

A Study On The Importance Of Pre-Hoc And Post- Hoc ANOVA Tests In Agriculture Research

S.Sujatha, Dr.S.Mohan Prabhu

Abstract : The importance of statistical techniques in agriculture research is prominent. Data collection, numerical information, hypothesis testing, and accurate result played a vital role in the development and growth of agricultural research. One of the most powerful hypothesis testing in agriculture research is Analysis of Variance (ANOVA), which is the testing for homogeneity of means of more than two normal populations. This test can be applied to the selection of fertilizer, seed types, increase the amount of yield and equipment reliability. This paper discusses the importance of pre-hoc and post-hoc ANOVA test. This study helps to improve the efficiency of data processing, provide the accurate results, reduce the experimental error and cost, and also improving the agricultural research design.

Keywords : ANOVA, Experimental error, Post-hoc and Pre-hoc.

1 INTRODUCTION

The most powerful research is a global provider of research design and statistical consulting. It supports society, academic, corporate, medical/health and non-profit researchers in designing, collecting analyzing, reporting efficient and accurate interpretation. Research must always be of high quality in order to produce sufficient knowledge that is applicable outside of the research setting. Furthermore, the results of the research study may have implications for policy, to introduce new idea and future project implementation. Once the research results have acquired, publishing them is the moral obligation of every scientist. When statistical techniques are correctly applied, statistical analyses tend to produce accurate results. Appropriate use of statistical tools will guide the researchers in research for proper characterization, presentation, summarization and interpretation of the results of the agricultural research.

1.1 Objective of the Study

Objective of this study is to know the importance of pre and post-hoc ANOVA tests. It helps the researcher ensure that they are not drawing false conclusion from their analysis and to improve the research designs.

2 IMPORTANCE OF PRE-HOC TESTS IN ANOVA

In analyses of statistical tools all parametric tests assume some certain characteristic about the data, also known as assumptions. Violation of these assumptions changes the inference of the research and interpretation of the results. Therefore all research, whether for a journal articles thesis, or dissertation, must follow these assumptions for reliable interpretation. Depending on the parametric analysis, the assumptions vary.

2.1 Assumptions for ANOVA test

- The observations are independent,
- Parent population from which samples are taken is normal

• Author name is S.Sujatha, Assistant Professor of Statistics, Arignar Anna Government Arts College, Namakkal, Tamilnadu, India.

• Co Author name is Dr.S.Mohan Prabhu, Assistant Professor & Head, Department of Statistics, Muthayammal Arts and Science College, Rasipuram, Namakkal, Tamilnadu, India.

- Equality (homogeneity) of variances and
- Various treatment effects and environmental effects are additive in nature.

2.2 Assessing ANOVA assumptions

a. Assumptions of Independence of observation

The independence assumptions are based on the process data is collected. Appropriate data collections methods help ensure the independence assumption. Independence of observation means each participant is only counted as one observation.

b. Assumptions of Normality

Most of the parametric tests need that the assumption of normality be met. When the sample size is sufficiently large, the normality assumption is not needed at all as the Central limit theorem ensures that the distribution of disturbance term will approximately normality. When dealing with small samples, it is important to check for a possible violation of the normality assumption. If the assumption of normality is not valid, the inference of the tests will be unreliable. Normality means that the distribution of the test is normally distributed with 0 mean with 1 standard deviation and a bell shaped curve. Some of the tests for testing normality are Skewed and Kurtosis, Shapiro-Wilk's W test and Kolmogorov-Smirnov test.

2.3 Assumptions of Equality of Variances

Same variances across samples are called homogeneity of variances. The Bartlett's test and Levene's test can be used to verify this assumption.

(i) Bartlett's test

Let $S_i^2 = (1/n_i - 1) \sum (X_{ij} - \bar{X}_i)^2$ ($i = 1, 2, \dots, k$) be the unbiased estimate of the population variance, obtained from the i th sample X_{ij} , ($j = 1, 2, \dots, n_i$) and based on $v_i = (n_i - 1)$ d.f, all the k -samples being independent.

Under the null hypothesis that the samples come from the same population with variance σ^2 are homogeneous.

The Test Statistic

$$\chi^2 = \sum_{i=1 \text{ to } k} (v_i \log_e (S^2 / S_i^2)) / [1 + 1/3(K-1) \{ \sum_{i=1 \text{ to } k} 1/v_i - 1/v \}]$$

where $S^2 = (\sum v_i S_i^2) / v$, $\sum v_i = v$ and $v_i = n_i - 1$ follows chi-square distribution with $(k-1)$ degrees of freedom.

(ii) Levene's tests

Levene's test is an alternative to the Bartlett test. The Levene's test is less sensitive than the Bartlett test to departures from normality. If the data come from normal, or nearly normal, distribution, then Bartlett's test has better performance.

Let Y_{ij} is the i th sample from the j th unit. Under the null hypothesis that the samples come from the same population with variance σ^2 are homogeneous. The Test Statistic

$$F_{\text{Levene}} = \frac{((N-k) \sum_{i=1}^k (n_i (\bar{Z}_i - \bar{Z})^2)) / ((K-1) \sum_{i=1}^k \sum_{j=1}^{n_i} (Z_{ij} - \bar{Z}_i)^2)}{i=1 \text{ to } k \quad j=1 \text{ to } n_i}$$

$Z_{ij} = |Y_{ij} - \text{median } Y_i|$, \bar{Z}_i = group mean of the Z_{ij} and \bar{Z} = Over all mean of the Z_{ij} follows F distribution with $(k-1, N-k)$ degrees of freedom.

2.4 Linear Additive Model

The linear model can be written as

$$X_{ij} = \mu + \alpha_j + \epsilon_{ij}$$

where

X_{ij} denotes i th sample from the j th unit

μ is the general mean effect

α_j explains the influence of j 'th location

ϵ_{ij} are random disturbances

Hence, an observed value X_{ij} is the sum of

three parts:

- ✓ The overall mean of the observation X_{ij}
- ✓ Treatment effect
- ✓ Error effect from a normally distributed population.

When testing hypotheses, running analyses on data that has violated the assumptions of the statistical test can result in both false negative and false positive, depending on the particular assumption violated. This assumption testing helps the researcher to ensure that they are not drawing false conclusion from their analysis.

3 IMPORTANCE OF POST-HOC TESTS IN ANOVA

The testing for homogeneity of means of more than two normal populations is carried out by ANOVA. In F-test, accept Null hypothesis, it shows that treatment means are equal, if reject the Null hypothesis, it shows that treatment means are not equal. that is there are significant difference among the treatment means. But the question remains unanswered, which of them differ significantly with one another and which do not. Various post-hoc tests have been evolved for comparing differences among treatment means by a number of statisticians as named below. These tests are known as multiple range tests.

- ✓ Least significant difference test or Critical Difference test or multiple test
- ✓ Student-Newman-Keuls test.
- ✓ Duncan's multiple range test.
- ✓ Tukey's test.

3.1 Least significant difference test

The null hypothesis: $H_0: \mu_i = \mu_j$

$$C.D = t_{n-k} (\alpha/2) \left(\sqrt{MSSE \left(\frac{1}{n_i} + \frac{1}{n_j} \right)} \right)$$

when sample sizes are not equal.

If $n_i = n$ for all $i = 1, 2, \dots, k$ i.e. If each treatment replicated n times, i.e. sample sizes are equal, then

$$C.D = t_{n-k} (\alpha/2) \left(\sqrt{2MSSE/N} \right)$$

where MSSE is the Mean sum of squares due to error. Compare the absolute difference between each pair of averages to the corresponding CD. If $|\bar{y}_i - \bar{y}_j| > CD$, conclude that population means μ_i and μ_j differ significantly.

3.2 Student-Newman-Keuls test

The Student-Newman Keuls (SNK test) method is a stepwise multiple comparisons procedure used to identify sample means that are significantly different from each other. The Newman-Keuls method is similar to Tukey's range test as both procedures use studentized range statistics. Unlike Tukey's range test, the Newman-Keuls method uses different critical values for different pairs of mean comparisons. Thus, the procedure is more likely to reveal significant differences between group means and to commit type I errors by incorrectly rejecting null hypothesis when it is true. i.e. the Newman-Keuls procedure is more powerful but less conservative than Tukey's range test.

The null hypothesis:

$$H_0: \bar{X}_A = \bar{X}_B$$

where A and B could be any possible pair.

Step 1: Order the means from largest to smallest.

Step 2: Calculate the SE (Standard Error) using the mean squared error from ANOVA table. If the sample sizes are equal, use formula (i). If sample sizes are not equal, use formula (ii).

$$S_{AB} = \sqrt{\frac{MSE_{error}}{n}} \quad \text{(ii). } S_{AB} = \sqrt{\frac{MS_{Error}}{2} \left(\frac{1}{n_A} + \frac{1}{n_B} \right)}$$

Step 3: Calculate the q-value using the following formula:

$$q = \frac{\bar{X}_A - \bar{X}_B}{S_{AB}}$$

Step 4: Find the $q_{\alpha}(k, u)$ critical value from the q critical value table. The rows are number of treatments (k) and columns are the degrees of freedom (u) for MSE.

Step 5: Compare the calculated value q with critical value $q_{\alpha}(k, u)$. If the calculated value is greater than the table value then reject the null hypothesis. We conclude that the two means are not equal. If null hypothesis is accepted, the two means are equal. If two means are equal, stop the test. We conclude that there is no difference between any pairs of means. If the two means are not equal, repeat Steps 2 to 5 for the next highest and the lowest mean of $k-1$ treatments and compare the calculated value of q and the critical value of $q_{\alpha}(k-1, u)$. Continue the procedure until a pair of means that are equal.

3.3 Duncan's multiple range test

Duncan's Multiple Range (DMRT) Test is powerful than SNK test. DMRT is more useful than the LSD when larger pairs of means are being compared, especially when those values are in a table DMRT tends to require larger differences between means compared to the LSD, which guards against Type I error.

The null hypothesis:

$$H_0: \bar{X}_p = \bar{X}_1$$

Step 1: Order the means from largest to smallest of p -treatment means.

Step 2: Calculate the SE (Standard Error) using the mean squared error from ANOVA table. If the sample sizes are equal, use formula (i)

$$S_x = \sqrt{\frac{MSE_{error}}{n}}$$

For unequal sample sizes replace n by harmonic mean nh of the (n_i) in (i).

$$nh = p / \left(\sum (1/n_i) \right)$$

Step 3: Compute the expected range

$$R_p = \frac{\bar{x}_p - \bar{x}_1}{s_{\bar{x}}}$$

Step 4: Find the $r \alpha, (p, u)$ is the Duncan's Significant Range Value with parameters p and u (=MSE degrees of freedom).

Step 5: Compare the calculated value R_p with critical value $r \alpha, (p, u)$. If the calculated value is greater than the table value then reject the null hypothesis. We conclude that the two means are not equal. If null hypothesis is accepted, the two means are equal. Next the range of largest and the smallest is computed. Compare the calculated value R_{p-1} with critical value $r \alpha, (p-1, u)$. These comparison are continued until all means have been compared with largest mean.

3.4 Tukey's test

The Tukey Test also called Tukey's Honest Significant Difference test, is also a post-hoc test based on the studentized range distribution. The test compares all possible pairs of means.

The null hypothesis : $H_0 : \mu_i = \mu_j$

Step 1 : Compute Tukey's test

$$T\alpha = q_{\alpha, (k, v)} \sqrt{\frac{MSE_{error}}{n}}$$

for equal sample sizes.

Step 2 : Compute the difference of sample means $|\bar{y}_i - \bar{y}_j|$. If $|\bar{y}_i - \bar{y}_j| > T\alpha$ reject H_0 the two means are significantly different. This procedure is continuing until compares all possible pairs of means.

4 CONCLUSION

Hence an adequate knowledge of statistical methods and the appropriate use of statistical tests are important. The proper knowledge about the basic statistical methods will go a long way in improving the agricultural research designs. It is very necessary that a researcher known the basic concepts of the statistical methods used for conduct of a research study. In this regard, it is important not only to obtain the relevant knowledge of statistical methods but to improve the skills applying this knowledge in various research activities.

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