPARISON CONT'D

- The problem of **multiplicity** is serious when you are testing many hypotheses, say thousands of hypotheses.
- **Example: Gene Expression Analysis**
- A data is collected on gene expressions on 10,000 genes. This kind of research is done if you are trying to find genes responsible for cancer. If those genes are correctly detected, you can study their structure and come up with a cure.
- $H_0^i: \mu_i = 0$ vs. $H_a^i: \mu_i \neq 0$, $i = 1, 2, \dots, 10000$
- If we test each of the hypotheses at $\alpha = 0.05$, then 5% of them (**500 hypotheses**) will be falsely discovered even if all nulls are true.

FAMILYWISE ERROR RATE (FEW)

- Instead of using Type-I error rate, we should use a different type of error rate

- $\alpha_F = \text{P(Falsely reject at least one hypotheses)}$

- If there are m hypotheses each tested at α_I , then approximately

- $\alpha_F \leq 1 - (1 - \alpha_I)^m$

- Or we can say: $\alpha_F \leq m * \alpha_I$

- This implies that

- if $\alpha_I = \frac{0.05}{m}$, then $\alpha_F \leq 0.05$.

TABLE 9.5

A comparison of the familywise error rate α_F for m independent multiple tests

| m , Number of multiple tests | α_I Probability of a Type I Error on an Individual Test | | |
|--------------------------------|--|------|------|
| | .10 | .05 | .01 |
| 1 | .100 | .050 | .010 |
| 2 | .190 | .097 | .020 |
| 3 | .271 | .143 | .030 |
| 4 | .344 | .185 | .039 |
| 5 | .410 | .226 | .049 |
| . | . | . | . |
| . | . | . | . |
| . | . | . | . |
| 10 | .651 | .401 | .096 |

BONFERRONI METHOD

- If there are m hypotheses, then we can test individual hypothesis at $\alpha = \frac{0.05}{m}$ using standard method such as t-test. This will guarantee that
- $\alpha_F = \text{P}(\text{Falsely reject at least one null}) \leq 0.05.$
- Problem with this approach: If m is large, $\alpha = \frac{0.05}{m}$ will be very small, and the chance of rejecting H_0 will be small. In other word, the power of **Bonferroni** is very poor.

BEYOND BONFERRONI

- In addition to **Bonferroni**, there are many methods of **Multiple Comparisons**. Some of them are

1. **Fisher's Least Significant Difference (LSD)**

2. **Tukey's Method**

3. **Dunnette's Method**

- Recall that the purpose is to test

- $H_0^{ij} : \mu_i = \mu_j$

- $H_a^{ij} : \mu_i \neq \mu_j$

- In all of the methods we reject H_0^{ij} if

- $|\bar{y}_i - \bar{y}_j| > C, \text{ a constant}$



BOOK EXAMPLE 9.3

- A study was done to test 5 different agents used to control weeds. Each of these agents were applied to sample of 6 one-acre plots. The hay was harvested and the total yield was recorded.

| Agent | 1 | 2 | 3 | 4 | 5 |
|-----------|-------|-------|-------|-------|-------|
| Type | None | Bio1 | Bio2 | Chm1 | Chm2 |
| \bar{y} | 1.175 | 1.293 | 1.328 | 1.415 | 1.500 |
| s | .1204 | .1269 | .1196 | .1249 | .1265 |
| n | 6 | 6 | 6 | 6 | 6 |

- The question is that if there is a difference between the agents, which agent provides the best yield.

EXAMPLE 9.3: ASSUMPTIONS

- First, we check the validity of assumptions among the agents.
- $H_0: \sigma_1 = \sigma_2 = \sigma_3 = \sigma_4 = \sigma_5$
- In R: `with(exmp9.3, levene.test(yield, agent))`
- H_0 : Data is generated from normal distribution for each type of food.

Test for Equal Variances: yield versus Agent

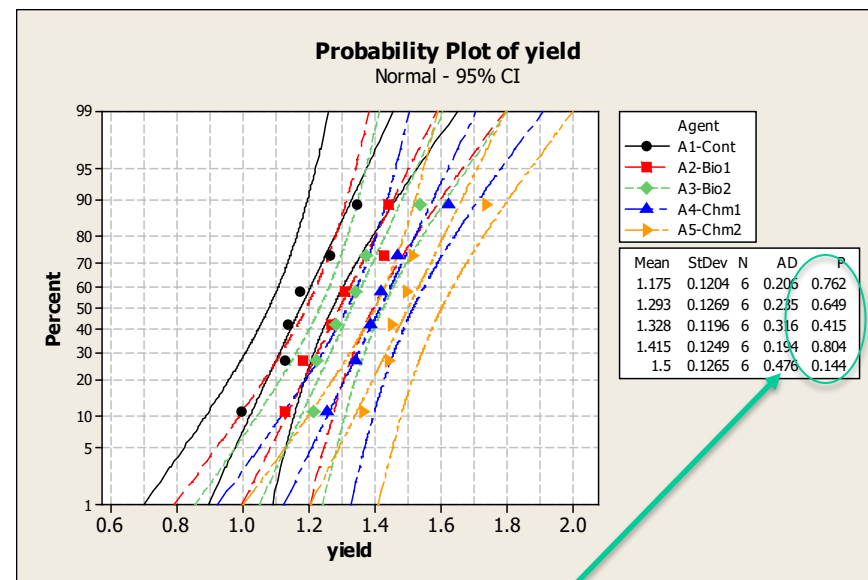
95% Bonferroni confidence intervals for standard deviations

| Agent | N | Lower | StDev | Upper |
|---------|---|-----------|----------|----------|
| A1-Cont | 6 | 0.0657789 | 0.120394 | 0.419543 |
| A2-Bio1 | 6 | 0.0693292 | 0.126892 | 0.442187 |
| A3-Bio2 | 6 | 0.0653430 | 0.119596 | 0.416762 |
| A4-Chm1 | 6 | 0.0682488 | 0.124914 | 0.435296 |
| A5-Chm2 | 6 | 0.0691068 | 0.126485 | 0.440768 |

Bartlett's Test (Normal Distribution)
Test statistic = 0.03, p-value = 1.000

Levene's Test (Any Continuous Distribution)
Test statistic = 0.04, p-value = 0.996

- Levene's test p – value is 0.996. Fail to reject equality of the variances



- Large p – values. Fail to reject Normality assumption.

EXAMPLE 9.3: ANOVA

- Next, we perform ANOVA to test if there is a difference among the agents.

- $H_0: \mu_1 = \mu_2 = \cdots = \mu_5$
 $H_a: \mu_i \neq \mu_j$ for some pairs (i, j)

➤ In R: `summary(model <- aov(yield~agent, data= exmp9.3))`

One-way ANOVA: yield versus Agent

| Source | DF | SS | MS | F | P |
|--------|----|--------|--------|------|-------|
| Agent | 4 | 0.3647 | 0.0912 | 5.96 | 0.002 |
| Error | 25 | 0.3825 | 0.0153 | | |
| Total | 29 | 0.7472 | | | |

S = 0.1237 R-Sq = 48.81% R-Sq(adj) = 40.62%

- TS. $F = \frac{SS_B/df_B}{SS_E/df_E} = 5.96$
- $p - value = P(F > 5.96) = 0.0016$
- **Reject** H_0 , and conclude that there is a difference among the agents.

- In the ANOVA, we only conclude that yields are different under different agents.
- How do we say which agent is the best? Are chemical agents better than the biological agents?
- All of these questions can be answered by all pairwise comparisons.
- $H_0^{ij} : \mu_i = \mu_j$
 $H_a^{ij} : \mu_i \neq \mu_j$
- There are 10 pairs.

WHAT TO DO?

(a) We need to control

$$\alpha_F = \mathbf{P(\text{false rejections of even one null})} = \mathbf{0.05}$$

(b) To achieve (a), we might lose power of true discovery.

- We will discuss four methods
 1. Bonferroni
 2. Fisher's LSD (Least Significant Difference)
 3. Tukey's
 4. Dunnette's
- Later we will look into the **pros** and **cons** for these methods.
Keep two things in mind.

BONFERRONI'S METHOD

- **Use TS.** $t_{ij} = \frac{\bar{y}_i - \bar{y}_j}{s_p \sqrt{\left(\frac{1}{n_i} + \frac{1}{n_j}\right)}}$ with Type-I error of $\frac{\alpha}{m}$.

- Here s_p is the pooled standard deviation that estimates the common standard deviation σ . Here, we can estimate σ by

- $\hat{\sigma} = \sqrt{MSE}$, where $MSE = \frac{SS_E}{df_E}$

- We say that pair (μ_i, μ_j) are significantly different if

- **Formula**

$$|\bar{y}_i - \bar{y}_j| > t_{\alpha/2m} \sqrt{MSE \left(\frac{1}{n_i} + \frac{1}{n_j} \right)} \quad (m \text{ is \# of hypotheses})$$

EXAMPLE 9.3: BONFERRONI'S METHOD



| Agent | 1 | 2 | 3 | 4 | 5 |
|-----------|-------|-------|-------|-------|-------|
| Type | None | Bio1 | Bio2 | Chm1 | Chm2 |
| \bar{y} | 1.175 | 1.293 | 1.328 | 1.415 | 1.500 |
| s | .1204 | .1269 | .1196 | .1249 | .1265 |
| n | 6 | 6 | 6 | 6 | 6 |

ANOVA

One-way ANOVA: yield versus Agent

| Source | DF | SS | MS | F | P |
|--------|----|--------|--------|------|-------|
| Agent | 4 | 0.3647 | 0.0912 | 5.96 | 0.002 |
| Error | 25 | 0.3825 | 0.0153 | | |
| Total | 29 | 0.7472 | | | |

S = 0.1237 R-Sq = 48.81% R-Sq(adj) = 40.62%

- $SS_E = \sum (n_i - 1)s_i^2 = 0.3825, df_E = 25$

- $MSE = \frac{SSE}{df_e} = \frac{0.3825}{25} = 0.0153$

- $\frac{\alpha}{2m} = \frac{0.05}{2*10} = 0.0025, t_{\alpha/2m} = 3.361$

- $\mu_i \neq \mu_j$ if $|\bar{y}_i - \bar{y}_j| > 3.361 \sqrt{0.0153 \left(\frac{1}{6} + \frac{1}{6} \right)} = 0.24002$

Pairwise comparisons using t tests with pooled SD

data: yield and agent

| | Bio1 | Bio2 | Chm1 | Chm2 |
|------|--------|--------|--------|--------|
| Bio2 | 1.0000 | - | - | - |
| Chm1 | 0.9999 | 1.0000 | - | - |
| Chm2 | 0.0770 | 0.2371 | 1.0000 | - |
| None | 1.0000 | 0.4208 | 0.0250 | 0.0012 |

P value adjustment method: bonferroni

- ✓ Agent 1 vs. 5: $|1.500 - 1.175| = 0.325 > 0.24002$
- ✓ Agent 1 vs. 4: $|1.415 - 1.175| = 0.240 < 0.24002$
- ✓ Agent 1 vs. 3: $|1.328 - 1.175| = 0.153 < 0.24002$
- ✓ Agent 1 vs. 2: $|1.293 - 1.175| = 0.118 < 0.24002$



- Thus, we only find that **Chm2(Agent 5)** is different from **Control(Agent 1)**.

➤ In R: `with(exmp9.3, pairwise.t.test(yield, agent, p.adj = "bonf"))`

FISHER'S LSD



- Formula:** $|\bar{y}_i - \bar{y}_j| > t_{\alpha/2} \sqrt{MSE \left(\frac{1}{n_i} + \frac{1}{n_j} \right)}$

- Example 9.3**

| Agent | 1 | 2 | 3 | 4 | 5 |
|-----------|-------|-------|-------|-------|-------|
| \bar{y} | 1.175 | 1.293 | 1.328 | 1.415 | 1.500 |

- $\frac{\alpha}{2} = 0.025$, $MSE = 0.0153$, $t_{\alpha/2} = 2.060$, $n_i = n_j = 6$

- $|\bar{y}_i - \bar{y}_j| > 2.06 * \sqrt{0.0153 \left(\frac{1}{6} + \frac{1}{6} \right)} = 0.14711$

- ✓ 1 vs. 5: $|1.500 - 1.175| = 0.325 > 0.14711$
- ✓ 1 vs. 4: $|1.415 - 1.175| = 0.240 > 0.14711$
- ✓ 1 vs. 3: $|1.328 - 1.175| = 0.153 > 0.14711$
- ✓ 1 vs. 2: $|1.293 - 1.175| = 0.118 < 0.14711$

Agent 3,4 and 5 are different from control

Agent 2 and 5 are different

- ✓ 2 vs. 5: $|1.500 - 1.293| = 0.207 > 0.14711$
- ✓ 2 vs. 4: $|1.415 - 1.293| = 0.122 < 0.14711$
- ✓ 2 vs. 3: $|1.328 - 1.293| = 0.035 < 0.14711$

```
Pairwise comparisons using t tests with pooled SD
data: yield and agent
      Bio1    Bio2    Chm1    Chm2
Bio2 0.62849 -        -        -
Chm1 0.09999 0.23449 -        -
Chm2 0.00770 0.02371 0.24511 -
None 0.11091 0.04208 0.00250 0.00012
P value adjustment method: none
```

- In R: `with(exmp9.3, pairwise.t.test(yield, agent, p.adj = "none"))` →

TUKEY'S METHOD

- For the common sample sizes, $n_i = n$

Formula: $|\bar{y}_i - \bar{y}_j| > q_\alpha(t, df_E) \sqrt{\frac{MSE}{n}}$

- where $q_\alpha(t, df_E)$ is the upper-tail value of the studentized range statistics (Given in Table 10)

Example 9.3,

- $t = 5, df_E = 25, n = 6,$
- From Table 10, $q_{0.05}(5, 25) = 4.158$

- $q_\alpha(t, df_E) \sqrt{\frac{MSE}{n}} = 4.158 * \sqrt{\frac{0.0153}{6}} = 0.20997$

- ✓ 1 vs. 5: $|1.500 - 1.175| = 0.325 > 0.20997$
- ✓ 1 vs. 4: $|1.415 - 1.175| = 0.240 > 0.20997$
- ✓ 1 vs. 3: $|1.328 - 1.175| = 0.153 < 0.20997$
- ✓ 1 vs. 2: $|1.293 - 1.175| = 0.118 < 0.20997$

Agents 4 and 5 are different from control

No Significant difference between agents 2,3,4 and 5

- ✓ 2 vs. 5: $|1.500 - 1.293| = 0.207 < 0.20997$
- ✓ 2 vs. 4: $|1.415 - 1.293| = 0.122 < 0.20997$
- ✓ 2 vs. 3: $|1.328 - 1.293| = 0.035 < 0.20997$

➤ In R: TukeyHSD(model)

| Tukey multiple comparisons of means 95% family-wise confidence level | | | | | |
|---|-------------|--------------|-------------|-----------|-------|
| Fit: aov(formula = yield ~ agent, data = exmp9_3) | | | | | |
| \$agent | | diff | lwr | upr | p adj |
| Bio2-Bio1 | 0.03498333 | -0.174742851 | 0.24470952 | 0.9876001 | |
| Chm1-Bio1 | 0.12198333 | -0.087742851 | 0.33170952 | 0.4472475 | |
| Chm2-Bio1 | 0.20698333 | -0.002742851 | 0.41670952 | 0.0543204 | |
| None-Bio1 | -0.11801667 | -0.327742851 | 0.09170952 | 0.4796636 | |
| Chm1-Bio2 | 0.08700000 | -0.122726185 | 0.29672618 | 0.7410383 | |
| Chm2-Bio2 | 0.17200000 | -0.037726185 | 0.38172618 | 0.1460064 | |
| None-Bio2 | -0.15300000 | -0.362726185 | 0.05672618 | 0.2342349 | |
| Chm2-Chm1 | 0.08500000 | -0.124726185 | 0.29472618 | 0.7567356 | |
| None-Chm1 | -0.24000000 | -0.449726185 | -0.03027382 | 0.0192441 | |
| None-Chm2 | -0.32500000 | -0.534726185 | -0.11527382 | 0.0010368 | |

TUKEY'S METHOD CONT'D

- **Remark for unequal sample sizes:**
- If sample sizes n_i s are not same, then a modified Tukey's test is

$$|\bar{y}_i - \bar{y}_j| > \frac{q_\alpha(t, df_E)}{\sqrt{2}} \sqrt{MSE \left(\frac{1}{n_i} + \frac{1}{n_j} \right)}$$

- This is also called **Tukey-Kramer's Method**.

- **Comparing with a control**
- **Assume that the sample sizes are same, i.e., $n_i = n$**

$$|\bar{y}_i - \bar{y}_c| > d_{\alpha}(t - 1, df_E) \sqrt{\frac{2MSE}{n}}$$

- **Note that this method is only used for comparing with a control.**
- **$d_{\alpha}(t - 1, df_E)$ can be obtained from Table 11.**
- **For the book example 9.3, Agent 1 is the control.**
 - $t = 5, df_E = 25, n = 6,$
 - **From Table 11, $d_{0.05}(5 - 1, 24) = 2.28$**
- $d_{\alpha}(t - 1, df_e) \sqrt{\frac{2MSE}{n}} = 2.28 * \sqrt{2 * \frac{0.0153}{6}} = 0.16282$

DUNNETT'S METHOD: EXAMPLE 9.3

- $H_0^i: \mu_i = \mu_c$
- $H_a^i: \mu_i \neq \mu_c$
- **Reject H_0^i if $|\bar{y}_i - \bar{y}_c| > 0.16282$**

| Agent | 1 | 2 | 3 | 4 | 5 |
|-----------|-------|-------|-------|-------|-------|
| \bar{y} | 1.175 | 1.293 | 1.328 | 1.415 | 1.500 |

- ✓ **5 vs. 1: $|1.500 - 1.175| = 0.325 > 0.16282$**
- ✓ **4 vs. 1: $|1.415 - 1.175| = 0.240 > 0.16282$**
- ✓ **3 vs. 1: $|1.328 - 1.175| = 0.153 < 0.16282$**
- ✓ **2 vs. 1: $|1.293 - 1.175| = 0.118 < 0.16282$**

Only the chemical agents 4 and 5 are different from control. No biological agents are different from control.

- **In R:**

- `library("DescTools")`
- `with(exmp9.3, DunnettTest(yield, agent, control = "None"))`

```
Dunnett's test for comparing several treatments with a control :
95% family-wise confidence level

$None
      diff      lwr.ci      upr.ci      pval
Biol-None 0.1180167 -0.06822422 0.3042576 0.30714
Bio2-None 0.1530000 -0.03324089 0.3392409 0.12932
Chm1-None 0.2400000 0.05375911 0.4262409 0.00887 **
Chm2-None 0.3250000 0.13875911 0.5112409 0.00044 ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

COMPARISON OF **BONFERRONI**, **LSD, TUKEY'S AND DUNNETT'S** METHODS.



- For the Book example 9.3, we had $\mu_i \neq \mu_j$ if
- Bonferroni: $|\bar{y}_i - \bar{y}_j| > 0.24002$
- Fisher's LSD: $|\bar{y}_i - \bar{y}_j| > 0.14711$
- Tukey's: $|\bar{y}_i - \bar{y}_j| > 0.20997$
- Dunnett's: $|\bar{y}_i - \bar{y}_j| > 0.16282$
- Not all method control familywise error rate. Although the power of discovery for Fisher's LSD is better than other methods, you cannot say that

P(False discovery of at least one null) = 0.05

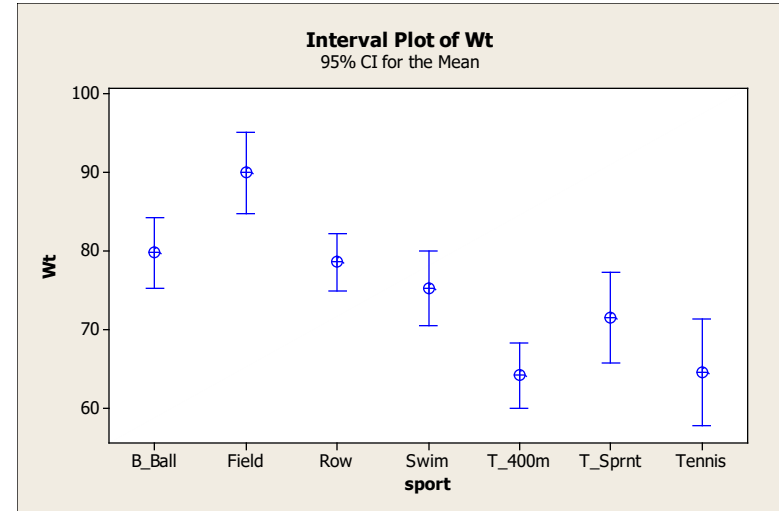
- **Confidence Interval of Wt for different Sports**

- **Individual Confidence Interval**

- Does **NOT** consider the **familywise error**

- $\bar{y}_i \pm t_{\alpha/2} * s_p \sqrt{\frac{1}{n_i}}$

- where $s_p = \frac{\sum_{i=1}^t (n_i - 1) s_i^2}{(\sum_{i=1}^t n_i) - t}$

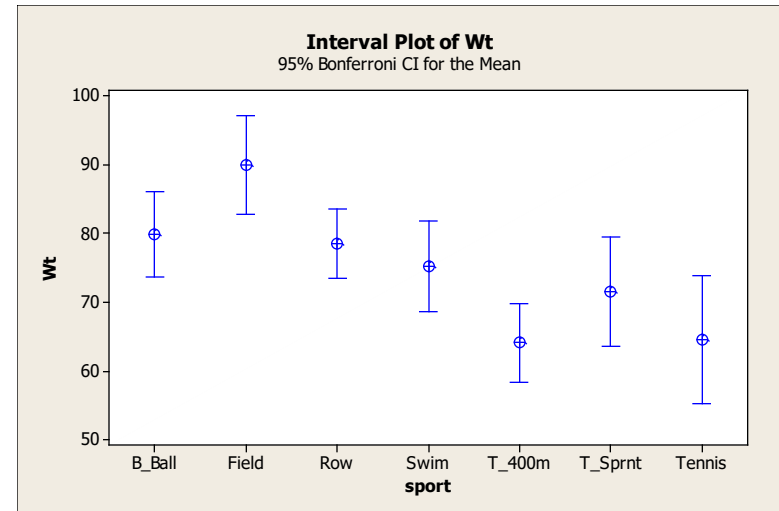


- **Bonferroni's Method**

- **Conservative**

- $\bar{y}_i \pm t_{\alpha/2m} * s_p \sqrt{\frac{1}{n_i}}$

- where $m = 7$



- **Minitab**

- Pairwise comparison of **Wt** for different **Sports**

- **Fisher's Method**

- Does **NOT** consider the **familywise error**

Grouping Information Using Fisher Method

| sport | N | Mean | Grouping |
|---------|----|-------|----------|
| Field | 19 | 89.97 | A |
| B_Ball | 25 | 79.78 | B |
| Row | 37 | 78.54 | B |
| Swim | 22 | 75.15 | B C |
| T_Sprnt | 15 | 71.51 | C D |
| Tennis | 11 | 64.47 | D E |
| T_400m | 29 | 64.05 | E |

Means that do not share a letter are significantly different.

- **Bonferroni's Method**

- **Conservative**

Grouping Information Using Bonferroni Method

| sport | N | Mean | Grouping |
|---------|----|-------|----------|
| Field | 19 | 89.97 | A |
| B_Ball | 25 | 79.78 | A B |
| Row | 37 | 78.54 | B |
| Swim | 22 | 75.15 | B C |
| T_Sprnt | 15 | 71.51 | B C D |
| Tennis | 11 | 64.47 | C D |
| T_400m | 29 | 64.05 | D |

Means that do not share a letter are significantly different.

- **Tukey's Method**

- Consider the **familywise error**

Grouping Information Using Tukey Method

| sport | N | Mean | Grouping |
|---------|----|-------|----------|
| Field | 19 | 89.97 | A |
| B_Ball | 25 | 79.78 | A B |
| Row | 37 | 78.54 | B |
| Swim | 22 | 75.15 | B C |
| T_Sprnt | 15 | 71.51 | B C D |
| Tennis | 11 | 64.47 | C D |
| T_400m | 29 | 64.05 | D |

Means that do not share a letter are significantly different.

- **Dunnett's Method**

- Comparing with a **Control** group

Grouping Information Using Dunnett Method

| Level | N | Mean | Grouping |
|------------------|----|-------|----------|
| B_Ball (control) | 25 | 79.78 | A |
| Field | 19 | 89.97 | |
| Row | 37 | 78.54 | A |
| Swim | 22 | 75.15 | A |
| T_Sprnt | 15 | 71.51 | A |
| Tennis | 11 | 64.47 | |
| T_400m | 29 | 64.05 | |

Means not labeled with letter A are significantly different from control level mean.

CONCLUSION

- Excluding Fisher LSD, the other methods control **familywise** error rate. However, Bonferroni has the poorest discovery rate. Discovery rate for the Tukey's is better than Bonferroni, but not as good as Dunnett's. However, Dunnett's used only to compare with the control.
- In other words, Bonferroni, Tukey and Dunnett's all have familywise error rate of 0.05. **If the objective is to compare only with a control, then Dunnett's is more powerful among three. Otherwise, Tukey's is more powerful than Bonferroni.**
- Although Bonferroni is not very powerful, it does have advantage that it can be used in any situation (whether it is one factor or multifactor analyses) whenever there are multiple hypotheses.